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msd

The Rebound Effect of Carbon Offsets on Air Travel

Author	Linda Meister, 14-533-475
Date of submission	05 December 2023
Reviewer	Prof. Dr. Beat Hintermann
	University of Basel, Faculty of Business and Economics, Public Economics
Focus Area	Economics

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Abstract

This study examines a possible rebound effect of carbon offsets on air travel through a stated preference survey. The study is designed as a discrete choice experiment combined with a randomised control trail. A total of 1221 participants from the German-, French- and Italian-speaking parts of Switzerland were asked to select their preferred mode choice (train, night train, car, or airplane) for an intracontinental holiday in hypothetical scenarios based on several attributes. The findings indicate that biospheric or altruistic environmental concern negatively affect the decision to fly, while egoistic environmental concern has a positive effect. There is weak evidence that integrated carbon offsets increase the probability of flight choice, leading to a direct rebound effect of 1.2%-points. In contrast, voluntary carbon offsets are found to have no effect on flight choice. The findings of this thesis suggest that fears that carbon offsets will do more damage than they will benefit are misplaced.

Statement of plagiarism

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Linda Meister, 14-533-475

05 December 2023

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1 Introduction

"The Paris Agreement", the key outcome of the UN Climate Change Conference (COP21) 2015 in Paris sets the target to limit average global warming below 2 degrees Celsius, and preferably below 1.5 degrees Celsius compared to pre-industrial levels (United Nations Framework Convention on Climate Change, 2015). This demands substantial reductions in anthropogenic greenhouse gases (GHG) by mid-century. Aviation, one of the contributing sectors of CO_2 emissions is not included in the Paris Agreement. However, the International Civil Aviation Organization (ICAO) presented a plan in 2022 to reach net zero carbon emissions from international aviation by 2050 (n.d.).

CO_2 emissions generated by aviation have notably increased in the last 20 years, peaking at around 1000 Mt in 2019 (International Energy Agency [IEA], 2023a). After a steep decline in 2020 caused by the Covid-19 pandemic, aviation emissions rebounded to 800 Mt of CO_2 in 2022, comprising over 2% of total global anthropogenic CO_2 emissions. Anticipated growth in air travel demand in coming years is expected to raise CO_2 emissions beyond 2019 levels. This is particularly concerning because aviation emissions may contribute three times more to global warming than CO_2 emissions due to nitrous oxides (NO_x) and contrail cirrus (Lee et al., 2021).

There are two major solutions to reduce GHG emissions from aviation: technological innovations such as sustainable aviation fuel (SAF) and behavioural change. Behavioural change includes less flying, the selection of efficient flight options and carbon offsetting (Gössling & Dolnicar, 2022). Unlike SAF, carbon offsetting does not reduce emissions from flights directly, but reduces the emissions elsewhere.

Carbon offsets for aviation can be divided into voluntary carbon offsets (VCOs) and integrated carbon offsets (ICOs). Voluntary carbon offsets can be defined as "simply a way for individuals or organizations, in this case airline passengers and corporate customers, to "neutralize" their proportion of an aircraft's carbon emissions on a particular journey by investing in carbon reduction projects" (International Air Transport Association [IATA], n.d., para. 2). Economically speaking, VCOs are the purchase of a public good to neutralize a public bad (Blasch & Ohndorf, 2015). In contrast, ICOs are automatically included in the ticket price and paid by the airline.

If well-managed, carbon offsetting offers several benefits. It can reduce CO_2 emissions relative to a baseline scenario (Becken & Mackey, 2017; Guix et al., 2022), direct investments to innovative climate mitigation projects, motivate policymakers to adopt more effective environmental policies (Guix et al., 2022) and contribute to sustainable development in the project region (Stiftung myclimate, n.d.).

Despite these benefits, extensive critique of carbon offsetting is being raised as well. There are for example concerns that carbon offsetting may hinder people from altering their behaviour unless its presented as a temporary or complementary strategy (Becken & Mackey, 2017; Gössling et al., 2007; Kotchen, 2009) and "could do more harm than good" (Bösehans et al., 2020, p. 2). In case of VCOs, airlines shift the responsibility to reduce the environmental impact of flying to their customers and encourage them to continue flying (Guix et al., 2022). According a meta study conducted by Kerner and Brudermann (2021) there are two main issues; the reliability of carbon offset projects and the potential behavioural rebound effects.

Dorner (2019) defines the behavioural rebound effect as "any increase in environmental damage from a decrease in pro-environmental behaviours and increase in consumption, following a decrease in marginal environmental damage from consumption" (p. 2). It can be divided into the direct and indirect rebound effect. The direct rebound effect is directly related to the activity, e.g. increased car use as a consequence of improved fuel efficiency (Kerner & Brudermann, 2021). The indirect rebound effect may result in increased environmental damage in other areas, for example if the money saved from driving a fuel efficient car is spent on buying more meat. With regards to carbon offsetting for flights, both types of rebound effects are possible. The direct rebound effect applies to flights that would not have been taken without the option of offsetting (Kerner & Brudermann, 2021). The indirect rebound effect happens, when flight passengers behave in a more carbon-intensive manner elsewhere, such as taking a helicopter ride at their holiday destination or opting for an SUV at the car rental. Additionally, if consumers are inconsistent with their offsetting by only offsetting their initial flight and later flying more without offsetting, this also constitutes an indirect rebound effect. This thesis focuses solely on the direct rebound effect.

When examining the net carbon effect, the different types of rebound effects vary (Kerner & Brudermann, 2021). If the offset projects are reliable and there are no limits to offsetting capacities, the direct rebound effect will raise the total number of air travellers, but not net emissions. However, if emissions are not entirely offset, the direct rebound effect is highly significant. On the contrary, emissions resulting from the indirect rebound effect raise net emissions in every case, as they only offset the initial flight emissions.

There is limited and conflicting empirical research regarding the rebound effect of carbon offsets. A study by Blasch and Farsi (2014) about motivations for buying carbon offsets indicates, that those who purchase VCOs also participate in other mitigation activities. The research findings suggest, that VCOs are complements rather than substitutes and that there is no evidence for a behavioural rebound effect. This is supported by Lange et al. (2017) which analysed the relationship between past offsetting behaviour and different pro-environmental activities. Their results indicate a positive correlation between offsetting and pro-environmental behaviour.

By contrast, Warburg et al.'s (2021) experimental study implies that VCOs raise the chances of consumers selecting environmentally critically products. When consumers need to decide between an environmentally friendly and an environmentally critically product, most people anticipate guilt and avoid cognitive dissonance and therefore choose the environmentally friendly product. The introduction of VCOs however alters this trend which leads to consumers now selecting the environmentally critically product. This phenomenon arises not only among consumers who purchase VCOs but also for those who do not; the option itself is sufficient to engage in environmental critical consumption choices. Furthermore, a field study conducted in the US demonstrates a clear rebound effect arising from households participating in a programme aimed at offsetting their electricity consumption (Harding & Rapson, 2019).

A recent choice experiment conducted by Bösehans et al. (2020) explores the potential of ICOs to reduce guilt and increase flight choices. The findings indicate that individuals with strong biospheric values experience more guilt when flying than others which prevents them from flying in the first place. Nonetheless, the research shows that ICOs do not reduce guilt for environmentally conscious air travellers, neither do they promote flights. The authors argue that it is possible, that for offsets to have a guilt-reducing and flight-encouraging effect, offsets must be done voluntarily and on own expenses.

Therefore, the aim of this master thesis is to address the research gap of how VCOs affect flight choice and examine the potential rebound effects of both VCOs and ICOs in a comprehensive manner. The overall research objective is how carbon offsets influence flight choice. The study examines how environmental concern influences flight choice and whether flying increases feelings of guilt among environmentally conscious travellers. ICOs and VCOs could serve as a strategy to reduce guilt and cognitive dissonance, leading to a rebound effect and potentially increased net emissions.

To investigate the research objective, an online choice experiment was developed in collaboration with Jakob Roth and Laura Schwab, PhD candidates in Public Economics at the University of Basel.

Participants were asked to imagine that they were planning a one-week holiday trip to a European destination of their choice, 700 km distant from their home. Subsequently, the participants were presented with seven choice sets in which they had to choose between four modes of transport: train, night train, (e-)car or airplane, based on several attributes. The attributes included travel cost, travel time, comfort and for airplane in addition ICOs and SAF. Participants were also informed about the GHG emissions associated with each mode of travel. The first six choice sets were part of a discrete choice experiment (DCE), while choice set seven was part of a randomised controlled trial (RCT). Individuals in the treatment group were given the opportunity to voluntarily offset their flight emissions at an additional cost. Environmental concern was assessed using a shortened and adapted version of the environmental concerns scale by Schultz (2001).

The survey was part of a LINK [1]summer holiday survey, and in line with LINK's recruitment target of 750 German-speaking, 250 French-speaking and 200 Italian-speaking participants in Switzerland, a total of 1221 completed surveys were received.

The data was analysed with a focus on flight choice and carbon offsets by conducting multiple regressions. In addition, Roth and Schwab (2023) presented first results of a discrete choice analysis with a special focus on flight and train related preferences in a study report and are currently working on a research paper. The results of this thesis imply that biospheric or altruistic environmental concern negatively affect flight choice, while a positive influence exists for voluntary carbon offsetting for those who fly. Nevertheless, offsetting does not reduce guilt and therefore does not seem to be an appropriate strategy to overcome cognitive dissonance associated with flying. Still, integrated carbon offsets weakly increase the probability of flight choice, leading to a direct rebound effect of 1.2%-points. In contrast, it appears that voluntary carbon offsets have no impact on flight choice. If integrated carbon offsets would be obliged and emissions would be effectively offset by at least 1.2%, the rebound effect of 1.2%-points will not result in an increase in net emissions. Any effective compensation beyond this threshold will result in a reduction of net emissions. The findings indicate that fear of carbon offsets doing greater damage than benefit is misplaced.

The thesis is structured as follows. Section 2 provides an overview on carbon offset projects, carbon offsets in the airline industry and sustainable aviation fuel. Section 3 follows with theory on environmental concern, motivation for voluntary carbon offset purchases and the psychological mechanisms behind the behavioural rebound effect. Subsequently, section 4 presents the study design and the data. Section 5 details the results, followed by section 6 with the discussion. Finally, the thesis is disclosed in section 7 with the conclusion.

[1] LINK is a market research institute, https://www.link.ch/en

2 Background

The following section briefly presents carbon offsetting and SAF as two strategies to mitigate GHG emissions from aviation. First, carbon offset projects and the criticisms of them are explained, followed by an overview of carbon offsetting practices in the aviation industry. Last, the technology behind SAF and its potential are described.

2.1 Carbon offset projects

The concept of carbon offsets is built on the principle of "additionality", which differentiates the emission reductions generated by an offset project from the unobserved baseline emissions that would have occurred in absence of the project (Becken & Mackey, 2017). For every ton of emissions reduced, an equivalent carbon credit can be obtained and monetized within structured regulatory systems or thorough voluntary offset markets.

There are three primary methods for carbon offsetting – energy projects, reforestation or forest protection projects (Becken & Mackey, 2017). Carbon offsets from energy projects avoid an extra ton of fossil fuel CO_2, leading to a relative decrease in atmospheric carbon stock. Investing in reforestation projects generates carbon credits by regrowing biomass on previously cleared land. Although the biomass acts as a carbon sink, reforestation cannot be considered as neutralizing the release of fossil fuels into the atmosphere because the newly grown forest replenishes the previously removed biomass carbon stock. In contrast, forest protection projects focus on implementing forest management strategies to prevent future deforestation and the associated release of biomass carbon emissions. Carbon credits are generated by the difference to the counterfactual baseline scenario, which is built by the continuation of historical deforestation trends. In practice, this means that the worse the scenario, the more carbon credits can be sold to protect the forest.

Carbon offsets projects, especially forest protection projects, have recently received a lot of negative attention in the media and their credibility has been questioned (e.g. (Aregger, 2023; Fischer & Knuth, 2023; Lüthy, 2023; Schmidli, 2023). In January 2023, joint investigation by Die Zeit, The Guardian and SourceMaterial showed that millions of unreliable carbon credit certificates have been sold over the years, as numerous forest protection projects certified by the main certification company Verra are overvalued (Fischer & Knuth, 2023). A quasi-experimental study by West et al. (2020) compares the ex-post impact estimates and the forest loss reduction claims of Verra-certified projects with ex-ante baseline assessments. Their findings suggest that the methodologies used to quantify carbon credits tend to greatly overemphasize the impacts on avoided deforestation. Meanwhile, much attention has focused on the Kariba project in Zimbabwe, one of the world's largest offset projects operated by the Swiss company South Pole. It has been criticized not only for being overvalued, but also for alleged malfeasance, non-transparent cash flows, and low local impact (Blake, 2023; Schmidli, 2023). On October 17th, 2023, Verra announced, that the Kariba project is on hold with immediate effect and that they will investigate the allegations (Verra, 2023).

2.2 Carbon offsets in airline industry

CO_2 emissions for aviation are partly offset by airlines due to regulations. Flights within and from Switzerland to the European Economic Area (EEA) have been subject to the EU emission trading system (ETS) since 2020 (Federal Office for the Environment [FOEN], 2022). The emission scheme makes CO_2 intensive activities less cost-effective and gradually lowers the total amount of emission permits. Switzerland is also part of the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) (Bundesamt für Zivilluftfahrt BAZL, 2022). CORSIA's goal is to establish a carbon-neutral growth in international air traffic. This means, total emissions may continue to increase, but all emissions above the baseline (average CO_2 emissions in the years 2019 and 2020) must be offset by the airlines. Outside the EEA there is little regulation of CO_2 emissions from domestic flights and not all countries participate in CORSIA (Carbon Offset Research and Education [CORE], no date). Additionally, neither ETS nor CORSIA account for non-CO_2 greenhouse gas emissions and the effects of combusting jet fuel at high altitudes. Therefore, it can be argued that there is still room for further offsets of aviation emissions on the voluntary carbon market.

EasyJet announced in 2019 as the first airline that it would offset 100% of its flight and operational CO_2 emissions without additional costs for passengers (Healy, 2022). However, the company ended ICOs by the end of 2022 and started offering VCOs in January 2023 (easyJet, n.d.). British Airways has been offsetting all flights within the UK since 2020 on its own expenses and provides VCOs for flights outside the UK (British Airways, 2019). To the authors knowledge, no other airline currently offers ICOs.

It is challenging to quantify the demand for VOCs in air travel. A study in 2020 found that out of 116 airlines, 41 provided VCOs to their customers; either with the option to purchase it directly on their website (37 airlines) or providing a link to a carbon offset provider (4 airlines) (Guix et al., 2022). Nevertheless, participant rates in VCOs can only be estimated, as airline passengers may purchase the offset directly during the booking process or from an offset provider of their choice. Based on a panel study conducted by Ritchie et al. (2020) in Australia, less than 10% of air travellers purchase VCOs.

The calculated climate footprint of a flight is not standardized and varies depending on the airline or carbon offset provider used. Niklass et al. (2019) investigated the algorithms of major carbon offset providers; the Swiss organizations myclimate and South Pole and the German organization atmosfair, and the calculation tool provided by the German Federal Environment Agency (UBA). The methods of the four tools vary; yet all tools encompass both the CO_2 and non-CO_2 effects on climate, in contrast to those of airlines. For instance, Lufthansa uses myclimate's methodology for their footprint algorithm but accounts for CO_2 emissions only, disregarding non-CO_2 emissions (Compensaid & Stiftung myclimate, 2020). They justify this based on scientific uncertainties regarding the radiative force of non-CO_2 emissions and the fact that the ICAO has not yet agreed upon a multiplier. Conversely, British Airways takes into account non-CO_2 effects, but solely with a radiative forcing index of 1 and deducts the emissions that are already incorporated in the UK and EU ETS (British Airways, n.d.).

In practice, a round-trip flight in economy class from Zurich to Berlin has a carbon footprint of 335 kg of CO_2 equivalent (CO_2e)[2] at myclimate[3], 175 kg of CO_2 at Lufthansa [4], and 107 kg of CO_2e at British Airways[5]. It should be noted that customers will require further research to fully comprehend the calculation of these footprints. Additionally, data on carbon offsets provided by airlines is often unclear and insufficient. According to a study from Guix et al. (2022), which examined 37 airlines providing VCOs, 56% of the carbon offsetting claims were trustworthy while 44% were misleading. Furthermore, the cost of carbon credits varies widely depending on the type of carbon offset project and location.

[2] CO_2e represent GHG (non-CO_2 emissions) whose global warming potential have been standardized to that of CO_2.

[3] https://co2.myclimate.org/de/flight_calculators/new

[4] https://lufthansa.compensaid.com/de/contribute/flights

[5] https://ba.chooose.today

2.3 Sustainable aviation fuel

Sustainable aviation fuel (SAF) is the umbrella term to describe a non-conventional aviation fuel with reduced GHG emissions that can be used with the current aircraft fleet, though there is no standardized definition yet (Bullerdiek et al., 2021). SAF can be distinguished into three main types: biomass SAF based on lipids from oil crops or waste, starch, sugar and ligno-celluloses material, electricity based SAF and hybrid SAF, which combines both types. Depending on the feedstock and technology used, GHG emission reductions relative to conventional aviation fuel can range from 55% to 98%. However, currently certified SAF are limited to a maximum blending ratio of 50% with fossil kerosine (European Union Aviation Safety [EASA], 2023). Furthermore, SAF production costs are up to six times higher than those for fossil kerosine (Barke et al., 2022).

Currently, SAF represents less than 0.1% of all aviation fuel consumed globaly (IEA, 2023b). To incite demand and encourage commercial adaptation for SAF, a number of policies are being implemented. On October 18th, 2023, the EU finalized the ReFuelEU Aviation Initiative as part of the 'Fit for 55' package (European Parliament, 2023). The EU's new regulations will require a designated percentage of SAF at all EU airports. Specifically, the minimum share of SAF must be 2% by 2025, gradually increasing to 70% by 2050. These regulations also mandate that a particular percentage of synthetic aviation fuel is necessary. As defined by the law, SAF includes biofuels, recycled carbon-based fuels and synthetic fuels like e-kerosene. Fuels originating from food or feed crops are specifically excluded. Due to the increased cost of fuel, it is expected that air fares will increase by about 8% by 2050 compared to the baseline (Soone, 2022).

While the policy introduced SAF will likely be passed on to customers through increased ticket prices, some airlines currently provide an optional surcharge for SAF as an alternative to carbon offsets (see e.g., footnote 3 and 5). Studies investigating the willingness to pay for SAF, revealed that customers are willing to pay a price premium of up to 13% (Goding et al., 2018; Rains et al., 2017; Rice et al., 2020).

3 Theory

The following section explains the concept of environmental concern, the motivation for voluntary carbon offsetting and the psychological mechanisms for a rebound effect.

3.1 Environmental concern

For decades researchers have examined environmental attitudes, norms, and environmental concern. There is compelling evidence that supports a correlation between attitudes and behaviours (Kim & Hunter, 1993; Sheppard et al., 1988). However, different conceptualizations and measures exist for environmental attitudes and concerns. A review study by Cruz and Manata (2020) suggest that scholars use the environmental concerns scale by Schultz (2001). Not only did the scale demonstrate the highest level of reliability compared to all other evaluated instruments, but it is also one of the most concise.

Schultz (2001) based his concept on the value-belief-norm-theory posited by Stern et al. (1999), which suggests that environmental concern is impacted by egoistic, social-altruistic and biospheric value orientations. Expanding on this theory, Schultz built a three-factor model for environmental concern, distinguishing the significance of valued objects organized around self (egoistic), other people (altruistic) and all living things (biospheric). An individual's environmental concern and pro-environmental behaviour may not be determined solely by their nature relatedness but could also be motivated by egoistic or altruistic motives. It is important to consider these different possible motivations when studying pro-environmental behaviour.

The literature presents varying findings on the relationship between different types of environmental concern and pro-environmental behaviour. Three studies indicate a positive correlation between biospheric environmental concern and pro-environmental behaviour (Rhead et al., 2015; Schultz, 2001; Schultz et al., 2005), consistent with recent studies by Chng and Borzino (2021) and Tamar et al. (2021) on biospheric value orientation. Contradictory, Weber et al. (2020) found that biospheric concern did not significantly influence sustainable eating habits, whereas altruistic concern did. In contrast, studies by Rhead et al. (2015) and Schultz et al. (2005) failed to establish any impact of altruistic concern on behaviour. Schultz et al. (2005) present evidence suggesting that egoistic concern negatively predicts pro-environmental behaviour. However, Chng and Borzino (2021) and Weber et al. (2020) do not support this claim.

For air travel, the concept of environmental concerns can be applied as follows:

1. Individuals with high levels of egoistic concern prioritize the impact of environmental damage on their personal well-being. In these cases, the decision to stop flying depends on whether the benefits of reducing GHG emissions outweigh the costs of choosing an alternative mode of travel. Given the abstract and uncertain consequences of climate change on an individual level, it seems unlikely that one would stop flying for this reason.

2. Individuals who possess high altruistic concern feel empathy for others who may be affected by environmental damages. They are more likely to abstain from flying when they perceive that their actions could negatively impact others. This appears to be a reasonable course of action considering the consequences of climate change on vulnerable populations and future generations.

3. Individuals who hold a strong biospheric concern prioritize the environmental impact on the overall ecosystem. They choose not to fly if they perceive the costs on the biosphere to outweigh the benefits. Considering the greenhouse gas emissions associated with air travel in comparison to other modes of transportation, such a decision is justifiable.

This leads to the following research question (RQ) and hypotheses (H):

RQ1: How does environmental concern influence an individual's flight choices?

H1a: Altruistic and biospheric environmental concern are negative predictors of choosing flight.

H1b: Egoistic environmental concern is a positive predictor of choosing flight.

3.2 Motivation for voluntary carbon offsets purchases

In recent years, extensive research has focused on the motivation for VCOs purchases (see Ritchie et al., 2021). The primary factors identified are the feeling of warm glow (Blasch & Ohndorf, 2015; Schwirplies & Ziegler, 2016), environmental concern (Blasch & Farsi, 2014; Schwirplies & Ziegler, 2016) knowledge and awareness of VCOs (Blasch & Ohndorf, 2015; Denton et al., 2020; Lu & Wang, 2018), perceived effectiveness and trust in VCOs (Denton et al., 2020) and social norms (Blasch & Farsi, 2014; Blasch & Ohndorf, 2015). Offset purchasers are more likely to be young, highly educated and to have a high income (Blasch & Farsi, 2014). Further, avoiding guilt serves as an important driver for VCOs purchases (Blasch & Farsi, 2014; Blasch & Ohndorf, 2015; Choi et al., 2018; Higham & Cohen, 2011). Additionally, "the propensity to offset and the sensitivity of offsetting costs are context-dependent" (Blasch & Farsi, 2014). Ritchie et al. (2020) discovered, that people who consistently avoid offsetting, are often frequent flyers, tend to engage in business-related travel and are likely have a high emission lifestyle. This aligns with the study conducted by Blasch and Farsi (2014), which reports a correlation between pro-environmental behaviour and offsetting.

The willingness to pay for VCOs mainly depends on the internalized norms to behave environmentally friendly and partly on income (Blasch & Ohndorf, 2015). A choice experiment by Choi et al. (2018), reveals that Australian residents experience more guilt over frequent domestic flights compared to intercontinental flights and are willing to pay a significantly higher amount for offsets on domestic flights than on intercontinental flights.

The literature review leads to the following research questions and hypotheses:

RQ2: What are an individuals' attitudes towards carbon offsets?

RQ3: How does environmental concern influence voluntary carbon offsetting?

H3a: When choosing to fly, altruistic and biospheric environmental concern are positive predictors of voluntary carbon offsetting.

H3b: When choosing to fly, egoistic environmental concern is a negative predictor of voluntary carbon offsetting.

3.3 Psychological mechanisms for a potential rebound effect

There are conflicting psychological mechanisms surrounding the potential rebound effect of carbon offsets. One concept is the cognitive dissonance theory, which is defined by Aronson (1969) the following:

> Dissonance is a negative drive state which occurs whenever an individual simultaneously holds two cognitions (ideas, beliefs, opinions) which are psychologically inconsistent. … Since the occurrence of dissonance is presumed to be unpleasant, individuals strive to reduce it by adding "consonant" cognitions or by changing one or both cognitions to make them "fit together" better: i.e., so that they become more consonant with each other. (p. 2-3)

Individuals with a climate-friendly attitude may experience cognitive dissonance, often associated with guilt, when performing environmental harmful actions, such as flying (Kerner & Brudermann, 2021; Warburg et al., 2021). This phenomenon is supported by the value-belief-norm theory, which postulates that individuals who hold strong biospheric values feel accountable for the consequences of their environmentally harmful behaviour, leading to feelings of guilt (Stern et al., 1999). McDonald et al. (2015) analysed how green air travellers alleviate the unpleasant feeling of cognitive dissonance by either changing their behaviour, such as reduce or stop flying altogether, or more commonly, altering their attitudes and justifying why they continue to fly. An additional method of reducing cognitive dissonance might be carbon offsetting – or, in other words "the voluntary carbon offset market gives consumers a way to pay for their sins of emissions" (Kotchen, 2009).

A related concept is moral licensing, as defined by Merritt et al. (2010): "Past good deeds can liberate individuals to engage in behaviours that are immoral, unethical, or otherwise problematic, behaviours that they would otherwise avoid for fear of feeling or appearing immoral" (p. 344). Therefore, previous good behaviour leads to an accumulation of moral credits, which reduces cognitive dissonance by morally licensing ongoing negative behaviour. Research has indicated the presence of moral licensing in several behaviours that include attitudes towards job hiring, racism, charity donations and environmentally-conscious consumption (Blanken et al., 2015). Consequently, carbon offsetting could operate as a moral licensing strategy. The "morally good behaviour" of offsetting could license the "immoral behaviour" of flying (Kerner & Brudermann, 2021). Nevertheless, moral licensing can manifest in both similar and diverse domains. A study by Mazar and Zhong (2010) highlights, that people who purchase green products, are more likely to cheat and steal compared to those who opt for conventional products. This finding has implications for carbon offsetting flights, as individuals may unconsciously engage in carbon-intensive activities at their holiday destination, resulting in an indirect rebound effect as discussed by Kerner and Brudermann (2021).

The twin effect of moral licensing is moral cleansing, "which refers to actions people engage in when their moral self-worth has been threatened" (Sachdeva et al., 2009, p. 523). The past negative behaviour is compensated with an ongoing positive behaviour. Moral licensing and moral cleansing can be combined under the framework of moral balancing (Cornelissen et al., 2013). People do not strive to achieve moral perfection, but rather to balance themselves at a reasonable level (Nisan, 1991).

Contrary to the theory of moral licensing is research on moral consistency. The self-perception theory suggests that individuals form their attitudes by observing their preceding behaviour, which subsequently influences their future behaviour (Bem, 1972). Hence, individuals who engage in good behaviour see themselves as moral people, which leads them to engage in good behaviour in the future. A study conducted by Cornelissen et al. (2013) investigated how an outcome-based mindset or an rule-based mindset influences how past behaviour shapes future moral behaviour. Individuals with an outcome-based mindset assess the consequences of their actions and prioritise the end outcome, resulting in a moral balancing effect. Conversely, those with a rule-based mindset tend to follow duties and obligations, leading to moral consistency.

An alternative explanation for a potential rebound effect is that people fully believe in the effectiveness of carbon offsetting. If people are convinced that offsetting has the same effect as reducing emissions for example by using SAF, then flying will no longer be more environmentally damaging than alternative modes of travel. Consequently, there is no reason to feel guilty about flying and therefore no motivation to reduce flying, even among environmentally conscious individuals.

Cognitive dissonance theory suggests that environmentally conscious individuals experience an unpleasant feeling und guilt when flying, which may be reduced if flights are offset, or the flight uses SAF. Doing something positive for the environment can lead to a warm glow (see 3.2), so in addition to feeling less guilty, individuals may feel good if their flight is offset or uses SAF. This leads to the following research question and hypotheses:

RQ4: How do individuals feel about their travel mode choice?

H4a: Individuals with high altruistic or biospheric environmental concern feel guilty about their travel mode choice when choosing flights.

H4b: Individuals with high altruistic or biospheric environmental concern feel less guilty when flights are offset or when the flight uses sustainable aviation fuel.

H4c: Individuals with high altruistic or biospheric environmental concern feel worse about their travel mode choice when choosing flights.

H4d: Individuals with high altruistic or biospheric environmental concern feel better when flights are offset or when the flight uses sustainable fuel.

To control for the potential rebound effect, the following research questions and hypotheses are formulated:

RQ5: How do carbon offsets influence an individuals' flight choices?

H5a: Individuals are more likely to choose flight when carbon emissions are offset by the airline, leading to a rebound effect.

H5b: The rebound effect of integrated carbon offsets is enhanced for individuals with high biospheric or altruistic environmental concern.

H5c: The possibility of voluntarily carbon offsets increases an individual’s flight choice and thereby leading to a rebound effect.

H5d: The rebound effect of voluntary carbon offsets is enhanced for individuals with high biospheric or altruistic environmental concern.

H5e: Individuals do not perceive carbon offsets as equivalent to emission reductions by sustainable aviation fuel.

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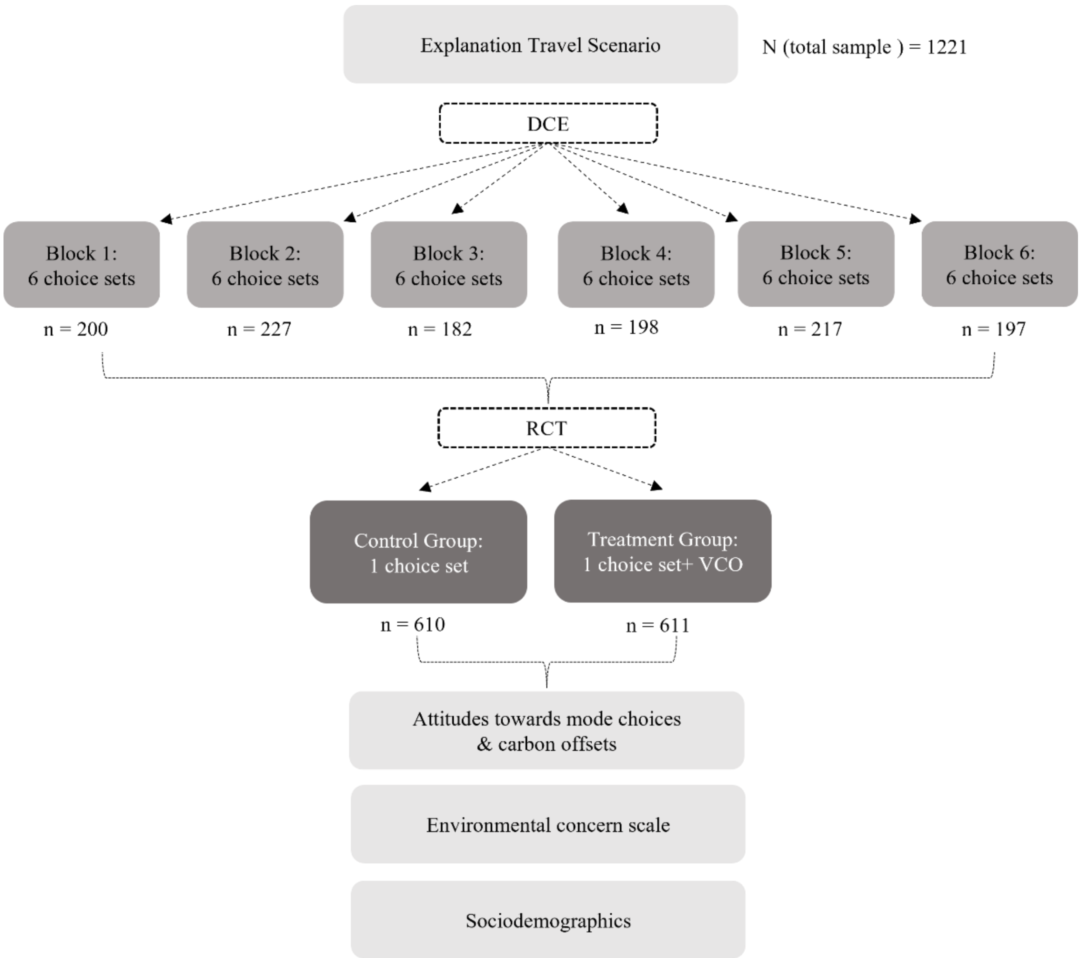
4 Study design & data

4.1 Study design

To address the research questions, utilizing existing data was not feasible as the data on carbon offset purchases is not publicly accessible, and one needs specific information regarding individual travel and offset behaviour as well as attitudes. Therefore, in collaboration with Jakob Roth and Laura Schwab I developed an online survey with a hypothetical travel scenario. The questionnaire was designed using Qualtrics in German and then translated into French and Italian with Deepl Translator (15.04.2023) and the assistance of anonymous reviewers. Selected parts from the questionnaire in German can be found in appendix A.

Figure 1: Survey structure



As illustrated in Figure 1, participants were first requested to imagine planning a one-week holiday trip to a European destination of their choice. The destination is easily accessible and about 700 km distance from home (e.g., Rome, Berlin, Barcelona, or London). These destinations were chosen as they are easily reachable via various modes of transportation, not just by air. To enhance the authenticity and personalisation of the scenario, respondents were asked with whom they imagined travelling. Thereafter, they were presented with seven choice sets, for which they had to decide between four means of transport: train, night train, (e-)car, or airplane, based on several attributes. The (e-)car option was only shown to people which have access to a (e-)car. The initial six choice sets formed part of a discrete choice experiment (DCE), choice set 7 relates to a randomised controlled trial (RCT).

Figure 2 depicts an example choice set shown to participants. Attributes were chosen based on the research questions (sustainable fuel, offset and emissions) and their significance for travel mode choice according to previous research (travel cost, travel time and comfort). It is worth noting that other attributes, such as delay probability or train schedules, were also considered but deemed less essential to prevent the choice options from becoming overly complex.

Figure 2: Example choice set shown to participants

Travel cost	75 CHF	50 CHF	75 CHF	135 CHF
Travel time door-to-door	9:30 h	6:35 h	8:25 h	4:05 h
Comfort				Economy
Sustainable fuel				☑
Offset				☒
Emissions in kg CO2e	132 kg	29 kg	44 kg	212 kg ÷ 2 = 106 kg

The attributes were explained to the participants in the introductory text as well as in an info button below each choice set. Consult appendix B for calculation details for the attribute levels. The levels for travel costs and travel time are as follows:

$x_{Cost,i}$: Travel cost (incl. luggage and eventual offset for flight), measured in CHF

$x_{Cost,T} \in \{53, 92, 115, 142\}$

$x_{Cost,NT} \in \{53, 92, 115, 142\}$

$x_{Cost,C} \in \{53, 68, 92\}$

$x_{Cost,AP} \in \{68, 115, 142\}$

$x_{Time,i}$: Travel time (door-to-door), measured in hh:mm

$x_{Time,T} \in \{6{:}35, 7{:}40, 8{:}25\}$

$x_{Time,NT} \in \{7{:}40, 8{:}25, 9{:}30\}$

$x_{Time,C} \in \{7{:}40, 8{:}25, 9{:}30\}$

$x_{Time,AP} \in \{3{:}35, 4{:}30\}$

For comfort two levels for trains and three categories for night trains were included. Flights were always in economy and (e-)car not further explained.

$x_{Comfort,i}$: Comfort level, indicated by individual dummies

$x_{Comfort,T} \in \{\text{2nd class, 1st class}\}$

$x_{Comfort,NT}$ ∈ {6-bed couchette, 4-bed couchette, 2-bed sleeper cabin}

Sustainable fuel was only included for airplanes and explained as follows: “Sustainable fuel is a mixture of conventional kerosene and fuel 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 the emissions is shown as follows: 212/2 = 106 kg”. This definition does not include all possible feedstocks for SAF production (see section 2.3), but the most important ones in a comprehensible way. A GHG reduction of 50% was chosen, because this is approximately the maximum reduction that is currently possible and is straightforward.

$x_{SAF,i}$: Reduced emissions by sustainable fuel, indicated by a dummy

$x_{SAF,T}$ ∈ {Yes, No}

Offsets were solely included for airplanes and introduced by the following statement “the CO_2 emissions of the flight are offset by investments in renewable energy, energy efficiency measures, forest protection, reforestation or the renaturation of moorland”. Only CO_2 and no non-CO_2 emissions were included, as done by the analysed airlines in section 2.2. Because the offsets were included in the ticket price and not voluntary, this attribute reflects ICOs.

$x_{ICO,i}$: Integrated carbon offsets, indicated by a dummy

$x_{ICO,T}$ ∈ {Yes, No}

CO_2e emissions were maintained constant per travel mode across all choice sets. By displaying the emissions for each travel mode, participants were enabled to make an informed decision on the sustainability of a specific travel mode.

Each attribute was orthogonalized using nGene with several constraints (see (Roth & Schwab, 2023). In total there were 36 different choice sets and participants were randomly assigned to one of 6 blocks, each containing 6 choice sets. Choice sets within a block and travel modes within a choice set were randomised to eliminate bias.

Following this, the RCT was conducted, and participants were presented with a seventh choice set. They were randomly allocated to either the control or treatment group. The choice sets as in Figure 3, for both control and treatment group were identical. The attributes were not orthogonalized for this choice set. The travel costs of all travel modes were fixed to the same price, to control for other preferences. Despite multiple reviews, the comfort level for train travel was accidentally omitted. However, since it is absent from both the control and treatment groups, it should not affect the RCT analysis. Sustainable fuel and (integrated) carbon offsets were both defined as “not applicable”.

Participants of the treatment group were shown the following extra information: “In this scenario you have the option to voluntarily offset your flight emissions for an additional cost of CHF 10.- “. When clicking on flight, participants were asked if they want to voluntarily offset their flight emissions for CHF 10.-. [6]

[6] This is an average cost for offsetting a flight with 700 km distance at myclimate (https://co2.myclimate.org/de/flight_calculators/new). However, costs on airline websites are lower.

Figure 3: 7th choice set for control and treatment group

Travel cost	92 CHF	92 CHF	92 CHF	92 CHF
Travel time door-to-door	08:25 h	7:40 h	09:30 h	4:30 h
Comfort				Economy
Sustainable fuel				☒
Offset				☒
Emissions in kg CO2e	132 kg	29 kg	44 kg	212 kg

After completing the 7th choice set, both the control and treatment group proceeded with the same questionnaire. In order to examine whether they experienced any sense of guilt or warm glow, they were presented with the number of times they had chosen flight, and then asked to rate how good and how guilty they felt about their choice of travel mode on a Likert scale from 1 to 5.

The following questions assessed participants' prior knowledge, past behaviour, and attitudes towards offsetting and their awareness of Switzerland's inclusion in the EU ETS. Then, environmental concern was assessed using a shortened and adapted version of the scale by Schultz (2001). This version contains 10 items as Cruz and Manata (2020) advised discarding two invalid items. Table 1 shows the final scale. The scale assessing environmental concern was positioned at the conclusion of the questionnaire to prevent priming effects.

Table 1: English and German version of the environmental concerns scale

English version	**German version**
People around the world are generally concerned about environmental problems because of the consequences that result from harming nature. However, people differ in the consequences that concern them the most. Please rate each of the following items from 1 (not important) to 7 (supreme importance) in response to the question: I am concerned about environmental problems because of the consequences for …	Menschen auf der ganzen Welt sind von Umweltproblemen durch die Zerstörung der Natur betroffen. Allerdings unterscheiden sich Menschen darin, welche Auswirkungen ihnen am wichtigsten erscheinen. Wie wichtig sind Ihnen persönlich die Folgen von Umweltproblemen für...?[a]
Biospheric concern	
Plants	Pflanzen
Marine life	Meereslebewesen
Birds	Vögel
Animals (Mammals)[b]	Tiere (Säugetiere)[b]
Egoistic concern	
Me	Mich selbst
My health	Meine Gesundheit
My future	Meine Zukunft
Altruistic concern	
All people	Alle Menschen
My children (Future generations)[c]	Meine Kinder (Zukünftige Generationen)[c]

Note: English version based on Schultz (2001); German version based on the translation of Dornhoff et al. (2019); French and Italian version are based on the German version, translated with DeepL Translator (15.04.2023) and reviewed by anonymous colleagues.

[a] Participants were asked to rate the importance of the consequences from 1 (not important) to 5 (important).

[b] Animals were replaced with Mammals for a better distinction from birds and marine life.

[c] My children were replaced with Future Generations to also include participants without children.

Lastly, participants were asked sociodemographic questions about their place of living, household, and gross income. Data on age, gender, and education was provided by LINK.

4.2 Pre-test

Before the actual survey, two pre-tests were conducted, to detect potential issues with the questionnaire prior the field phase. A pre-test should mainly check for the following aspects: reliability and validity of the survey instruments, as well as comprehensibility of the survey questions (Döring & Bortz, 2016). The first pre-test took place between the 21st and 23rd of April 2023, and was filled out by 55 participants. The participants were requested to provide feedback on issues related to grammar, technical problems, and comprehensibility. Based on the feedback, the following aspects were adjusted:

- Optimization of mobile version
- Information about survey length in the introduction text
- Info button with explanation about attributes level for every choice set

- New design of choice sets to make it more self-explanatory: pictures instead of icons for comfort levels, icons for sustainable fuel and offset, display 50% reduction of emissions when sustainable fuel
- Environmental concern scale: replacement of item ‘animal’ with ‘mammals’ for better distinction from birds and marine life
- Better explanation how to rank importance for travel mode attributes

Additionally, Roth and Schwab conducted a pre-test estimation of the DCE and found that the mode choice car was chosen significantly less than other options. To increase its attractiveness, the cost levels of the car option were lowered. Following the revised design and attribute levels, a second pre-test with 14 participants was conducted between the 13th and 14th of May 2023. The overall feedback on the second pre-test was good, and only minor wordings were adapted.

4.3 Data description

The questionnaire was part of a LINK summer holiday survey and distributed through LINK from May 16, 2023, to May 21, 2023. In accordance with LINK’s recruitment target of 750 German-speaking, 250 French-speaking and 200 Italian-speaking participants, we received a total of 1’221 completed survey responses. Data cleansing was carried out by Roth and Schwab. As presented in Table 2, 16.1% of the total 1620 participants were excluded from the survey as they had no intentions of planning summer holidays, which was the main focus of LINK. Furthermore, an additional 8.5% of the respondents were excluded due to providing incomplete answers.

Table 2: Dropouts vs completed answers

	N	Percent
No planned holidays	261	16.1
Incomplete answers	138	8.5
Survey completes	1221	75.4
Total	1620	100.0

Table 3 illustrates that the sample participants possess higher education levels in comparison to the Microcensus 2021, and there is a larger proportion of individuals aged between 36 and 60 years (Federal Statistical Office, 2023). Moreover, the sample exhibits a greater percentage of households with income above CHF 10,000, though it also shows a lesser fraction of respondents who declined to disclose their household income. Consequently, it becomes challenging to determine if the study sample indeed has higher income levels in comparison to the Swiss population. The difference in access to an electric car can probably be explained by the fact that ownership and access is included in the study sample and the Microcensus only reports ownership (same for car). The difference in language originates to LINK’s recruitment target. Besides these characteristics, the study sample represents the Swiss population. The differences of the characteristics between the control and treatment groups for the RCT have been tested using a t-test. The majority of these comparisons were found to be insignificant, indicating that the study sample was randomised.

Table 3: Comparison of study sample to the Microcensus 2021

		This Study			Microcensus
Category	Level	Control	p-value (Diff.)	Treatment	
Access To Car	Yes	86.2	0.878	85.9	84.7
	No	13.8	0.878	14.1	15.3
Access To E-Car	Yes	3.3	0.543	3.9	1.5
	No	96.7	0.543	96.1	98.5
Age	Below 36 Years	30.7	0.649	29.5	34.8
	Between 36 And 60 Years	51.1	0.440	48.9	38.9
	Above 60 Years	18.2	0.136	21.6	26.3
Gender	Female	48.6	0.668	50.1	50.5
	Male	51.4	0.668	49.9	49.5
Education	Mandatory	4.4	0.884	4.3	12.1
	Secondary	45.7	0.196	42.1	41.7
	Tertiary	49.8	0.179	53.7	34.1
Household Income	Below 10,000 CHF	59.5	0.981	59.6	56.6
	Above 10,000 CHF	28.4	0.864	28.8	19.7
	Unknown	12.1	0.783	11.6	23.7
Language	German	61.0	0.541	62.7	68.7
	French	20.0	0.370	22.1	25.5
	Italian	19.1	0.078*	15.2	5.8
Urbanity Level	Urban	59.8	0.083*	64.6	64.4
	Agglomeration	26.4	0.01	20.1	20.3
	Rural	13.8	0.472	15.2	15.3
N		610		611	57,090

Notes: Except for p-values, all numbers denote percentages. Sample of Microcensus 2021 from Federal Statistical Office (2023).

*p<0.1; **p<0.05; ***p<0.01 (based on two-sided testing).

5 Results

This chapter outlines the econometric analyses, starting with a description of the environmental concern scale, followed by an evaluation of the hypotheses. Further analyses will finish the chapter. All econometric analyses were carried out using RStudio (see appendix C for the RScript).

5.1 Environmental concern scale

As outlined in chapters 3.1 and 4.1, the environmental concern scale created by Schultz (2001) consists of three factors. Cronbach's alpha[7] reliability for the four biospheric items (plants, marine life, birds and mammals) is 0.91 and for the three egoistic items (me, my health and my future) is also 0.91. Spearman's brown[8] coefficient for the two altruistic items (all people and future generations) is 0.88. To calculate the scale scores of these three elements, the items are averaged. To simplify the interpretation of scale scores in regression models, the scores have been centered. Table 4 presents the summary statistics of the environmental concern scale. The mean scale score for biospheric concern is 4.443, whilst for altruistic concern 4.313 and for egoistic concern it is 4.215. It is notable that the scale scores overall are high with no great variability.

Table 4: Summary statistics of environmental concern scale

Scale score	N	Mean	Min	Q1	Median	Q3	Max
Biospheric Env. Concern	1221	4.443	1.000	4.000	5.000	5.000	5.000
Centered Biospheric Env. Concern	1221	0.000	-3.443	-0.443	0.557	0.557	0.557
Altruistic Env. Concern	1221	4.313	1.000	4.000	5.000	5.000	5.000
Centered Altruistic Env. Concern	1221	0.000	-3.313	-0.313	0.687	0.687	0.687
Egoistic Env. Concern	1221	4.215	1.000	3.667	4.333	5.000	5.000
Centered Egoistic Env. Concern	1221	0.000	-3.215	-0.548	0.118	0.785	0.785

Note: Individuals were asked to rate importance of the items on a scale from 1 (not important) to 5 important).

[7] Cronbach's alpha evaluates the reliability of a multiple-item scale by assessing the amount of shared variance or covariance among items (Collins, 2007). It produces a score between 0 and 1, where higher values indicate greater internal consistency.

[8] For a two-item scale the Spearman-Brown formula is recommended, which assesses the split-half reliability to estimate reliability of the total scale (Eisinga et al., 2013).

5.2 Evaluation of hypotheses

5.2.1 Evaluation of hypotheses 1a & 1b

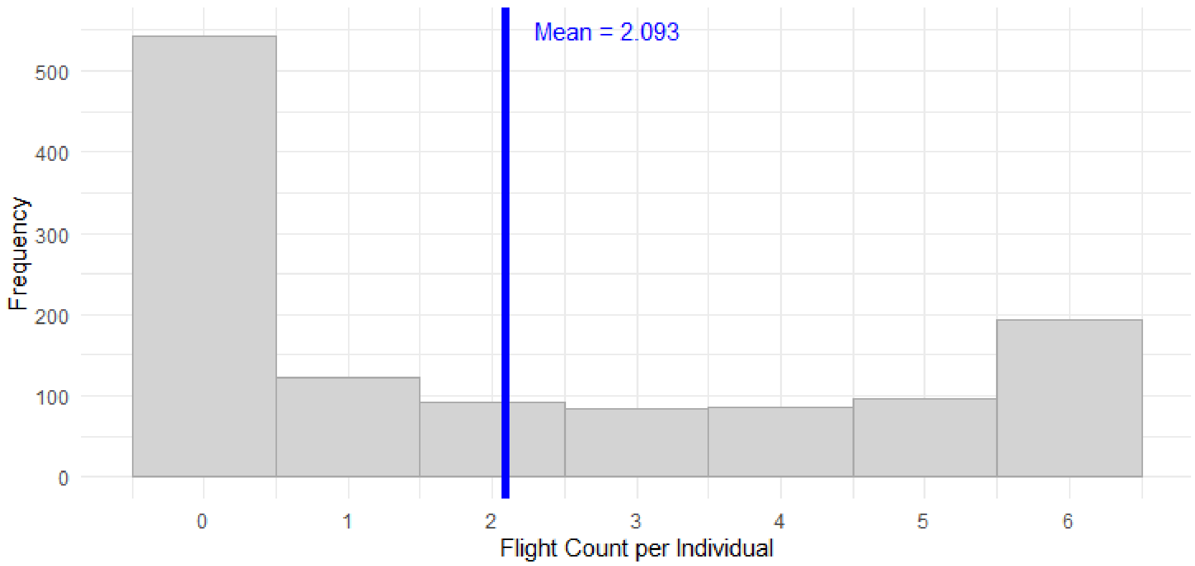
For the evaluation of the first research question "How does environmental concern influence an individual's flight choices?", the following hypotheses were defined:

H1a: Altruistic and biospheric environmental concern are negative predictors of choosing flight.

H1b: Egoistic environmental concern is a positive predictor of choosing flight.

The following analysis focuses on choice sets 1 to 6. According to Figure 4, on average participants selected the flight option two times out of six (mean = 2.093). Nonetheless, the majority of individuals (n = 543) never selected the flight option.

Figure 4: Flight count per individual for choice sets 1 to 6



Notes: Total N = 1221. The histogram shows the flight counts per individual for their choice sets 1 to 6. Choice set 7 (RCT) is not included.

For the regression analysis, the dependent variable is *Flight Count*, indicating the total count of flight choices per individual for their choice sets 1 to 6. The 7th choice set, the RCT, is not included in the analysis, as the treatment group has the option to purchase VCOs. Only including the control group would be possible by including an offset, but this makes the interpretation of the coefficient estimates extremely difficult and is therefore rejected. The dependent variables are *Biospheric Environmental Concern* (centered), *Altruistic Environmental Concern* (centered) and *Egoistic Environmental Concern* (centered). Control variables are sociodemographic variables: *Female* (male as the base category), *Young (< 36 Years)*, *Old (> 60 Years)* (age 36 to 60 serves as the base category), *Mandatory Education*, *Tertiary Education* (secondary education serves as the base category), *High Income* (based on the median of the Swiss equivalence income, low income as the base category), *French Speaking*, *Italian Speaking* (German as the base category), *Agglomeration*, *Urban* (rural as the base category), *Car Access* and *E-Car Access*, as well as the travel scenario: *Travelling With Children* and *Travelling Alone* (travelling with family without children, with partner, with friends or other serves as the base category).

For count data, Poisson regression is the most commonly applied regression method (Cameron & Trivedi, 2013). An important assumption of the Poisson distribution is that the mean and variance are equal. However, in this instance, the variance (5.480) exceeds the mean (2.093), suggesting overdispersion. For more correct standard errors, one may use the adjusted Poisson regression or the quasi-Poisson regression (Zeileis et al., 2023). Note that the quasi-Poisson regression uses a quasi-maximum likelihood estimation, a more generalized version of the Poisson pseudo-maximum likelihood (PPLM) estimation, which is specialized on panel data analysis. Both the adjusted Poisson and the quasi-Poisson model account for overdispersion while retaining a similar structure than the Poisson model. They use the same mean function as the Poisson regression, but the adjusted Poisson regression corrects the standard errors using sandwich covariances, while the quasi-Poisson regression does so via estimated dispersion parameters. This implies that both models produce coefficient estimates equivalent to those of the standard Poisson model but with adjusted standard errors. However, an additional issue is the excess of zero counts, visible in Figure 4. Consequently, a zero-augmented model may be employed, which expands the mean function by increasing the probability of zero counts (Kennedy, 2013). There are two options, the first which is the hurdle Poisson model. This is a two-stage model: a dichotomous model for structural zeros, followed by a truncated Poisson model for the positive counts. The second model is the zero-inflated Poisson (ZIP) model, a more generalised version of the hurdle model that allows not only structural but also random zeros. When considering flight choice, both structural and random zeros seem reasonable. Some individuals which never selected flight, might be in general willing to fly, but did not in their 6 choice sets due to situational factors.

Table 5 presents the regression estimates for the adjusted Poisson models, quasi-Poisson models and ZIP models. The hurdle model's regression estimates are comparable to those of the ZIP models and are available in appendix D. The Poisson models were calculated using the base R package (R Core Team, 2023) and standard error corrected using the *sandwich* package (Zeileis, 2006; Zeileis et al., 2020). ZIP and hurdle models were calculated using the *pscl* package (Zeileis et al., 2008). Estimates for the adjusted Poisson and quasi-Poisson models differ only minimally in their standard errors. The first three columns represent models 1, 2 and 3 without control variables, the next three columns represent models 4, 5 and 6 with sociodemographic control variables, and the final three columns represent models 7, 8 and 9 with the travel scenario related control variables. In the ZIP models, identical regressors have been used for the count and the zero component. The ZIP models are clearly superior to the adjusted Poisson models and quasi-Poisson models in terms of fit; estimated number of zeros is equivalent to the observed number of zeros; lowest log likelihood; lowest Akaike information criterion; lowest Bayesian information criterion. Therefore, the subsequent interpretation of the results is exclusively based on the ZIP models. The zero component of the ZIP models describe the odds of not flying. Model 3 demonstrates, that one unit increase in biospheric environmental concern, holding other variables constant, increases the odds that individuals never fly by 26.7% ($\exp(0.237) \approx 1.267$) at the 5%-significance level; one unit increase in altruistic concern increases the odds by 37.8% ($\exp(0.321) \approx 1.378$) at the 1%- significance level; one unit increase in egoistic concern decreases the odds by 30.1% ($\exp(-0.358) \approx 0.698$) at the 1%-significance level. When including the sociodemographic control variables (model 6) and travel scenario control variables (model 9), the effect of biospheric concern is not significantly different from zero at the 10%-significance level. This suggests, that biospheric concern correlates with the control variables. Being old increases the odds of zero flights by 154.2% ($p < 0.01$), mandatory education by 121% ($p < 0.05$), high income by 27.3% ($p < 0.1$) having e-car access by 161.2% ($p < 0.01$) and travelling alone by 45.9% ($p < 0.1$). It is important to note, that the costs levels of the flight option were approximately the same than for the other travel modes (see 4.1). Being young decreases the odds by 38% ($p < 0.01$) and living in an urban area by 31.3 % ($p < 0.05$). However, when the flight counts of individuals who choose to fly at least once are analysed (see count component), it is evident that altruistic, biospheric, and egoistic environmental concern do not have any significant effects at the 10%-significance level in all three ZIP models (3, 6 and 9). Thus, environmental concern significantly influences whether individuals are willing to fly, but not how frequently they fly. Among those who fly, being old increases the expected flight counts by 14% ($p < 0.05$) and being young decreases the expected flight counts by 11.8% ($p < 0.05$). This finding is intriguing as it suggests that while being old is a positive indicator for not flying at all, those who do tend to fly even more than other age groups, being young is exactly the opposite; they fly more often at least once, but less than others. Living in an urban area increases the expected flight counts by 15.1% ($p < 0.05$) and speaking French by 9.5% ($p < 0.1$).

In conclusion, the findings support hypotheses 1a and 1b. Biospheric environmental concern is a negative predictor of flight choice at the 5%-significant level, while altruistic environmental concern is a negative predictor at the 1%-significant level. Additionally, egoistic environmental concern is a positive predictor of flight choice at the 1%-significant level.

Table 5: Estimation results from count models about flight choice

	Dependent variable: Flight Choice								
	adj. Pois	quasi-Pois	ZIP[a]	adj. Pois	quasi-Pois	ZIP[a]	adj. Pois	quasi-Pois	ZIP[a]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Count Component									
Constant	0.731***	0.731***	1.299***	0.385***	0.385**	1.048***	0.440***	0.440***	1.064***
	(0.032)	(0.032)	(0.021)	(0.143)	(0.152)	(0.105)	(0.147)	(0.157)	(0.108)
Biospheric Env. Concern[b]	-0.096**	-0.096*	-0.009	-0.063	-0.063	-0.023	-0.065	-0.065	-0.024
	(0.048)	(0.049)	(0.034)	(0.049)	(0.051)	(0.034)	(0.049)	(0.051)	(0.034)
Altruistic Env. Concern[b]	-0.133***	-0.133***	-0.009	-0.123***	-0.123**	-0.023	-0.127***	-0.127***	-0.023
	(0.045)	(0.047)	(0.033)	(0.045)	(0.048)	(0.033)	(0.045)	(0.049)	(0.034)
Egoistic Env. Concern[b]	0.114**	0.114**	-0.03	0.107**	0.107**	-0.021	0.107**	0.107**	-0.019
	(0.05)	(0.051)	(0.036)	(0.049)	(0.051)	(0.035)	(0.049)	(0.052)	(0.036)
Female				0.012	0.012	0.027	0.004	0.004	0.025
				(0.066)	(0.068)	(0.044)	(0.065)	(0.068)	(0.044)
Young (< 36 Years)				0.043	0.043	-0.117**	0.031	0.031	-0.126**
				(0.067)	(0.073)	(0.048)	(0.07)	(0.076)	(0.05)
Old (> 60 Years)				-0.349***	-0.349***	0.139**	-0.360***	-0.360***	0.131**
				(0.109)	(0.097)	(0.062)	(0.113)	(0.1)	(0.064)
Mandatory Education				-0.296	-0.296	0.073	-0.279	-0.279	0.076
				(0.197)	(0.183)	(0.12)	(0.196)	(0.184)	(0.12)
Tertiary Education				0.046	0.046	-0.025	0.051	0.051	-0.023
				(0.066)	(0.068)	(0.044)	(0.067)	(0.068)	(0.044)
High Income				-0.038	-0.038	0.054	-0.04	-0.04	0.051
				(0.066)	(0.068)	(0.044)	(0.066)	(0.068)	(0.045)
French Speaking				0.107	0.107	0.092*	0.104	0.104	0.091*
				(0.078)	(0.08)	(0.052)	(0.078)	(0.08)	(0.052)
Italian Speaking				0.021	0.021	0.068	0.018	0.018	0.067
				(0.089)	(0.089)	(0.058)	(0.088)	(0.089)	(0.058)
Agglomeration				0.117	0.117	0.083	0.117	0.117	0.084
				(0.114)	(0.116)	(0.076)	(0.115)	(0.116)	(0.077)

Urban		0.286***	0.286***	0.141**	0.291***	0.291***	0.141**
		(0.099)	(0.102)	(0.067)	(0.099)	(0.102)	(0.067)
Car Access		0.204**	0.204**	0.111*	0.176*	0.176*	0.11
		(0.095)	(0.099)	(0.066)	(0.096)	(0.101)	(0.067)
E-car Access		-0.589**	-0.589***	-0.109	-0.584**	-0.584***	-0.099
		(0.242)	(0.224)	(0.147)	(0.242)	(0.224)	(0.148)
Travelling With Children					-0.032	-0.032	-0.028
					(0.084)	(0.086)	(0.057)
Travelling Alone					-0.199	-0.199*	-0.038
					(0.121)	(0.116)	(0.076)
	ZIP[c]			ZIP [c]			ZIP [c]
	(3)			(6)			(9)
Zero Component							
Constant	-0.289***			-0.002			-0.109
	(0.061)			(0.287)			(0.297)
Biospheric Env. Concern[b]	0.237**			0.11			0.113
	(0.103)			(0.107)			(0.107)
Altruistic Env. Concern[b]	0.321***			0.284***			0.287***
	(0.1)			(0.104)			(0.104)
Egoistic Env. Concern[b]	-0.358***			-0.329***			-0.325***
	(0.101)			(0.104)			(0.105)
Female				0.008			0.024
				(0.132)			(0.133)
Young (< 36 Years)				-0.491***			-0.478***
				(0.155)			(0.159)
Old (> 60 Years)				0.920***			0.933***
				(0.166)			(0.173)
Mandatory Education				0.819***			0.793**
				(0.316)			(0.317)
Tertiary Education				-0.185			-0.194
				(0.134)			(0.135)

High Income						0.240*			0.241*
						(0.134)			(0.135)
French Speaking						-0.045			-0.037
						(0.16)			(0.16)
Italian Speaking						0.102			0.109
						(0.173)			(0.174)
Agglomeration						-0.084			-0.078
						(0.21)			(0.211)
Urban						-0.364*			-0.376**
						(0.186)			(0.187)
Car Access						-0.256			-0.194
						(0.191)			(0.195)
E-car Access						0.962***			0.960***
						(0.34)			(0.34)
Travelling With Children									0.027
									(0.171)
Travelling Alone									0.378*
									(0.212)
Observations	1221	1221	1221	1221	1221	1221	1221	1221	1221
No. of parameters	4	4	8	16	16	32	18	18	36
Log Likelihood	-2875.306		-2202.460	-2821.689		-2147.987	-2817.582		-2146.076
Akaike Inf. Crit.	5758.613		4420.920	5675.377		4359.974	5671.163		4364.152
Bayesian Inf. Crit.	5779.042		4461.780		5757.096	4523.412	5763.097		4548.019
Exp. no. of zeros	156	156	543	170	170	543	171	171	543

Notes: adj. Pois = adjusted Poisson Model, quasi-Pois = quasi-Poisson Model, ZIP = zero-inflated Poisson Model. Standard errors in parantheses, for adj. Pois corrected for heteroscedasticity and overdispersion.

[a] Count component: Poisson model with log link. [b] *Biospheric*, *Altruistic* and *Egoistic Env. Concern* are centered. [c] Zero component: binomial model with logit link.

*p<0.1; **p<0.05; ***p<0.01

5.2.2 Evaluation of hypotheses 3a & 3b

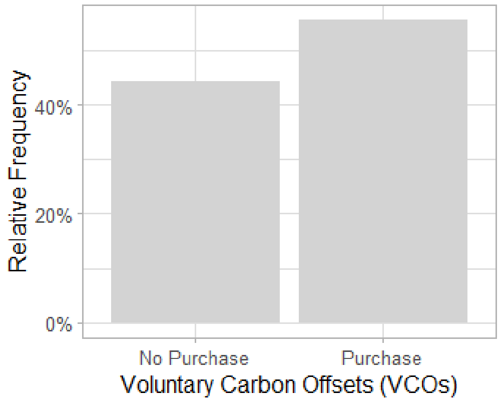
This chapter addresses the research question "How does environmental concern influence voluntary carbon offsetting?" by assessing the following hypotheses:

H3a: When choosing to fly, altruistic and biospheric environmental concern are positive predictors of voluntary carbon offsetting.

H3b: When choosing to fly, egoistic environmental concern is a negative predictor of voluntary carbon offsetting.

The following analysis includes data from choice set 7, where individuals in the treatment group had the possibility to voluntarily offset their flight emissions. Figure 5 displays the results for those who opted to fly. A majority of individuals (56%) purchased VCOs.

Figure 5: Relative frequency of voluntary carbon offsets (VCOs) purchases among those who fly



Notes: Total N = 232. The barplot shows the relative frequency weather individuals purchase voluntary carbon offsets (VCOs) in choice set 7. Subset of individuals who choose flight (n = 232) among the treatment group (n = 611).

The regression of VCOs choice on environmental concern is made on a subset of individuals who choose flight (n = 232) among the subset of the treatment group (n = 611). The treatment group is a random subset of the total sample, however the probability of being included in the flight subset is related to endogenous variables and nonrandomly. This problem is called self-selection bias and can be addressed with the Heckman selection model (Heckman, 1979). The Heckman selection model divides the regression into two regression equations, the selection equation, which models the binary selection decision (*Flight Choice*), and the outcome equation, which represents the binary response of interest (*VCOs Purchase*). The Heckman selection model can be calculated using either the the maximum likelihood estimator (MLE) or the two-step estimator, which splits the estimation into two separate steps. The MLE is expected to be more efficient than the two-step estimator as mentioned by Kennedy (2013). Nevertheless, difficulties were encountered when estimating the MLE in R, hence it was proceeded with the more robust two-step estimator as a second-best alternative.

1. Selection equation: A probit model was applied to the binary selection decision and the predicted probabilities of being selected (Inverse Mills Ratio (IMR)) were calculated. The binary variable was *Flight Choice*, with *Biospheric, Altruistic, Egoistic Environmental*

Concern, and control variables as independent variables. The exclusion restriction required having at least one variable that is not included in the outcome equation.

2. Outcome equation: Ordinary least squares regression (OLS) was used to estimate the response of interest, with the inclusion of the IMR as an additional regressor. The binary dependent variable was *VCOs Purchase,* while *Biospheric, Altruistic, Egoistic Environmental Concern* and control variables were considered as the independent variables.

The estimation outcomes from the Heckman two-step model are illustrated in Table 6. The calculations were executed in R with the *sampleSelection* package (Toomet & Henningsen, 2008) and *ssmrob* package for the robust version (Zhelonkin & Ronchetti, 2021). The exclusion restrictions for model 1 include the sociodemographic variables *Car Access* and *E-Car Access* as well as the travel scenario variables *Travelling With Children* and *Travelling alone.* It may be assumed that these factors influence mode choice, but it is not reasonable to assume that they influence the decision to purchase VCOs. It could be speculated though that individuals who own an e-car are more environmentally conscious, which in turn may impact carbon offsetting. This is supported by Table 5, which demonstrates a significant negative correlation between e-car access and air travel. Thus, *E-Car Access* and *Car Access* are included in the outcome equation of model 2, with only Travelling *With Children* and *Travelling Alone* acting as the exclusion restrictions. However, according to Table 6, model 1 has the better model fit. Model 1 displays an IMR of -0.705 at the 5%-significance level, indicating that individuals who chose flight are unlikely to purchase VCOs. Model 2's IMR of -1.178 is not significant at the 10%-significance level. Additionally, the correlation coefficient (rho), between the errors of model 2's two equations (-1.133) exceed the range of -1 and 1. The rho value of Model 1 (-0.950) suggests a negative correlation between the errors. This implies that factors affecting flight choice are negatively related to VCOs purchases, which seems reasonable. Finally, the estimated coefficients of e-car access and car access in model 2's outcome equation are not significant, and as a result, model 1 should be preferred.

As shown in the selection equation of model 1 in Table 6, altruistic environmental concern has a significant negative impact on flight choice. In contrast, neither biospheric nor egoistic concern had a significant effect on flight choice, unlike the regression results of choice set 1 to 6 (see Table 5). Nevertheless, according to the outcome equation, biospheric environmental concern positively influences VCOs purchase, whereas egoistic concern has a negative effect, both at the 1%-significance level. Altruistic concern, on the other hand, had no significant effect at the 10% level of significance.

Overall, hypothesis 3a can only be partly confirmed. Biospheric environmental concern is a positive predictor of voluntary carbon offsetting when choosing to fly, whereas altruistic environmental concern has no significant effect. On the other hand, hypothesis 3b can be confirmed: egoistic environmental concern is a negative predictor of voluntary carbon offsetting when choosing to fly.

Table 6: Estimation results from Heckman two-step models about VCOs purchases

	selection			
	Selection Equation	Outcome Equation	Selection Equation	Outcome Equation
	1)		2)	
Dependent variable:	*Flight Choice*	*VCOs Purchase*	*Flight Choice*	*VCOs Purchase*
Constant	-0.549** (0.245)	1.256*** (0.452)	-0.549** (0.245)	1.844* (0.986)
Biospheric Env. Concern[a]	-0.122 (0.093)	0.220*** (0.07)	-0.122 (0.093)	0.259** (0.106)
Altruistic Env. Concern[a]	-0.158** (0.080)	0.076 (0.066)	-0.158** (0.080)	0.124 (0.104)
Egoistic Env. Concern[a]	0.115 (0.084)	-0.163*** (0.061)	0.115 (0.084)	-0.198** (0.093)
Female	-0.001 (0.114)	0.145* (0.088)	-0.001 (0.114)	0.141 (0.114)
Young (< 36 Years)	0.290** (0.129)	-0.228** (0.111)	0.290** (0.129)	-0.322* (0.188)
Old (> 60 Years)	-0.316** (0.152)	0.172 (0.141)	-0.316** (0.152)	0.286 (0.239)
Mandatory Education	-0.601** (0.304)	0.214 (0.286)	-0.601** (0.304)	0.413 (0.479)
Tertiary Education	0.195* (0.112)	-0.130 (0.094)	0.195* (0.112)	-0.189 (0.147)
High Income	-0.045 (0.114)	0.144* (0.084)	-0.045 (0.114)	0.157 (0.111)
French Speaking	0.176 (0.134)	-0.129 (0.105)	0.176 (0.134)	-0.177 (0.154)
Italian Speaking	0.126 (0.155)	0.080 (0.133)	0.126 (0.155)	0.039 (0.18)
Agglomeration	0.236 (0.185)	-0.037 (0.147)	0.236 (0.185)	-0.105 (0.217)
Urban	0.239 (0.158)	-0.027 (0.128)	0.239 (0.158)	-0.098 (0.198)
Car Access	-0.046 (0.161)		-0.046 (0.161)	-0.026 (0.15)
E-car Access	-0.846** (0.359)		-0.846** (0.359)	0.553 (0.621)
Travelling With Children	0.033 (0.151)		0.033 (0.151)	
Travelling Alone	-0.297* (0.179)		-0.297* (0.179)	
Observations	611		611	
sigma	0.741		1.071	
rho	-0.950		-1.101	
Inverse Mills Ratio	-0.705** (0.34)		-1.178 (0.791)	

Notes: Total N = 611, censored N = 379, observed N = 232. VCOs = voluntary carbon offsets. Standard errors in parentheses, corrected for heteroskedasticity. Heteroskedasticity for the selection equation is confirmed by the Breusch-Pagan test and White test, for the outcome equation confirmed by the White test.

[a] Biospheric, Altruistic and Egoistic Env. Concern are centered.

*p<0.1; **p<0.05; ***p<0.01

5.2.3 Evaluation of hypotheses 4a, 4b, 4c & 4d

Research question 4, "How do individuals feel about their travel mode choice?" will be answered by examing the following hypotheses:

H4a: Individuals with high altruistic or biospheric environmental concern feel guilty about their travel mode choice when choosing flights.

H4b: Individuals with high altruistic or biospheric environmental concern feel less guilty when flights are offset or when the flight uses sustainable aviation fuel.

H4c: Individuals with high altruistic or biospheric environmental concern feel worse about their travel mode choice when choosing flights.

H4d: Individuals with high altruistic or biospheric environmental concern feel better when flights are offset or when the flight uses sustainable fuel.

Table 7 presents how individuals feel in general about their travel mode choice, categorized into subsamples of individuals with 0 to 7 flight choices. On average, individuals who never choose flight feel best (mean = 3.975) and the least guilty (mean = 2.011). However, a less clear picture is observed when comparing the subsamples with at least one flight choice. Individuals with 5 flights on average feel the most guilt, while those with 7 flights feel the least. Furthermore, the data suggests that individuals experience the lowest level of well-being with 6 flights and the highest level with 7 flights.

Table 7: Summary statistics of feeling guilty and feeling good about travel mode

Variable	Subsample	N	Mean	Min	Q1	Median	Q3	Max
Feeling Guilty About Travel Mode	All	1221	2.315	1.000	1.000	2.000	3.000	5.000
	0 Flights	522	2.011	1.000	1.000	2.000	3.000	5.000
	1 Flight	112	2.446	1.000	2.000	2.000	3.000	5.000
	2 Flight	77	2.688	1.000	2.000	3.000	4.000	4.000
	3 Flights	85	2.494	1.000	2.000	3.000	3.000	5.000
	4 Flights	68	2.691	1.000	2.000	3.000	3.000	5.000
	5 Flights	80	2.888	1.000	2.000	3.000	4.000	5.000
	6 Flights	93	2.581	1.000	2.000	3.000	3.000	5.000
	7 Flights	184	2.337	1.000	1.000	2.000	3.000	5.000
Feeling Good About Travel Mode	All	1221	3.703	1.000	3.000	4.000	5.000	5.000
	0 Flights	522	3.975	1.000	3.000	4.000	5.000	5.000
	1 Flight	112	3.562	1.000	3.000	4.000	4.000	5.000
	2 Flight	77	3.403	1.000	3.000	3.000	4.000	5.000
	3 Flights	85	3.541	1.000	3.000	4.000	4.000	5.000
	4 Flights	68	3.324	2.000	3.000	3.000	4.000	5.000
	5 Flights	80	3.388	1.000	3.000	3.000	4.000	5.000
	6 Flights	93	3.280	1.000	3.000	3.000	4.000	5.000
	7 Flights	184	3.707	1.000	3.000	4.000	5.000	5.000

Note: Each individual was confronted with 7 choice sets, so total flight choices were between 0 and 7. At the end they were asked how they agree with the statement "I feel guilty about my travel mode choice" and "I feel good about my travel mode choice" on a scale from 1 (= strongly disagree) to 5 (= strongly agree).

Table 8 illustrates the OLS regression estimates of *Feeling Guilty About Travel Mode* on *Biospheric, Altruistic* and *Egoistic Environmental Concern*. In order to avoid endogeneity, the regression was conducted separately on eight subsamples with zero to seven flight choices. For individuals which zero or up to three flight choices, environmental concern did not have a significant impact on guilt. However, when selecting flights between four to six times, guilt increases significantly at 1%- and 5%-significance level due to altruistic environmental concern. Biospheric environmental concern significantly increases guilt for five or seven flight choices at the 10%-significance level. On the contrary, egoistic environmental concern has a non-significant negative effect in most subsamples.

Table 8: Regression estimates from linear models for feeling guilty about travel mode choice

	Dependent variable: Feeling Guilty About Travel Mode Choice							
	OLS							
	Subsample 0 Flights 0)	Subsample 1 Flight 1)	Subsample 2 Flights 2)	Subsample 3 Flights 3)	Subsample 4 Flights 4)	Subsample 5 Flights 5)	Subsample 6 Flights 6)	Subsample 7 Flights 7)
Constant	2.030***	2.121***	2.716***	2.023***	2.241***	2.066**	2.039***	2.492***
	(0.215)	(0.495)	(0.611)	(0.493)	(0.781)	(0.831)	(0.653)	(0.463)
Biospheric Env. Concern[a]	-0.064	0.134	0.151	0.003	-0.354	0.473*	-0.166	0.232*
	(0.084)	(0.197)	(0.233)	(0.186)	(0.237)	(0.241)	(0.227)	(0.134)
Altruistic Env. Concern[a]	0.047	0.175	0.183	0.037	0.558***	0.534**	0.400*	0.072
	(0.078)	(0.171)	(0.272)	(0.206)	(0.206)	(0.226)	(0.206)	(0.14)
Egoistic Env. Concern[a]	-0.01	-0.074	0.033	-0.052	0.13	-0.316	-0.08	-0.061
	(0.075)	(0.177)	(0.26)	(0.225)	(0.214)	(0.221)	(0.203)	(0.144)
Control Variables	✓	✓	✓	✓	✓	✓	✓	✓
Observations	522	112	77	85	68	80	93	184
Adjusted R^2	0.015	-0.027	-0.026	0.056	0.075	0.202	0.101	0.035
F Statistic	1.475* (df = 17; 504)	0.827 (df = 17; 94)	0.886 (df = 17; 59)	1.309 (df = 16; 68)	1.318 (df = 17; 50)	2.177** (df = 17; 62)	1.607* (df = 17; 75)	1.391 (df = 17; 166)

Notes: Total N = 1221. Standard errors in parentheses. Homoscedasticity was checked with the White test. All regressions include the following control variables: *Female, Young (< 36 Years), Old (> 60 Years)* (age 36 to 60 as the base category), *Mandatory Education, Tertiary Education* (secondary education as the base category), *High income, French Speaking, Italian Speaking* (German as the base category), *Agglomeration, Urban* (rural as the base category), *Car Access, E-Car Access, Travelling With Children* and *Travelling Alone* (travelling with family without children, with partner, with friends or other serves as the base category). Full regression outputs showing the control variables are provided in appendix E.

[a] Biospheric, Altruistic and Egoistic Env. Concern are centered.

*p<0.1; **p<0.05; ***p<0.01

Table 9 presents the regression estimates for the relationship between guilt and environmental concern, including interaction effects on flight specific attributes. The analysis excludes individuals who did not take any flights. The regressor *Flights with ICOs* counts the number of flights with integrated carbon offsets that individuals selected, with a maximum of six. *Flights with VCOs* is a binary variable that indicates whether individuals purchased VCOs at choice set 7. *Flights with SAF* counts the number of flights that were chosen with sustainable aviation fuel, with a maximum of six.

The regression analysis produces conflicting results. First, individuals with high biospheric environmental concern are considered. Those who selected flight on a single occasion felt more guilty if the flight had ICOs ($p < 0.01$). Opting for VCOs reduced guilt, with significant effect only visible in the frequent flyers' subsample ($p < 0.05$, subsample 7). Flights that used SAF increased guilt for the four-flight subsample ($p < 0.01$). Secondly, individuals with high altruistic environmental concern are studied. ICOs significantly decrease guilt when only choosing one flight ($p < 0.05$), however increase guilt when choosing seven flights ($p < 0.1$). VCOs decreased guilt, but only significantly for the five-flight subsample ($p < 0.1$). SAF led to a significant decrease in guilt for frequent flyers who reported having seven flights ($p < 0.01$). Finally, for individuals who have high egoistic environmental concern, guilt significantly reduces when using ICOs for both the subsample with two flights ($p < 0.05$) and the subsample with seven flights ($p < 0.05$). On the other hand, VCOs and SAF increase guilt for frequent flyers who have seven flight options ($p < 0.05$, $p < 0.01$).

Table 9: Regression estimates from linear models for feeling guilty about travel mode choice with interactions effects

	Dependent variable: Feeling Guilty About Travel Mode Choice						
	OLS						
	Subsample 1 Flight 1)	Subsample 2 Flights 2)	Subsample 3 Flights 3)	Subsample 4 Flights 4)	Subsample 5 Flights 5)	Subsample 6 Flights 6)	Subsample 7 Flights 7)
Constant	2.023***	1.846**	2.230***	3.022***	1.25	2.192***	2.683***
	(0.517)	(0.835)	(0.638)	(0.942)	(1.106)	(0.795)	(0.599)
Biospheric Env. Concern[a]	-0.411	-0.047	1.25	-1.244*	0.216	-1.045	-0.654
	(0.307)	(0.476)	(0.78)	(0.736)	(1.036)	(1.167)	(0.852)
Altruistic Env. Concern[a]	0.578*	0.226	-0.084	1.266**	1.612	0.692	-0.014
	(0.344)	(0.523)	(0.735)	(0.548)	(1.091)	(1.003)	(0.74)
Egoistic Env. Concern[a]	-0.173	0.585	-0.577	0.081	-0.524	-0.028	0.384
	(0.336)	(0.594)	(0.513)	(0.598)	(1.127)	(0.801)	(0.84)
Flights With ICOs	0.342	0.352	-0.13	-0.001	-0.089	-0.121	-0.176
	(0.232)	(0.268)	(0.203)	(0.226)	(0.216)	(0.202)	(0.142)
Flights With VCOs	0.372	0.44	0.579	0.07	0.696**	0.076	0.165
	(0.642)	(0.489)	(0.352)	(0.456)	(0.324)	(0.325)	(0.211)
Flights With SAF	0.073	0.388	0.022	0.037	0.139	0.149	0.078
	(0.243)	(0.257)	(0.139)	(0.15)	(0.122)	(0.141)	(0.063)
Biospheric Env. Concern[a] * Flights With ICOs	1.087***	0.519	-0.467	-0.677	0.333	0.188	0.206
	(0.383)	(0.475)	(0.419)	(0.423)	(0.44)	(0.447)	(0.279)
Altruistic Env. Concern[a] * Flights With ICOs	-0.826**	0.583	0.102	-0.277	-0.786	-0.199	0.447*
	(0.334)	(0.588)	(0.423)	(0.258)	(0.522)	(0.408)	(0.237)
Egoistic Env. Concern[a] * Flights With ICOs	0.477	-1.569**	0.359	0.363	0.134	0.31	-0.565**
	(0.369)	(0.647)	(0.416)	(0.392)	(0.503)	(0.319)	(0.26)
Biospheric Env. Concern[a] * Flights With VCOs	-0.252	0.83	-0.604	-0.372	-0.901	-0.028	-0.822**
	(1.566)	(0.948)	(0.972)	(1.205)	(0.659)	(0.656)	(0.381)
Altruistic Env. Concern[a] * Flights With VCOs	0.305	-0.326	-1.15	-0.92	-1.080*	-0.24	-0.161
	(0.765)	(0.772)	(1.178)	(0.98)	(0.575)	(0.577)	(0.353)
Egoistic Env. Concern[a] * Flights With VCOs	-0.48	0.797	0.846	1.215	0.791	-0.218	0.667**
	(0.776)	(0.801)	(0.808)	(1.328)	(0.613)	(0.515)	(0.334)

Biospheric Env. Concern[a] * Flights With SAF	0.159	-0.152	-0.236	0.997***	-0.165	0.253	0.154
	(0.387)	(0.436)	(0.273)	(0.325)	(0.207)	(0.209)	(0.113)
Altruistic Env. Concern[a] * Flights With SAF	-0.262	-0.759	-0.028	-0.142	0.359	0.138	-0.417***
	(0.345)	(0.5)	(0.381)	(0.238)	(0.222)	(0.199)	(0.12)
Egoistic Env. Concern[a] * Flights With SAF	-0.161	0.618	-0.135	-0.249	-0.142	-0.355	0.350***
	(0.383)	(0.495)	(0.362)	(0.255)	(0.229)	(0.258)	(0.128)
Controll Variables	✓	✓	✓	✓	✓	✓	✓
Observations	112	77	85	68	80	93	184
Adjusted R^2	0.06	0.013	0.033	0.164	0.214	0.055	0.151
F Statistic	1.244 (df = 29; 82)	1.035 (df = 29; 47)	1.104 (df = 28; 56)	1.452 (df = 29; 38)	1.744** (df = 29; 50)	1.183 (df = 29; 63)	2.121*** (df = 29; 154)

Notes: Total N = 699. ICOs = integrated carbon offsets, VCOs = voluntary carbon offsets, SAF = sustainable aviation fuel. Standard errors in parentheses. Homoscedasticity was checked with the White test. All regressions include the following control variables: *Female*, *Young (< 36 Years), Old (> 60 Years)* (age 36 to 60 as the base category), *Mandatory Education*, *Tertiary Education* (secondary education as the base category), *High income*, *French Speaking*, *Italian Speaking* (German as the base category), *Agglomeration*, *Urban* (rural as the base category), *Car Access*, *E-Car Access*, *Travelling With Children* and *Travelling Alone* (travelling with family without children, with partner, with friends or other serves as the base category). Full regression outputs showing the control variables are provided in appendix E.

[a] Biospheric, Altruistic and Egoistic Env. Concern are centered.

*p<0.1; **p<0.05; ***p<0.01

Table 10 presents the OLS regression estimates of *Feeling Good About Travel Mode* on *Biospheric*, *Altruistic* and *Egoistic Environmental Concern*. It was found that individuals who never chose to fly felt better when they had higher levels of biospheric environmental concern ($p < 0.01$). However, when choosing five flights, they felt worse ($p < 0.1$). Similarly, altruistic environmental concern had a negative influence on mood when five flights were chosen ($p < 0.05$). Egoistic environmental concern had a positive effect on the subsamples with one ($p < 0.1$), 3 ($p < 0.1$) and five flights ($p < 0.01$).

Table 10: Regression estimates from linear models for feeling good about travel mode choice

	Dependent variable: Feeling Good About Travel Mode Choice							
	OLS							
	Subsample 0 Flights	Subsample 1 Flight	Subsample 2 Flights	Subsample 3 Flights	Subsample 4 Flights	Subsample 5 Flights	Subsample 6 Flights	Subsample 7 Flights
	0)	1)	2)	3)	4)	5)	6)	7)
Constant	4.388***	3.772***	3.744***	3.442***	3.517***	4.799***	3.598***	4.045***
	(0.192)	(0.397)	(0.518)	(0.479)	(0.669)	(0.63)	(0.603)	(0.409)
Biospheric Env. Concern[a]	0.197***	-0.201	0.242	-0.116	0.224	-0.318*	0.024	-0.076
	(0.075)	(0.158)	(0.197)	(0.181)	(0.203)	(0.182)	(0.209)	(0.118)
Altruistic Env. Concern[a]	0.087	-0.009	-0.052	-0.153	-0.286	-0.383**	-0.262	-0.104
	(0.070)	(0.137)	(0.231)	(0.201)	(0.176)	(0.172)	(0.19)	(0.123)
Egoistic Env. Concern[a]	0.028	0.279*	-0.093	0.377*	0.035	0.719***	-0.037	0.152
	(0.067)	(0.142)	(0.221)	(0.218)	(0.184)	(0.168)	(0.187)	(0.127)
Control Variables	✓	✓	✓	✓	✓	✓	✓	✓

Observations	522	112	77	85	68	80	93	184
Adjusted R^2	0.082	0.098	-0.017	0.084	-0.007	0.29	0.071	0.061
F Statistic	3.746*** (df = 17; 504)	1.706* (df = 17; 94)	0.927 (df = 17; 59)	1.482 (df = 16; 68)	0.973 (df = 17; 50)	2.902*** (df = 17; 62)	1.412 (df = 17; 75)	1.696** (df = 17; 166)

Notes: Total N = 1221. Standard errors in parentheses. Homoscedasticity was checked with the White test. All regressions include the following control variables: *Female*, *Young (< 36 Years), Old (> 60 Years)* (age 36 to 60 as the base category), *Mandatory Education*, *Tertiary Education* (secondary education as the base category), *High income*, *French Speaking*, *Italian Speaking* (German as the base category), *Agglomeration*, *Urban* (rural as the base category*)*, *Car Access*, *E-Car Access*, *Travelling With Children* and *Travelling Alone* (travelling with family without children, with partner, with friends or other serves as the base category). Full regression outputs showing the control variables are provided in appendix E.

[a] Biospheric, Altruistic and Egoistic Env. Concern are centered.

*p<0.1; **p<0.05; ***p<0.01

Table 11 shows the regression estimates for feeling good with the travel mode choice on environmental concern with interaction effects on flight specific attributes. Individuals with zero flights are excluded from the subsample analysis. In alignment with the results for feeling guilty, the regression estimates do not provide a definitive view. Individuals with high biospheric environmental concern and one flight choice felt better when the flight had ICOs ($p < 0.05$) and worse when choosing five flights ($p < 0.1$). SAF made them feel better when choosing three flights ($p < 0.1$), but worse when choosing 4 ($p < 0.1$) or 7 flights ($p < 0.1$). VOCs were found to have no significant effect. For individuals with high levels of altruistic environmental concern, VCOs showed a positive effect when choosing five flights ($p < 0.05$), and SAF showed a positive effect when choosing one flight ($p < 0.001$) or three flights ($p < 0.1$). SAF made individuals with high egoistic environmental concern feel worse when choosing one flight ($p < 0.1$) or three flights ($p < 0.1$), but better when choosing six flights ($p < 0.1$).

Table 11: Regression estimates from linear models for feeling good about travel mode choice with interaction effects

	Dependent variable: Feeling Good About Travel Mode Choice						
	OLS						
	Subsample 1 Flight	Subsample 2 Flights	Subsample 3 Flights	Subsample 4 Flights	Subsample 5 Flights	Subsample 6 Flights	Subsample 7 Flights
	1)	2)	3)	4)	5)	6)	7)
Constant	3.816***	4.387***	3.018***	2.920***	6.309***	3.452***	4.421***
	(0.407)	(0.714)	(0.59)	(0.912)	(0.778)	(0.733)	(0.562)
Biospheric Env. Concern[a]	-0.634**	-0.121	-0.614	0.484	1.125	0.845	0.178
	(0.242)	(0.407)	(0.722)	(0.712)	(0.729)	(1.075)	(0.799)
Altruistic Env. Concern[a]	-0.646**	0.261	-1.724**	-0.065	-1.155	-0.775	0.149
	(0.271)	(0.447)	(0.68)	(0.531)	(0.768)	(0.924)	(0.694)
Egoistic Env. Concern[a]	0.868***	-0.679	1.449***	0.356	0.859	0.022	-0.834
	(0.265)	(0.508)	(0.475)	(0.58)	(0.793)	(0.738)	(0.788)
Flights With ICOs	-0.136	-0.133	0.217	0.024	-0.288*	0.05	-0.058
	(0.182)	(0.229)	(0.188)	(0.219)	(0.152)	(0.186)	(0.133)
Flights With VCOs	0.579	-0.511	-0.01	0.121	-0.403*	0.046	-0.286
	(0.505)	(0.418)	(0.326)	(0.442)	(0.228)	(0.299)	(0.198)
Flights With SAF	-0.177	-0.325	-0.033	-0.04	-0.113	-0.112	-0.038
	(0.192)	(0.22)	(0.128)	(0.145)	(0.086)	(0.13)	(0.059)
Biospheric Env. Concern[a] * Flights With ICOs	0.739**	-0.126	-0.192	0.469	-0.590*	-0.179	0.076
	(0.302)	(0.406)	(0.387)	(0.41)	(0.31)	(0.412)	(0.262)
Altruistic Env. Concern[a] * Flights With ICOs	0.208	0.243	0.421	0.009	0.374	0.401	-0.26
	(0.263)	(0.503)	(0.392)	(0.25)	(0.368)	(0.376)	(0.223)
Egoistic Env. Concern[a] * Flights With ICOs	-0.356	0.766	-0.12	-0.537	0.119	-0.449	0.361
	(0.291)	(0.554)	(0.385)	(0.38)	(0.354)	(0.294)	(0.244)
Biospheric Env. Concern[a] * Flights With VCOs	0.705	0.366	0.297	0.484	0.627	-0.143	0.359
	(1.233)	(0.811)	(0.9)	(1.167)	(0.463)	(0.605)	(0.358)
Altruistic Env. Concern[a] * Flights With VCOs	0.48	0.025	1.04	0.36	0.933**	-0.248	0.046
	(0.602)	(0.66)	(1.09)	(0.949)	(0.404)	(0.532)	(0.331)
Egoistic Env. Concern[a] * Flights With VCOs	-0.284	-0.159	-1.082	-1.119	-0.961**	0.598	0.028
	(0.611)	(0.685)	(0.748)	(1.286)	(0.431)	(0.475)	(0.313)
Biospheric Env. Concern[a] * Flights With SAF	0.061	0.328	0.492*	-0.573*	-0.134	-0.249	-0.195*
	(0.305)	(0.373)	(0.252)	(0.315)	(0.145)	(0.193)	(0.106)
Altruistic Env. Concern[a] * Flights With SAF	0.841***	-0.192	0.614*	-0.097	-0.058	-0.181	0.175
	(0.271)	(0.428)	(0.352)	(0.23)	(0.156)	(0.183)	(0.112)
Egoistic Env. Concern[a] * Flights With SAF	-0.552*	-0.152	-0.562*	0.356	-0.078	0.418*	-0.002
	(0.302)	(0.423)	(0.335)	(0.247)	(0.161)	(0.237)	(0.12)
Control Variables	✓	✓	✓	✓	✓	✓	✓
Observations	112	77	85	68	80	93	184
Adjusted R^2	0.205	0.004	0.15	-0.165	0.399	0.029	0.067
F Statistic	1.986*** (df = 29; 82)	1.010 (df = 29; 47)	1.531* (df = 28; 56)	0.674 (df = 29; 38)	2.805*** (df = 29; 50)	1.096 (df = 29; 63)	1.454* (df = 29; 154)

Notes: Total N = 699. ICOs = integrated carbon offsets, VCOs = voluntary carbon offsets, SAF = sustainable aviation fuel. Standard errors in parentheses. Homoscedasticity was checked with the White test. All regressions include the following control variables: *Female*, *Young (< 36 Years)*, *Old (> 60 Years)* (age 36 to 60 as the base category), *Mandatory Education*, *Tertiary*

Education (secondary education as the base category), *High income*, *French Speaking*, *Italian Speaking* (German as the base category), *Agglomeration*, *Urban* (rural as the base category), *Car Access*, *E-Car Access*, *Travelling With Children* and *Travelling Alone* (travelling with family without children, with partner, with friends or other serves as the base category). Full regression outputs showing the control variables are provided in appendix E.

[a] Biospheric, Altruistic and Egoistic Env. Concern are centered.

*p<0.1; **p<0.05; ***p<0.01

In conclusion, the findings only partially support hypotheses 4a and 4c. Biospheric and altruistic environmental concern increase guilt and individuals feel less positive about their mode choice when choosing flight, but only for frequent flyers. On the contrary, hypotheses 4b and 4d are not supported by the data. Depending on the number of flights taken, ICOs, VCOs and SAF either have a positive or negative effect on guilt and feeling positive about travel mode choice.

5.2.4 Evaluation of hypotheses 5a, 5b & 5e

This chapter evaluates the following hypotheses to address the research question of how carbon offsets affect an individual's flight choices:

H5a: Individuals are more likely to choose flight when carbon emissions are offset by the airline, leading to a rebound effect.

H5b: The rebound effect is enhanced for individuals with high biospheric or altruistic environmental concern.

H5e: Individuals do not perceive carbon offsets as equivalent to emission reductions by sustainable aviation fuel.

The discrete choice analysis is the optimal method to discuss the hypotheses as choice sets 1 to 6 are designed for discrete choice modelling. Roth and Schwab (2023) investigated individual preferences for mode choice by conducting a multinomial logit (MNL) model, a mixed model, and a hybrid mixed logit model. The MNL model, with airplane as the reference category, showed significant regression estimates for both ICOs (0.063 (0.037), $p < 0.1$) and SAF (0.142 (0.053), $p < 0.05$). This indicates that the attributes ICOs and SAF considerably increase the utility of flying. Nonetheless, the coefficient estimations are not straightforward to interpret, and the regression results do not indicate which effect is greater. Consequently, a two-sided t-test was calculated to test the null hypothesis that both coefficients are equal. The findings reveal a t-statistic of 1.222 with 7325 degrees of freedom and a p-value of 0.222. The null hypothesis is not rejected at the 10% level of significance, indicating that the coefficients of ICOs and SAF do not differ significantly.

The post-estimation of the MNL model indicates the willingness to pay for SAF of CHF 12.94 ($p < 0.01$) and CHF 5.71 for ICOs ($p < 0.1$). Furthermore, the model shows that ICOs increases the predicted flight choice probability by 0.97%-points, whereas SAF increases it by approximately 2.68%-points. Moreover, the partworth analysis for MNL shows that SAF is more important than ICOs for mode choice. However, the previously mentioned t-test showed no significant difference between ICOs and SAF, so this partworth analysis cannot be interpreted directly.

As an alternative method, the data was analysed using a linear fixed-effects panel model. Calculations were carried out in R with the *plm* package (Croissant & Millo, 2008). Table 12 displays that model 1 regresses the binary variable *Flight Choice* on the binary variable *ICOs*. Model 2 includes the interaction terms of *ICOs* with *Biospheric*, *Altruistic* and *Egoistic Environmental Concern*. In model 3, *SAF* is included as well as all other mode choices attributes as control variables. In addition, all regressions include fixed effects on entities (N = 1221). There is no need for fixed effects on blocks, since all attributes are orthogonalized and choice sets in blocks are randomised.

Regression estimates from model 1 and model 2 suggest that ICOs increase the probability of flight choice by 1.2%-points at the 10%-significance level. However, there is no significant interaction effect observed with biospheric, altruistic and egoistic environmental concern. Model 3, which includes all mode choice attributes, improves the fit of the model, but the effect of ICOs on flight choice is no longer significant. SAF increase the probability of flight choice by 2.5%- points at the 1%-significance level. Yet, as for the MNL Model, it is necessary to test whether the coefficients differ significantly. A two-sided t-test reveals a t-statistic of -1.481 with 7325 degrees of freedom and a p-value of 0.139. The null hypothesis cannot be rejected at the 10%-significance level. This suggest that the coefficients for ICOs and SAF are not significantly different.

Table 12: Regression estimates from linear fixed-effects panel model for flight choice

	Dependent variable: Flight Choice		
		panel linear	
	(1)	(2)	(3)
ICOs	0.012*	0.012*	0.009
	(0.007)	(0.007)	(0.007)
SAF			0.025***
			(0.008)
Flight-ICOs * Biospheric Env. Concern[a]		0.0001	0.004
		(0.012)	(0.012)
Flight-ICOs * Altruistic Env. Concern[a]		0.004	0.002
		(0.012)	(0.012)
Flight-ICOs * Egoistic Env. Concern[a]		0.003	0.002
		(0.011)	(0.011)
Control Variables			✓
Observations	7,326	7,326	7,326
Adjusted R^2	-0.199	-0.200	-0.139
F Statistic	2.818* (df = 1; 6104)	0.917 (df = 4; 6101)	22.581*** (df = 15; 6090)

Notes: Total N = 7326, entities = 1221, T = 6. ICOs = integrated carbon offsets, SAF = sustainable aviation fuel. Standard errors in parentheses, clustered and corrected for heteroskedasticity and autocorrelation. Heteroskedasticity for model 2 confirmed by the Breusch-Pagan test and White test, for model 3 confirmed by the Breusch-Pagan test. Model 3 includes the following control variables: *Flight-Cost*, *Flight-Time*, *Train-Cost*, *Train-Time*, *Train-Comfort*, *Nighttrain-Cost*, *Nighttrain-Time*, *Nighttrain-Comfort*, *Car-Cost*, *Car-Time*. All regressions include fixed effects on entities. Full regression outputs showing the control variables are provided in appendix F.

[a] Biospheric, Altruistic and Egoistic Env. Concern are centered.

*p<0.1; **p<0.05; ***p<0.01

Table 13 displays the conditional average treatment effect (CATE) of ICOs on individuals with high or low environmental concerns, according to model 3's regression estimates. Neither individuals at the

75th nor the 25th percentile of biospheric, altruistic or egoistic environmental concern experience a significant effect at the 10%-significance level.

Table 13: Conditional average treatment effect (CATE) of ICOs on Q1 and Q3 of environmental concerns

Linear Combination of Coefficients	Estimate
Flight-ICOs + Flight-ICOs * Biospheric Env. Concern * *Q3Biospheric Env. Concern*	0.011 (0.010)
Flight-ICOs + Flight-ICOs * Altruistic Env. Concern * *Q3Altruistic Env. Concern*	0.011 (0.010)
Flight-ICOs + Flight-ICOs * Egoistic Env. Concern * *Q3Egoistic Env. Concern*	0.011 (0.011)
Flight-ICOs + Flight-ICOs * Biospheric Env. Concern * *Q1Biospheric Env. Concern*	0.007 (0.009)
Flight-ICOs + Flight-ICOs * Altruistic Env. Concern * *Q1Altruistic Env. Concern*	0.008 (0.008)
Flight-ICOs + Flight-ICOs * Egoistic Env. Concern * *Q1Egoistic Env. Concern*	0.008 (0.009)

Notes: Total N = 7326, entities = 1221, T = 6. ICOs = integrated carbon offsets. Standard errors in parentheses, clustered and corrected for heteroskedasticity and autocorrelation. Linear combination of coefficients of regression model 3 of Table 12. Regression includes entities fixed effects.

*p<0.1; **p<0.05; ***p<0.01

In conclusion, hypothesis 5a can be supported. Both the MNL model and the linear fixed-effects panel model provide weak evidence that ICOs increase the probability of flight choice and thus lead to a rebound effect. On the other hand, hypothesis 5b cannot be verified. The impact of ICOs on flight choices is not related to environmental concerns. Lastly, hypothesis 5e cannot be proven. It cannot be demonstrated significantly that the effect of SAF on flight choice exceeds the effect of ICOs on flight choice.

5.2.5 Evaluation of hypotheses 5c & 5d

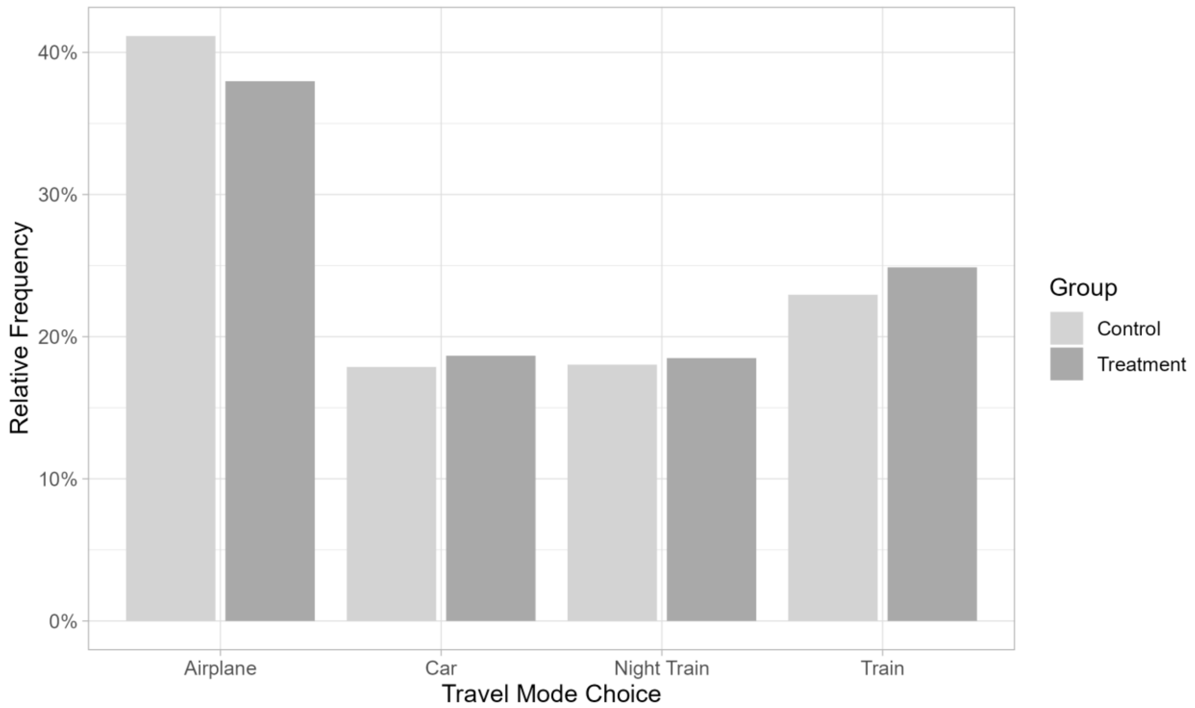
This chapter complements the research question “How do carbon offsets influence an individual’s flight choice?” with a focus on voluntary carbon offsets by evaluating the following hypotheses:

H5c: The possibility of voluntarily carbon offsets increases an individual’s flight choice and thereby leading to a rebound effect.

H5d: The rebound effect is enhanced for individuals with high biospheric or altruistic environmental concern.

The effect of VCOs on flight choice will be examined using choice set 7, which has been designed as an RCT. Figure 6 shows the travel mode choice split by the treatment group (n = 611), who had the possibility to voluntarily offset their flight carbon emissions, and the control group (n = 610). It is notable that only 38% of the treatment group chose to fly, compared to 41% of the control group. However, both a two-sided proportion test (p-value = 0.282) and a Fisher’s exact test (p-value = 0.266) indicate no significant difference in flight choice between the two groups.

Figure 6: Travel mode choice split by treatment and control group



Notes: Total N = 1221, control group = 610, treatment group = 611. The barplot shows the travel mode choice split by the control and treatment group for choice set 7. The treatment group had the possibility to voluntarily offset their flight carbon emissions.

Table 14 displays the regression estimates derived from linear probability models with *Flight Choice* as the binary dependent variable. In model 1, *Treatment (VCOs)* is the binary independent variable, indicating treatment group (1) or control group (0). Model 2 includes *Biospheric*, *Altruistic* and *Egoistic Environmental Concern*. Model 3 additionally includes the interaction terms with *Treatment (VCOs)*. In model 4, all sociodemographic control variables were included and in model 5, the travel scenario control variables were added. The models were checked for multicollinearity using a correlation matrix and variance inflation factors (VIF), which were all below 5. As a rule of thumb, VIF above 10 indicate problematic multicollinearity (Kennedy, 2013). According to ANOVA and adjusted R^2, model 4 appears to have the best model fit, but due to continuity, all models are presented.

Consistent with the results of the proportion test and Fisher's exact test, all 5 models show that the possibility of voluntary carbon offsetting has a slightly negative but not significant effect on flight choice. Model 2 shows that a unit increase in biospheric environmental concern is associated with a decrease in the probability of opting for a flight by 4.5%-points ($p < 0.1$), and that an increase in altruistic concern decreases the probability of flight choice by 5.7%-points ($p < 0.05$). Additionally, a unit increase in egoistic concern increases the probability of flight choice by 3.9%-points ($p < 0.1$). But, when interaction terms with treatment are introduced, the effects of environmental concerns are insignificant. A post-hoc power calculation for model 4 with a 5%-significance level indicates a very low power (*Treatment (VCOs):* 6.4%, *Biospheric Concern*: 5.2%, *Altruistic Concern*: 9.6%, *Egoistic Concern*: 6.0%). Power refers to the probability of not committing a type II error, which occurs when a study fails to reject a false null hypothesis. The absence of significance of the coefficients may therefore be explained not only by the truly small effect, but also by low power and small sample size. Nevertheless, post-hoc power calculations have been criticised widely for their lack of usefulness. According to Lenth

(2007), the post-hoc power calculation is directly linked to the p-value of the regression and it provides no new information.

Table 14: Regression estimates from linear probability models for flight choice

	Dependent variable: Flight Choice[a]				
	OLS				
	(1)	(2)	(3)	(4)	(5)
Constant	0.411***	0.409***	0.409***	0.264***	0.276***
	(0.020)	(0.020)	(0.020)	(0.061)	(0.063)
Treatment (VCOs)[b]	-0.032	-0.027	-0.027	-0.022	-0.021
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Biospheric Env. Concern[c]		-0.045*	-0.033	-0.009	-0.010
		(0.023)	(0.032)	(0.032)	(0.032)
Altruistic Env. Concern[c]		-0.057**	-0.054	-0.047	-0.046
		(0.022)	(0.033)	(0.033)	(0.033)
Egoistic Env. Concern[c]		0.039*	0.030	0.023	0.021
		(0.022)	(0.033)	(0.032)	(0.032)
Treatment (VCOs) * Biospheric Env. Concern[c]			-0.025	-0.036	-0.033
			(0.047)	(0.047)	(0.047)
Treatment (VCOs) * Altruistic Env. Concern[c]			-0.003	-0.010	-0.014
			(0.044)	(0.044)	(0.044)
Treatment (VCOs) * Egoistic Env. Concern[c]			0.017	0.017	0.020
			(0.044)	(0.043)	(0.043)
Sociodemographic Control Var.				✓	✓
Travel Scenario Control Var.					✓
Observations	1,221	1,221	1,221	1,221	1,221
Adjusted R^2	0.0002	0.011	0.009	0.032	0.031
F Statistic	1.288 (df = 1; 1219)	4.485*** (df = 4; 1216)	2.613** (df = 7; 1213)	3.111*** (df = 19; 1201)	2.864*** (df = 21; 1199)

Notes: VCOs = voluntary carbon offsets. Standard errors in parentheses, corrected for heteroskedasticity. Heteroskedasticity was confirmed by the Breusch-Pagan test and White test. Model 4 includes the following control variables: *Female*, *Young (< 36 Years)*, *Old (> 60 Years)* (age 36 to 60 as the base category), *Mandatory Education*, *Tertiary Education* (secondary education as the base category), *High income*, *French Speaking*, *Italian Speaking* (German as the base category), *Agglomeration*, *Urban* (rural as the base category), *Car Access*, *E-Car Access*. Model 5 includes in addition: *Travelling With Children* and *Travelling Alone* (travelling with family without children, with partner, with friends or other serves as the base category). Full regression outputs showing the control variables are provided in appendix F.

[a] Flight Choice is binary (0/1).

[b] Treatment (VCOs) is binary, indicating treatment group (1) or control group (0).

[c] Biospheric, Altruistic and Egoistic Env. Concern are centered.

*p<0.1; **p<0.05; ***p<0.01

Although no significant average treatment effect (ATE) was found, it is possible that a conditional average treatment effect (CATE) exists amongst those with either high or low environmental concerns.

Table 15 presents the estimates of the linear combinations of coefficients based on the regression estimates from model 4. The results demonstrate that there is likewise no effect at the 10%-significance level for either individuals at the 75th or 25th percentile of environmental concerns.

Table 15: Conditional average treatment effect (CATE) of Treatment (VCOs) on Q1 and Q3 of environmental concerns

Linear Combination of Coeffcients	Estimate
Treatment (VCOs) + Treatment (VCOs) * Biospheric Env. Concern * *Q3Biospheric Env. Concern*	-0.042 (0.037)
Treatment (VCOs) + Treatment (VCOs) * Altruistic Env. Concern * *Q3Altruistic Env. Concern*	-0.029 (0.040)
Treatment (VCOs) + Treatment (VCOs) * Egoistic Env. Concern * *Q3Egoistic Env. Concern*	-0.009 (0.045)
Treatment (VCOs) + Treatment (VCOs) * Biospheric Env. Concern * *Q1Biospheric Env. Concern*	-0.007 (0.036)
Treatment (VCOs) + Treatment (VCOs) * Altruistic Env. Concern * *Q1Altruistic Env. Concern*	-0.019 (0.032)
Treatment (VCOs) + Treatment (VCOs) * Egoistic Env. Concern * *Q1Egoistic Env. Concern*	-0.031 (0.036)

Notes: Total N = 1221. VCOs = voluntary carbon offsets. Standard errors in parentheses, corrected for heteroskedasticity and autocorrelation. Linear combination of coefficients of regression model 4 of Table 14.

*p<0.1; **p<0.05; ***p<0.01

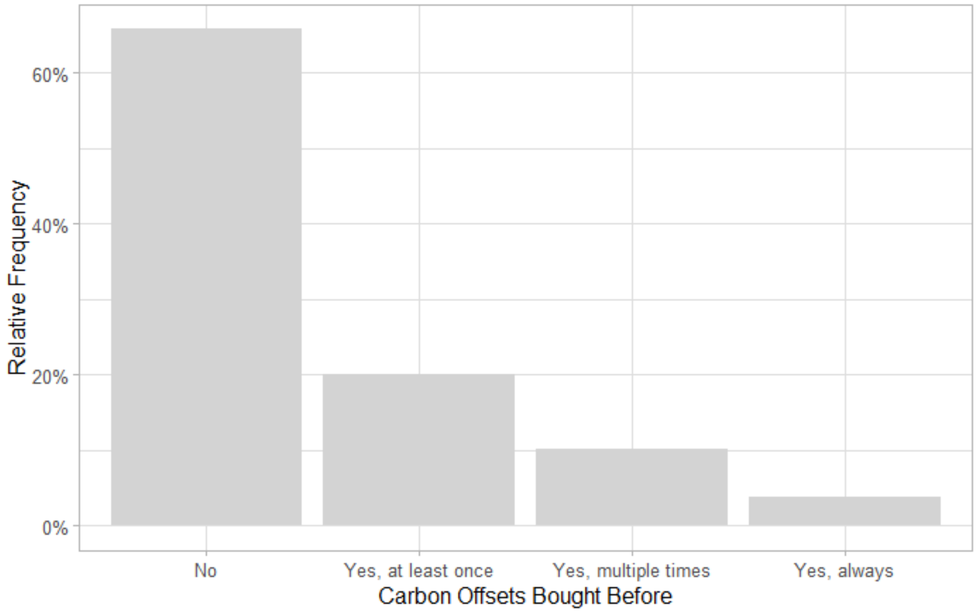
In summary, neither hypothesis H5c nor H5d can be confirmed. The possibility of voluntary carbon offsetting does not have a statistically significant effect on flight choice on average, nor does it have an effect for individuals with high biospheric or altruistic environmental concern. This study suggests that there is no rebound effect of VCOs on flight choice.

5.3 Additional analysis

The following chapter presents the descriptive statistics to adress the research question "What are individual's attitudes towards carbon offsets?".

According to the results, 80% of participants were aware of carbon offsets before participating in the survey. Nonetheless, the majority of these participants (66%) had never offset their flight emissions before (see Figure 7). 20% of the participants had offset their flight emissions at least once, 10% had done it multiple times and only 4% had always done so.

Figure 7: Previous history of offsetting flight carbon emissions

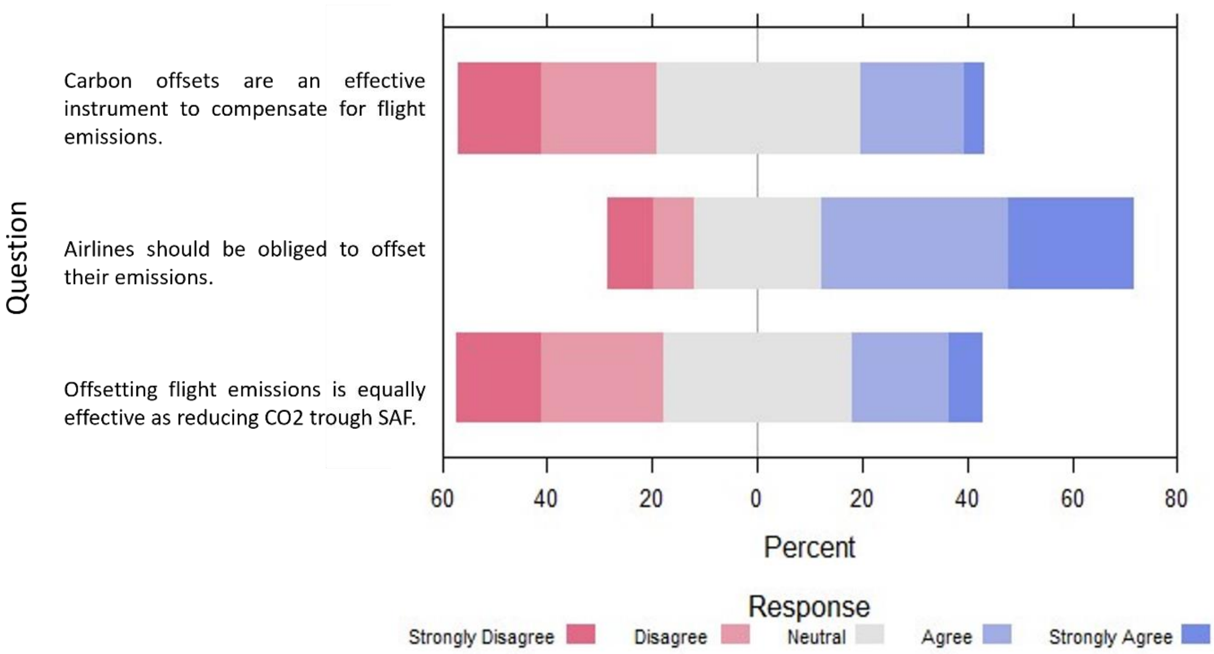


Notes: Total N = 1219. Participants were asked if they have offset their flight carbon emissions in the past (includes integrated carbon offsets and voluntary carbon offsets).

Figure 8 illustrates the participant's attitudes towards carbon offsets. Participants are conflicted about the effectiveness of carbon offsets. 24% of participants either agree or strongly agree that carbon offsets are effective in offsetting flight emission, while 39% remain neutral, and 37% either disagree or strongly disagree. These views align with the attitudes towards the statement that offsetting flight emissions are equally effective as reducing CO_2 through SAF. 24% of respondents agree or strongly agree with the statement, and 36% are being neutral. However, 39% disagree or strongly disagree, indicating that offsetting is less effective as reducing CO_2 through SAF. It is noteworthy that 59% of respondents agree or strongly agree that airlines should be obliged to offset their emissions, while 25% are neutral and 16% disagree or strongly disagree.

Finally, out of the total sample (N = 1221), only 13% of participants were aware that flights within Europe (including Switzerland) fall under the EU ETS regulations. On the contrary, 80% were uncertain, while 7% wrongly assumed that this is not accurate. Of those who knew about Switzerland's participation in the EU ETS, 62% of the treatment group who chose to fly did purchase VCOs. There was no significant difference in VCO purchase between those who had knowledge about the EU ETS and those who did not, according to a t-test ($p < 0.435$). Hence, it seems that awareness of ETS participation does not affect voluntary carbon offsetting.

Figure 8: Attitudes towards carbon offsets



Notes: Total N = 1221. SAF = sustainable aviation fuel. Participants were asked to rate the items on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

6 Discussion

The objective of this master thesis is to investigate how carbon offsets influence individuals' flight choice, thereby potentially leading to a rebound effect. Subsequently, the outcomes are discussed and integrated into the existing research.

The results indicate that biospheric and altruistic environmental concern negatively affect flight choice among other travel modes, whereas egoistic environmental concern positively affects flight choice. These results align with the environmental concerns theory proposed by Schultz (2001) which distinguishes three motives for environmental concern based on the importance of the impact of environmental damage on oneself (egoistic), others (altruistic), and the ecosystem (biospheric). Previous research on the relationship between the different types of environmental concern and pro-environmental behaviour has been inconsistent, with most studies showing a positive relationship between biospheric and altruistic environmental concern and pro-environmental behaviour (Rhead et al., 2015; Schultz, 2001; Schultz et al., 2005; Weber et al., 2020). On the other hand, the findings of this study show that if individuals are willing to fly, their biospheric, altruistic and egoistic environmental concern have no significant impact on how frequently they choose air travel. This is an interesting finding, as it suggests that individuals behave either strictly pro-environmentally or not at all.

The RCT demonstrates that more than half of the individuals who were given the possibility to voluntarily offset their flight emissions did so. The findings suggest that biospheric environmental concern positively influences voluntary carbon offsetting, whilst altruistic environmental concern has no significant effect. Conversely, egoistic environmental concern is found to negatively predict voluntary carbon offsetting. Only one third of participants who knew about carbon offsets before taking part in the study reported to have offset their flight emissions at least once before. Therefore, it can be assumed that the proportion of VCOs purchases indicated in the study does not reflect actual behaviour. Denton et al. (2020) found that perceived effectiveness and trust in carbon offset projects are important drivers of VCOs purchases. However, only 24% of survey respondents agree that carbon offsets are effective in offsetting flight emissions, while 39% remain neutral, and 37% disagree. The discrepancy between low perceived effectiveness and a high proportion of VCOs choices in the study might be explained by a priming effect of the study design. Moreover, voluntary carbon offsetting does not seem to be affected by awareness of Switzerland's participation in the EU ETS. It is possible that individuals do not view the trading system of the EU ETS as equally effective as voluntary carbon offsetting, or at least that they do not consider the EU ETS to be effective enough. However, it is not certain that participants have really understood how the EU ETS works.

On average, travellers who choose flight consistently, have the lowest level of guilt among all who chose flight at least once. It can be hypothesized, that frequent flyers do not experience the feeling of flight shame. This, in turn, may be the reason why they are frequent flyers. If flying is not perceived as something bad that makes you feel guilty, there is no reason to limit flying. However, the study suggests that individuals with high biospheric or altruistic environmental concern feel more guilty and feel less positive about their mode choice when choosing flight compared to others, but only for frequent flyers. Conversely, the hypothesis that individuals with high altruistic and biospheric environmental concern feel less guilty and feel better when flights are offset, or the flight uses sustainable fuel is not supported. Depending on the number of flights taken, ICOs, VCOs and SAF have either a positive or negative effect on guilt and positive feelings about the choice of travel mode. It is notable that the subsamples, split into 0 to 7 flight choices, are small and this may affect the detection of consistent effects. Furthermore, participants were only asked to rate their feelings about their mode choice once, at the end of the questionnaire and not after every choice set. However, the study results support the findings of Bösehans et al. (2020), which indicate that individuals with strong biospheric values experience greater guilt when flying than others, resulting in flight avoidance, as ICOs cannot reduce guilt. Additionally, when considering that participants perceive the effectiveness of carbon offsets as relatively low, it is reasonable that carbon offsets do not reduce guilt and are not a suitable strategy to reduce cognitive dissonance associated with flying.

The findings of this study present weak evidence that ICOs increase the probability of flight choice, resulting in a direct rebound effect. According to the linear fixed-effects panel model, ICOs have a marginal probability effect of 1.2%-points on the likelihood of choosing flight. This result is consistent to the findings of the MNL model by Roth and Schwab (2023), which found that ICOs increase choice probability by 0.97%-points. However, this study finds, in contrast to the hypothesis, that the impact of ICOs on flight choice is not related to environmental concerns.

Moreover, the study suggests that SAF increases the likelihood of selecting a flight by 2.5%-points. Although the coefficient estimate of SAF exceeds the one of ICO, the effect cannot be proven to be significantly greater. However, only 24% of participants agree with the statement that offsetting flight emissions is as effective as reducing CO_2 through SAF, 36% are neutral and 39% disagree. It can therefore be assumed that participants understand the difference between effective emission reduction and compensation.

The analysis of the RCT with the possibility to voluntarily offset carbon emissions for the treatment group, comes to a different result than for the ICOs. Unsuspectedly, the proportion of flight choice of the treatment group is slightly lower than the one of the control groups. However, the difference is statistically insignificant. VCOs appear to not have a statistically significant effect on flight choice on average, nor do they have an effect for individuals with high biospheric or altruistic environmental concern. So, this thesis suggests that there is no rebound effect of VCOs on flight choice. These findings are different from those of Bösehans et al. (2020). Their experimental study, which focused only on ICOs, found no effect of ICOs on guilt and flight choice. The authors therefore suggest that voluntarily offsetting one's own expenses may be necessary for guilt-reducing and flight-encouraging effects. However, this thesis reveals the opposite outcome, wherein ICOs result in a small rebound effect, whereas VCOs do not.

Remarkably, 59% of participants agree that airlines should be obliged to offset their emissions, while 25% are neutral and 16% disagree. Therefore, it is crucial to consider how the rebound effect of ICOs could affect net emissions, given the questionable effectiveness of carbon offset projects. Imagining the following scenario: Airlines offset all flights, resulting in a 1.2% increase in the number of air travellers. If flight emissions are effectively offset by at least 1.2%[9], then the rebound effect of 1.2%-point will not increase net emissions. Effective compensations above this threshold will reduce net emissions. Therefore, while ICOs may lead to a small rebound effect, this thesis cannot support the concern that carbon offsets “could do more harm than good” as found by Bösehans et al. (2020, p. 2).

Limitations

There are limitations to this master's thesis, particularly in terms of the study design. A stated preference survey only assesses self-reported behaviour and may not reflect actual behaviour. Respondents' answers may be biased towards appearing more environmentally conscious due to the information they were given about the CO_2e emissions of the different travel modes. Although the choice sets were designed

[9] $1.2 / 1.012 = 1.186 \approx 1.2$ (for detailed calculation see appendix G).

to represent realistic travel scenarios, some important attributes may have been missing. The choice sets presented to individuals were complex, and it cannot be guaranteed that respondents carefully considered all the information and made their decisions based on the attribute levels. It is worth noting that the no offset condition was theoretical, as respondents who typically purchase VCOs may still consider carbon offsets even when not explicitly presented as part of their choice set.

Furthermore, it is worth noting that the scale scores of the participants for all three types of environmental concern are high overall, with no great variability. This indicates the possibility of a selective sample. However, as the sample is quite representative of the Swiss population, this is unlikely to be the case. Instead, the environmental concerns scale developed by Schultz (2001) may not have been the most suitable instrument for assessing environmental consciousness.

Additionally, the envisioned destination was 700 km distant and could be reached by different travel modes. This is different when planning intercontinental holidays. Consequently, the findings of this research should only be applied to destinations where there are plausible alternative travel modes.

Finally, the study design only addresses direct rebound effects related to flights, but not indirect rebound effects in other domains. Therefore, the effect of carbon offsets on other carbon-intensive activities cannot be measured.

7 Conclusion

The objective of this thesis was to examine how carbon offsets influence individual's flight choice, thereby potentially leading to a rebound effect. A rebound effect could be of great relevance as the aviation sector needs to cut its greenhouse gas emissions in order to reduce global warming. There is concern, that if carbon offsets are not effective, the rebound effect might lead to increased net emissions.

The findings suggest that strong biospheric or altruistic environmental concern has a negative impact on flight choice and, for people who fly, a positive impact on voluntary carbon offsetting. Nonetheless, opting for offset flights does not lower feelings of guilt and therefore does not seem to be an appropriate strategy for reducing the cognitive dissonance associated with flying.

The results indicate weak evidence, that integrated carbon offsets increase the probability of flight choice, resulting in a direct rebound effect of 1.2%-points. Nevertheless, contrary to predictions, ICOs' impact on flight choice is not related to environmental concerns. In contrast, it seems that voluntary carbon offsets do not affect flight choice on average, nor do they affect individuals with high biospheric or altruistic environmental concern.

The majority of participants support an obligation for all airlines to offset their emissions. If the emissions would be offset effectively by at least 1.2%, the rebound effect of 1.2%-points will not result in a net increase in emissions. All effective compensation beyond this threshold will reduce net emissions. The findings of this thesis therefore indicate that the fear of carbon offsets doing greater damage than benefit is misplaced.

The study further suggests that SAF increases the likelihood of selecting a flight by 2.5%-points. Given that SAF is one of the main strategies to decarbonize the aviation sector, this rebound effect may be relevant. Further research could explore this issue in depth.

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AI tools

ChatGTP, version 3.5, OpenAi: https://chat.openai.com/

Help with coding for RStudio

DeepL Translate, Deepl SE: https://www.deepl.com/translator

Translation of survey questionnaire from German to French and Italian

DeepL Write, Deepl SE: https://www.deepl.com/write

Grammatical revision of text passages

A Appendix

Selected items of survey questionnaire in German

Figure 9: Explanation of travel scenario

Wir kommen nun zum zweiten Frageblock. Um diesen ausfüllen zu können, folgt auf der nächsten Seite ein Erklärungstext. Es handelt sich dabei um den einzigen längeren Text in dieser Umfrage. Bitte lesen Sie ihn aufmerksam durch.

expl_scenario_desk

Stellen Sie sich vor, Sie planen eine **etwa einwöchige Ferienreise** in einen **europäischen Ort** Ihrer Wahl.
Die Destination ist gut erreichbar und etwa **700 km** Luftlinie von zuhause entfernt (z.B. Rom, Berlin, Barcelona oder London).

Wir zeigen Ihnen sieben Szenarien, in denen Sie sich jeweils entscheiden müssen, ob Sie mit dem **Zug, Nachtzug, Auto oder Flugzeug** reisen würden.
Beispielszenario:

Reisekosten	75 CHF	50 CHF	75 CHF	135 CHF
Reisezeit Tür zu Tür	9:30 h	6:35 h	8:25 h	4:05 h
Komfort				Economy
Nachhaltiger Treibstoff				☑
Kompensiert				☒
Emissionen in kg CO2e	132 kg	29 kg	44 kg	212 kg ÷ 2 = 106 kg

Figure 10: Description of attribute levels

Zwischen den Szenarien verändern sich einige Eigenschaften der Reise, die hier kurz beschrieben werden. Bitte lesen Sie das Folgende aufmerksam durch.

Reisekosten (in CHF)**:**

- Reisekosten pro Person inkl. aller Kosten wie allfällige Mautgebühren bei Autos oder CO2-Kompensation bei Flugreisen.

Reisezeit (in h:min)**:**

- Gesamte Reisezeit, von Tür zu Tür (inkl. Wartezeiten am Gate bei Flügen, u.ä.)
- Variiert je nach Szenario wegen Strassenausbau, Zugverbindung etc.

Komfort:

- Flug immer Economy.
- Der Komfort beim Auto entspricht Ihrem Auto.
- Für Zug und Nachtzug gibt es folgende Komfortlevels:

Nachhaltiger Treibstoff (Ja / Nein)**:**

- Nur bei Flugoption
- Nachhaltiger Treibstoff ist eine Mischung aus herkömmlichem Kerosin und Treibstoff der aus erneuerbaren Quellen gewonnen wird. Dafür wird CO2 aus der Atmosphäre genommen oder aus Pflanzenabfall recycelt und mithilfe eines chemischen Verfahrens zu künstlichem Treibstoff umgewandelt. Durch die Verwendung von diesem gemischten Kerosin werden nur noch halb so viele neue Treibhausgase in die Atmosphäre ausgestossen. Die Einsparung von 50% der Emissionen wird folgendermassen angezeigt: 212 kg / 2 = 106 kg.

CO2-Kompensation (Ja / Nein):

- Nur bei Flugoption
- Die CO2-Emissionen des Fluges werden durch Investitionen in erneuerbare Energien, Energieeffizienzmassnahmen sowie Waldschutz, Wiederaufforstung oder die Renaturierung von Moorgebieten ausgeglichen.

Emissionen (in kg CO2-Äquivalente (CO2e))**:**

- Effektive neu ausgestossene Treibhausgas-Emissionen der Reise, pro Person

Alle Angaben gelten jeweils für die Hinreise, mit der Annahme, dass für die Rückreise alle Eigenschaften gleichbleiben.

Figure 11: Option for voluntary carbon offsetting for treatment group in RCT

ACHTUNG NEU:
In diesem Szenario haben Sie die Möglichkeit, die Flugemissionen **freiwillig** für zusätzliche Kosten von **CHF 10** zu kompensieren.

Reisekosten	92 CHF	92 CHF	92 CHF	92 CHF
Reisezeit Tür zu Tür	7:40 h	08:25 h	09:30 h	4:30 h
Komfort				Economy
Nachhaltiger Treibstoff				☒
Kompensiert				☒
Emissionen in kg CO2e	29 kg	132 kg	44 kg	212 kg

Möchten Sie die Emissionen von Ihrem Flug freiwillig für CHF 10 kompensieren?
- ○ Ja
- ○ Nein

Figure 12: Questions about feelings for travel mode choice

Sie haben sich insgesamt **${e://Field/sumFlights} von 7 Mal** für den **Flug** entschieden. Bitte geben Sie an, inwieweit Sie jeder der folgenden Aussagen zustimmen.

	1 = Stimme überhaupt nicht zu	2 = Stimme nicht zu	3 = Stimme weder zu noch nicht zu	4 = Stimme zu	5 = Stimme völlig zu
Meine Verkehrsmittelwahl gibt mir ein gutes Gefühl.	○	○	○	○	○
Ich habe ein schlechtes Gewissen bezüglich meiner Verkehrsmittelwahl.	○	○	○	○	○

Figure 13: Questions about knowledge, buying history and attitudes towards carbon offsets

Wir möchten nun gerne Ihre Meinung zu **CO2-Kompensationen bei Flugreisen** erfahren. Für die Spende an ein Klimaschutzprojekt wie **erneuerbare Energien, Energieeffizienzmassnahmen, Waldschutz, Renaturierung und Aufforstung** werden CO2-Zertifikate ausgestellt. Der Flug stösst weiterhin CO2- und Nicht-CO2-Emissionen (z.B. Kondensstreifen) aus, jedoch wird die entsprechende CO2-Menge* bei den Klimaschutzprojekten eingespart, was zu einer **relativen Reduktion von CO2 in der Atmosphäre** führt.

*Einige Anbieter berücksichtigen nur CO2, andere auch Nicht-CO2-Emissionen.

Ich habe bereits vor dieser Umfrage von CO2-Kompensationen gehört.

○ Ja

○ Nein

Ich habe in der Vergangenheit meine Flüge mit CO2-Zertifikaten ausgeglichen.

○ Nein

○ Ja, mindestens einmal

○ Ja, mehrmals

○ Ja, immer

Bitte geben Sie an, inwieweit Sie jeder der folgenden Aussagen zustimmen.

	1 = Stimme überhaupt nicht zu	2 = Stimme nicht zu	3 = Stimme weder zu noch nicht zu	4 = Stimme zu	5 = Stimme völlig zu
CO2-Kompensationen sind ein effektives Mittel um Flugemissionen auszugleichen.	○	○	○	○	○
Ich bin der Meinung, dass die Fluggesellschaften verpflichtet werden sollten, ihre Emissionen zu kompensieren.	○	○	○	○	○
Ich bin der Meinung, dass die Kompensation von Flugemissionen gleich effektiv ist wie eine CO2-Reduktion durch nachhaltigen Treibstoff.	○	○	○	○	○

Figure 14: Questions on environmental concern

Menschen auf der ganzen Welt sind von **Umweltproblemen** durch die Zerstörung der Natur betroffen. Allerdings unterscheiden sich Menschen darin, welche Auswirkungen ihnen am wichtigsten erscheinen. Wie wichtig sind Ihnen persönlich die **Folgen** von Umweltproblemen für...?

	1 = Nicht wichtig	2	3	4	5 = Wichtig
Pflanzen	○	○	○	○	○
Meereslebewesen	○	○	○	○	○
Vögel	○	○	○	○	○
Säugetiere	○	○	○	○	○
Sie selbst	○	○	○	○	○
Ihre Gesundheit	○	○	○	○	○
Ihre Zukunft	○	○	○	○	○
Alle Menschen	○	○	○	○	○
Zukünftige Generationen	○	○	○	○	○

B Appendix

Calculation of attribute levels

The orthogonalized attribute levels of travel time and travel cost as well as emission levels are based on detailed calculations, which are explained in the following section.

We have maintained a consistent travel distance of approximately 700 kilometres from home as the crow flies, encompassing cities such as Rome (684 km), London (777 km), and Berlin (671 km)[10]. All subsequent calculations are based on these three cities. Unless otherwise specified, an average among the outcomes for these destinations was used. As the distance was kept constant, the emissions associated with this travel remained fixed. However, travel time and cost were treated independently, recognising their potential for variation due to factors such as congested roads, missed connections, or delays.

To estimate travel times, we relied on approximate durations sourced from Google Maps[11]. For instance, the journey from Zurich to Rome was estimated at approximately 6:52 h by train, 9:26 h by car, and 1:30 h minutes by plane. Considering door-to-door travel times, we added 30 min for travelling to and from the airport as well as waiting time of 1:30 h minutes to 2:00 h at the gate. Accordingly, this resulted in a realistic door-to-door travel time of 3:35 h minutes to 4:30 h for the flight option. Regarding the night train, our calculation considered train schedules and the slower pace of night trains to allow for approximately 8 h of sleep.

Cost levels for train and night train travel were determined using data collected from railway operators in Switzerland, Italy, Germany, and Austria. These prices demonstrate considerable variations across operators and are subject to seasonal fluctuations, especially during holidays. To establish cost levels for air travel, information was sourced from the popular platform Skyscanner[12]. These prices are also affected by seasonality, a factor we have taken into account in our cost level variations. In our calculation of flight costs, we have included a fixed fee of CHF 40 for checked baggage, based on prices observed at Easyjet[13]. However, the cost for car travel differs among alternatives as it is dependent on the number of individuals travelling. Although we had information on the approximate number of people travelling in our scenario, we decided not to include it in the cost calculation in order to maintain the simplicity of the survey design, which used pictures to present choice situations. Therefore, the cost levels associated with car travel were not dynamically linked to previous responses. Instead, we assumed an equal distribution of travel costs between two paying individuals. Considering an average distance of 886 km to the three cities, an average fuel consumption of 7.48 L/100km for the Swiss average car (Sacchi & Bauer, 2023) and a fuel price of 1.75 CHF/L (as of May 2023, in 2023 Swiss francs), this led us to a base price of 57 CHF per person for a single trip. Additional toll charges apply to some destinations (e.g., from Como to Rome, tolls amount to 45.90 €[14]), therefore we have allowed travel costs to fluctuate between 53 and 92 CHF.

[10] Beeline-distances were approximated using https://www.luftlinie.org/

[11] https://www.google.ch/maps

[12] https://www.skyscanner.ch/

[13] https://www.easyjet.com/

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

The emissions calculations for each mode of travel were based mainly on data from the mobitool by Sacchi and Bauer (2023). For flights, an aircraft with 122 seats and an average occupancy rate of 76% was assumed. Emission levels for train travel depend heavily on the electricity mix used in the corresponding countries. Given the limited travel time within Switzerland in the scenario, an average based on the German (0.033 kg CO_2e/pkm[15]), Italian (0.060 kg CO_2e/pkm), and French (0.013 kg CO_2e/pkm) electricity mixes was computed, assuming 425 seats with an occupancy rate of 55%. For night trains, these emissions were multiplied by a factor of 1.5 to accommodate the increased space per passenger. When analysing cars, the average fuel consumption data from the Swiss fleet provided by Sacchi and Bauer (2023) was used, but adjusted for an average of two passengers instead of 1.6. The emission calculations for e-cars factored in several elements. These levels depended on the electricity mix of the chosen country, considering that the initial charge is presumably done in Switzerland (only for one-way trips). Referring to Sacchi and Bauer (2023), a return trip would require six charges using the average e-car in Switzerland. It was factored that one of these charges would occur in Switzerland (19.2 g CO_2e/pkm) and the average carbon intensity of Germany, Italy, and France (36.7 g CO_2e/pkm) for the remaining charges. It's important to note that the calculations in Sacchi and Bauer (2023) aim to encompass all emissions, not just those directly related to fuel use. Therefore, only the emissions from the electricity consumed were adjusted, keeping emissions from manufacturing, street infrastructure, maintenance, etc., at the Swiss level. Table 16 shows the final emissions of each travel mode per pkm and the resulting overall emissions for a one-way trip in our specific scenario.

Table 16: Emissions by mode of travel

Mode	Distance in km	kg CO2e/pkm	Total kg CO2e
Train	920	0.032	29
Night Train	920	0.048	44
Car	886	0.149	132
E-car	886	0.104	93
Airplane	718	0.292	212

.

[15] pkm = passenger-kilometre

C Appendix

RScript

```
#### DCE long data

dce <- read.csv("data/DCE_data_20230602.csv")

#...............................................................
### conversion of variable types

#..............................................................
# conversion of env. concern variables in to biospheric, egoistic and alturistic

library(dplyr)
unique(dce$envirconcern_likert_1)
class(dce$envirconcern_likert_1)
dce$ec_bio_1 <- recode(dce$envirconcern_likert_1,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)
unique(dce$ec_bio_1)
class(dce$ec_bio_1)

dce$ec_bio_2 <- recode(dce$envirconcern_likert_2,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)

dce$ec_bio_3 <- recode(dce$envirconcern_likert_3,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)

dce$ec_bio_4 <- recode(dce$envirconcern_likert_4,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)

dce$ec_ego_1 <- recode(dce$envirconcern_likert_5,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)

dce$ec_ego_2 <- recode(dce$envirconcern_likert_6,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)

dce$ec_ego_3 <- recode(dce$envirconcern_likert_7,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)

dce$ec_alt_1 <- recode(dce$envirconcern_likert_8,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)

dce$ec_alt_2 <- recode(dce$envirconcern_likert_9,
                "1 = Nicht wichtig" = 1,
                "2" = 2,
                "3" = 3,
                "4" = 4,
                "5 = Wichtig" = 5)

### creating env. concern indices (biospheric, egoistic and altruistic)

#cronbachs alpha
library(psych)
# biospheric ec
alpha(subset(dce, select = c(ec_bio_1,ec_bio_2, ec_bio_3, ec_bio_4)), check.keys =TRUE) # 0.92 --> too high? redundant items?
# egoistic ec
alpha(subset(dce, select = c(ec_ego_1, ec_ego_2, ec_ego_3)), check.keys =TRUE) # 0.91 --> to high?
# Spearman (for only 2 items) for altruistic
cor.test(dce$ec_alt_1, dce$ec_alt_2, method="spearman")# rho of 0.79 -> strong

# creating index for biospheric ec by averaging ec_bio_1 to 4
dce$ec_bio_idx <- rowMeans(dce[, c("ec_bio_1", "ec_bio_2", "ec_bio_3", "ec_bio_4")], na.rm = TRUE) # calculating average for each row
class(dce$ec_bio_idx)
unique(dce$ec_bio_idx)
summary(dce$ec_bio_idx)

# creating index for egoistic ec by averaging ec_ego_1 to 3
dce$ec_ego_idx <- rowMeans(dce[, c("ec_ego_1", "ec_ego_2", "ec_ego_3")], na.rm = TRUE) # calculating average for each row
class(dce$ec_ego_idx)
unique(dce$ec_ego_idx)
summary(dce$ec_ego_idx)

# creating index for altruistic ec by averaging ec_alt_1 to 2
dce$ec_alt_idx <- rowMeans(dce[, c("ec_alt_1", "ec_alt_2")], na.rm = TRUE) # calculating average for each row
class(dce$ec_alt_idx)
unique(dce$ec_alt_idx)
summary(dce$ec_alt_idx)

#...................................................................
## centralize ec indices --> mean becomes zero
```

```
dce$cent_ec_bio_idx <- dce$ec_bio_idx - mean(dce$ec_bio_idx, na.rm = TRUE)
summary(dce$cent_ec_bio_idx)
dce$cent_ec_alt_idx <- dce$ec_alt_idx - mean(dce$ec_alt_idx, na.rm = TRUE)
dce$cent_ec_ego_idx <- dce$ec_ego_idx - mean(dce$ec_ego_idx, na.rm = TRUE)

## creating summary statistics for ec
summary(dce$cent_ec_bio_idx)
summary(dce$cent_ec_alt_idx)
summary(dce$cent_ec_ego_idx)
#..................................................................
unique(dce$b7_vco_treat) # shows vco choice after flight selection in treatment group
class(dce$b7_vco_treat)
dce$b7_vco_treat <- ifelse(dce$b7_vco_treat == "Nein", 0, 1) # Nein is 0 and Ja is 1
class(dce$b7_vco_treat) # numeric
dce$b7_vco_treat <- as.integer(dce$b7_vco_treat)

unique(dce$t.tcost) # shows attribute levels of costs of the train in the different scenarios
unique(dce$choice) # 1 = train, 2 = night train, 3 = car, 4 = airplane
unique(dce$value) # eq. to choice but in letters
unique(dce$setid) # all observations from 1 to 8547
str(dce)

#.................................................................
#### Import Data Wide
  #   allwdce =  ALL wide data wide


allwdce <- read.csv("data/data_wide_20230602.csv")

#..............................................................................

#### Cleaning columns to make it smaller
###   wdce

wdce <- allwdce
# deleting all unnessary columns
wdce <-
  wdce[, !(
    names(wdce) %in% c(
      "StartDate",
      "EndDate",
      "IPAddress",
      "Duration..in.seconds.",
      "RecordedDate" ,
      "ResponseId",
      "UserLanguage" ,
      "Progress" ,
      "Metainfo_Browser" ,
      "Metainfo_Version" ,
      "Metainfo_Operating.System",
      "Metainfo_Resolution",
      "F300_kontinent" ,
      "F310_europa_schweiz"  ,
      "F400_reisedauer" ,
      "F460_transportmittel" ,
      "F470_unterkunft"  ,
      "F500_reiseart"    ,
      "F510_feriendestinat"    ,
      "F520_social_impact_1" ,
      "F520_social_impact_2"  ,
      "F520_social_impact_3"  ,
      "F520_social_impact_4"   ,
      "F520_social_impact_5" ,
      "F520_social_impact_6"   ,
      "F520_social_impact_7"  ,
      "F520_social_impact_8"  ,
      "F600_ferienpartner"  ,
      "F100_overtourismus_1" ,
      "F100_overtourismus_1_4_TEXT" ,
      "F200_overtourismus_2" ,
      "F200_overtourismus_2_4_TEXT",
      "timing_expl_set_desk_First.Click" ,
      "timing_expl_set_desk_Last.Click" ,
      "timing_expl_set_desk_Page.Submit" ,
      "timing_expl_set_desk_Click.Count",
      "timing_expl_sce_mob_First.Click"  ,
      "timing_expl_sce_mob_Last.Click"  ,
      "timing_expl_sce_mob_Click.Count" ,
      "timing_expl_offsets_First.Click" ,
      "timing_expl_offsets_Last.Click"  ,
      "timing_expl_offsets_Click.Count" ,
      "timing_expl_offsets_Page.Submit" ,
      "Q_URL"  ,
      "Q_SurveyVersionID"  ,
      "i_survey"    ,
      "img_key_de"    ,
      "img_key_fr"    ,
      "img_key_it"    ,
      "src"       ,
      "issue"       ,
      "destination" ,
      "d" ,
      "complete_survey"   ,
      "Q_TotalDuration"   ,
      "Date"   ,
      "duration_minutes" ,
      "timing_expl_sce_mob_Page.Submit",
      "TID",
     "BFS_ID",
     "canton_home",
     "municipality"
        )
  )]

#.....................................................................

### Manipulation data wdce
###
###

wdce$car_yes_no <- factor(wdce$car_yes_no)
str(wdce$car_yes_no)
levels(wdce$car_yes_no)

wdce$car_yes <- wdce$car_yes_no
levels(wdce$car_yes)
library(dplyr)
wdce <- wdce %>%
  mutate(car_yes = recode(wdce$car_yes,
                    "Nein" = 0,
                    "Ja, ich besitze ein Auto" = 1,
                    "Ja, ich habe Zugang zu einem Auto" = 1))
```

```
wdce$car_yes <- as.integer(wdce$car_yes)
wdce <- wdce %>% rename(car = car_yes)

wdce$travel_type_scenario <-
factor(wdce$travel_type_scenario)
str(wdce$travel_type_scenario)
class(wdce$travel_type_scenario)
levels(wdce$travel_type_scenario) #checks for factor levels
# re-order the levels
wdce$travel_type_scenario <-
factor(wdce$travel_type_scenario, levels = c("Reise
alleine", "Reise mit Kindern", "Reise mit Familie ohne
Kinder (z.B. Eltern/Verwandte)", "Reise mit Partner*in",
"Reise mit Freund*innen", "Andere"))
levels(wdce$travel_type_scenario) #checks for factor levels

wdce$children <- wdce$travel_type_scenario
wdce$chilren <- as.character(wdce$children)
wdce$children <- ifelse(wdce$children %in% c("Reise mit
Kindern"), 1, 0)
wdce$children <- as.integer(wdce$children)
wdce$alone <- wdce$travel_type_scenario
wdce$alone <- as.character(wdce$alone)
wdce$alone <- ifelse(wdce$alone %in% c("Reise alleine"),
1, 0)
wdce$alone <- as.integer(wdce$alone)

wdce$car_fuel <- factor(wdce$car_fuel)
wdce$car_fuel <- factor(wdce$car_fuel, levels =
c("Benzin", "Diesel", "Hybrid", "Elektrisch", "Andere"))
levels(wdce$car_fuel)

wdce$ecar_yes <- wdce$car_fuel
wdce$ecar_yes <- as.character(wdce$ecar_yes)
wdce$ecar_yes <- ifelse(wdce$ecar_yes %in%
c("Elektrisch"), 1, 0)
wdce$ecar_yes <- as.integer(wdce$ecar_yes)
wdce <- wdce %>% rename(e_car = ecar_yes)

wdce$offsets_known_before
wdce$offsets_known_before <-
as.logical(wdce$offsets_known_before == "Ja")

wdce$offsets_known_before <-
as.integer(wdce$offsets_known_before)
wdce$offsets_known_before <-
as.factor(wdce$offsets_known_before)

wdce$offsets_bought_befor <-
factor(wdce$offsets_bought_befor)
levels(wdce$offsets_bought_befor)
# reorder
wdce$offsets_bought_befor <-
factor(wdce$offsets_bought_befor,
                    levels = c("Nein", "Ja, mindestens
einmal", "Ja, mehrmals", "Ja, immer"))
levels(wdce$offsets_bought_befor)

levels(wdce$offsets_known_before)<- c("No", "Yes")
wdce$offsets_attitude_1 <- factor(wdce$offsets_attitude_1,
levels = c("1 = Stimme überhaupt nicht zu", "2 = Stimme
nicht zu", "3 = Stimme weder zu noch nicht zu", "4 =
Stimme zu", "5 = Stimme völlig zu"))
levels(wdce$offsets_attitude_1) <- c("Strongly Disagree",
"Disagree", "Neutral", "Agree", "Strongly Agree")

wdce$offsets_attitude_2 <- factor(wdce$offsets_attitude_2,
levels = c("1 = Stimme überhaupt nicht zu", "2 = Stimme
nicht zu", "3 = Stimme weder zu noch nicht zu", "4 =
Stimme zu", "5 = Stimme völlig zu"))
levels(wdce$offsets_attitude_2) <- c("Strongly Disagree",
"Disagree", "Neutral", "Agree", "Strongly Agree")

wdce$offsets_attitude_3 <- factor(wdce$offsets_attitude_3,
levels = c("1 = Stimme überhaupt nicht zu", "2 = Stimme
nicht zu", "3 = Stimme weder zu noch nicht zu", "4 =
Stimme zu", "5 = Stimme völlig zu"))
levels(wdce$offsets_attitude_3) <- c("Strongly Disagree",
"Disagree", "Neutral", "Agree", "Strongly Agree")

wdce$ETS_yes_no_unsure <-
factor(wdce$ETS_yes_no_unsure)
wdce$ETS_yes_no_unsure <-
factor(wdce$ETS_yes_no_unsure, levels = c("Ja", "Nein",
"Ich weiss es nicht")) #reorder
levels(wdce$ETS_yes_no_unsure)

wdce$ETS_yes <- wdce$ETS_yes_no_unsure
wdce$ETS_yes <- as.character(wdce$ETS_yes_no_unsure)
wdce$ETS_yes <- ifelse(wdce$ETS_yes_no_unsure %in%
c("Ja"), 1, 0)
wdce$ETS_yes <- as.integer(wdce$ETS_yes)


# dummy for old and young (middle is baseline)
wdce$young <- ifelse(wdce$Alter < 36, 1, 0)
wdce$young <- as.integer(wdce$young)
wdce$old <- ifelse(wdce$Alter > 60, 1, 0)
wdce$old <- as.integer(wdce$old)
wdce <- wdce %>% rename(age = Alter)

wdce$hh_income <- factor(wdce$hh_income)
wdce$hh_income <- factor(wdce$hh_income, levels =
c("Weniger als CHF 2'000", "CHF 2'000 - 4'000", "CHF
4'001 - 6'000",
                    "CHF 6'001 - 8'000", "CHF
8'001 - 10'000", "CHF 10'001 - 12'000",
                    "CHF 12'001 -
14'000","CHF 14'001 - 16'000","Mehr als CHF 16'000",
                    "Ich weiss nicht", "Keine
Antwort"))
levels(wdce$hh_income)

wdce$hh_size <- factor(wdce$hh_size)
wdce$hh_size <- factor(wdce$hh_size, levels = c("1", "2",
"3", "4", "5", "6", "7 oder mehr", "Keine Antwort"))
levels(wdce$hh_size)

wdce$treatment <- factor(wdce$treatment)
levels(wdce$treatment)
wdce <- wdce %>%
  mutate(treatment = recode(wdce$treatment,
              "Control" = 0,
              "Treated" = 1))
wdce$treatment <- as.integer(wdce$treatment)

class(wdce$Q_Language)
wdce$Q_Language <- factor(wdce$Q_Language, levels =
c("DE", "FR", "IT"))
```

```
levels(wdce$Q_Language)
wdce <- wdce %>% rename(language = Q_Language)

wdce <- wdce %>% rename(gender = Gender)
class(wdce$gender)
wdce$gender <- factor(wdce$gender, levels = c(1, 2), labels = c("male", "female")) #according to LINK
levels(wdce$gender)

unique(wdce$Abgeschlossene.Bildung)
wdce$Abgeschlossene.Bildung <- factor(wdce$Abgeschlossene.Bildung, ordered = TRUE, levels = c(1, 2, 3), labels = c("mandatory", "secondary", "tertiary"))
wdce <- wdce %>% rename(education = Abgeschlossene.Bildung)
levels(wdce$education)
wdce$tertiary <- ifelse(wdce$education == "tertiary", 1, 0)
wdce$mandatory <- ifelse(wdce$education == "mandatory", 1, 0)

## conversion of env. concern variables in to biospheric, egoistic and alturistic

unique(wdce$envirconcern_likert_1)
class(wdce$envirconcern_likert_1)
wdce$ec_bio_1 <- recode(wdce$envirconcern_likert_1,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)
class(wdce$ec_bio_1)

wdce$ec_bio_2 <- recode(wdce$envirconcern_likert_2,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)

wdce$ec_bio_3 <- recode(wdce$envirconcern_likert_3,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)

wdce$ec_bio_4 <- recode(wdce$envirconcern_likert_4,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)

wdce$ec_ego_1 <- recode(wdce$envirconcern_likert_5,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)

wdce$ec_ego_2 <- recode(wdce$envirconcern_likert_6,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)

wdce$ec_ego_3 <- recode(wdce$envirconcern_likert_7,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)

wdce$ec_alt_1 <- recode(wdce$envirconcern_likert_8,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)

wdce$ec_alt_2 <- recode(wdce$envirconcern_likert_9,
              "1 = Nicht wichtig" = 1,
              "2" = 2,
              "3" = 3,
              "4" = 4,
              "5 = Wichtig" = 5)
#.......................................................................

### creating env. concern indices (biospheric, egoistic and altruistic)

#cronbachs alpha
library(psych)
  # biospheric ec
alpha(subset(wdce, select = c(ec_bio_1,ec_bio_2, ec_bio_3, ec_bio_4)), check.keys =TRUE) # 0.92 --> too high? redundant items?
  # egoistic ec
?alpha
alpha(subset(wdce, select = c(ec_ego_1, ec_ego_2, ec_ego_3)), check.keys =TRUE) # 0.91 --> to high?

# Spearman's brown (for only 2 items) for altruistic
 # first Spearman's rank
altr_spearmans_rank <- cor(wdce$ec_alt_1, wdce$ec_alt_2, method = "spearman")
altr_spearmans_brown <- (2 * altr_spearmans_rank) / (1 + altr_spearmans_rank)
altr_spearmans_brown ## 0.88

# creating index for biospheric ec by averaging ec_bio_1 to 4
wdce$ec_bio_idx <- rowMeans(wdce[, c("ec_bio_1", "ec_bio_2", "ec_bio_3", "ec_bio_4")], na.rm = TRUE) # calculating average for each row
class(wdce$ec_bio_idx)
unique(wdce$ec_bio_idx)
summary(wdce$ec_bio_idx)


# creating index for egoistic ec by averaging ec_ego_1 to 3
wdce$ec_ego_idx <- rowMeans(wdce[, c("ec_ego_1", "ec_ego_2", "ec_ego_3")], na.rm = TRUE) # calculating average for each row
class(wdce$ec_ego_idx)
unique(wdce$ec_ego_idx)
```

```
summary(wdce$ec_ego_idx)

# creating index for altruistic ec by averaging ec_alt_1 to 2
wdce$ec_alt_idx <- rowMeans(wdce[, c("ec_alt_1", "ec_alt_2")], na.rm = TRUE) # calculating average for each row
class(wdce$ec_alt_idx)
unique(wdce$ec_alt_idx)
summary(wdce$ec_alt_idx)

## centralize ec indices --> mean becomes zero
wdce$cent_ec_bio_idx <- wdce$ec_bio_idx - mean(wdce$ec_bio_idx, na.rm = TRUE)
summary(wdce$cent_ec_bio_idx)
wdce$cent_ec_alt_idx <- wdce$ec_alt_idx - mean(wdce$ec_alt_idx, na.rm = TRUE)
summary(wdce$cent_ec_alt_idx)
wdce$cent_ec_ego_idx <- wdce$ec_ego_idx - mean(wdce$ec_ego_idx, na.rm = TRUE)

## creating summary statistics for ec
summary(wdce$ec_bio_idx)
summary(wdce$ec_alt_idx)
summary(wdce$ec_ego_idx)

#centralised indices
summary(wdce$cent_ec_bio_idx)
summary(wdce$cent_ec_alt_idx)
summary(wdce$cent_ec_ego_idx)

###
# Summary statistics about env concern
library(vtable)
?st
st(wdce, vars = c('ec_bio_idx', 'cent_ec_bio_idx', 'ec_alt_idx', 'cent_ec_alt_idx', 'ec_ego_idx', 'cent_ec_ego_idx'),
  add.median = TRUE,
  digits = 6,
  file = 'st_ec.html') # saves a html file)

#..................................................................

### Creating 25th and 75th percentile of ec concern

hist(wdce$cent_ec_bio_idx) # unusual distribution --> stark rechtsgeneigt
mean(wdce$cent_ec_bio_idx)  # almost zero
median(wdce$cent_ec_bio_idx) # 0.5565111
cent_ec_bio_perc_75 <- quantile(wdce$cent_ec_bio_idx, 0.75)
cent_ec_bio_perc_75  # 0.5565111  --> as median! very unusual
cent_ec_bio_perc_90 <- quantile(wdce$cent_ec_bio_idx, 0.90)
cent_ec_bio_perc_90 # same --> no big variance in data, all very high values

# to control for not-centralised data --> same
hist(wdce$ec_bio_idx) # unusual distribution
mean(wdce$ec_bio_idx) # 4.44
median(wdce$ec_bio_idx) # 5
ec_bio_perc_75 <- quantile(wdce$ec_bio_idx, 0.75)
ec_bio_perc_75 # 5
ec_bio_perc_90 <- quantile(wdce$ec_bio_idx, 0.90)
ec_bio_perc_90  # 5

hist(wdce$cent_ec_alt_idx) # unusual distribution --> stark rechtsgeneigt
median(wdce$cent_ec_alt_idx) # 0.68
cent_ec_alt_perc_75 <- quantile(wdce$cent_ec_alt_idx, 0.75)
cent_ec_alt_perc_75 # 0.6871417
cent_ec_alt_perc_90 <- quantile(wdce$cent_ec_alt_idx, 0.90)
cent_ec_alt_perc_90 # 0.6871417 # same as 75th

hist(wdce$cent_ec_ego_idx) #--> unusual distribution, auch rechtsgeneit aber weniger als bio oder alt
median(wdce$cent_ec_ego_idx) # 0.120
cent_ec_ego_perc_75 <- quantile(wdce$cent_ec_ego_idx, 0.75)
cent_ec_ego_perc_75 # 0.7848758
cent_ec_ego_perc_90 <- quantile(wdce$cent_ec_ego_idx, 0.90)
cent_ec_ego_perc_90 # 0.7848758 --> same as 75th!

cent_ec_bio_perc_25 <- quantile(wdce$cent_ec_bio_idx, 0.25)
cent_ec_alt_perc_25 <- quantile(wdce$cent_ec_alt_idx, 0.25)
cent_ec_ego_perc_25 <- quantile(wdce$cent_ec_ego_idx, 0.25)
cent_ec_bio_perc_25  # -0.443
cent_ec_alt_perc_25 # -0.313
cent_ec_ego_perc_25 # -0.548
#............................................................


##creating a new variable wdce$b7_choice with mode choice scenario 7 for for control and treatm together (mob & desk)

# first double check if only one non-NA value per row in the 4 variables
   # Check if there is exactly one non-NA value per row in the four variables
num_non_na <- rowSums(!is.na(wdce[c("b7_control_desk", "b7_control_mob", "b7_treatm_desk", "b7_treatm_mob")])) == 1
  # Check if all rows have exactly one non-NA value
all_rows_have_one_non_na <- all(num_non_na)
   # Count the number of rows with exactly one non-NA value
num_rows_with_one_non_na <- sum(num_non_na)
rm(all_rows_have_one_non_na)
rm(num_non_na)
rm(num_rows_with_one_non_na)

library(dplyr)
#create new variable wdce$b7_choice with mode choice in b7 (rct)
wdce <- wdce %>%
  mutate(b7_choice = coalesce(b7_control_desk, b7_control_mob, b7_treatm_desk, b7_treatm_mob))
unique(wdce$b7_choice)
# create new binary variable wdce$b7_flight_yes with flight choice
```

```
wdce$b7_flight_yes <- ifelse(wdce$b7_choice == "Airplane", 1, 0)
summary(wdce$b7_flight_yes)

# create new variable wdce$b7_vco_treat combining mob & desk (1 for Ja, 0 for Nein, NA)
library(dplyr)
wdce <- wdce %>%
  mutate(
    b7_vco_treat = case_when(
      b7_vco_treat_mob == "Ja" | b7_vco_treat_desk == "Ja" ~ 1,
      b7_vco_treat_mob == "Nein" | b7_vco_treat_desk == "Nein" ~ 0,
      is.na(b7_vco_treat_mob) & is.na(b7_vco_treat_desk) ~ NA_integer_
    )
  )
table(wdce$b7_vco_treat)
### there is a mistake in the variable b7_vco_treat bc it consists of 233 values (104 = 0 and 129 = 1)
  # but there are only 232 flight choices in treatment group
# Create the subset_treat dataframe
subset_mistake <- subset(wdce, b7_vco_treat == 0 & (b7_treatm_desk != "Airplane" | b7_treatm_mob != "Airplane"))
print(subset_mistake)
  # id 420 has choosen train at b7_choice but still choosen VCO --> logical mistake in the survey --> report in MA!
# manually change value to 0
wdce$b7_vco_treat[wdce$id == 420] <- NA
subset420 <- (subset(wdce, id == 420))
print(subset420)
table(wdce$b7_vco_treat)
#.................................................

library(dplyr)
# "Meine Verkehrsmittel Wahl gibt mir ein gutes Gefühl" (1 = Stimme überhaupt nicht zu bis 5 = Stimme völlig zu)
wdce <- wdce %>% rename(feeling_travelmode_good = feeling_travelmode_1)
unique(wdce$feeling_travelmode_good)
wdce$feeling_travelmode_good <- recode(wdce$feeling_travelmode_good,
                 "1 = Stimme überhaupt nicht zu" = 1,
                 "2 = Stimme nicht zu" = 2,
                 "3 = Stimme weder zu noch nicht zu" = 3,
                 "4 = Stimme zu" = 4,
                 "5 = Stimme völlig zu" = 5
)
class(wdce$feeling_travelmode_good)
unique(wdce$feeling_travelmode_good)
hist(wdce$feeling_travelmode_good)

# make inverse (damit vergleichbar mit feeling_travelmode_guilty)
wdce$feeling_travelmode_good_inverse <- 6 - wdce$feeling_travelmode_good

# feeling guilty" - Ich habe ein schlechtes Gewissen bezüglich meiner Verkehrsmittelwahl (1 = Stimme überhaupt nicht zu bis 5 = Stimme völlig zu)
wdce <- wdce %>% rename(feeling_travelmode_guilty = feeling_travelmode_2)
wdce$feeling_travelmode_guilty <- recode(wdce$feeling_travelmode_guilty,
                 "1 = Stimme überhaupt nicht zu" = 1,
                 "2 = Stimme nicht zu" = 2,
                 "3 = Stimme weder zu noch nicht zu" = 3,
                 "4 = Stimme zu" = 4,
                 "5 = Stimme völlig zu" = 5
)
hist(wdce$feeling_travelmode_guilty)
#.................................................................
### SAMPLE DESCRIPTION

## N total sample
nrow(wdce)

# N per block (DCE)
table(wdce$block_nr)

# N per control and treatmetn (RCT)
table(wdce$treatment)

### Comparison with microzensus and comparison control and treatment group

table(wdce$car, wdce$treatment)
t.test(car~treatment, wdce)
t.test(e_car~treatment, wdce)
t.test(young~treatment, wdce)
t.test(old~treatment, wdce)
wdce$middleage <- ifelse(wdce$young == 0 & wdce$old == 0, 1, 0)
t.test(middleage~treatment, wdce)
t.test(female~treatment, wdce)
t.test(mandatory~treatment, wdce)
t.test(tertiary~treatment, wdce)
wdce$secondary <- ifelse(wdce$mandatory == 0 & wdce$tertiary == 0, 1, 0)
t.test(secondary~treatment, wdce)

#............................................................
 ### income high and low based on median income! adjusted for household size & kids
table(wdce$incL)
table(wdce$incH)
table(wdce$inc_na)
mean(dce$incH == 1) * 100
mean(dce$incL  == 1) *100
mean(dce$inc_na == 1)*100

t.test(incL~treatment, wdce)
t.test(incH~treatment, wdce)
t.test(inc_na~treatment, wdce)

#.......................................................................
table(wdce$hh_income) ## income irrelevant of house hold size - for comparison with microcensus
class(wdce$hh_income)

# Create a new factor variable wdce$income_micro
wdce$income_micro <- ifelse(
```

```
  wdce$hh_income %in% c("CHF 10'001 - 12'000", "CHF 12'001 - 14'000", "CHF 14'001 - 16'000", "Mehr als CHF 16'000"),
  'above_10k',
  ifelse(
   wdce$hh_income %in% c("Weniger als CHF 2'000", "CHF 2'000 - 4'000", "CHF 4'001 - 6'000", "CHF 6'001 - 8'000", "CHF 8'001 - 10'000"),
   'below_10k',
   ifelse(
    wdce$hh_income %in% c('Ich weiss nicht', 'Keine Antwort'),
    'unknown',
    NA  # If none of the conditions match, assign NA (or another appropriate value)
   )
  )
)

# Convert the newly created variable to a factor
wdce$income_micro <- factor(wdce$income_micro)

table(wdce$income_micro)
# Create binary variables based on wdce$income_micro categories
wdce$inc_above_10k <- ifelse(wdce$income_micro == 'above_10k', 1, 0)
wdce$inc_below_10k <- ifelse(wdce$income_micro == 'below_10k', 1, 0)
wdce$inc_unknown <- ifelse(wdce$income_micro == 'unknown', 1, 0)

t.test(inc_above_10k~treatment, wdce)
t.test(inc_below_10k~treatment, wdce)
t.test(inc_unknown~treatment, wdce)

#.......................................

table(wdce$language)
wdce$german <- ifelse(wdce$language == 'DE', 1, 0)
wdce$french <- ifelse(wdce$language == 'FR', 1, 0)
wdce$italian <- ifelse(wdce$language == 'IT', 1, 0)
t.test(german~treatment, wdce)
t.test(french~treatment, wdce)
t.test(italian~treatment, wdce)

t.test(urban~treatment, wdce)
t.test(rural~treatment, wdce)
wdce$agglo <- ifelse(wdce$urban == 0 & wdce$rural == 0, 1, 0)
t.test(agglo~treatment, wdce)

#...................................................

### ANALYSIS
# .............................................

## RQ1: How does environmental concern influence an individual’s flight choices?
# Hypotheses:
# H1a. Altruistic and biospheric environmental concern are a negative predictor of choosing flight.
# H1b. Egoistic environmental concern is a positive predictor of choosing flight.

## Data: scenarios 1-6

### Data without offset (only scenarios 1-6)
##

# create variable with flight counts over all 6 scenarios
# List of variables to check for "Airplane"
airplane_vars_small <- c(
  "b1_c5_desk",
  "b1_c22_desk",
  "b1_c29_desk",
  "b1_c30_desk",
  "b1_c31_desk",
  "b1_c33_desk",
  "b1_c5_mob",
  "b1_c22_mob",
  "b1_c29_mob",
  "b1_c30_mob",
  "b1_c31_mob",
  "b1_c33_mob",
  "b2_c2_desk",
  "b2_c12_desk",
  "b2_c16_desk",
  "b2_c23_desk",
  "b2_c25_desk",
  "b2_c35_desk",
  "b2_c2_mob",
  "b2_c12_mob",
  "b2_c16_mob",
  "b2_c23_mob",
  "b2_c25_mob",
  "b2_c35_mob",
  "b3_c3_desk",
  "b3_c17_desk",
  "b3_c19_desk",
  "b3_c21_desk",
  "b3_c34_desk",
  "b3_c36_desk",
  "b3_c3_mob",
  "b3_c17_mob",
  "b3_c19_mob",
  "b3_c21_mob",
  "b3_c34_mob",
  "b3_c36_mob",
  "b4_c7_desk",
  "b4_c10_desk",
  "b4_c11_desk",
  "b4_c20_desk",
  "b4_c24_desk",
  "b4_c27_desk",
  "b4_c7_mob",
  "b4_c10_mob",
  "b4_c11_mob",
  "b4_c20_mob",
  "b4_c24_mob",
  "b4_c27_mob",
  "b5_c6_desk",
  "b5_c9_desk",
  "b5_c14_desk",
  "b5_c15_desk",
  "b5_c26_desk",
  "b5_c32_desk",
  "b5_c6_mob",
  "b5_c9_mob",
```

```
  "b5_c14_mob",
  "b5_c15_mob",
  "b5_c26_mob",
  "b5_c32_mob",
  "b6_c1_desk",
  "b6_c4_desk",
  "b6_c8_desk",
  "b6_c13_desk",
  "b6_c18_desk",
  "b6_c28_desk",
  "b6_c1_mob",
  "b6_c4_mob",
  "b6_c8_mob",
  "b6_c13_mob",
  "b6_c18_mob",
  "b6_c28_mob"

)
# Calculate the count of "Airplane" in each specified variable and store the results in a list
airplane_counts_small <- lapply(airplane_vars_small, function(var) {
  grepl("Airplane", wdce[[var]], fixed = TRUE)
})
# Sum the counts for each row and store the result in the new variable wdce$flightcount_dce
wdce$flightcount_dce <- rowSums(do.call(cbind, airplane_counts_small))
summary(wdce$flightcount_dce)

### Descriptive statistics

## Histogram: Histogram: Flight count per individual for choice set 1 to 6

hist(wdce$flightcount_dce,
     xlab = "Flight Count per Individual",
     ylab = "Frequency",
     main = "",
     cex.lab = 1.1,   # Adjust the font size (e.g., 1.2 for size 12)
     cex.axis = 1.1,
     ylim = c(0, 600),    # Set the y-axis limits from 0 to 600
     col = "lightgrey",
     border = "darkgrey")
abline(v = mean(wdce$flightcount_dce), col = "blue", lwd = 2)
legend("topright", legend = paste("Mean = ", round(mean(wdce$flightcount_dce), 3)), col = "blue", lwd = 2)
?hist

library(ggplot2)

# Create a histogram using ggplot2 with modified x-axis labels, y-axis labels, and mean line label
ggplot(data = wdce, aes(x = flightcount_dce)) +
  geom_histogram(binwidth = 1, color = "darkgrey", fill = "lightgrey") +
  labs(x = "Flight Count per Individual", y = "Frequency") +
  scale_x_continuous(breaks = seq(0, 6, by = 1)) +  # Set x-axis breaks from 0 to 6
  scale_y_continuous(breaks = seq(0, 600, by = 100)) +  # Adjust y-axis breaks from 0 to 600 with 100-steps
  theme_minimal() +
  geom_vline(aes(xintercept = mean(flightcount_dce)), color = "blue", size = 2) +
  annotate("text", x = mean(wdce$flightcount_dce) + 0.7, y = 550,
           label = paste("Mean =", round(mean(wdce$flightcount_dce), 3)), color = "blue")


## add N in the description of the histogram in the paper
length(wdce$flightcount_dce)
nrow(wdce) # same

# --> nicht poisson distribution! too many zeros
summary(wdce$flightcount_dce)
?hist

## summary statistics
library(vtable)

st(wdce, vars = c('flightcount_dce'),
   add.median = TRUE,
   file = 'st_flightcount_dce.html') # saves a html file
?st
var(wdce$flightcount_dce)
mean(wdce$flightcount_dce)

## frequency --> to tell in text
table(wdce$flightcount_dce)

#......................................................
## Model 1 (data: 6 scenarios)
#

# Poisson 1 - only ec
poisson1 <- glm(
  flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
  data = wdce,
  family = poisson(link = "log")
)
summary(poisson1)
BIC(poisson1)

# Adjusted Poisson 1
# sandwich SE (robust sandwich covariance for cross-section data)
#--> acounts for heteroscedasticity and potential overdispersion
coeftest(poisson1, vcov. = sandwich)
poiss_cov_sandw_1 <- sandwich (poisson1)
poiss_sandw_se1 <- sqrt(diag(poiss_cov_sandw_1))

#### Quasi-Poisson regression 1 - only ec
##
q_poisson1 <- glm(
  flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
  data = wdce,
  family = quasipoisson(link = "log")
)

summary(q_poisson1) # with default SE (robust SE makes no sense here)
BIC(poisson1)
```

```
### Hurdle Model 1
##
#
library(pscl)
citation("pscl")

## Hurdle 1
hurdle1 <- hurdle (flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
                data = wdce,
                dist = "poisson")
summary(hurdle1)# -> zero hurdle coefficients describe the odds of having a positive count

# table Can either show zero component or count component
stargazer( hurdle1,
        title = "Hurde Model 1 - Regression Estimates",
        dep.var.labels = " Flight Choice",
        column.labels = c ("Hurdle"),
        intercept.bottom = FALSE,
        zero.component = TRUE, # Shows count component
        type = "text")


## Zero-Inflated Poisson (ZIP) 1
# very similiar to Hurdle but more general version, zeros can be structural or random
?zeroinfl
zip1 <- zeroinfl(flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
              data = wdce,
              dist = "poisson")
summary(zip1)

?stargazer
stargazer( hurdle1, zip1,
        title = "Hurde Model  & Zero-Inflated Poisson Model 1- Regression Estimates",
        dep.var.labels = " Flight Choice",
        column.labels = c ("Hurdle", "ZIP"),
        intercept.bottom = FALSE,
        zero.component = TRUE, # Shows ZERO component
        type = "text")
# almost the same

stargazer( hurdle1, zip1,
        title = "Hurde Model  & Zero-Inflated Poisson Model 1- Regression Estimates",
        dep.var.labels = " Flight Choice",
        column.labels = c ("Hurdle", "ZIP"),
        intercept.bottom = FALSE,
        zero.component = FALSE, # Shows COUNT component
        type = "text")
.........................................
## Model 2 ec & socio demographics

# Poisson 2 -  ec & socio demographics
poisson2 <- glm(
  flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
  data = wdce,
  family = poisson(link = "log")
)
summary(poisson2)

#Adjusted Poisson 2
# sandwich SE
coeftest(poisson2, vcov. = sandwich)
poiss_sandw_cov2 <- sandwich (poisson2)
poiss_sandw_se2 <- sqrt(diag(poiss_sandw_cov2))

# Quasi-Poisson 2 -  ec & socio demographics
#
q_poisson2 <- glm(
  flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
  data = wdce,
  family = quasipoisson(link = "log")
)
summary(q_poisson2)

# Hurdle 2 - ec & socio demographics
#
hurdle2 <- hurdle (flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
               + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
               data = wdce,
               dist = "poisson")

summary(hurdle2) # better likelihood than hurdle 1 #-2145

## Zero-Inflated Poisson (ZIP) 2
zip2 <- zeroinfl(flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
              + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
              data = wdce,
              dist = "poisson")
summary(zip2)

#...........................

# Model 3: -  ec, socio demographics & travel scenario
#

# Poisson 3 -  ec, socio demographics & travel scenario
poisson3 <- glm(
  flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
  + children + alone,
  data = wdce,
  family = poisson(link = "log")
)
summary(poisson3)

#Adj. Poisson 3
# sandwich SE
coeftest(poisson3, vcov. = sandwich)
```

```
poiss_sandw_cov3 <- sandwich (poisson3)
poiss_sandw_se3 <- sqrt(diag(poiss_sandw_cov3))

# Quasi - Poisson 3 -  ec, socio demographics & travel scenario
#
q_poisson3 <- glm(
  flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
  + children + alone,
  data = wdce,
  family = quasipoisson(link = "log")
)
summary(q_poisson3)

# Hurdle 3  - ec, socio demographics & travel scenario
#
hurdle3 <- hurdle (flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce,
                dist = "poisson")
summary(hurdle3) #better likelihood than hurdle 2

## Zero-Inflated Poisson (ZIP) 3
zip3 <- zeroinfl(flightcount_dce ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
              + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
              + children + alone,
              data = wdce,
              dist = "poisson")
summary(zip3)

#...............................................

### TABLES SHOWING RESULTS

# Table with Adj. Poisson and Quasi-Poisson Model 1-3
#
stargazer(
  poisson1,
  q_poisson1,
  poisson2,
  q_poisson2,
  poisson3,
  q_poisson3,
  title = "Regression Estimates",
  dep.var.labels = " Flight Choice",
  column.labels = c (
    "Adj. Pois 1",
    "Quasi-Pois 1" ,
    "Adj. Pois 2",
    "Quasi-Pois 2" ,
    "Adj. Pois 3",
    "Quasi-Pois 3"
  ),
  covariate.labels = c("Constant","Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
                "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High income",
                "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
                "Travelling With Children", "Travelling Alone" ),
  se = list (poiss_sandw_se1, NULL,  poiss_sandw_se2, NULL, poiss_sandw_se3,  NULL),
  no.space = TRUE,
  model.names = TRUE,
  model.numbers = FALSE, # omits numbering of models
  intercept.bottom = FALSE,
  keep.stat = c("n", "ll", "aic", "bic"),
  out = "adj_qpoisson_123.html"
)

### combine in excel table with ZIP

## Table with Hurdle 1-3 & ZIP 1-3 ZERO COMPONENT
stargazer(
  hurdle1, zip1, hurdle2, zip2, hurdle3, zip3,
  title = "Hurdle & Zero-Inflated Poisson Model - Regression Estimates for Zero Component",
  dep.var.labels = " Flight Choice",
  intercept.bottom = FALSE,
  column.labels = c ( "Zero Comp. 1",  "Zero Comp. 1", "Zero Comp. 2", "Zero Comp. 2", "Zero Comp. 3", "Zero Comp. 3"),
  covariate.labels = c("Constant","Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
                "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
                "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
                "Travelling With children", "Travelling Alone"  ),
  zero.component = TRUE, # zero coefficients shown
  align = TRUE,
  no.space = TRUE ,
  model.names = TRUE, # shows model names (OLS, probit etc)
  model.numbers = FALSE,
  keep.stat = c("n", "ll", "aic", "bic"),
  out = "hurdle_zip_zero_123.html"
)

## Table with Hurdle 1-3 & ZIP 1-3 COUNT COMPONENT
# # how to interpret?
stargazer(
  hurdle1, zip1, hurdle2, zip2, hurdle3, zip3,
  title = "Hurdle & Zero-Inflated Poisson Model - Regression Estimates for Count Component",
  dep.var.labels = " Flight Choice",
  intercept.bottom = FALSE,
  column.labels = c ( "Count Comp. 1", "Count Comp. 1", "Count Comp. 2","Count Comp. 2", "Count Comp. 3" ,"Count Comp. 3"),
  covariate.labels = c("Constant","Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
```

```
            "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
            "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
            "Travelling With children", "Travelling Alone"  ),
  zero.component = FALSE, # count component shown
  align = TRUE,
  no.space = TRUE ,
  model.names = TRUE, # shows model names (OLS, probit etc)
  model.numbers = FALSE,
  keep.stat = c("n", "ll", "aic", "bic"),
  out = "hurdle_zip_count_123.html"
)

## Table with Hurdle 1-3
stargazer(
  hurdle1, hurdle2, hurdle3,
  title = "Hurdle Model - Regression Estimates for Zero Component",
  dep.var.labels = " Flight Choice",
  intercept.bottom = FALSE,
  column.labels = c ( "Zero Comp. 1", "Zero Comp. 2", "Zero Comp. 3"),
  covariate.labels = c("Constant","Biospheric env. concern", "Altruistic env. concern", "Egoistic env. concern",
            "Female", "Young (< 36 years)" , "Old (> 60 years)", "Mandatory education", "Tertiary education", "High income",
            "French speaking", "Italian speaking", "Agglomeration", "Urban", "Car access", "E-car access",
            "Travelling with children", "Travelling alone"  ),
  zero.component = TRUE, # zero coefficients shown
  no.space= TRUE,
  model.names = TRUE,
  out = "hurdle_zero_123.html"
)

## Table with Hurdle 1-3 COUNT COMPONENT
stargazer(
  hurdle1, hurdle2, hurdle3,
  title = "Hurdle Model - Regression Estimates for Count Component",
  dep.var.labels = " Flight Choice",
  intercept.bottom = FALSE,
  column.labels = c ( "Count Comp. 1", "Count Comp. 2", "Count Comp. 3"),
  zero.component = FALSE, # count component shown
  out = "hurdle_count_123.html"
)

#........................................................
### Comparison of Poisson (ML-Poisson), Adj-Poisson (Sandwich) & Quasi-Poisson, Hurdle & ZIP

mean(wdce$flightcount_dce)
var(wdce$flightcount_dce)

## Comparison Models 1

# No of parameters Models 1
length(coef(poisson1)) # 4 -> Adj. Poisson 1
length(coef(q_poisson1)) # 4 -> Quasi-Poisson 1
length(coef(hurdle1))  # 8 -->Hurdle 1
length(coef(zip1))    # 8 -->ZIP 1
#
comp <- list ("Pois" = poisson1, "Quasi-Pois" = q_poisson1, "Hurdle-Pois" = hurdle1, "ZIP" = zip1)
# shows coefficients of ML-Pois, Quasi-Pois, Hurdle-Pois, ZIP
sapply(comp, function (x) coef (x) [1:8])

# shows SE of ML-Pois, Adj-Pois, Quasi-Pois and Hurdle-Pois, ZIP (not the zero augmentation)
cbind("Pois" = sqrt(diag(vcov(poisson1))),
     "Adj.-Pois" = sqrt(diag(sandwich(poisson1))),
     sapply (comp[-1], function (x) sqrt (diag(vcov(x) )) [1:4]))

# show likelihoods
rbind (logLik = sapply (comp, function (x) round (logLik(x), digits = 0)),
      Df = sapply (comp, function (x) attr (logLik (x), "df")))

# show zero counts that are captured by models
round(c("Obs" = sum(wdce$flightcount_dce < 1),
       "Pois" = sum(dpois (0, fitted (poisson1))),
       "Adj.-Pois" = sum(dpois (0, fitted (poisson1))),
       "Pois-Hurdle" = sum (predict (hurdle1, type = "prob") [,1]),
       "ZIP" = sum(predict(zip1, type = "prob") [,1])
))
# --> Pois-Hurdle & ZIP captures Zeros better!

## AIC
library(AICcmodavg)
models_hurdle<- list(hurdle1, hurdle2, hurdle3)
aictab(cand.set = models_hurdle, )
print(aictab(cand.set = models_hurdle, second.ord = FALSE), digits = 3)

models_zip <- list(zip1, zip2, zip3)
aictab(cand.set = models_zip, second.ord = FALSE)
print(aictab(cand.set = models_zip, second.ord = FALSE), digits = 3)

models_poisson <- list(poisson1, poisson2, poisson3)
aictab(cand.set = models_poisson, second.ord = FALSE)
print(aictab(cand.set = models_poisson, second.ord = FALSE), digits = 3)

## NA
models_q_poisson <- list(q_poisson1, q_poisson2, q_poisson3)
aictab(cand.set = models_q_poisson, second.ord = FALSE)
print(aictab(cand.set = models_q_poisson, second.ord = FALSE), digits = 3)

## BIC
bictab(cand.set = models_hurdle, second.ord = FALSE)
print(bictab(cand.set = models_hurdle, second.ord = FALSE), digits = 3)

bictab(cand.set = models_zip)
print(bictab(cand.set = models_zip, second.ord = FALSE), digits = 3)
```

```
bictab(cand.set = models_poisson)
print(bictab(cand.set = models_poisson, second.ord = FALSE), digits = 3)

# No of parameters Models 2
length(coef(poisson2)) # 16
length(coef(q_poisson2)) # 16
length(coef(hurdle2))  # 32
length(coef(zip2))    # 32

# --> Pois-Hurdle & ZIP captures Zeros better
comp2 <- list ("Pois" = poisson2, "Quasi-Pois" = q_poisson2, "Hurdle-Pois" = hurdle2, "ZIP" = zip2)
# shows coefficients of Pois, Quasi-Pois, Hurdle-Pois, ZIP
sapply(comp2, function (x) coef (x) [1:32])

# shows SE of Pois, Adj-Pois, Quasi-Pois and Hurdle-Pois, ZIP (not the zero augmentation)
cbind("Pois" = sqrt(diag(vcov(poisson2))),
     "Adj.-Pois" = sqrt(diag(sandwich(poisson2))),
     sapply (comp2[-1], function (x) sqrt (diag(vcov(x) )) [1:32]))

# show likelihoods
rbind (logLik = sapply (comp2, function (x) round (logLik(x), digits = 0)),
      Df = sapply (comp2, function (x) attr (logLik (x), "df")))
# --> quasi-poission and adj-poisson don't have a  fitted likelihood (that's correct)
# ---> logLik ML-Pois > logLik Hurdle-Pois (hurdle-pois is better)

# show zero counts that are captured by models
round(c("Obs" = sum(wdce$flightcount_dce < 1),
       "Pois" = sum(dpois (0, fitted (poisson2))),
       "Adj.-Pois" = sum(dpois (0, fitted (poisson2))),
       "Pois-Hurdle" = sum (predict (hurdle2, type = "prob") [,1]),
       "ZIP" = sum(predict(zip2, type = "prob") [,1])
))

## Comparison Models 3

# No of parameters Models 3
length(coef(poisson3)) # 18 -> Adj. Poisson 3
length(coef(q_poisson3)) # 18 -> Quasi-Poisson 3
length(coef(hurdle3))  # 36 -->Hurdle 3
length(coef(zip3))    # 36 -->ZIP 3
## Comparison Models 3  --> add manually in regression table
#

comp3 <- list ("Pois" = poisson3, "Quasi-Pois" = q_poisson3, "Hurdle-Pois" = hurdle3, "ZIP" = zip3)
# shows coefficients of Pois, Quasi-Pois, Hurdle-Pois, ZIP
sapply(comp3, function (x) coef (x) [1:36])

# shows SE of Pois, Adj-Pois, Quasi-Pois and Hurdle-Pois, ZIP (not the zero augmentation)
cbind("Pois" = sqrt(diag(vcov(poisson3))),
     "Adj.-Pois" = sqrt(diag(sandwich(poisson3))),
     sapply (comp3[-1], function (x) sqrt (diag(vcov(x) )) [1:18]))

# show likelihoods
rbind (logLik = sapply (comp3, function (x) round (logLik(x), digits = 0)),
      Df = sapply (comp3, function (x) attr (logLik (x), "df")))
# --> quasi-poission and adj-poisson don't have a  fitted likelihood (that's correct)
# ---> logLik ML-Pois > logLik Hurdle-Pois (hurdle-pois is better)

# show zero counts that are captured by models
round(c("Obs" = sum(wdce$flightcount_dce < 1),
       "Pois" = sum(dpois (0, fitted (poisson3))),
       "Adj.-Pois" = sum(dpois (0, fitted (poisson3))),
       "Pois-Hurdle" = sum (predict (hurdle3, type = "prob") [,1]),
       "ZIP" = sum(predict(zip3, type = "prob") [,1])
))

# No of parameters Models 3
length(coef(poisson3)) # 18 -> Adj. Poisson 3
length(coef(q_poisson3)) # 18 -> Quasi-Poisson 3
length(coef(hurdle3))  # 36 -->Hurdle 3
length(coef(zip3))    # 36 -->ZIP 3

#.......................................................................................

### RQ2: What are individual's attitudes towards Carbon Offsets?

## Descriptive Statistics

library(psych)
library(dplyr)
library(tidyr)
library(HH)

#......................................................................
### Offsets known before and offsets bought before
##

table(wdce$offsets_known_befor) # Has NAs --> delete
table(wdce$offsets_bought_befor) # Has NAs -> not a problem
levels(wdce$offsets_bought_befor)


which(is.na(wdce$offsets_known_before))
offsets_known_befor_noNA <- wdce$offsets_known_befor[-c(808, 1118)] ## delete the two na rows
table(offsets_known_befor_noNA) # N 1219

offsets_bought_befor_noNA <- wdce$offsets_bought_befor[-c(808, 1118)] ## delete the same two rows that same vector lenght
table(offsets_bought_befor_noNA) ## doesnt work -there are deleted anyway
table(wdce$offsets_bought_befor)

### Barplot with Relative  Frequency of Offsets known before
```

```
#Create a data frame with counts of "YEs" and "No"
offs_known <- table(wdce$offsets_known_before)
offs_known_df <- as.data.frame(offs_known)
offs_known_df

# Rename the columns for clarity
colnames(offs_known_df) <- c("Offsets_known", "Frequency")

# Calculate the relative frequency in percentage
offs_known_df$Relative_Frequency <- (offs_known_df$Frequency / sum(offs_known_df$Frequency))

# Create a barplot using ggplot2 with relative frequencies
barplot_offs_known <- ggplot(offs_known_df, aes(x = Offsets_known, y = Relative_Frequency)) +
  geom_bar(stat = "identity", fill = "lightgrey") +  # Add the bars
  labs(x = "Carbon Offsets Known Before", y = "Relative Frequency") +
  scale_y_continuous(labels = scales::percent_format(scale = 100)) + # Format as percentages
  theme_light() +
  theme(text = element_text(size = 12))  # Set font size to 12

barplot_offs_known

#..........................................................
### Barplot with Relative  Frequency of Offsets Bought before
#

levels(wdce$offsets_bought_befor) <- c("No", "Yes, at least once", "Yes, multiple times", "Yes, always")

# Create a data frame with counts responsed
offs_bought <- table(wdce$offsets_bought_befor)
offs_bought_df <- as.data.frame(offs_bought)
offs_bought_df

# Rename the columns for clarity
colnames(offs_bought_df) <- c("Offsets_bought", "Frequency")

# Calculate the relative frequency in percentage
offs_bought_df$Relative_Frequency <- (offs_bought_df$Frequency / sum(offs_bought_df$Frequency))

offs_bought_df$Relative_Frequency

# Create a barplot using ggplot2 with relative frequencies
barplot_offs_bought <- ggplot(offs_bought_df, aes(x = Offsets_bought, y = Relative_Frequency)) +
  geom_bar(stat = "identity", fill = "lightgrey") +  # Add the bars
  labs(x = "Carbon Offsets Bought Before", y = "Relative Frequency") +
  scale_y_continuous(labels = scales::percent_format(scale = 100)) + # Format as percentages
  theme_light() +
  theme(text = element_text(size = 12))  # Set font size to 12

barplot_offs_bought

#.............................................................

## Diverging Bar Chart of Offsets Attitude

offs_attitude_sumtab <- wdce %>%
  dplyr::select(offsets_attitude_1, offsets_attitude_2, offsets_attitude_3) %>%
  pivot_longer(cols = everything(), names_to = "Item", values_to = "Response") %>%
  mutate(Item = as.factor(Item)) %>%
  table()

rownames(offs_attitude_sumtab) <- c(
  "Carbon Offsets are an effective instrument to compensate for flight emissions.",
  "Airlines should be obliged to offset their emissions.",
  "Offsetting flight emissions is equally effective as reducing CO2 through SAF."
)

offs_attitude_sumtab

likert(offs_attitude_sumtab,
       as.percent= "noRightAxis",
       main = "",
       ylab = "Question",
       xlim = c(-60,-40,-20, 0, 20, 40, 80),
       scales = list(y = list(cex = 1))
)
?likert

# Calculate percentages
percentages <- round(offs_attitude_sumtab / rowSums(offs_attitude_sumtab) * 100, 2)

# Initialize an empty list to store individual data frames for each question
percentages_list <- list()

# Loop through each question and create a data frame with percentages
for (i in 1:ncol(percentages)) {
  percentages_df <- data.frame(
    Response = rownames(percentages),
    Item = rep(colnames(percentages)[i], nrow(percentages)),
    Percentage = percentages[, i]
  )
  percentages_list[[i]] <- percentages_df
}

# Combine all data frames into one
percentages_table <- do.call(rbind, percentages_list)

percentages_table

#...................................................

## Awareness of EU ETS

table(wdce$ETS_yes_no_unsure)
length(wdce$ETS_yes_no_unsure)
```

```
# Create a table of the factor variable
response_table <- table(wdce$ETS_yes_no_unsure)

# Calculate percentages
percentages <- prop.table(response_table) * 100

# Display percentages
percentages

## Relation of ETS knowledge & VCO purchase
table(wdce$ETS_yes_no_unsure, wdce$b7_vco_treat)
table(wdce$ETS_yes, wdce$b7_vco_treat) # of the one who knew: 13 did not offset (38%), 21 did offset (62%)
t.test(b7_vco_treat ~ ETS_yes, wdce) ## p-value: 0.4354 --> no difference!
# ......................................................................
## RQ3: How does environmental concern influence voluntary carbon offsetting?
#H3a.   When choosing to fly, altruistic and biospheric environmental concern are positive predictors of voluntary carbon offsetting
#H3b. When choosing to fly, Egoistic environmental concern is a negative predictor of voluntary carbon offsetting

#.................................................................

# data: subset of treatment group
wdce_treatment <- wdce[wdce$treatment == 1, ]
# because heckman 2step doesn't work when subset directly in formula (chooses wrong 970 observations)
# correct subsample 611
nrow(wdce_treatment)
# ..............................
#### Descriptive statistics

table(wdce_treatment$b7_flight_yes,
wdce_treatment$b7_vco_treat)

## Barplot with VCO, relative frequencies

library(ggplot2)

# Create a data frame with counts of "No Purchase" and "Purchase"
vco <- table(ifelse(wdce_treatment$b7_vco_treat == 0, "No Purchase", "Purchase"))
vco_df <- as.data.frame(vco)

# Rename the columns for clarity
colnames(vco_df) <- c("VCO", "Frequency")

# Calculate the relative frequency in percentage
vco_df$Relative_Frequency <- (vco_df$Frequency / sum(vco_df$Frequency))

# Create a barplot using ggplot2
barplot_vco <- ggplot(vco_df, aes(x = VCO, y = Relative_Frequency)) +
  geom_bar(stat = "identity", fill = "lightgrey") +  # Add the bars
  labs(x = "Voluntary Carbon Offsets (VCOs)", y = "Relative Frequency") +
  theme_light() +
  theme(text = element_text(size = 12)) +  # Set font size to 12
  scale_y_continuous(labels = scales::percent_format(scale = 100))  # Format as percentages

barplot_vco
ggsave("barplot_vco.png", plot = barplot_vco) ## default size
## change size  width = 8, height = 6, dpi = 300

## N of subset flight Yes of Treatment group
table(wdce_treatment$b7_flight_yes) ## 232
#.....................................................

### Heckman Model
## to account for self-selection bias ("choosing flight")

# dependent variable for selection: flight choice (in subset treatment)
table(wdce_treatment$b7_flight_yes)

# dependent variable for outcome:
table(wdce_treatment$b7_vco_treat)

library(sampleSelection)
?selection
citation("sampleSelection")

## Heckman Model 1 -ML estimation
heck_ml_1 <- selection(b7_flight_yes ~
                  cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                 + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                 + children + alone,
                 b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
                 method = "ml",
                 data = wdce_treatment)

summary(heck_ml_1)
# Problem:
### Return code 8: successive function values within relative tolerance limit (reltol)

#....................................................................

## Heckman Model 1 - 2step method
heck_2step_1 <- selection(b7_flight_yes ~
                   cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                  + children + alone,
                  b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
                  method = "2step",
                  data = wdce_treatment)
summary(heck_2step_1)

library(robustbase)
library(ssmrob)
citation("ssmrob")
```

```
# Robust two-stage Heckman Model 1:
# only works for two-stage, not for ML
heck_2step_rob_1 <- ssmrob(selection = b7_flight_yes ~
                    cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                   + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                   + children + alone,
                   outcome = b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
                   data = wdce_treatment)
summary(heck_2step_rob_1)

#..................................................................
## Heckman Model 2 -ML estimation

heck_ml_2 <- selection(b7_flight_yes ~
                 cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
               + gender + young + old + mandatory + tertiary + incH + language + interm + urban
               + car + e_car
               + children + alone,
               b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
               + gender + young + old + mandatory + tertiary + incH + language + interm + urban,
               method = "ml",
               data = wdce_treatment)
summary(heck_ml_2) # PROBLEM
# Return code 3: Last step could not find a value above the current.
# Boundary of parameter space?
# Consider switching to a more robust optimisation method temporarily

## Heckman Model 2 - 2step method
heck_2step_2 <- selection(b7_flight_yes ~
                   cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                 + gender + young + old + mandatory + tertiary + incH + language + interm + urban
                 + car + e_car
                 + children + alone,
                 b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                 + gender + young + old + mandatory + tertiary + incH + language + interm + urban,
                 method = "2step",
                 data = wdce_treatment)
summary(heck_2step_2)

# Robust two-stage Heckman Model 2:
# only works for two-stage, not for ML
heck_2step_rob_2 <- ssmrob(selection = b7_flight_yes ~
                    cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                  + children + alone,
                  outcome = b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                  + gender + young + old + mandatory + tertiary + incH + language + interm + urban,
                  data = wdce_treatment)
summary(heck_2step_rob_2)
  ## best model fit (significant IMR, rho in exepted range)
#............................................................
## Heckman Model 3 -ML estimation --> with car + e_car in outcome equation
heck_ml_3 <- selection(b7_flight_yes ~
                 cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
               + gender + young + old + mandatory + tertiary + incH + language + interm + urban
               + car + e_car
               + children + alone,
               b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
               + gender + young + old + mandatory + tertiary + incH + language + interm + urban
               + car + e_car,
               method = "ml",
               data = wdce_treatment)
summary(heck_ml_3)
# PROBLEM
# Return code 3: Last step could not find a value above the current.
# Boundary of parameter space?
# Consider switching to a more robust optimisation method temporarily

## Heckman Model 3 - 2step method  --> with car + e_car in outcome equation
heck_2step_3 <- selection(b7_flight_yes ~
                   cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                 + gender + young + old + mandatory + tertiary + incH + language + interm + urban
                 + car + e_car
                 + children + alone,
                 b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                 + gender + young + old + mandatory + tertiary + incH + language + interm + urban
                 + car + e_car,
                 method = "2step",
                 data = wdce_treatment)
summary(heck_2step_3)
# car & e_car are not significant in outcome equation


# Robust two-stage Heckman Model 3:
# only works for two-stage, not for ML
heck_2step_rob_3 <- ssmrob(selection = b7_flight_yes ~
                    cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                  + children + alone,
                  outcome = b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                  + gender + young + old + mandatory + tertiary + incH + language + interm + urban
                  + car + e_car,
                  data = wdce_treatment)
summary(heck_2step_rob_3)

#..................................................
```

```
###  Model 2 & 3 for 2step Method with Robust SE
  # shown in thesis

### manually addin excel
summary(heck_2step_rob_2)
summary(heck_2step_rob_3)
 # manually calculate rho (IMR / Sigma)

# ....................................................

## AIC and BIC

library(AICcmodavg)

summary(heck_2step_1)
# Compute the log-likelihood
log_lik_heck_2step_1 <- -485.84
# Number of parameters in your model
num_parameters_heck_2step_1 <- (18+4-3)
# Number of observations in your data
num_observations <- nrow(wdce_treatment)
# AIC
aic_heck_2step_1 <- -2 * log_lik_heck_2step_1 + 2 * num_parameters_heck_2step_1
print(aic_heck_2step_1)
# BIC
bic_heck_2step_1 <- -2 * log_lik_heck_2step_1 + log(num_observations) * num_parameters_heck_2step_1
print(bic_heck_2step_1)

# AIC & BIC Heck ML

AIC(heck_ml_1) #log Lik.' 1131.29 (df=24)
AIC(heck_ml_2) #log Lik. # 31039.681 (df=34)
AIC(heck_ml_3) # log Lik. # 1134.649 (df=36)
BIC(heck_ml_1)
BIC(heck_ml_2)
BIC(heck_ml_3)

#.................................

## The Breusch-Pagan Test

# Ho = Residuals are distributed with equal variance (i.e., homoskedasticity)
# H1 = Residuasl are distributed with unequal variance (i.e., heteroskedasticity)
library(lmtest)
?lmtest

# Selection equation of the Heckman model 2
bptest(lm (b7_flight_yes ~
          cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_treatment))
# -->, 5.29e-05 --> H0 can be rejected, there is heteroskedasticity

# outcome equation of the Heckman model 2
bptest(lm (b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban,
        data = wdce_treatment))
# --> p-value 0.610, Ho can not be rejected, there is homoskededasticity

## The white Test (see Kennedy (2013))
# Ho = Residuals are distributed with equal variance (i.e., homoskedasticity)
# H1 = Residuasl are distributed with unequal variance (i.e., heteroskedasticity)

library("whitestrap")

# Selection equation of the Heckman model 2
white_test(lm (b7_flight_yes ~
            cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
            + children + alone,
            data = wdce_treatment))
# p-value == 0 --> H0 can be rejected, there is heteroskedasticity

# outcome equation of the Heckman model 2
white_test(lm (b7_vco_treat ~ cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + gender + young + old + mandatory + tertiary + incH + language + interm + urban,
            data = wdce_treatment))
#  -> p-value = 0.021 < 0.05 --> H0 can be rejected, there is heteroskedasticity

#.........................................................

### RQ4: How do individuals feel about their travel mode choice?
#Hypotheses:
# H4a:  Individuals with high altruistic and biospheric environmental concern feel guilty about their travel mode choice when choosing flights.
# H4b:  Individuals with high altruistic and biospheric environmental concern feel less guilty when flights are offset, or when the flight uses sustainable fuel.
#H4c:  Individuals with high altruistic and biospheric environmental concern feel worse about their travel mode choice when choosing flights.
# H4d:  Individuals with high altruistic and biospheric environmental concern feel better when flights are offset, or when the flight uses sustainable fuel.

## Preparare Data

## create variable with flight counts over all 7 scenarios (DCE + RCT)
# List of variables to check for "Airplane"
airplane_vars_all <- c(
  "b1_c5_desk",
  "b1_c22_desk",
  "b1_c29_desk",
  "b1_c30_desk",
  "b1_c31_desk",
  "b1_c33_desk",
  "b1_c5_mob",
```

```
"b1_c22_mob",
"b1_c29_mob",
"b1_c30_mob",
"b1_c31_mob",
"b1_c33_mob",
"b2_c2_desk",
"b2_c12_desk",
"b2_c16_desk",
"b2_c23_desk",
"b2_c25_desk",
"b2_c35_desk",
"b2_c2_mob",
"b2_c12_mob",
"b2_c16_mob",
"b2_c23_mob",
"b2_c25_mob",
"b2_c35_mob",
"b3_c3_desk",
"b3_c17_desk",
"b3_c19_desk",
"b3_c21_desk",
"b3_c34_desk",
"b3_c36_desk",
"b3_c3_mob",
"b3_c17_mob",
"b3_c19_mob",
"b3_c21_mob",
"b3_c34_mob",
"b3_c36_mob",
"b4_c7_desk",
"b4_c10_desk",
"b4_c11_desk",
"b4_c20_desk",
"b4_c24_desk",
"b4_c27_desk",
"b4_c7_mob",
"b4_c10_mob",
"b4_c11_mob",
"b4_c20_mob",
"b4_c24_mob",
"b4_c27_mob",
"b5_c6_desk",
"b5_c9_desk",
"b5_c14_desk",
"b5_c15_desk",
"b5_c26_desk",
"b5_c32_desk",
"b5_c6_mob",
"b5_c9_mob",
"b5_c14_mob",
"b5_c15_mob",
"b5_c26_mob",
"b5_c32_mob",
"b6_c1_desk",
"b6_c4_desk",
"b6_c8_desk",
"b6_c13_desk",
"b6_c18_desk",
"b6_c28_desk",
"b6_c1_mob",
"b6_c4_mob",
"b6_c8_mob",
"b6_c13_mob",
"b6_c18_mob",
"b6_c28_mob",
"b7_control_desk",
"b7_control_mob",
"b7_treatm_desk",
"b7_treatm_mob"
)
# Calculate the count of "Airplane" in each specified variable and store the results in a list
airplane_counts_all <- lapply(airplane_vars_all, function(var) {
  grepl("Airplane", wdce[[var]], fixed = TRUE)
})
# Sum the counts for each row and store the result in the new variable wdce$flightcount_all
wdce$flightcount_all <- rowSums(do.call(cbind, airplane_counts_all))
summary(wdce$flightcount_all)
table(wdce$flightcount_all)

#make new variable indication if min. 1 flight choice in all 7 scenarios (1/0) --> for selection model
wdce$flightcount_min_1_all <- ifelse(wdce$flightcount_all >= 1, 1, 0)
table(wdce$flightcount_min_1_all)

## make new variable with count of all ICO compensated flights wdce$ico_flights_sum
# first create variable in dce$
dce$count_ico_flights <- ifelse(dce$value=="Airplane" &
                                dce$f.comp == 1,1,0)

library(dplyr)
ico_flights_sum <- dce %>% group_by(id) %>%
  summarise(ico_flights_sum = sum(count_ico_flights))
unique(ico_flights_sum)
class(ico_flights_sum)
# Merge the ico_flights_sum data with wdce based on the "id" column
wdce <- merge(wdce, ico_flights_sum, by = "id", all.x = TRUE)
table(wdce$ico_flights_sum) # flight count of all ICO flights
class(wdce$ico_flights_sum)

## variable with count of VCO compensated flights  -> 1 or 0
table(wdce$b7_vco_treat)
wdce$vco_flights_sum <- wdce$b7_vco_treat ## copy variable with new name to make it more consistent for regression
table(wdce$vco_flights_sum) ## many NAs (for control group or no flight choice)
# change all NA's to 0
wdce$vco_flights_sum[is.na(wdce$vco_flights_sum)] <- 0
table(wdce$vco_flights_sum)


## make new variable with count of all SAF flights, wdce$saf_flights_sum
# first create variable in dce$
dce$count_saf_flights <- ifelse(dce$value=="Airplane" &
                                dce$f.techno == 1,1,0)
library(dplyr)
saf_flights_sum <- dce %>% group_by(id) %>%
```

```
  summarise(saf_flights_sum = sum(count_saf_flights))
unique(saf_flights_sum)
class(saf_flights_sum)
# Merge the saf_flights_sum data with wdce based on the "id" column
wdce <- merge(wdce, saf_flights_sum, by = "id", all.x = TRUE)
table(wdce$saf_flights_sum)

#...................................................

####### Feeling guilty


# Data: all 7 scenarios

#.............................................................
### Group 0 - 0 flights


# create subset dataframe
wdce_gr0 <- subset(wdce, flightcount_all == 0)

# LM Model 1: only EC
lm_gr0_guilt_1 <- lm(feeling_travelmode_guilty ~
                       cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
                     data = wdce_gr0)
summary(lm_gr0_guilt_1)
stargazer(lm_gr0_guilt_1, type = "text")

# LM Model 2: EC & sociodemographics
lm_gr0_guilt_2 <- lm(feeling_travelmode_guilty ~
                       cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                     + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
                     data = wdce_gr0)
summary(lm_gr0_guilt_2)

# LM Model 3: EC, sociodemographics & travel scenario
lm_gr0_guilt_3 <- lm(feeling_travelmode_guilty ~
                       cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                     + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                     +children + alone,
                     data = wdce_gr0)
summary(lm_gr0_guilt_3)
#............................................

### Group 1 - 1 flight

# create subset dataframe
wdce_gr1 <- subset(wdce, flightcount_all == 1)

# LM Model 1: only EC
lm_gr1_guilt_1 <- lm(feeling_travelmode_guilty ~
                       cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
                     data = wdce_gr1)
summary(lm_gr1_guilt_1)

# LM Model 2: EC & ICO, SAF, VCO
lm_gr1_guilt_2 <- lm(feeling_travelmode_guilty ~
                       cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                     + ico_flights_sum + vco_flights_sum + saf_flights_sum,
                     data = wdce_gr1)
summary(lm_gr1_guilt_2)

# LM Model 3: EC, Ico, SAF, VCO & interaction
lm_gr1_guilt_3 <- lm(feeling_travelmode_guilty ~
                       cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                     + ico_flights_sum + vco_flights_sum + saf_flights_sum
                     + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
                     + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
                     + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum,
                     data = wdce_gr1)
summary(lm_gr1_guilt_3)

# LM Model 4: EC, Ico, SAF, VCO & interaction + sociodemographics
lm_gr1_guilt_4 <- lm(feeling_travelmode_guilty ~
                       cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                     + ico_flights_sum + vco_flights_sum + saf_flights_sum
                     + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
                     + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
                     + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
                     + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
                     data = wdce_gr1)
summary(lm_gr1_guilt_4)

# LM Model 5: EC, Ico, SAF, VCO & interaction + sociodemographics + Travel scenario
lm_gr1_guilt_5 <- lm(feeling_travelmode_guilty ~
                       cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                     + ico_flights_sum + vco_flights_sum + saf_flights_sum
                     + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
                     + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
                     + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
```

```
        + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr1)
summary(lm_gr1_guilt_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr1_guilt_7 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
        + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr1)
summary(lm_gr1_guilt_7)
#.......................................................

### Group 2 - 2 flights

# create subset dataframe
wdce_gr2 <- subset(wdce, flightcount_all == 2)

# LM Model 1: only EC
lm_gr2_guilt_1 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx,
        data = wdce_gr2)
summary(lm_gr2_guilt_1)

# LM Model 2: EC & ICO, SAF, VCO
lm_gr2_guilt_2 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum +
saf_flights_sum,
        data = wdce_gr2)
summary(lm_gr2_guilt_2)

# LM Model 3: EC, Ico, SAF, VCO & interaction
lm_gr2_guilt_3 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum +
saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum,
        data = wdce_gr2)
summary(lm_gr2_guilt_3)

# LM Model 4: EC, Ico, SAF, VCO & interaction +
sociodemographics
lm_gr2_guilt_4 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum +
saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car,
        data = wdce_gr2)
summary(lm_gr2_guilt_4)


# LM Model 5: EC, Ico, SAF, VCO & interaction +
sociodemographics + Travel scenario
lm_gr2_guilt_5 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum +
saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr2)
summary(lm_gr2_guilt_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr2_guilt_7 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
        + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr2)
summary(lm_gr2_guilt_7)
#............................................................
### Group 3 - 3 flights

# create subset dataframe
wdce_gr3 <- subset(wdce, flightcount_all == 3)


# LM Model 1: only EC
lm_gr3_guilt_1 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx,
        data = wdce_gr3)
summary(lm_gr3_guilt_1)

# LM Model 2: EC & ICO, SAF, VCO
lm_gr3_guilt_2 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
```

```
        + ico_flights_sum + vco_flights_sum + saf_flights_sum,
        data = wdce_gr3)
summary(lm_gr3_guilt_2)

# LM Model 4: EC, Ico, SAF, VCO & interaction
lm_gr3_guilt_3 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum,
        data = wdce_gr3)
summary(lm_gr3_guilt_3)

# LM Model 4: EC, Ico, SAF, VCO & interaction + sociodemographics
# all ecars are NA
lm_gr3_guilt_4 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
        data = wdce_gr3)
summary(lm_gr3_guilt_4)

# LM Model 5: EC, Ico, SAF, VCO & interaction + sociodemographics + Travel scenario
# all e-cars are NA
lm_gr3_guilt_5 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr3)
summary(lm_gr3_guilt_5)

# LM Model 6: Without Ecar bc all missing values - exact same output as in 5 but used to make linear combination (bc no missing values)
lm_gr3_guilt_6 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car
        + children + alone,
        data = wdce_gr3)
summary(lm_gr3_guilt_6)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr3_guilt_7 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr3)
summary(lm_gr3_guilt_7)
#.....................................................................
### Group 4 - 4 flights

# create subset dataframe
wdce_gr4 <- subset(wdce, flightcount_all == 4)

# LM Model 1: only EC
lm_gr4_guilt_1 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
        data = wdce_gr4)
summary(lm_gr4_guilt_1)

# LM Model 2: EC & ICO, SAF, VCO
lm_gr4_guilt_2 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum,
        data = wdce_gr4)
summary(lm_gr4_guilt_2)

# LM Model 4: EC, Ico, SAF, VCO & interaction
lm_gr4_guilt_3 <- lm(feeling_travelmode_guilty ~
         cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
```

```
            + ico_flights_sum + vco_flights_sum + saf_flights_sum
            + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
            + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
            + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum,
            data = wdce_gr4)
summary(lm_gr4_guilt_3)

# LM Model 4: EC, Ico, SAF, VCO & interaction + sociodemographics
lm_gr4_guilt_4 <- lm(feeling_travelmode_guilty ~
            cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + ico_flights_sum + vco_flights_sum + saf_flights_sum
            + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
            + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
            + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
            + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
            data = wdce_gr4)
summary(lm_gr4_guilt_4)



# LM Model 5: EC, Ico, SAF, VCO & interaction + sociodemographics + Travel scenario
lm_gr4_guilt_5 <- lm(feeling_travelmode_guilty ~
            cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + ico_flights_sum + vco_flights_sum + saf_flights_sum
            + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
            + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
            + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
            + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
            + children + alone,
            data = wdce_gr4)
summary(lm_gr4_guilt_5)     # ec alt has pos. effect, interaction ec bio: saf has pos. effect
# ec bio has neg. effect

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr4_guilt_7 <- lm(feeling_travelmode_guilty ~
            cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
            + children + alone,
            data = wdce_gr4)
summary(lm_gr4_guilt_7)
#.............................................

### Group 5 - 5 Flights

# create subset dataframe
wdce_gr5 <- subset(wdce, flightcount_all == 5)

# LM Model 1: only EC
lm_gr5_guilt_1 <- lm(feeling_travelmode_guilty ~
            cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
            data = wdce_gr5)
summary(lm_gr5_guilt_1)  # ec alt und ec bio has pos. effect

# LM Model 2: EC & ICO, SAF, VCO
lm_gr5_guilt_2 <- lm(feeling_travelmode_guilty ~
            cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + ico_flights_sum + vco_flights_sum + saf_flights_sum,
            data = wdce_gr5)
summary(lm_gr5_guilt_2)   # ec alt has pos. effect,
# vco has pos. effect

# LM Model 4: EC, Ico, SAF, VCO & interaction
lm_gr5_guilt_3 <- lm(feeling_travelmode_guilty ~
            cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + ico_flights_sum + vco_flights_sum + saf_flights_sum
            + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
            + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
            + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum,
            data = wdce_gr5)
summary(lm_gr5_guilt_3)     # vco has pos. effect

# LM Model 4: EC, Ico, SAF, VCO & interaction + sociodemographics
lm_gr5_guilt_4 <- lm(feeling_travelmode_guilty ~
            cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + ico_flights_sum + vco_flights_sum + saf_flights_sum
            + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
            + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
```

```
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
        data = wdce_gr5)
summary(lm_gr5_guilt_4)

# LM Model 5: EC, Ico, SAF, VCO & interaction + sociodemographics + Travel scenario
lm_gr5_guilt_5 <- lm(feeling_travelmode_guilty ~
        cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr5)
summary(lm_gr5_guilt_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr5_guilt_7 <- lm(feeling_travelmode_guilty ~
        cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr5)
summary(lm_gr5_guilt_7)
#..............................................
### Group 6 - 6 Flights

# create subset dataframe
wdce_gr6 <- subset(wdce, flightcount_all == 6)

# LM Model 1: only EC
lm_gr6_guilt_1 <- lm(feeling_travelmode_guilty ~
        cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx,
        data = wdce_gr6)
summary(lm_gr6_guilt_1)

# LM Model 2: EC & ICO, SAF, VCO
lm_gr6_guilt_2 <- lm(feeling_travelmode_guilty ~
        cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum,
        data = wdce_gr6)
summary(lm_gr6_guilt_2)

# LM Model 4: EC, Ico, SAF, VCO & interaction
lm_gr6_guilt_3 <- lm(feeling_travelmode_guilty ~
        cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum,
        data = wdce_gr6)
summary(lm_gr6_guilt_3)

# LM Model 4: EC, Ico, SAF, VCO & interaction + sociodemographics
lm_gr6_guilt_4 <- lm(feeling_travelmode_guilty ~
        cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
        data = wdce_gr6)
summary(lm_gr6_guilt_4)

# LM Model 5: EC, Ico, SAF, VCO & interaction + sociodemographics + Travel scenario
lm_gr6_guilt_5<- lm(feeling_travelmode_guilty ~
        cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
        + ico_flights_sum + vco_flights_sum + saf_flights_sum
        + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
        + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
        + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
        + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
        + children + alone,
        data = wdce_gr6)
summary(lm_gr6_guilt_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr6_guilt_7 <- lm(feeling_travelmode_guilty ~
        cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
```

```
                + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr6)
summary(lm_gr6_guilt_7)
#.............................................
### Group 7 - 7 Flights

# create subset dataframe
wdce_gr7 <- subset(wdce, flightcount_all == 7)


# LM Model 1: only EC
lm_gr7_guilt_1 <- lm(feeling_travelmode_guilty ~
                 cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx,
                data = wdce_gr7)
summary(lm_gr7_guilt_1)

# LM Model 2: EC & ICO, SAF, VCO
lm_gr7_guilt_2 <- lm(feeling_travelmode_guilty ~
                 cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
                + ico_flights_sum + vco_flights_sum +
saf_flights_sum,
                data = wdce_gr7)
summary(lm_gr7_guilt_2)

# LM Model 4: EC, Ico, SAF, VCO & interaction
lm_gr7_guilt_3 <- lm(feeling_travelmode_guilty ~
                 cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
                + ico_flights_sum + vco_flights_sum +
saf_flights_sum
                + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
                + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
                + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum,
                data = wdce_gr7)
summary(lm_gr7_guilt_3)

# LM Model 4: EC, Ico, SAF, VCO & interaction +
sociodemographics
lm_gr7_guilt_4 <- lm(feeling_travelmode_guilty ~
                 cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
                + ico_flights_sum + vco_flights_sum +
saf_flights_sum
                + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
                + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
                + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum
                + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car,
                data = wdce_gr7)
summary(lm_gr7_guilt_4)

# LM Model 5: EC, Ico, SAF, VCO & interaction +
sociodemographics + Travel scenario
lm_gr7_guilt_5<- lm(feeling_travelmode_guilty ~
                 cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
                + ico_flights_sum + vco_flights_sum +
saf_flights_sum
                + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
                + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
                + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum
                + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr7)
summary(lm_gr7_guilt_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr7_guilt_7 <- lm(feeling_travelmode_guilty ~
                 cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
                + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr7)
summary(lm_gr7_guilt_7)   #ec bio pos.

#.............................
## is there Heteroskedasticity? see Kennedy (2013)

## The white Test (see Kennedy (2013))
# Ho = Residuals are distributed with equal variance (i.e.,
homoskedasticity)
# H1 = Residuasl are distributed with unequal variance (i.e.,
heteroskedasticity)

library("whitestrap")
citation("whitestrap")
white_test(lm_gr1_guilt_1) # 0.599954 > 0.05 --> Ho can
not be rejected, there is homoskededasticit
white_test(lm_gr1_guilt_2) # 0.822092 --> Ho can not be
rejected, there is homoskededasticit
white_test(lm_gr1_guilt_3) #  0.096915 --> Ho can not be
rejected, there is homoskededasticit
white_test(lm_gr1_guilt_4) # 0.04651 --> --> H0 can be
rejected, there is heteroskedasticity!!!
# the only Model wher there is heteroskedasticity --> so
ignore???
white_test(lm_gr1_guilt_5) #  0.055476 --> Ho can not be
rejected, there is homoskededasticit
white_test(lm_gr1_guilt_7) #   0.319704 --> Ho can not be
rejected, there is homoskededasticit


white_test(lm_gr2_guilt_1) # 0.990405 > 0.05 --> Ho can
not be rejected, there is homoskededasticit
```

white_test(lm_gr2_guilt_2) # 0.070489 --> Ho can not be rejected, there is homoskededasticit
white_test(lm_gr2_guilt_3) # 0.005108 --> H0 can be rejected, there is heteroskedasticity!!!
white_test(lm_gr2_guilt_4) # 0.006074 --> --> H0 can be rejected, there is heteroskedasticity!!!
white_test(lm_gr2_guilt_5) # 0.002738 --> H0 can be rejected, there is heteroskedasticity!!!
white_test(lm_gr2_guilt_7) # 0.025986 --> H0 can be rejected, there is heteroskedasticity!!!

white_test(lm_gr3_guilt_1) # 0.484429 > 0.05 --> Ho can not be rejected, there is homoskededasticit
white_test(lm_gr3_guilt_2) # P-value: 0.383006 --> Ho can not be rejected, there is homoskededasticit
white_test(lm_gr3_guilt_3) # 0.2215025 --> Ho can not be rejected, there is homoskededasticit
white_test(lm_gr3_guilt_4) # 0.227089 --> --> o can not be rejected, there is homoskededasticit
white_test(lm_gr3_guilt_5) # 0.674631 --> Ho can not be rejected, there is homoskededasticit
white_test(lm_gr3_guilt_7) # 0.396314 --> Ho can not be rejected, there is homoskededasticit

white_test(lm_gr4_guilt_1) # 0.471788 > 0.05 --> Ho can not be rejected, there is homoskededasticit
white_test(lm_gr4_guilt_2) # 0.209189 --> Ho can not be rejected, there is homoskededasticity
white_test(lm_gr4_guilt_3) # 0.229161 --> Ho can not be rejected, there is homoskededasticit
white_test(lm_gr4_guilt_4) # 0.319143 --> -Ho can not be rejected, there is homoskededasticit
white_test(lm_gr4_guilt_5) # 0.403283 --> -Ho can not be rejected, there is homoskededasticitY
white_test(lm_gr4_guilt_7) # 0.271287 --> -Ho can not be rejected, there is homoskededasticitY

white_test(lm_gr5_guilt_5) # 0.074853 --> -Ho can not be rejected, there is homoskededasticitY
white_test(lm_gr5_guilt_7) # 0.07859 --> -Ho can not be rejected, there is homoskededasticitY

white_test(lm_gr6_guilt_5) # 0.481916 --> -Ho can not be rejected, there is homoskededasticitY
white_test(lm_gr6_guilt_7) # 0.196506 --> -Ho can not be rejected, there is homoskededasticitY

white_test(lm_gr7_guilt_5) # 0.2027933 --> -Ho can not be rejected, there is homoskededasticitY
white_test(lm_gr7_guilt_7) # 0.020108 --> -Ho can not be rejected, there is homoskededasticitY

--> only group 2 showed heteroskedastiy, therefore decide to stay with default SE
#..

Show Model 7 of group 1 to 4 in a table
stargazer(lm_gr1_guilt_7, lm_gr2_guilt_7, lm_gr3_guilt_7,lm_gr4_guilt_7,
title = "Regression Estimates",
dep.var.labels = "Feeling guilty about travel mode choice",
column.labels = c("1 Flight", "2 Flights", "3 Flights", "4 Flights"),
covariate.labels = c("Constant", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
"Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
"French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
"Travelling With Children", "Travelling Alone"
),
align = TRUE,
intercept.bottom = FALSE,
no.space = TRUE,
model.names = TRUE,
model.numbers = FALSE,
omit.stat = c("rsq", "ser"), # omit R squared and Res. St. Error
out = "guilty_gr1to4_7.html"
)

Show Model 7 of group 5 to 7
stargazer(lm_gr5_guilt_7, lm_gr6_guilt_7, lm_gr7_guilt_7,
title = "Regression Estimates",
dep.var.labels = "Feeling guilty about travel mode choice",
column.labels = c("5 Flights", "6 Flights", "7 Flights"),
covariate.labels = c("Constant", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
"Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
"French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
"Travelling With Children", "Travelling Alone"
),
align = TRUE,
intercept.bottom = FALSE,
no.space = TRUE,
model.names = TRUE,
model.numbers = FALSE,
omit.stat = c("rsq", "ser"), # omit R squared and Res. St. Error
out = "guilty_gr5to7_7.html"
)

Show Model 5 of group 1 to 4 in a table
stargazer(lm_gr1_guilt_5, lm_gr2_guilt_5, lm_gr3_guilt_5,lm_gr4_guilt_5,
title = "Regression Estimates",
dep.var.labels = "Feeling guilty about travel mode choice",
column.labels = c("1 Flight", "2 Flights", "3 Flights", "4 Flights"),
covariate.labels = c("Constant", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",

```
                "Flights With ICO", "Flights With VCO", "Flights With SAF",
                "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
                "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
                "Travelling With Children", "Travelling Alone",
                "Biospheric Env. Concern * Flights With ICO", "Altruistic Env. Concern * Flights With ICO", "Egoistic Env. Concern * Flights With ICO",
                "Biospheric Env. Concern * Flights With VCO", "Altruistic Env. Concern * Flights With VCO", "Egoistic Env. Concern * Flights With VCO",
                "Biospheric Env. Concern * Flights With SAF", "Altruistic Env. Concern * Flights With SAF", "Egoistic Env. Concern * Flights With SAF"
        ),
        align = TRUE,
        intercept.bottom = FALSE,
        no.space = TRUE,
        model.names = TRUE,
        model.numbers = FALSE,
        omit.stat    = c( "rsq", "ser"), # omit R squared and Res. St. Error
        out = "guilty_gr1to4_5.html"
)


## Show Model 5 of group 5 to 7
stargazer(lm_gr5_guilt_5, lm_gr6_guilt_5, lm_gr7_guilt_5,
        title = "Regression Estimates",
        dep.var.labels = "Feeling guilty about travel mode choice",
        column.labels = c("5 Flights", "6 Flights", "7 Flights"),
        covariate.labels = c("Constant", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
                "Flights With ICO", "Flights With VCO", "Flights With SAF",
                "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
                "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
                "Travelling With Children", "Travelling Alone",
                "Biospheric Env. Concern * Flights With ICO", "Altruistic Env. Concern * Flights With ICO", "Egoistic Env. Concern * Flights With ICO",
                "Biospheric Env. Concern * Flights With VCO", "Altruistic Env. Concern * Flights With VCO", "Egoistic Env. Concern * Flights With VCO",
                "Biospheric Env. Concern * Flights With SAF", "Altruistic Env. Concern * Flights With SAF", "Egoistic Env. Concern * Flights With SAF"
        ),
        align = TRUE,
        intercept.bottom = FALSE,
        no.space = TRUE,
        model.names = TRUE,
        model.numbers = FALSE,
        omit.stat    = c( "rsq", "ser"), # omit R squared and Res. St. Error
        out = "guilty_gr5to7_5.html"
)

#.................

##### Feeeling Good about Travel Mode

# Data: all 7 scenarios

### Group 0 - 0 flights

summary(wdce_gr0$feeling_travelmode_good)


# LM Model 3: EC, sociodemographics & travel scenario
lm_gr0_good_3 <- lm(feeling_travelmode_good ~
              cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
            +children + alone,
            data = wdce_gr0)
summary(lm_gr0_good_3)
#....................................
### Group 1 - 1 flight
#

summary(wdce_gr1$feeling_travelmode_good)

# LM Model 5: EC, Ico, SAF, VCO & interaction + sociodemographics + Travel scenario
lm_gr1_good_5 <- lm(feeling_travelmode_good ~
              cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + ico_flights_sum + vco_flights_sum + saf_flights_sum
            + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
            + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
            + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
            + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
            + children + alone,
            data = wdce_gr1)
summary(lm_gr1_good_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr1_good_7 <- lm(feeling_travelmode_good ~
              cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
            + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
            + children + alone,
            data = wdce_gr1)
summary(lm_gr1_good_7)
```

```
#..........................................
### Group 2 - 2 flights
#

summary(wdce_gr2$feeling_travelmode_good)

# LM Model 5: EC, Ico, SAF, VCO & interaction +
sociodemographics + Travel scenario
lm_gr2_good_5 <- lm(feeling_travelmode_good ~
            cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
          + ico_flights_sum + vco_flights_sum +
saf_flights_sum
          + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
          + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
          + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum
          + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
          + children + alone,
          data = wdce_gr2)
summary(lm_gr2_good_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr2_good_7 <- lm(feeling_travelmode_good ~
            cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
          + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
          + children + alone,
          data = wdce_gr2)
summary(lm_gr2_good_7)

#...............................
### Group 3 - 3 flights
#
summary(wdce_gr3$feeling_travelmode_good)


# LM Model 5: EC, Ico, SAF, VCO & interaction +
sociodemographics + Travel scenario
# all e-cars are NA
lm_gr3_good_5 <- lm(feeling_travelmode_good ~
            cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
          + ico_flights_sum + vco_flights_sum +
saf_flights_sum
          + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
          + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
          + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum
          + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
          + children + alone,
          data = wdce_gr3)
summary(lm_gr3_good_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr3_good_7 <- lm(feeling_travelmode_good ~
            cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
          + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
          + children + alone,
          data = wdce_gr3)
summary(lm_gr3_good_7)
#......................................
### Group 4 - 4 flights
summary(wdce_gr4$feeling_travelmode_good)

# LM Model 5: EC, Ico, SAF, VCO & interaction +
sociodemographics + Travel scenario
lm_gr4_good_5 <- lm(feeling_travelmode_good ~
            cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
          + ico_flights_sum + vco_flights_sum +
saf_flights_sum
          + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
          + cent_ec_bio_idx:vco_flights_sum +
cent_ec_alt_idx:vco_flights_sum +
cent_ec_ego_idx:vco_flights_sum
          + cent_ec_bio_idx:saf_flights_sum +
cent_ec_alt_idx:saf_flights_sum +
cent_ec_ego_idx:saf_flights_sum
          + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
          + children + alone,
          data = wdce_gr4)
summary(lm_gr4_good_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr4_good_7 <- lm(feeling_travelmode_good ~
            cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
          + gender + young + old + mandatory + tertiary
+ incH + language + interm + urban + car + e_car
          + children + alone,
          data = wdce_gr4)
summary(lm_gr4_good_7)
#..............................................
### Group 5 - 5 Flights
summary(wdce_gr5$feeling_travelmode_good)

# LM Model 5: EC, Ico, SAF, VCO & interaction +
sociodemographics + Travel scenario
lm_gr5_good_5 <- lm(feeling_travelmode_good ~
            cent_ec_bio_idx + cent_ec_alt_idx +
cent_ec_ego_idx
          + ico_flights_sum + vco_flights_sum +
saf_flights_sum
          + cent_ec_bio_idx:ico_flights_sum +
cent_ec_alt_idx:ico_flights_sum +
cent_ec_ego_idx:ico_flights_sum
```

```
                + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
                + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
                + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr5)
summary(lm_gr5_good_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr5_good_7 <- lm(feeling_travelmode_good ~
                 cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr5)
summary(lm_gr5_good_7)
#.....................................
### Group 6 - 6 Flights
#
summary(wdce_gr6$feeling_travelmode_good)


# LM Model 5: EC, Ico, SAF, VCO & interaction + sociodemographics + Travel scenario
lm_gr6_good_5<- lm(feeling_travelmode_good ~
                 cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                + ico_flights_sum + vco_flights_sum + saf_flights_sum
                + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
                + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
                + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
                + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr6)
summary(lm_gr6_good_5)


# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr6_good_7 <- lm(feeling_travelmode_good ~
                 cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr6)
summary(lm_gr6_good_7)
#.................................
### Group 7 - 7 Flights
summary(wdce_gr7$feeling_travelmode_good)


# LM Model 5: EC, Ico, SAF, VCO & interaction + sociodemographics + Travel scenario
lm_gr7_good_5<- lm(feeling_travelmode_good ~
                 cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                + ico_flights_sum + vco_flights_sum + saf_flights_sum
                + cent_ec_bio_idx:ico_flights_sum + cent_ec_alt_idx:ico_flights_sum + cent_ec_ego_idx:ico_flights_sum
                + cent_ec_bio_idx:vco_flights_sum + cent_ec_alt_idx:vco_flights_sum + cent_ec_ego_idx:vco_flights_sum
                + cent_ec_bio_idx:saf_flights_sum + cent_ec_alt_idx:saf_flights_sum + cent_ec_ego_idx:saf_flights_sum
                + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr7)
summary(lm_gr7_good_5)

# LM Model 7: EC, sociodemographics + Travel scenario
## without ico, vco, saf
lm_gr7_good_7 <- lm(feeling_travelmode_good ~
                 cent_ec_bio_idx + cent_ec_alt_idx + cent_ec_ego_idx
                + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
                + children + alone,
                data = wdce_gr7)
summary(lm_gr7_good_7)
#.........................................................................................................
## is there Heteroskedasticity? see Kennedy (2013)
##

## The white Test (see Kennedy (2013))
# Ho = Residuals are distributed with equal variance (i.e., homoskedasticity)
# H1 = Residuasl are distributed with unequal variance (i.e., heteroskedasticity)

library("whitestrap")

white_test(lm_gr1_good_5) #  0.486226 --> Ho can not be rejected, there is homoskedasticit
white_test(lm_gr1_good_7) #  0.085594 --> Ho can not be rejected, there is homoskedasticit

white_test(lm_gr2_good_5) #  0.637956 -->> Ho can not be rejected, there is homoskedasticit
white_test(lm_gr2_good_7) #  0.509765-->Ho can not be rejected, there is homoskedasticit!

white_test(lm_gr3_good_5) #  0. 0.29653 --> Ho can not be rejected, there is homoskedasticit
white_test(lm_gr3_good_7) #  0.268984 --> Ho can not be rejected, there is homoskedasticit
```

```
white_test(lm_gr4_good_5) #  0.366548 --> -Ho can not be rejected, there is homoskededasticitY
white_test(lm_gr4_good_7) #  0.826016 --> -Ho can not be rejected, there is homoskededasticitY

white_test(lm_gr5_good_5) #  0.288417 --> -Ho can not be rejected, there is homoskededasticitY
white_test(lm_gr5_good_7) #  0.920624 --> -Ho can not be rejected, there is homoskededasticitY

white_test(lm_gr6_good_5) #  0.98232 --> -Ho can not be rejected, there is homoskededasticitY
white_test(lm_gr6_good_7) #  0.865738--> -Ho can not be rejected, there is homoskededasticitY

white_test(lm_gr7_good_5) #  0.711037 --> -Ho can not be rejected, there is homoskededasticitY
white_test(lm_gr7_good_7) #  0.621403 --> -Ho can not be rejected, there is homoskededasticitY

### --> NO heteroskedasticity

#.........................................................................................
## Show Model 7 of group 1 to 4 in a table
stargazer(lm_gr1_good_7, lm_gr2_good_7, lm_gr3_good_7,lm_gr4_good_7,
        title = "Regression Estimates",
        dep.var.labels = "Feeling Good About Travel Mode Choice",
        column.labels = c("1 Flight", "2 Flights", "3 Flights", "4 Flights"),
        covariate.labels = c("Constant", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
                        "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
                        "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
                        "Travelling With Children", "Travelling Alone"
        ),
        align = TRUE,
        intercept.bottom = FALSE,
        no.space = TRUE,
        model.names = TRUE,
        model.numbers = FALSE,
        omit.stat     = c( "rsq", "ser"), # omit R squared and Res. St. Error
        out = "good_gr1to4_7.html"
)


## Show Model 7 of group 5 to 7
stargazer(  lm_gr5_good_7,  lm_gr6_good_7, lm_gr7_good_7,
        title = "Regression Estimates",
        dep.var.labels = "Feeling Good About Travel Mode Choice",
        column.labels = c( "5 Flights", "6 Flights", "7 Flights"),
        covariate.labels = c("Constant", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
                        "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
                        "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
                        "Travelling With Children", "Travelling Alone"
        ),
        align = TRUE,
        intercept.bottom = FALSE,
        no.space = TRUE,
        model.names = TRUE,
        model.numbers = FALSE,
        omit.stat     = c( "rsq", "ser"), # omit R squared and Res. St. Error
        out = "good_gr5to7_7.html"
)

## Show Model 5 of group 1 to 4 in a table
stargazer(lm_gr1_good_5, lm_gr2_good_5, lm_gr3_good_5,lm_gr4_good_5,
        title = "Regression Estimates",
        dep.var.labels = "Feeling Good About Travel Mode Choice",
        column.labels = c("1 Flight", "2 Flights", "3 Flights", "4 Flights"),
        covariate.labels = c("Constant", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
                        "Flights With ICO", "Flights With VCO", "Flights With SAF",
                        "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
                        "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
                        "Travelling With Children", "Travelling Alone",
                        "Biospheric Env. Concern * Flights With ICO", "Altruistic Env. Concern * Flights With ICO", "Egoistic Env. Concern * Flights With ICO",
                        "Biospheric Env. Concern * Flights With VCO", "Altruistic Env. Concern * Flights With VCO", "Egoistic Env. Concern * Flights With VCO",
                        "Biospheric Env. Concern * Flights With SAF", "Altruistic Env. Concern * Flights With SAF", "Egoistic Env. Concern * Flights With SAF"
        ),
        align = TRUE,
        intercept.bottom = FALSE,
        no.space = TRUE,
        model.names = TRUE,
        model.numbers = FALSE,
        omit.stat     = c( "rsq", "ser"), # omit R squared and Res. St. Error
        out = "good_gr1to4_5.html"
)

## Show Model 5 of group 5 to 7
stargazer(lm_gr5_good_5, lm_gr6_good_5, lm_gr7_good_5,
        title = "Regression Estimates",
        dep.var.labels = "Feeling Good About Travel Mode Choice",
```

```
        column.labels = c("5 Flights", "6 Flights", "7 Flights"),
        covariate.labels = c("Constant", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
                             "Flights With ICO", "Flights With VCO", "Flights With SAF",
                             "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
                             "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
                             "Travelling With Children", "Travelling Alone",
                             "Biospheric Env. Concern * Flights With ICO", "Altruistic Env. Concern * Flights With ICO", "Egoistic Env. Concern * Flights With ICO",
                             "Biospheric Env. Concern * Flights With VCO", "Altruistic Env. Concern * Flights With VCO", "Egoistic Env. Concern * Flights With VCO",
                             "Biospheric Env. Concern * Flights With SAF", "Altruistic Env. Concern * Flights With SAF", "Egoistic Env. Concern * Flights With SAF"
        ),
        align = TRUE,
        intercept.bottom = FALSE,
        no.space = TRUE,
        model.names = TRUE,
        model.numbers = FALSE,
        omit.stat     = c( "rsq", "ser"), # omit R squared and Res. St. Error
        out = "good_gr5to7_5.html"
)

#....................................................................
### Descriptive statistics - guilty and good
# copy in excel
library(vtable)

st(wdce_gr0, vars = c('feeling_travelmode_guilty', 'feeling_travelmode_good'),
   add.median = TRUE,
   file = 'st_guilt_good_0.html') # saves a html file)

st(wdce_gr1, vars = c('feeling_travelmode_guilty', 'feeling_travelmode_good'),
   add.median = TRUE,
   file = 'st_guilt_good_1.html') # saves a html file)

st(wdce_gr2, vars = c('feeling_travelmode_guilty', 'feeling_travelmode_good'),
   add.median = TRUE,
   file = 'st_guilt_good_2.html') # saves a html file)

st(wdce_gr3, vars = c('feeling_travelmode_guilty', 'feeling_travelmode_good'),
   add.median = TRUE,
   file = 'st_guilt_good_3.html') # saves a html file)

st(wdce_gr4, vars = c('feeling_travelmode_guilty', 'feeling_travelmode_good'),
   add.median = TRUE,
   file = 'st_guilt_good_4.html') # saves a html file)

st(wdce_gr5, vars = c('feeling_travelmode_guilty', 'feeling_travelmode_good'),
   add.median = TRUE,
   file = 'st_guilt_good_5.html') # saves a html file)

st(wdce_gr6, vars = c('feeling_travelmode_guilty', 'feeling_travelmode_good'),
   add.median = TRUE,
   file = 'st_guilt_good_6.html') # saves a html file)

st(wdce_gr7, vars = c('feeling_travelmode_guilty', 'feeling_travelmode_good'),
   add.median = TRUE,
   file = 'st_guilt_good_7.html') # saves a html file)

#....................................................................

### RQ5: How do integrated carbon offsets influence an individuals' flight choices?
# Hypotheses:
# H5a: Individuals are more likely to choose flight when carbon emissions are offset by the airline, leading to a rebound effect.
# H5b:  The rebound effect is enhanced for individuals with high biospheric and altruistic environmental concern.
# H5c: Individuals do not regard carbon offsets as equivalent to emission reductions by sustainable aviation fuel.

#.................
## dce long data!
# only Data scenarios 1 - 6  --> Panel Data

dce_6 <- dce[!(dce$variable == "b7_rct"), ] #subset which deletes all rows with b7_rct

overview_dce_6 <- data.frame(
  Variable = names(dce_6),
  Class = sapply(dce_6, function(x) class(x)[1]),
  First_Observations = sapply(dce_6, function(x) paste(head(x, n = 3), collapse = ", "))
)

# new dummy variable indication flight choice
dce_6$flight_yes <- ifelse(dce_6$value == "Airplane", 1, 0)

unique(dce_6$variable)
class(dce_6$variable)
class(dce_6$id)
#....................................................................................

### Fixed-Effects Panel Model
##
library(plm)

## Model 1 - Only ICO
#

plm1 <- plm(flight_yes ~ f.comp,
           data = dce_6,
           index = c("id"),
           model = "within")
```

```
summary(plm1) ## Balanced Panel: n = 1221, T = 6, N = 7326

coeftest(plm1, vcov. = vcovHC, type = "HC1") # # shows coefficient heteroskedasticity and autocorrelation-consistent (HAC) standard errors --> clustered SE
## HC1 automatically detects plm and makes clustered SE
plm_cov1 <- vcovHC(plm1, type = "HC1")
plm_robust.se1 <- sqrt(diag(plm_cov1)) # matrix wit robust standard errors

## Model 2: only ICO & interaction
#
plm2 <- plm(flight_yes ~ f.comp +
        + f.comp:cent_ec_bio_idx + f.comp:cent_ec_alt_idx + f.comp:cent_ec_ego_idx,
        data = dce_6,
        index = c("id"),
        model = "within") #
summary(plm2) ## Balanced Panel: n = 1221, T = 6, N = 7326

coeftest(plm2, vcov. = vcovHC, type = "HC1") # # s# shows coefficient heteroskedasticity and autocorrelation-consistent (HAC) standard errors --> clustered SE
plm_cov2 <- vcovHC(plm2, type = "HC1")
plm_robust.se2 <- sqrt(diag(plm_cov2)) # matrix wit robust standard errors

## Model 3- with all other attributes
#
plm3 <- plm(flight_yes ~ f.comp
        + f.techno + f.fcost + f.ftime  + t.tcost + t.ttime + t.tcomf + nt.ntcost + nt.nttime + nt.ntcomf + c.ccost + c.ctime
        + f.comp:cent_ec_bio_idx + f.comp:cent_ec_alt_idx + f.comp:cent_ec_ego_idx,
        data = dce_6,
        index = c("id"),
        model = "within") #
summary(plm3) ## Balanced Panel: n = 1221, T = 6, N = 7326

coeftest(plm3, vcov. = vcovHC, type = "HC1") # # s# shows coefficient heteroskedasticity and autocorrelation-consistent (HAC) standard errors --> clustered SE
plm_cov3 <- vcovHC(plm3, type = "HC1")
plm_robust.se3 <- sqrt(diag(plm_cov3)) # matrix wit robust standard errors

#,..................................................................
## Test if fixed effects also on block makes a difference -- no!  but "unbalanced panel"

## Model 1 - Only ICO
#

plm1b <- plm(flight_yes ~ f.comp,
        data = dce_6,
        index = c("id", "block_nr"),
        model = "within")
summary(plm1b) ## Unbalanced Panel: n = 1221, T = 6-6, N = 7326

coeftest(plm1b, vcov. = vcovHC, type = "HC1") # # shows coefficient heteroskedasticity and autocorrelation-consistent (HAC) standard errors --> clustered SE
## HC1 automatically detects plma and makes clustered SE
plm_cov1b <- vcovHC(plm1b, type = "HC1")
plm_robust.se1b <- sqrt(diag(plm_cov1b)) # matrix wit robust standard errors

## Model 2 with fixed effects also on scenarios
plm2b <- plm(flight_yes ~ f.comp +
        + f.comp:cent_ec_bio_idx + f.comp:cent_ec_alt_idx + f.comp:cent_ec_ego_idx,
        data = dce_6,
        index = c("id", "block_nr"), # also fixed effects over block
        model = "within")
summary(plm2b) ## Unbalanced Panel: n = 1221, T = 6-6, N = 7326
summary(plm2)
## -> no difference to fixed effects only on id

coeftest(plm2b, vcov. = vcovHC, type = "HC1") # # shows coefficient heteroskedasticity and autocorrelation-consistent (HAC) standard errors --> clustered SE
## HC1 automatically detects plma and makes clustered SE
plm_cov2b <- vcovHC(plm2b, type = "HC1")
plm_robust.se2b <- sqrt(diag(plm_cov2b)) # matrix wit robust standard errors

## compare coefficietns from plm2 and plm2b

# Extract coefficients from both models
coef_plm2 <- coef(plm2)
coef_plm2b <- coef(plm2b)

# Compare coefficients
coeff_diff2 <- coef_plm2 - coef_plm2b
coeff_diff2 # zero!

plm3b <- plm(flight_yes ~ f.comp
        + f.techno  + f.fcost + f.ftime + t.tcost + t.ttime + t.tcomf + nt.ntcost + nt.nttime + nt.ntcomf + c.ccost + c.ctime
        + f.comp:cent_ec_bio_idx + f.comp:cent_ec_alt_idx + f.comp:cent_ec_ego_idx,
        data = dce_6,
        index = c("id", "block_nr"), # with fixed effects on block
        model = "within") #
summary(plm3b) ## same results as only on id
## Unbalanced Panel: n = 1221, T = 6-6, N = 7326
coeftest(plm3b, vcov. = vcovHC, type = "HC1") # # shows coefficient heteroskedasticity and autocorrelation-consistent (HAC) standard errors --> clustered SE
## HC1 automatically detects plma and makes clustered SE
plm_cov3b <- vcovHC(plm3b, type = "HC1")
plm_robust.se3b <- sqrt(diag(plm_cov3b)) # matrix wit robust standard errors

## compare coefficients from plm3 and plm3b
#

# Extract coefficients from both models
coef_plm3 <- coef(plm3)
```

```
coef_plm3b <- coef(plm3b)

# Compare coefficients
coeff_diff3 <- coef_plm3 - coef_plm3b
coeff_diff3 # zero!
## leave index only to id!

#.........................................................................
### Is there Heteroskedasticity`?`
##

## The Breusch-Pagan Test (see Kennedy 2013)

# Ho = Residuals are distributed with equal variance (i.e., homoskedasticity)
# H1 = Residuasl are distributed with unequal variance (i.e., heteroskedasticity)
library(lmtest)
bptest(plm1) # --> p-value = 0.3722 > 0.05 --> Ho can not be rejected, there is homoskededasticity
bptest(plm2) # --> p-value =  7.948e-10 < 0.05 --> H0 can be rejected, there is heteroskedasticity
bptest(plm3) # --> p-value = 2.2e-16 < 0.05 --> H0 can be rejected, there is heteroskedasticity

## The white Test (see Kennedy (2013))
# Ho = Residuals are distributed with equal variance (i.e., homoskedasticity)
# H1 = Residuasl are distributed with unequal variance (i.e., heteroskedasticity)

library("whitestrap")
white_test(plm1)# --> p-value = 0.967703 > 0.05 --> Ho can not be rejected, there is homoskededasticity
white_test(plm2)# --> p-value =  0.444519 < 0.05 --> H0 can be rejected, there is heteroskedasticity
white_test(plm3)# --> p-value = 0.064984 > 0.05 --> Ho can not be rejected, there is homoskededasticity
#### to be save, use robust-SE!
#.........................................................................................
### Show tables

library(stargazer)

## with fixed effects only on 'id', clustered standard errors - Model 1 - 3
stargazer(plm1, plm2, plm3,
        title = "Regression Estimates with Clustered Standard Errors",
        dep.var.labels = " Flight Choice",
        out = "plm_123_rq5.html",
        se = list (plm_robust.se1, plm_robust.se2, plm_robust.se3),
        covariate.labels = c("Flight-ICO", "Flight-SAF","Flight-Cost", "Flight-Time",
                        "Train-Cost", "Train-Time", "Train-Comfort",
                        "Nightt.-Cost", "Nightt.-Time", "Nightt.-Comfort",
                        "Car-Cost", "Car-Time",
                        "Flight-ICO * Biospheric Env. Concern", "Flight-ICO * Altruistic Env. Concern", "Flight-ICO * Egoistic Env. Concern"),
        align = TRUE,
        intercept.bottom = FALSE,
        no.space = TRUE ,
        model.names = TRUE, # shows model names (OLS, probit etc)
        model.numbers = TRUE, # automatically numbers models --ok here bc no column labels,
        omit.stat     =   c( "rsq") # omit R squared

)
#........................................................

### Conditional Average Treatment Effect (CATE)

### Whats the effect of the ICO on the 75th percentile of ec concern?
##

library(multcomp)

## Model 3

## 75th percentile of ec bio

# create matrix with one row and number of columns equal to nr of coefficients
coefeq_plm3_bio <- matrix(data=0, nrow=1, ncol=length(plm3$coefficients))
coefeq_plm3_bio
# give column names equal to coefficient names
colnames(coefeq_plm3_bio) <- names(plm3$coefficients)
coefeq_plm3_bio
# set values for matrix elements
coefeq_plm3_bio[1, "f.comp"] <- 1 # set ICO to 1
coefeq_plm3_bio[1, "f.comp:cent_ec_bio_idx"] <- cent_ec_bio_perc_75 # 75th percentile of ec bio
# leave values of ec alt and ec ego with 0 (bc centralised, average is approx. 0)
coefeq_plm3_bio
# average marginal effect
coefeq_plm3_bio %*% plm3$coefficients
# -->  0.01117427 but not sure if significant

# same as this:
plm3$coefficients["f.comp"] + plm3$coefficients["f.comp:cent_ec_bio_idx"]*cent_ec_bio_perc_75

## Hypothesis testing for linear combination
# Ho = beta (xico) + beta (xico:cent_ec_bio) * beta (cent_ec_bio at 75th percentile) = 0
# HA = beta (xico) + beta (xico:cent_ec_bio) * beta (cent_ec_bio at 75th percentile) unequal 0

#default SE
ametest_plm3_bio <- glht (model = plm3, linfct = coefeq_plm3_bio, rhs=0, alternative = c("two.sided"))
summary(ametest_plm3_bio)
# --> no significant marginal effect of treatment at the 75th percentile of ec bio, H0 cannot be rejected!

# with robust SE
ametest_plm3_bio_rob <- glht (model = plm3, linfct = coefeq_plm3_bio, rhs=0, alternative = c("two.sided"),  vcov = vcovHC(plm3, type = "HC1"))
summary(ametest_plm3_bio_rob)
```

--> no significant marginal effect of treatment at the 75th percentile of ec bio, H0 cannot be rejected!
no big difference to default SE
##...
75th percentile of ec alt

# create matrix with one row and number of columns equal to nr of coefficients
coefeq_plm3_alt <- matrix(data=0, nrow=1, ncol=length(plm3$coefficients))
# give column names equal to coefficient names
colnames(coefeq_plm3_alt) <- names(plm3$coefficients)
coefeq_plm3_alt
set values for matrix elements
coefeq_plm3_alt[1, "f.comp"] <- 1 # set ICO to 1
coefeq_plm3_alt[1, "f.comp:cent_ec_alt_idx"] <- cent_ec_alt_perc_75 # 75th percentile of ec alt
average marginal effect
coefeq_plm3_alt %*% plm3$coefficients
--> 0.01061955 but not sure if significant

same as this:
plm3$coefficients["f.comp"] + plm3$coefficients["f.comp:cent_ec_alt_idx"]*cent_ec_alt_perc_75

Hypothesis testing for linear combination
Ho = beta (xico) + beta (xico:cent_ec_alt) * (cent_ec_alt at 75th percentile) = 0
HA = beta (xico) + beta (xico:cent_ec_alt) * (cent_ec_alt at 75th percentile) unequal 0

#default SE
ametest_plm3_alt <- glht (model = plm3, linfct = coefeq_plm3_alt, rhs=0, alternative = c("two.sided"))
summary(ametest_plm3_alt)
# --> no significant marginal effect of treatment at the 75th percentile of ec alt, H0 cannot be rejected!

# with robust SE
ametest_plm3_alt_rob <- glht (model = plm3, linfct = coefeq_plm3_alt, rhs=0, alternative = c("two.sided"), vcov = vcovHC(plm3, type = "HC1"))
summary(ametest_plm3_alt_rob)
# --> no significant marginal effect of treatment at the 75th percentile of ec alt, H0 cannot be rejected!
# no big difference to default SE
#.............................
75th percentile of ec ego

# create matrix with one row and number of columns equal to nr of coefficients
coefeq_plm3_ego <- matrix(data=0, nrow=1, ncol=length(plm3$coefficients))
# give column names equal to coefficient names
colnames(coefeq_plm3_ego) <- names(plm3$coefficients)
coefeq_plm3_ego
set values for matrix elements
coefeq_plm3_ego[1, "f.comp"] <- 1 # set ICO to 1
coefeq_plm3_ego[1, "f.comp:cent_ec_ego_idx"] <- cent_ec_ego_perc_75 # 75th percentile of ec ego
average marginal effect
coefeq_plm3_ego %*% plm3$coefficients
--> 0.01087874 but not sure if significant

same as this:
plm3$coefficients["f.comp"] + plm3$coefficients["f.comp:cent_ec_ego_idx"]*cent_ec_ego_perc_75

Hypothesis testing for linear combination
Ho = beta (xico) + beta (xico:cent_ec_ego) * (cent_ec_ego at 75th percentile) = 0
HA = beta (xico) + beta (xico:cent_ec_ego) * (cent_ec_ego at 75th percentile) unequal 0

#default SE
ametest_plm3_ego <- glht (model = plm3, linfct = coefeq_plm3_ego, rhs=0, alternative = c("two.sided"))
summary(ametest_plm3_ego)
# --> no significant marginal effect of treatment at the 75th percentile of ec ego, H0 cannot be rejected!

# with robust SE
ametest_plm3_ego_rob <- glht (model = plm3, linfct = coefeq_plm3_ego, rhs=0, alternative = c("two.sided"), vcov = vcovHC(plm3, type = "HC1"))
summary(ametest_plm3_ego_rob)
# --> no significant marginal effect of treatment at the 75th percentile of ec ego, H0 cannot be rejected!
# no big difference to default SE
#...

25th th percentile of ec bio

# create matrix with one row and number of columns equal to nr of coefficients
coefeq_plm3_bio_25 <- matrix(data=0, nrow=1, ncol=length(plm3$coefficients))
coefeq_plm3_bio_25
# give column names equal to coefficient names
colnames(coefeq_plm3_bio_25) <- names(plm3$coefficients)
# set values for matrix elements
coefeq_plm3_bio_25[1, "f.comp"] <- 1 # set ICO to 1
coefeq_plm3_bio_25[1, "f.comp:cent_ec_bio_idx"] <- cent_ec_bio_perc_25 # 25th percentile of ec bio
leave values of ec alt and ec ego with 0 (bc centralised, average is approx. 0)
coefeq_plm3_bio_25
average marginal effect
coefeq_plm3_bio_25 %*% plm3$coefficients
--> 0.007264769 but not sure if significant

same as this:
plm3$coefficients["f.comp"] + plm3$coefficients["f.comp:cent_ec_bio_idx"]*cent_ec_bio_perc_25

Hypothesis testing for linear combination
Ho = beta (xico) + beta (xico:cent_ec_bio) * beta (cent_ec_bio at 25th percentile) = 0
HA = beta (xico) + beta (xico:cent_ec_bio) * beta (cent_ec_bio at 25th percentile) unequal 0

#default SE

```
ametest_plm3_bio_25 <- glht (model = plm3, linfct =
coefeq_plm3_bio_25, rhs=0, alternative = c("two.sided"))
summary(ametest_plm3_bio_25)
# --> no significant marginal effect of treatment at the 25th
percentile of ec bio, H0 cannot be rejected!

# with robust SE
ametest_plm3_bio_rob_25 <- glht (model = plm3, linfct =
coefeq_plm3_bio_25, rhs=0, alternative = c("two.sided"),
vcov = vcovHC(plm3, type = "HC1"))
summary(ametest_plm3_bio_rob_25)
# --> no significant marginal effect of treatment at the 25th
percentile of ec bio, H0 cannot be rejected!
# no big difference to default SE
#..............................
## 25th percentile of ec alt

# create matrix with one row and number of columns equal
to nr of coefficients
coefeq_plm3_alt_25 <- matrix(data=0, nrow=1,
ncol=length(plm3$coefficients))
# give column names equal to coefficient names
colnames(coefeq_plm3_alt_25) <-
names(plm3$coefficients)
coefeq_plm3_alt_25
# set values for matrix elements
coefeq_plm3_alt_25[1, "f.comp"] <- 1 # set ICO to 1
coefeq_plm3_alt_25[1, "f.comp:cent_ec_alt_idx"] <-
cent_ec_alt_perc_25 # 25th percentile of ec alt
# average marginal effect
coefeq_plm3_alt_25 %*% plm3$coefficients
# --> 0.00826056  but not sure if significant

# same as this:
plm3$coefficients["f.comp"] +
plm3$coefficients["f.comp:cent_ec_alt_idx"]*cent_ec_alt_
perc_25

## Hypothesis testing for linear combination
# Ho = beta (xico) + beta (xico:cent_ec_alt) *  (cent_ec_alt
at 25th percentile) = 0
# HA = beta (xico) + beta (xico:cent_ec_alt) *  (cent_ec_alt
at 25th percentile) unequal 0

#default SE
ametest_plm3_alt_25 <- glht (model = plm3, linfct =
coefeq_plm3_alt_25, rhs=0, alternative = c("two.sided"))
summary(ametest_plm3_alt_25)
# --> no significant marginal effect of treatment at the 75th
percentile of ec alt, H0 cannot be rejected!

# with robust SE
ametest_plm3_alt_rob_25 <- glht (model = plm3, linfct =
coefeq_plm3_alt_25, rhs=0, alternative = c("two.sided"),
vcov = vcovHC(plm3, type = "HC1"))
summary(ametest_plm3_alt_rob_25)
# --> no significant marginal effect of treatment at the 25th
percentile of ec alt, H0 cannot be rejected!
# no big difference to default SE
#..................................................................

## 25th percentile of ec ego

# create matrix with one row and number of columns equal
to nr of coefficients
coefeq_plm3_ego_25 <- matrix(data=0, nrow=1,
ncol=length(plm3$coefficients))
# give column names equal to coefficient names
colnames(coefeq_plm3_ego_25) <-
names(plm3$coefficients)
# set values for matrix elements
coefeq_plm3_ego_25[1, "f.comp"] <- 1 # set ICO to 1
coefeq_plm3_ego_25[1, "f.comp:cent_ec_ego_idx"] <-
cent_ec_ego_perc_25 # 25th percentile of ec ego
# average marginal effect
coefeq_plm3_ego_25 %*% plm3$coefficients
# -->   but not sure if significant

# same as this:
plm3$coefficients["f.comp"] +
plm3$coefficients["f.comp:cent_ec_ego_idx"]*cent_ec_eg
o_perc_25

## Hypothesis testing for linear combination
# Ho = beta (xico) + beta (xico:cent_ec_ego) * (cent_ec_ego
at 25th percentile) = 0
# HA = beta (xico) + beta (xico:cent_ec_ego) *
(cent_ec_ego at 25th percentile) unequal 0

#default SE
ametest_plm3_ego_25 <- glht (model = plm3, linfct =
coefeq_plm3_ego_25, rhs=0, alternative = c("two.sided"))
summary(ametest_plm3_ego_25)
# --> no significant marginal effect of treatment at the 75th
percentile of ec ego, H0 cannot be rejected!

# with robust SE
ametest_plm3_ego_rob_25 <- glht (model = plm3, linfct =
coefeq_plm3_ego_25, rhs=0, alternative = c("two.sided"),
vcov = vcovHC(plm3, type = "HC1"))
summary(ametest_plm3_ego_rob_25)
# --> no significant marginal effect of treatment at the 75th
percentile of ec ego, H0 cannot be rejected!
# no big difference to default SE
#..................................................................

#### H5c:    Individuals do not regard carbon offsets
as equivalent to emission reductions by sustainable aviation
fue

#..........................................................................
### MNL MOdel of DCE Report: Two sided T-Test of
Coefficients

#Ho: Coefficients are equal
#Ha: Coefficients are not equal


# Number of observations in your dataset
n <- 7326

# Coefficients and standard errors
beta1 <- 0.142
se1 <- 0.053

beta2 <- 0.063
se2 <- 0.037

# Calculate t-statistic
```

```
t_statistic_mnl <- (beta1 - beta2) / sqrt(se1^2 + se2^2)
print(t_statistic_mnl)

# Degrees of freedom
df <- n - 1  # Use the total number of observations in your dataset

# Two-tailed p-value
p_value_t_mnl <- 2 * (1 - pt(abs(t_statistic_mnl), df = 7325))
print(p_value_t_mnl)  ## 0.2216707
#...................................................................
## Linear fixed-effects panel model

summary(plm3)

## Two-sided T-Test to compare coefficients
#Ho: Coefficients are equal
#Ha: Coefficients are not equal

beta_f_comp <- 0.00899859
se_f_comp <- 0.00705851

beta_f_techno <- 0.02466465
se_f_techno <- 0.00788234

# Calculate t-statistic
t_statistic_lm <- (beta_f_comp - beta_f_techno) / sqrt(se_f_comp^2 + se_f_techno^2)
print(t_statistic_lm)

# Degrees of freedom
df <- 7326 - 1  # Use the total number of observations in your dataset

# Two-tailed p-value
p_value_t_lm <- 2 * pt(-abs(t_statistic_lm), df)
print(p_value_t_lm) ## 0.1387539 ---> Ho cannot be rejected!
#...............................................................................................
.......................................................

### RQ6: How do voluntary carbon offsets influence an individual's flight choice?
# Hypotheses:
  # H6a: The possibility of voluntarily carbon offsets increases an individual’s flight choice and thereby leading to a rebound effect.
 # H6b: The rebound effect is enhanced for high biospheric and altruistic environmental concern
#.........................................................................................
.......................................

## RCT data
### Descriptive statistics

table_b7_choice <- table(wdce$b7_choice, wdce$treatment)
print(table_b7_choice)

library(dplyr)
library(ggplot2)

### Barplot with relative Frequency of Travel Mode Choice per Group

# Create a data frame for the contingency table
mode_choice_table <- table(wdce$treatment, wdce$b7_choice)
mode_choice_df <- as.data.frame(mode_choice_table)

# Rename the columns for clarity
colnames(mode_choice_df) <- c("Group", "Travel_Mode", "Frequency")

# Calculate relative frequencies within each group

mode_choice_df <- mode_choice_df %>%
  group_by(Group) %>%
  mutate(Relative_Frequency = Frequency / sum(Frequency))

# Create a bar chart with relative frequencies
barplot_mode_choice <- ggplot(mode_choice_df, aes(x = Travel_Mode, y = Relative_Frequency, fill = Group)) +
  geom_bar(stat = "identity", position = "dodge2") +
  labs( x = "Travel Mode Choice", y = "Relative Frequency") +
  scale_y_continuous(labels = scales::percent_format(scale = 100)) + # Format as percentages
  scale_fill_manual(values = c("0" = "lightgrey", "1" = "darkgrey"),
    labels = c("0" = "Control", "1" = "Treatment")) +
theme_light() +
  theme(text = element_text(size = 12)) +
  geom_text(aes(label = sprintf("%.2f%%", Relative_Frequency * 100),
                  y = Relative_Frequency),
                position = position_dodge(width = 0.9), vjust = -0.5)

barplot_mode_choice
ggsave("barplot_mode_choice_rct.png", plot = barplot_mode_choice) ## default size
 ## change size  width = 8, height = 6, dpi = 300

  ## to add the values of the barcharts add
##      geom_text(aes(label = sprintf("%.2f%%", Relative_Frequency * 100),
 #           y = Relative_Frequency),
  #      position = position_dodge(width = 0.9), vjust = -0.5) +  # Adjust the vjust value to control label position

table(wdce$b7_flight_yes, wdce$treatment) # row is first variable (flight_yes), column second (treatment)
#.....................................................................................

## T-test for proportions: the proportions of flight choice significantly different for treatment and control group?
#
# Create a contingency table
flight_yes_table <- table(wdce$b7_flight_yes, wdce$treatment)

# Perform a two-sided t-test for proportions
ttest_result <- prop.test(flight_yes_table, alternative = "two.sided")
```

```
# Print the results
print(ttest_result)## p value  0.2816 --> cannot be rejected!

?prop.test

## Fisher's exact test: compares the null hypothesis "the odds-ration is equal to 1"

# Perform Fisher's exact test
fisher_test_result <- fisher.test(flight_yes_table, alternative = "two.sided")

# Print the results
print(fisher_test_result) ## p-value 0.2664 -> cannot be rejected!

?fisher.test
#..............................................................................
#..................................................................

### linear probability model
##

# lm 1: only treatment as regressor
lm1 <- lm(
  b7_flight_yes ~ treatment ,
  data = wdce
)
summary(lm1)

library(sandwich)
library(lmtest)
  # robust SE with vcovHC for heteroscedasticity-consistent (HC) covariances in (generalized) linear models
coeftest(lm1, vcov. = vcovHC, type = "HC1") # shows coefficient with robust standard errors
lm_cov1 <- vcovHC(lm1, type = "HC1")
lm_robust.se1 <- sqrt(diag(lm_cov1))  # matrix wit robust standard errors

# lm2: with ec
lm2 <- lm(b7_flight_yes ~ treatment
        + cent_ec_bio_idx + cent_ec_alt_idx +cent_ec_ego_idx ,
        data = wdce)
summary(lm2)

  # robust SE
coeftest(lm2, vcov. = vcovHC, type = "HC1") # shows coefficient with robust standard errors
lm_cov2 <- vcovHC(lm2, type = "HC1")
lm_robust.se2 <- sqrt(diag(lm_cov2))  # matrix wit robust standard errors

# lm3: with ec and interaction
lm3 <- lm(
  b7_flight_yes ~ treatment
  + cent_ec_bio_idx  + cent_ec_alt_idx + cent_ec_ego_idx
  + treatment:cent_ec_bio_idx + treatment:cent_ec_alt_idx + treatment:cent_ec_ego_idx ,
  data = wdce
)
summary(lm3)
  # robust SE
coeftest(lm3, vcov. = vcovHC, type = "HC1") # shows coefficient with robust standard errors
lm_cov3 <- vcovHC(lm3, type = "HC1")
lm_robust.se3 <- sqrt(diag(lm_cov3))  # matrix wit robust standard errors

# lm4: with ec, interaction & sociodemographics
lm4 <- lm(
  b7_flight_yes ~ treatment
  + cent_ec_bio_idx  + cent_ec_alt_idx + cent_ec_ego_idx
  + treatment:cent_ec_bio_idx  + treatment:cent_ec_alt_idx + treatment:cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car,
  data = wdce
)
summary(lm4)
 # robust SE
coeftest(lm4, vcov. = vcovHC, type = "HC1") # shows coefficient with robust standard errors
lm_cov4 <- vcovHC(lm4, type = "HC1")
lm_robust.se4 <- sqrt(diag(lm_cov4))  # matrix wit robust standard errors

# lm5:  with ec, interaction, sociodemographics & travel scenario
lm5 <- lm(
  b7_flight_yes ~ treatment
  + cent_ec_bio_idx  + cent_ec_alt_idx + cent_ec_ego_idx
  + treatment:cent_ec_bio_idx  + treatment:cent_ec_alt_idx + treatment:cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
  + children + alone,
  data = wdce
)
summary(lm5)
  # robust SE
coeftest(lm5, vcov. = vcovHC, type = "HC1") # shows coefficient with robust standard errors
lm_cov5 <- vcovHC(lm5, type = "HC1")
lm_robust.se5 <- sqrt(diag(lm_cov5))  # matrix wit robust standard errors

anova(lm1, lm2, lm3, lm4, lm5)
   # --> Model 2 and 4 best
anova(lm2, lm4, lm5) # Model 4 appears to be the most suitable choice, considering both statistical significance and model fit
anova(lm1, lm2, lm3, lm5)
#..........................................................................................

## Post-hoc power analyis of Model 4
library(pwr)
?pwr

## for treatment

# Extract t-value and degrees of freedom for 'treatment'
treatment_t_value <- -0.804  # replace with the actual t-value
df_residuals <- 1201  # replace with the actual degrees of freedom for residuals
```

```
# Calculate effect size (Cohen's f²)
f2 <- (treatment_t_value^2) / df_residuals

# Degrees of freedom for the numerator (number of predictors)
u <- 19

# Degrees of freedom for the denominator
v <- df_residuals

# Significance level
sig.level <- 0.05

# Perform power calculation
power_treat <- pwr.f2.test(u = u, v = v, f2 = f2, sig.level = sig.level)

# Print the result
print(power_treat) ##   power = 0.06360089 to low!

#...............................................................................v
## is there Heteroskedasticity?

## The Breusch-Pagan Test

# Ho = Residuals are distributed with equal variance (i.e., homoskedasticity)
# H1 = Residuasl are distributed with unequal variance (i.e., heteroskedasticity)
library(lmtest)
bptest(lm1) # --> p-value = 0.2608 > 0.05 --> Ho can not be rejected, there is homoskededasticity
bptest(lm2) # --> p-value = 0.0001264 < 0.05 --> H0 can be rejected, there is heteroskedasticity
bptest(lm3) # --> p-value = 0.0002278 < 0.05 --> H0 can be rejected, there is heteroskedasticity
bptest(lm4) # --> p-value = 2.008e-08 < 0.05 --> H0 can be rejected, there is heteroskedasticity
bptest(lm5) # --> p-value = 1.755e-07 < 0.05 --> H0 can be rejected, there is heteroskedasticity

## The white Test (see Kennedy (2013))

# Ho = Residuals are distributed with equal variance (i.e., homoskedasticity)
# H1 = Residuasl are distributed with unequal variance (i.e., heteroskedasticity)

library("whitestrap")
white_test(lm1)# --> p-value = 0.531425 > 0.05 --> Ho can not be rejected, there is homoskededasticity
white_test(lm2)# --> p-value = 7e-06 < 0.05 --> H0 can be rejected, there is heteroskedasticity
white_test(lm3)# --> p-value = 2e-06 < 0.05 --> H0 can be rejected, there is heteroskedasticity
white_test(lm4)# --> p-value = 0 < 0.05 --> H0 can be rejected, there is heteroskedasticity
white_test(lm5) # --> p-value = 0 < 0.05 --> H0 can be rejected, there is heteroskedasticity
#...................................................................................

### Is there multicollinearity?
## Correlation-Matrix

independent_variables_lm5_2 <- wdce[, c("treatment", "cent_ec_bio_idx", "cent_ec_alt_idx", "cent_ec_ego_idx",
                    "gender", "young", "old", "mandatory", "tertiary", "incH",
                    "language", "interm", "urban", "car", "e_car", "children", "alone")]

str(independent_variables_lm5_2)
# convert factors into numerical var
wdce$gender_as_num <- as.numeric(wdce$gender) - 1
# Create dummy variables for "FR" and "IT"
wdce$fr <- ifelse(wdce$language == "FR", 1, 0)
wdce$it <- ifelse(wdce$language == "IT", 1, 0)
  # adjust list with newly converted var
independent_variables_lm5_3 <- wdce[, c("treatment", "cent_ec_bio_idx", "cent_ec_alt_idx", "cent_ec_ego_idx",
                    "young", "old", "mandatory", "tertiary", "incH",
                    "interm", "urban", "car", "e_car", "children", "alone",
                    "gender_as_num", "fr", "it")]
str(independent_variables_lm5_3)

# Create the correlation matrix
correlation_matrix_lm5 <- cor(independent_variables_lm5_3)

# Print the correlation matrix
print(correlation_matrix_lm5)
library(stargazer)
stargazer(correlation_matrix_lm5, out = "correlation_matrix_lm5.html")

# Check for correlation coefficients above 0.8 or below -0.8
high_correlation_lm5 <- correlation_matrix_lm5 > 0.8 | correlation_matrix_lm5 < -0.8

# Print the pairs of variables with high correlation
high_correlation_pairs_lm5 <- which(high_correlation_lm5, arr.ind = TRUE)
print(high_correlation_pairs_lm5)
  #
  # --> only the diagonals (correlation with itself) ---> no multicollinearity!

### Condition index

library("car")

?vif
# Calculate the variance inflation factors (VIF) for the linear regression model

 #without centered variables (bc can produce meaningless and mileading collinearity diagnostics)
# lm7:  ec not centered
lm7 <- lm(
  b7_flight_yes ~ treatment
  + ec_bio_idx + ec_alt_idx + ec_ego_idx
  + treatment:ec_bio_idx + treatment:ec_alt_idx + treatment:ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH + language + interm + urban + car + e_car
  + children + alone,
  data = wdce
```

```
)
vif(lm7, type = "predictor") # predictor bc of interaction terms
 #
 ## --> all VIF below 5 --> no multicollinearity! (rule of thumb: above 5 is a problem, over 10 should be remedied)
#..................................................
## show lm 1 to 5 in table

# only robust SE
library(stargazer)
stargazer(lm1, lm2, lm3, lm4, lm5,
    title = "Linear Probability Model - Regression Estimates with Robust Standard Errors",
    dep.var.labels = " Flight Choice",
    out = "lm_12345__robust_rq6.html",
    se = list ( lm_robust.se1, lm_robust.se2, lm_robust.se3, lm_robust.se4, lm_robust.se5),
    align = TRUE,
    intercept.bottom = FALSE,
    covariate.labels = c("Constant", "Treatment (VCO) ", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
        "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
        "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
        "Travelling with Children", "Travelling Alone",
      "Treatment (VCO) * Biospheric Env. Concern", "Treatment (VCO) * Altruistic Env. Concern", "Treatment (VCO) * Egoistic Env. Concern" ),
    no.space = TRUE ,
    model.names = TRUE, # shows model names (OLS, probit etc)
    model.numbers = TRUE,
    omit.stat    = c( "rsq", "ser") # omit R squared and Res. St. Error,
)
?stargazer

## with default SE
library(stargazer)
stargazer(lm1, lm2, lm3, lm4, lm5,
    dep.var.labels = " Flight Choice",
    out = "lm_12345_RQ6.html",
    align = TRUE,
    intercept.bottom = FALSE,
    covariate.labels = c("Constant", "Treatment (VCO) ", "Biospheric Env. Concern", "Altruistic Env. Concern", "Egoistic Env. Concern",
        "Female", "Young (< 36 Years)" , "Old (> 60 Years)", "Mandatory Education", "Tertiary Education", "High Income",
        "French Speaking", "Italian Speaking", "Agglomeration", "Urban", "Car Access", "E-car Access",
        "Travelling with Children", "Travelling Alone",
        "Treatment (VCO) * Biospheric Env. Concern", "Treatment (VCO) * Altruistic Env. Concern", "Treatment (VCO) * Egoistic Env. Concern" ),
    no.space = TRUE ,
    model.names = TRUE, # shows model names (OLS, probit etc)
    model.numbers = TRUE # automatically numbers models --ok here bc no column labels,
)
.
# ..................................................................
#### Treatment Effects
##

## Average Treatment Effect (ATE)
 # (bc true randomization and representative sample)
coeftest(lm5)
  # --> treatment -0.021 (0.028), P-value 0.446 -> not significant
#..........................................................................................
.........
### Conditional Average Treatment Effect (CATE)
 # Whats the effect of the treatment on the 75th percentile of ec concern?

library(multcomp)

# 75th percentile on bio ec concern, average bio and ego concern (0) for lm4
coefeq_lm4_bio <- matrix(data = 0, nrow = 1, ncol = length(lm4$coefficients))
colnames(coefeq_lm4_bio) <- names(lm4$coefficients)

# Set values for matrix elements
coefeq_lm4_bio[1, "treatment"] <- 1
coefeq_lm4_bio[1, "treatment:cent_ec_bio_idx"] <- cent_ec_bio_perc_75

# Average marginal effect
marginal_effect_lm4_bio <- coefeq_lm4_bio %*% lm4$coefficients

# Hypothesis testing for linear combination
ametest_lm4_bio <- glht(model = lm4, linfct = coefeq_lm4_bio, rhs = 0, alternative = c("two.sided"))
summary(ametest_lm4_bio)

# Robust SE
ametest_lm4_bio_rob <- glht(model = lm4, linfct = coefeq_lm4_bio, rhs = 0, alternative = c("two.sided"),
          vcov = vcovHC(lm4, type = "HC1"))
summary(ametest_lm4_bio_rob)

coefeq_lm4_alt <- matrix(data = 0, nrow = 1, ncol = length(lm4$coefficients))
colnames(coefeq_lm4_alt) <- names(lm4$coefficients)

coefeq_lm4_alt[1, "treatment"] <- 1
coefeq_lm4_alt[1, "treatment:cent_ec_alt_idx"] <- cent_ec_alt_perc_75

marginal_effect_lm4_alt <- coefeq_lm4_alt %*% lm4$coefficients

ametest_lm4_alt <- glht(model = lm4, linfct = coefeq_lm4_alt, rhs = 0, alternative = c("two.sided"))
summary(ametest_lm4_alt)

ametest_lm4_alt_rob <- glht(model = lm4, linfct = coefeq_lm4_alt, rhs = 0, alternative = c("two.sided"),
```

```
                    vcov = vcovHC(lm4, type = "HC1"))
summary(ametest_lm4_alt_rob)

coefeq_lm4_ego <- matrix(data = 0, nrow = 1, ncol =
length(lm4$coefficients))
colnames(coefeq_lm4_ego) <- names(lm4$coefficients)

coefeq_lm4_ego[1, "treatment"] <- 1
coefeq_lm4_ego[1, "treatment:cent_ec_ego_idx"] <-
cent_ec_ego_perc_75

marginal_effect_lm4_ego <- coefeq_lm4_ego %*%
lm4$coefficients

ametest_lm4_ego <- glht(model = lm4, linfct =
coefeq_lm4_ego, rhs = 0, alternative = c("two.sided"))
summary(ametest_lm4_ego)

ametest_lm4_ego_rob <- glht(model = lm4, linfct =
coefeq_lm4_ego, rhs = 0, alternative = c("two.sided"),
                    vcov = vcovHC(lm4, type = "HC1"))
summary(ametest_lm4_ego_rob)
#..................................................

## 25 Percentile

coefeq_lm4_bio_25 <- matrix(data = 0, nrow = 1, ncol =
length(lm4$coefficients))
colnames(coefeq_lm4_bio_25) <- names(lm4$coefficients)

coefeq_lm4_bio_25[1, "treatment"] <- 1
coefeq_lm4_bio_25[1, "treatment:cent_ec_bio_idx"] <-
cent_ec_bio_perc_25

marginal_effect_lm4_bio_25 <- coefeq_lm4_bio_25 %*%
lm4$coefficients

ametest_lm4_bio_25 <- glht(model = lm4, linfct =
coefeq_lm4_bio_25, rhs = 0, alternative = c("two.sided"))
summary(ametest_lm4_bio_25)

ametest_lm4_bio_25_rob <- glht(model = lm4, linfct =
coefeq_lm4_bio_25, rhs = 0, alternative = c("two.sided"),
                    vcov = vcovHC(lm4, type = "HC1"))
summary(ametest_lm4_bio_25_rob)

coefeq_lm4_alt_25 <- matrix(data = 0, nrow = 1, ncol =
length(lm4$coefficients))
colnames(coefeq_lm4_alt_25) <- names(lm4$coefficients)

coefeq_lm4_alt_25[1, "treatment"] <- 1
coefeq_lm4_alt_25[1, "treatment:cent_ec_alt_idx"] <-
cent_ec_alt_perc_25

marginal_effect_lm4_alt_25 <- coefeq_lm4_alt_25 %*%
lm4$coefficients

ametest_lm4_alt_25 <- glht(model = lm4, linfct =
coefeq_lm4_alt_25, rhs = 0, alternative = c("two.sided"))
summary(ametest_lm4_alt_25)

ametest_lm4_alt_25_rob <- glht(model = lm4, linfct =
coefeq_lm4_alt_25, rhs = 0, alternative = c("two.sided"),
                    vcov = vcovHC(lm4, type = "HC1"))
summary(ametest_lm4_alt_25_rob)

coefeq_lm4_ego_25 <- matrix(data = 0, nrow = 1, ncol =
length(lm4$coefficients))
colnames(coefeq_lm4_ego_25) <- names(lm4$coefficients)

coefeq_lm4_ego_25[1, "treatment"] <- 1
coefeq_lm4_ego_25[1, "treatment:cent_ec_ego_idx"] <-
cent_ec_ego_perc_25

marginal_effect_lm4_ego_25 <- coefeq_lm4_ego_25 %*%
lm4$coefficients

ametest_lm4_ego_25 <- glht(model = lm4, linfct =
coefeq_lm4_ego_25, rhs = 0, alternative = c("two.sided"))
summary(ametest_lm4_ego_25)

ametest_lm4_ego_25_rob <- glht(model = lm4, linfct =
coefeq_lm4_ego_25, rhs = 0, alternative = c("two.sided"),
                    vcov = vcovHC(lm4, type = "HC1"))
summary(ametest_lm4_ego_25_rob)
#........................................................................................

### Logit model

# Logit 1: only treatment
log1 <- glm(
  b7_flight_yes ~ treatment,
  data = wdce, family = binomial
)
summary(log1)
  # robust standard errors
coeftest(log1, vcov. = vcovHC, type = "HC1")
covlog1 <- vcovHC(log1, type = "HC1")
robust.se.log1 <- sqrt(diag(covlog1))  # matrix wit robust
standard errors

# Logit 2: treatment & ec
log2 <- glm(
  b7_flight_yes ~ treatment
  + cent_ec_bio_idx  + cent_ec_alt_idx + cent_ec_ego_idx,
  data = wdce, family = binomial
)
summary(log2)
  #robust standard errors
coeftest(log2, vcov. = vcovHC, type = "HC1")
covlog2 <- vcovHC(log2, type = "HC1")
robust.se.log2 <- sqrt(diag(covlog2))  # matrix wit robust
standard errors

# Logit 3: treatment, ec & interaction
log3 <- glm(
  b7_flight_yes ~ treatment
  + cent_ec_bio_idx  + cent_ec_alt_idx + cent_ec_ego_idx
  + treatment:cent_ec_bio_idx  + treatment:cent_ec_alt_idx
+ treatment:cent_ec_ego_idx,
  data = wdce, family = binomial
)
summary(log3)
coeftest(log3, vcov. = vcovHC, type = "HC1")
covlog3 <- vcovHC(log3, type = "HC1")
robust.se.log3 <- sqrt(diag(covlog3))  # matrix wit robust
standard errors

# Logit 4: treatment, ec, interaction & socioemographics
log4 <- glm(
```

```
  b7_flight_yes ~ treatment
  + cent_ec_bio_idx  + cent_ec_alt_idx + cent_ec_ego_idx
  + treatment:cent_ec_bio_idx + treatment:cent_ec_alt_idx
+ treatment:cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH +
language + interm + urban + car + e_car,
  data = wdce, family = binomial
)
summary(log4)
coeftest(log4, vcov. = vcovHC, type = "HC1")
covlog4 <- vcovHC(log4, type = "HC1")
robust.se.log4 <- sqrt(diag(covlog4))  # matrix wit robust
standard errors

# Logit 5: treatment, ec, interaction, socioemographics &
travel scenario
log5 <- glm(
  b7_flight_yes ~ treatment
  + cent_ec_bio_idx  + cent_ec_alt_idx + cent_ec_ego_idx
  + treatment:cent_ec_bio_idx + treatment:cent_ec_alt_idx
+ treatment:cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH +
language + interm + urban + car + e_car
  + children + alone ,
  data = wdce, family = binomial
)
summary(log5)
coeftest(log5, vcov. = vcovHC, type = "HC1")
covlog5 <- vcovHC(log5, type = "HC1")
robust.se.log5 <- sqrt(diag(covlog5))  # matrix wit robust
standard error

# log6:  with ec, sociodemographics & travel scenario -
WITHOUT INTERACTION TO SHOW EFFECT ON EC
WHEN ALL OTHER COEFFICIENTS IN
log6 <- glm(
  b7_flight_yes ~ treatment
  + cent_ec_bio_idx  + cent_ec_alt_idx + cent_ec_ego_idx
  + gender + young + old + mandatory + tertiary + incH +
language + interm + urban + car + e_car
  + children + alone ,
  data = wdce, family = binomial
)
summary(log6)
coeftest(log6, vcov. = vcovHC, type = "HC1")
covlog6 <- vcovHC(log6, type = "HC1")
robust.se.log6 <- sqrt(diag(covlog6))  # matrix wit robust
standard error

#..........................................................................................
..........
## show all 5 logit models in table
library(stargazer)
?stargazer

 # robust and default SE
stargazer(log1, log1, log2, log2, log3, log3, log4, log4, log5,
log5,
        title = "Logit Model - Regression Estimates",
        out = "logit_12345_rq4.html",
        dep.var.labels = " Flight Choice",
        se = list (NULL, robust.se.log1, NULL,
robust.se.log2, NULL, robust.se.log3, NULL,
robust.se.log4, NULL, robust.se.log5),
        column.labels = c ("default", "robust", "default",
"robust", "default", "robust", "default", "robust", "default",
"robust"),
        align = TRUE,
        intercept.bottom = FALSE)

 # only robust SE
stargazer(log1,  log2,  log3,  log4, log5,
        title = "Logit Model - Regression Estimates with
Robust Standard Errors",
        out = "logit_12345_robust_rq4.html",
        dep.var.labels = " Flight Choice",
        se = list ( robust.se.log1,robust.se.log2,
robust.se.log3, robust.se.log4, robust.se.log5),
        align = TRUE,
        intercept.bottom = FALSE,
        covariate.labels = c("Constant", "Treatment (VCO) ",
"Biospheric env. concern", "Altruistic env. concern",
"Egoistic env. concern",
                        "Female", "Young (< 36 years)" , "Old
(> 60 years)", "Mandatory education", "Tertiary education",
"High income",
                        "French speaking", "Italian speaking",
"Agglomeration", "Urban", "Car access", "E-car access",
                        "Travelling with children", "Travelling
alone",
                        "Treatment (VCO) * Biospheric env.
concern",  "Treatment (VCO) * Altruistic env. concern",
"Treatment (VCO) * Egoistic env. concern" ),
        no.space = TRUE ,
        model.names = TRUE, # shows model names (OLS,
probit etc)
        model.numbers = TRUE # automatically numbers
models --ok here bc no column labels
        )
#.........................................................
#### Treatment Effects in Logit Model
coeftest(log5)

### Conditional treatment effects
# Whats the effect of the treatment on the 75th percentile of
ec concern?

library(multcomp)

## 75th percentile on bio ec concern, average bio and ego
concern (0)
#

coefeq_lm5_bio %*% log5$coefficients  # lm matrix goes
also for logit model (tested and same result)

## Hypothesis testing for linear combination
# Ho = beta xvco + beta xvco * cent_ec_bio at 75th
percentile = 0
# Ho = beta xvco + beta xvco * cent_ec_bio at 75th
percentile not 0

#default SE
ametest_log5_bio <- glht (model = log5, linfct =
coefeq_lm5_bio, rhs=0, alternative = c("two.sided"))
summary(ametest_log5_bio)
# --> no significant marginal effect of treatment at the 75th
percentile of ec bio, H0 cannot be rejected!
```

```
# with robust SE
ametest_log5_bio_rob <- glht (model = log5, linfct = coefeq_lm5_bio, rhs=0, alternative = c("two.sided"), vcov = vcovHC(log5, type = "HC1"))
summary(ametest_log5_bio_rob)
# --> no significant marginal effect of treatment at the 75th percentile of ec bio, H0 cannot be rejected!
# no big difference to default SE

?glht
## 75th percentile on alt ec concern, average bio and ego concern (0)
#

coefeq_lm5_alt %*% log5$coefficients
# --> -0.142 but not sure if significant

# Hypothesis testing for linear combination
# Ho = beta xvco + beta xvco * cent_ec_alt at 75th percentile = 0
# Ho = beta xvco + beta xvco * cent_ec_alt at 75th percentile not 0

# default SE
ametest_log5_alt <- glht (model = log5, linfct = coefeq_lm5_alt, rhs=0, alternative = c("two.sided"))
summary(ametest_log5_alt)
# --> no significant marginal effect of treatment at the 75th percentile of ec alt, H0 cannot be rejected!

# robust SE
ametest_log5_alt_rob <- glht (model = log5, linfct = coefeq_lm5_alt, rhs=0, alternative = c("two.sided"),
                    vcov = vcovHC(log5, type = "HC1"))
summary(ametest_log5_alt_rob)
# --> no significant marginal effect of treatment at the 75th percentile of ec alt, H0 cannot be rejected!

## 75th percentile on ego ec concern, average bio and alt concern (0)
#

coefeq_lm5_ego %*% log5$coefficients
# --> -0.0196 but not sure if significant

# Hypothesis testing for linear combination
# Ho = beta xvco + beta xvco * cent_ec_ego at 75th percentile = 0
# Ho = beta xvco + beta xvco * cent_ec_ego at 75th percentile not 0

# default SE
ametest_log5_ego <- glht (model = log5, linfct = coefeq_lm5_ego, rhs=0, alternative = c("two.sided"))
summary(ametest_log5_ego)
# --> no significant marginal effect of treatment at the 75th percentile of ec ego, H0 cannot be rejected!

# robust SE
ametest_log5_ego_rob <- glht (model = log5, linfct = coefeq_lm5_ego, rhs=0, alternative = c("two.sided"),
                    vcov = vcovHC(log5, type = "HC1"))
summary(ametest_log5_ego_rob)
# --> no significant marginal effect of treatment at the 75th percentile of ec ego, H0 cannot be rejected!
```

D Appendix

Evaluation of hypotheses 1a & 1b

Table 17: Estimation results from hurlde models about flight choice

	Dependent variable: Flight Choice		
	hurdle	*hurdle*	*hurdle*
	Hurdle 1	Hurdle 2	Hurdle 3
Count Component			
Constant	1.299^{***}	1.052^{***}	1.067^{***}
	(0.021)	(0.104)	(0.107)
Biospheric Env. Concern[a]	-0.011	-0.022	-0.023
	(0.033)	(0.034)	(0.034)
Altruistic Env. Concern[a]	-0.012	-0.022	-0.023
	(0.033)	(0.033)	(0.033)
Egoistic Env. Concern[a]	-0.027	-0.021	-0.02
	(0.035)	(0.035)	(0.035)
Female		0.024	0.022
		(0.044)	(0.044)
Young (< 36 Years)		-0.118^{**}	-0.126^{**}
		(0.048)	(0.05)
Old (> 60 Years)		0.139^{**}	0.132^{**}
		(0.062)	(0.064)
Mandatory Education		0.075	0.077
		(0.119)	(0.119)
Tertiary Education		-0.025	-0.024
		(0.044)	(0.044)
High Income		0.055	0.052
		(0.044)	(0.045)
French Speaking		0.090^{*}	0.089^{*}
		(0.052)	(0.052)
Italian Speaking		0.068	0.067
		(0.058)	(0.058)
Agglomeration		0.085	0.086
		(0.076)	(0.077)
Urban		0.141^{**}	0.141^{**}
		(0.067)	(0.067)
Car Access		0.107	0.106
		(0.066)	(0.067)
E-car Access		-0.111	-0.103
		(0.147)	(0.149)
Travelling With Children			-0.024
			(0.057)
Travelling Alone			-0.035
			(0.075)
Zero Component			
Constant	0.227^{***}	-0.118	-0.012
	(0.058)	(0.27)	(0.278)
Biospheric Env. Concern[a]	-0.227^{**}	-0.113	-0.117
	(0.098)	(0.102)	(0.102)

Altruistic Env. Concern[a]	-0.306***	-0.277***	-0.281***
	(0.094)	(0.098)	(0.098)
Egoistic Env. Concern[a]	0.334***	0.310***	0.306***
	(0.096)	(0.1)	(0.1)
Female		0.004	-0.012
		(0.126)	(0.127)
Young (< 36 Years)		0.430***	0.413***
		(0.144)	(0.148)
Old (> 60 Years)		-0.881***	-0.899***
		(0.163)	(0.17)
Mandatory Education		-0.778**	-0.749**
		(0.306)	(0.307)
Tertiary Education		0.171	0.181
		(0.128)	(0.128)
High Income		-0.219*	-0.222*
		(0.128)	(0.129)
French Speaking		0.07	0.064
		(0.153)	(0.154)
Italian Speaking		-0.083	-0.089
		(0.166)	(0.166)
Agglomeration		0.095	0.091
		(0.2)	(0.2)
Urban		0.383**	0.396**
		(0.177)	(0.178)
Car Access		0.282	0.224
		(0.179)	(0.183)
E-car Access		-0.953***	-0.949***
		(0.33)	(0.331)
Travelling With Children			-0.04
			(0.162)
Travelling Alone			-0.376*
			(0.202)
Observations	1221	1221	1221
No. of parameters	8	32	36
Log Likelihood	-2202.604	-2147.943	-2146.035
Akaike Inf. Crit.	4421.208	4359.886	4364.070
Bayesian Inf. Crit.	4462.068	4523.323	4547.937
Exp. no. of zeros	543	543	543

Notes : Standard errors in parantheses.

[a] *Biospheric*, *Altruistic* and *Egoistic Env. Concern* are centered.

*p<0.1; **p<0.05; ***p<0.01

E Appendix

Evaluation of hypotheses 4a, 4b, 4c & 4d

Table 18: Regression estimates including control variables from linear models for feeling guilty about travel mode choice

	Dependent variable: Feeling Guilty About Travel Mode Choice							
	OLS							
	Subsample 0 Flights 0)	Subsample 1 Flight 1)	Subsample 2 Flights 2)	Subsample 3 Flights 3)	Subsample 4 Flights 4)	Subsample 5 Flights 5)	Subsample 6 Flights 6)	Subsample 7 Flights 7)
Constant	2.030***	2.121***	2.716***	2.023***	2.241***	2.066**	2.039***	2.492***
	(0.215)	(0.495)	(0.611)	(0.493)	(0.781)	(0.831)	(0.653)	(0.463)
Biospheric Env. Concern[a]	-0.064	0.134	0.151	0.003	-0.354	0.473*	-0.166	0.232*
	(0.084)	(0.197)	(0.233)	(0.186)	(0.237)	(0.241)	(0.227)	(0.134)
Altruistic Env. Concern[a]	0.047	0.175	0.183	0.037	0.558***	0.534**	0.400*	0.072
	(0.078)	(0.171)	(0.272)	(0.206)	(0.206)	(0.226)	(0.206)	(0.14)
Egoistic Env. Concern[a]	-0.01	-0.074	0.033	-0.052	0.13	-0.316	-0.08	-0.061
	(0.075)	(0.177)	(0.26)	(0.225)	(0.214)	(0.221)	(0.203)	(0.144)
Female	0.018	0.211	0.043	0.355	0.097	-0.04	0.571**	0.301*
	(0.105)	(0.232)	(0.304)	(0.239)	(0.333)	(0.296)	(0.261)	(0.174)
Young (< 36 Years)	0.072	-0.069	0.234	0.623**	0.391	0.289	0.548*	0.255
	(0.132)	(0.283)	(0.338)	(0.248)	(0.337)	(0.337)	(0.278)	(0.214)
Old (> 60 Years)	-0.238*	-0.23	0.351	-0.197	0.369	0.182	0.448	-0.045
	(0.124)	(0.357)	(0.518)	(0.492)	(0.586)	(0.57)	(0.37)	(0.223)
Mandatory Education	-0.229	1.445	1.582	0.443	0.251	0.295	0.19	-0.291
	(0.219)	(1.224)	(1.281)	(0.638)	(0.671)	(0.648)	(0.775)	(0.536)
Tertiary Education	-0.196*	0.287	-0.007	0.378	0.224	0.505*	0.11	-0.268
	(0.107)	(0.243)	(0.273)	(0.239)	(0.332)	(0.277)	(0.262)	(0.179)
High Income	-0.113	-0.165	-0.164	-0.333	0.27	-0.319	0.159	0.072
	(0.105)	(0.235)	(0.281)	(0.263)	(0.334)	(0.317)	(0.261)	(0.178)
French Speaking	0.181	0.558*	-0.201	-0.145	0.037	0.476	0.428	0.106
	(0.126)	(0.308)	(0.345)	(0.317)	(0.363)	(0.366)	(0.319)	(0.206)
Italian Speaking	0.099	0.02	-0.608	0.11	-0.920*	0.008	-0.189	-0.092
	(0.138)	(0.279)	(0.518)	(0.32)	(0.464)	(0.434)	(0.326)	(0.232)
Agglomeration	-0.026	0.073	0.886*	0.142	0.147	0.468	0.109	-0.275
	(0.158)	(0.36)	(0.502)	(0.383)	(0.588)	(0.561)	(0.485)	(0.318)
Urban	0.094	0.167	0.127	-0.09	0.449	0.813	-0.229	-0.204
	(0.142)	(0.313)	(0.391)	(0.326)	(0.506)	(0.516)	(0.398)	(0.285)
Car Access	0.197	-0.003	-0.023	-0.077	-0.161	-0.047	-0.064	0.04
	(0.149)	(0.338)	(0.423)	(0.34)	(0.447)	(0.425)	(0.357)	(0.302)
E-car Access	-0.342	0.165	-0.621		0.266	1.007	-0.227	1.022
	(0.225)	(0.671)	(0.71)	0	(0.834)	(0.72)	(0.645)	(1.111)
Travelling With Children	-0.013	-0.035	-0.625	0.506*	-0.349	-0.113	-0.246	-0.135
	(0.136)	(0.33)	(0.398)	(0.297)	(0.401)	(0.386)	(0.329)	(0.219)

Travelling Alone	-0.355**	0.226	-0.524	0.434	0.466	-0.483	-0.008	-0.517*
	(0.157)	(0.579)	(0.407)	(0.349)	(0.542)	(0.513)	(0.441)	(0.301)
Observations	522	112	77	85	68	80	93	184
Adjusted R^2	0.015	-0.027	-0.026	0.056	0.075	0.202	0.101	0.035
F Statistic	1.475* (df = 17; 504)	0.827 (df = 17; 94)	0.886 (df = 17; 59)	1.309 (df = 16; 68)	1.318 (df = 17; 50)	2.177** (df = 17; 62)	1.607* (df = 17; 75)	1.391 (df = 17; 166)

Notes: Total N = 1221. Standard errors in parentheses. Homoscedasticity was checked with the White test.

[a] *Biospheric*, *Altruistic* and *Egoistic Env. Concern* are centered.

Table 19: Regression estimates including contral variables for feeling guilty about travael mode choice with interaction effects

	Dependent variable: Feeling Guilty About Travel Mode Choice						
	OLS						
	Subsample 1 Flight	Subsample 2 Flights	Subsample 3 Flights	Subsample 4 Flights	Subsample 5 Flights	Subsample 6 Flights	Subsample 7 Flights
	1)	2)	3)	4)	5)	6)	7)
Constant	2.023***	1.846**	2.230***	3.022***	1.25	2.192***	2.683***
	(0.517)	(0.835)	(0.638)	(0.942)	(1.106)	(0.795)	(0.599)
Biospheric Env. Concern[a]	-0.411	-0.047	1.25	-1.244*	0.216	-1.045	-0.654
	(0.307)	(0.476)	(0.78)	(0.736)	(1.036)	(1.167)	(0.852)
Altruistic Env. Concern[a]	0.578*	0.226	-0.084	1.266**	1.612	0.692	-0.014
	(0.344)	(0.523)	(0.735)	(0.548)	(1.091)	(1.003)	(0.74)
Egoistic Env. Concern[a]	-0.173	0.585	-0.577	0.081	-0.524	-0.028	0.384
	(0.336)	(0.594)	(0.513)	(0.598)	(1.127)	(0.801)	(0.84)
Flights With ICOs	0.342	0.352	-0.13	-0.001	-0.089	-0.121	-0.176
	(0.232)	(0.268)	(0.203)	(0.226)	(0.216)	(0.202)	(0.142)
Flights With VCOs	0.372	0.44	0.579	0.07	0.696**	0.076	0.165
	(0.642)	(0.489)	(0.352)	(0.456)	(0.324)	(0.325)	(0.211)
Flights With SAF	0.073	0.388	0.022	0.037	0.139	0.149	0.078
	(0.243)	(0.257)	(0.139)	(0.15)	(0.122)	(0.141)	(0.063)
Female	0.14	-0.013	0.378	0.132	0.135	0.530*	0.361**
	(0.236)	(0.355)	(0.271)	(0.397)	(0.317)	(0.291)	(0.168)
Young (< 36 Years)	0.078	0.231	0.686**	0.402	0.269	0.539*	0.274
	(0.284)	(0.366)	(0.279)	(0.378)	(0.384)	(0.305)	(0.207)
Old (> 60 Years)	-0.169	0.429	0.033	0.246	0.367	0.241	-0.19
	(0.364)	(0.539)	(0.523)	(0.64)	(0.661)	(0.39)	(0.221)
Mandatory Education	1.736	1.384	0.641	0.076	-0.421	0.228	-0.245
	(1.188)	(1.366)	(0.726)	(0.681)	(0.793)	(0.855)	(0.513)
Tertiary Education	0.402	-0.22	0.476*	-0.222	0.619**	-0.024	-0.265
	(0.247)	(0.306)	(0.257)	(0.398)	(0.3)	(0.293)	(0.175)
High Income	-0.297	-0.162	-0.468	0.575	-0.168	0.156	0.068
	(0.236)	(0.325)	(0.295)	(0.373)	(0.359)	(0.317)	(0.173)
French Speaking	0.23	-0.508	-0.309	-0.252	0.544	0.486	0.324
	(0.322)	(0.4)	(0.352)	(0.397)	(0.42)	(0.343)	(0.204)
Italian Speaking	0.09	-0.749	0.202	-0.733	0.428	-0.179	-0.29

	(0.306)	(0.608)	(0.329)	(0.498)	(0.49)	(0.358)	(0.226)
Agglomeration	-0.056	1.266**	-0.078	0.018	0.897	0.066	-0.143
	(0.358)	(0.614)	(0.441)	(0.607)	(0.62)	(0.52)	(0.305)
Urban	0.067	0.444	-0.235	-0.039	0.969*	-0.402	-0.113
	(0.317)	(0.459)	(0.359)	(0.544)	(0.556)	(0.439)	(0.282)
Car Access	-0.014	0.223	0.003	-0.537	0.067	-0.052	0.038
	(0.346)	(0.504)	(0.387)	(0.513)	(0.46)	(0.393)	(0.295)
E-car Access	-0.53	-0.749		0.429	0.71	-0.298	1.812*
	(0.681)	(0.737)	0	(0.849)	(0.829)	(0.692)	(1.066)
Travelling With Children	0.125	-0.576	0.569*	-0.737	-0.266	-0.172	-0.238
	(0.333)	(0.416)	(0.331)	(0.475)	(0.407)	(0.373)	(0.216)
Travelling Alone	0.467	-0.442	0.456	0.156	-0.195	0.036	-0.456
	(0.638)	(0.506)	(0.412)	(0.588)	(0.543)	(0.486)	(0.29)
Biospheric Env. Concern[a] * Flights With ICOs	1.087***	0.519	-0.467	-0.677	0.333	0.188	0.206
	(0.383)	(0.475)	(0.419)	(0.423)	(0.44)	(0.447)	(0.279)
Altruistic Env. Concern[a] * Flights With ICOs	-0.826**	0.583	0.102	-0.277	-0.786	-0.199	0.447*
	(0.334)	(0.588)	(0.423)	(0.258)	(0.522)	(0.408)	(0.237)
Egoistic Env. Concern[a] * Flights With ICOs	0.477	-1.569**	0.359	0.363	0.134	0.31	-0.565**
	(0.369)	(0.647)	(0.416)	(0.392)	(0.503)	(0.319)	(0.26)
Biospheric Env. Concern[a] * Flights With VCOs	-0.252	0.83	-0.604	-0.372	-0.901	-0.028	-0.822**
	(1.566)	(0.948)	(0.972)	(1.205)	(0.659)	(0.656)	(0.381)
Altruistic Env. Concern[a] * Flights With VCOs	0.305	-0.326	-1.15	-0.92	-1.080*	-0.24	-0.161
	(0.765)	(0.772)	(1.178)	(0.98)	(0.575)	(0.577)	(0.353)
Egoistic Env. Concern[a] * Flights With VCOs	-0.48	0.797	0.846	1.215	0.791	-0.218	0.667**
	(0.776)	(0.801)	(0.808)	(1.328)	(0.613)	(0.515)	(0.334)
Biospheric Env. Concern[a] * Flights With SAF	0.159	-0.152	-0.236	0.997***	-0.165	0.253	0.154
	(0.387)	(0.436)	(0.273)	(0.325)	(0.207)	(0.209)	(0.113)
Altruistic Env. Concern[a] * Flights With SAF	-0.262	-0.759	-0.028	-0.142	0.359	0.138	-0.417***
	(0.345)	(0.5)	(0.381)	(0.238)	(0.222)	(0.199)	(0.12)
Egoistic Env. Concern[a] * Flights With SAF	-0.161	0.618	-0.135	-0.249	-0.142	-0.355	0.350***
	(0.383)	(0.495)	(0.362)	(0.255)	(0.229)	(0.258)	(0.128)
Observations	112	77	85	68	80	93	184
Adjusted R^2	0.06	0.013	0.033	0.164	0.214	0.055	0.151
F Statistic	1.244 (df = 29; 82)	1.035 (df = 29; 47)	1.104 (df = 28; 56)	1.452 (df = 29; 38)	1.744** (df = 29; 50)	1.183 (df = 29; 63)	2.121*** (df = 29; 154)

Notes: Total N = 699. ICOs = integrated carbon offsets, VCOs = voluntary carbon offsets, SAF = sustainable aviation fuel. Standard errors in parentheses. Homoscedasticity was checked with the White test.

*p<0.1; **p<0.05; ***p<0.01

[a] *Biospheric*, *Altruistic* and *Egoistic Env. Concern* are centered.

Table 20: Regression estimates including control variables from linear models for feeling good about travel mode choice

	Dependent variable: Feeling Good About Travel Mode Choice							
	OLS							
	Subsample 0 Flights	Subsample 1 Flight	Subsample 2 Flights	Subsample 3 Flights	Subsample 4 Flights	Subsample 5 Flights	Subsample 6 Flights	Subsample 7 Flights
	0)	1)	2)	3)	4)	5)	6)	7)
Constant	4.388^{***}	3.772^{***}	3.744^{***}	3.442^{***}	3.517^{***}	4.799^{***}	3.598^{***}	4.045^{***}
	(0.192)	(0.397)	(0.518)	(0.479)	(0.669)	(0.63)	(0.603)	(0.409)
Biospheric Env. Concern[a]	0.197^{***}	-0.201	0.242	-0.116	0.224	-0.318^{*}	0.024	-0.076
	(0.075)	(0.158)	(0.197)	(0.181)	(0.203)	(0.182)	(0.209)	(0.118)
Altruistic Env. Concern[a]	0.087	-0.009	-0.052	-0.153	-0.286	-0.383^{**}	-0.262	-0.104
	(0.070)	(0.137)	(0.231)	(0.201)	(0.176)	(0.172)	(0.19)	(0.123)
Egoistic Env. Concern[a]	0.028	0.279^{*}	-0.093	0.377^{*}	0.035	0.719^{***}	-0.037	0.152
	(0.067)	(0.142)	(0.221)	(0.218)	(0.184)	(0.168)	(0.187)	(0.127)
Female	-0.12	-0.292	-0.155	-0.521^{**}	-0.12	-0.322	-0.315	-0.259^{*}
	(0.094)	(0.187)	(0.257)	(0.232)	(0.285)	(0.224)	(0.241)	(0.154)
Young (< 36 Years)	-0.035	-0.402^{*}	-0.134	-0.12	-0.315	0.01	-0.279	-0.336^{*}
	(0.119)	(0.227)	(0.287)	(0.241)	(0.288)	(0.255)	(0.257)	(0.189)
Old (> 60 Years)	-0.115	0.022	0.134	0.546	-0.234	-0.036	0.058	0.148
	(0.111)	(0.287)	(0.439)	(0.479)	(0.502)	(0.432)	(0.342)	(0.197)
Mandatory Education	0.185	0.559	-2.280^{**}	0.01	-0.666	-0.013	0.191	0.167
	(0.196)	(0.982)	(1.085)	(0.62)	(0.574)	(0.491)	(0.717)	(0.474)
Tertiary Education	0.009	0.122	0.043	-0.475^{**}	-0.212	-0.714^{***}	0.017	0.003
	(0.096)	(0.195)	(0.231)	(0.232)	(0.284)	(0.21)	(0.242)	(0.158)
High Income	0.183^{*}	-0.319^{*}	0.081	-0.012	-0.087	0.278	0.077	0.044
	(0.094)	(0.188)	(0.238)	(0.255)	(0.286)	(0.24)	(0.241)	(0.157)
French Speaking	-0.396^{***}	-0.462^{*}	-0.284	0.611^{*}	0.058	-0.651^{**}	-0.560^{*}	-0.297
	(0.113)	(0.247)	(0.292)	(0.308)	(0.311)	(0.278)	(0.295)	(0.182)
Italian Speaking	-0.312**	-0.176	0.034	-0.660^{**}	0.582	-0.254	0.201	0.233
	(0.123)	(0.224)	(0.439)	(0.311)	(0.398)	(0.329)	(0.302)	(0.205)
Agglomeration	0.111	-0.292	-0.239	-0.021	0.171	-0.379	0.029	0.078
	(0.141)	(0.289)	(0.426)	(0.373)	(0.503)	(0.425)	(0.449)	(0.281)
Urban	-0.083	-0.089	-0.198	0.281	-0.346	-0.841^{**}	0.062	-0.041
	(0.127)	(0.251)	(0.331)	(0.317)	(0.433)	(0.391)	(0.368)	(0.251)
Car Access	-0.355^{***}	0.416	-0.14	0.623^{*}	0.46	-0.357	-0.017	-0.308
	(0.133)	(0.271)	(0.358)	(0.33)	(0.382)	(0.323)	(0.33)	(0.267)
E-car Access	0.283	-0.861	0.267		-0.123	-0.085	-0.624	-0.878
	(0.201)	(0.538)	(0.602)	0	(0.714)	(0.546)	(0.596)	(0.981)
Travelling With Children	0.002	0.335	0.495	-0.311	-0.573	0.288	0.08	0.31
	(0.121)	(0.265)	(0.337)	(0.289)	(0.344)	(0.293)	(0.304)	(0.193)
Travelling Alone	-0.114	0.6	0.233	-0.262	-0.062	-0.249	-0.612	0.647^{**}
	(0.141)	(0.465)	(0.345)	(0.339)	(0.464)	(0.389)	(0.407)	(0.266)

Observations	522	112	77	85	68	80	93	184
Adjusted R^2	0.082	0.098	-0.017	0.084	-0.007	0.29	0.071	0.061
F Statistic	3.746*** (df = 17; 504)	1.706* (df = 17; 94)	0.927 (df = 17; 59)	1.482 (df = 16; 68)	0.973 (df = 17; 50)	2.902*** (df = 17; 62)	1.412 (df = 17; 75)	1.696** (df = 17; 166)

Notes: Total N = 1221. Standard errors in parentheses. Homoscedasticity was checked with the White test.

*p<0.1; **p<0.05; ***p<0.01

[a] *Biospheric*, *Altruistic* and *Egoistic Env. Concern* are centered.

Table 21: Regression estimates including control variables from linear models for feeling good about travel mode choice with interaction effects

	Dependent variable: Feeling Good About Travel Mode Choice						
	OLS						
	Subsample 1 Flight	Subsample 2 Flights	Subsample 3 Flights	Subsample 4 Flights	Subsample 5 Flights	Subsample 6 Flights	Subsample 7 Flights
	1)	2)	3)	4)	5)	6)	7)
Constant	3.816***	4.387***	3.018***	2.920***	6.309***	3.452***	4.421***
	(0.407)	(0.714)	(0.59)	(0.912)	(0.778)	(0.733)	(0.562)
Biospheric Env. Concern[a]	-0.634**	-0.121	-0.614	0.484	1.125	0.845	0.178
	(0.242)	(0.407)	(0.722)	(0.712)	(0.729)	(1.075)	(0.799)
Altruistic Env. Concern[a]	-0.646**	0.261	-1.724**	-0.065	-1.155	-0.775	0.149
	(0.271)	(0.447)	(0.68)	(0.531)	(0.768)	(0.924)	(0.694)
Egoistic Env. Concern[a]	0.868***	-0.679	1.449***	0.356	0.859	0.022	-0.834
	(0.265)	(0.508)	(0.475)	(0.58)	(0.793)	(0.738)	(0.788)
Flights With ICOs	-0.136	-0.133	0.217	0.024	-0.288*	0.05	-0.058
	(0.182)	(0.229)	(0.188)	(0.219)	(0.152)	(0.186)	(0.133)
Flights With VCO	0.579	-0.511	-0.01	0.121	-0.403*	0.046	-0.286
	(0.505)	(0.418)	(0.326)	(0.442)	(0.228)	(0.299)	(0.198)
Flights With SAF	-0.177	-0.325	-0.033	-0.04	-0.113	-0.112	-0.038
	(0.192)	(0.22)	(0.128)	(0.145)	(0.086)	(0.13)	(0.059)
Female	-0.227	-0.243	-0.348	-0.24	-0.299	-0.178	-0.236
	(0.186)	(0.303)	(0.25)	(0.384)	(0.223)	(0.268)	(0.157)
Young (< 36 Years)	-0.400*	-0.162	0.043	-0.274	-0.233	-0.291	-0.363*
	(0.224)	(0.313)	(0.258)	(0.366)	(0.27)	(0.281)	(0.194)
Old (> 60 Years)	-0.176	-0.16	0.592	-0.082	-0.412	0.253	0.239
	(0.287)	(0.461)	(0.484)	(0.619)	(0.465)	(0.359)	(0.207)
Mandatory Education	0.448	-2.451**	-0.095	-0.519	0.156	0.079	0.135
	(0.935)	(1.168)	(0.672)	(0.66)	(0.558)	(0.787)	(0.481)
Tertiary Education	0.222	0.157	-0.416*	0.037	-0.864***	0.125	0.08
	(0.194)	(0.262)	(0.238)	(0.385)	(0.211)	(0.27)	(0.164)
High Income	-0.391**	0.222	0.123	-0.28	0.392	0.211	0.022
	(0.185)	(0.278)	(0.273)	(0.361)	(0.252)	(0.292)	(0.163)
French Speaking	-0.719***	-0.141	0.685**	0.31	-0.375	-0.585*	-0.29
	(0.254)	(0.342)	(0.326)	(0.384)	(0.295)	(0.316)	(0.191)
Italian Speaking	-0.071	0.34	-0.699**	0.593	-0.299	0.171	0.316

	(0.241)	(0.52)	(0.305)	(0.483)	(0.345)	(0.33)	(0.212)
Agglomeration	-0.196	-0.221	-0.18	0.274	-0.893**	0.033	0.035
	(0.282)	(0.526)	(0.408)	(0.588)	(0.436)	(0.479)	(0.286)
Urban	0.09	-0.368	0.099	-0.078	-1.164***	0.173	-0.091
	(0.25)	(0.392)	(0.332)	(0.527)	(0.391)	(0.405)	(0.265)
Car Access	0.354	-0.486	0.667*	0.768	-0.445	-0.054	-0.406
	(0.272)	(0.431)	(0.358)	(0.497)	(0.324)	(0.362)	(0.276)
E-car Access	-0.804	0.263		0.057	-0.147	-0.598	-0.977
	(0.536)	(0.63)	0	(0.822)	(0.583)	(0.638)	(0.999)
Travelling With Children	0.27	0.486	-0.239	-0.383	0.25	0.063	0.292
	(0.262)	(0.356)	(0.306)	(0.46)	(0.286)	(0.343)	(0.203)
Travelling Alone	0.224	0.457	-0.158	0.324	-0.496	-0.519	0.566**
	(0.502)	(0.433)	(0.381)	(0.57)	(0.382)	(0.447)	(0.272)
Biospheric Env. Concern[a] * Flights With ICOs	0.739**	-0.126	-0.192	0.469	-0.590*	-0.179	0.076
	(0.302)	(0.406)	(0.387)	(0.41)	(0.31)	(0.412)	(0.262)
Altruistic Env. Concern[a] * Flights With ICOs	0.208	0.243	0.421	0.009	0.374	0.401	-0.26
	(0.263)	(0.503)	(0.392)	(0.25)	(0.368)	(0.376)	(0.223)
Egoistic Env. Concern[a] * Flights With ICOs	-0.356	0.766	-0.12	-0.537	0.119	-0.449	0.361
	(0.291)	(0.554)	(0.385)	(0.38)	(0.354)	(0.294)	(0.244)
Biospheric Env. Concern[a] * Flights With VCOs	0.705	0.366	0.297	0.484	0.627	-0.143	0.359
	(1.233)	(0.811)	(0.9)	(1.167)	(0.463)	(0.605)	(0.358)
Altruistic Env. Concern[a]* Flights With VCOs	0.48	0.025	1.04	0.36	0.933**	-0.248	0.046
	(0.602)	(0.66)	(1.09)	(0.949)	(0.404)	(0.532)	(0.331)
Egoistic Env. Concern[a] * Flights With VCOs	-0.284	-0.159	-1.082	-1.119	-0.961**	0.598	0.028
	(0.611)	(0.685)	(0.748)	(1.286)	(0.431)	(0.475)	(0.313)
Biospheric Env. Concern[a] * Flights With SAF	0.061	0.328	0.492*	-0.573*	-0.134	-0.249	-0.195*
	(0.305)	(0.373)	(0.252)	(0.315)	(0.145)	(0.193)	(0.106)
Altruistic Env. Concern[a] * Flights With SAF	0.841***	-0.192	0.614*	-0.097	-0.058	-0.181	0.175
	(0.271)	(0.428)	(0.352)	(0.23)	(0.156)	(0.183)	(0.112)
Egoistic Env. Concern[a] * Flights With SAF	-0.552*	-0.152	-0.562*	0.356	-0.078	0.418*	-0.002
	(0.302)	(0.423)	(0.335)	(0.247)	(0.161)	(0.237)	(0.12)
Observations	112	77	85	68	80	93	184
Adjusted R^2	0.205	0.004	0.15	-0.165	0.399	0.029	0.067
F Statistic	1.986*** (df = 29; 82)	1.010 (df = 29; 47)	1.531* (df = 28; 56)	0.674 (df = 29; 38)	2.805*** (df = 29; 50)	1.096 (df = 29; 63)	1.454* (df = 29; 154)

Notes: Total N = 699. ICOs = integrated carbon offsets, VCOs = voluntary carbon offsets, SAF = sustainable aviation fuel. Standard errors in parentheses. Homoscedasticity was checked with the White test.

*p<0.1; **p<0.05; ***p<0.01

[a] *Biospheric*, *Altruistic* and *Egoistic Env. Concern* are centered.

F Appendix

Evaluation of hypotheses 5a, 5b & 5e

Table 22: Regression estimates including control variables from linear fixed-effects panel model for flight choice

	Dependent variable: Flight Choice		
		panel	
		linear	
	(1)	(2)	(3)
ICOs	0.012*	0.012*	0.009
	(0.007)	(0.007)	(0.007)
SAF			0.025***
			(0.008)
Flight-Cost			-0.002***
			(0.0002)
Flight-Time			-0.043***
			(0.011)
Train-Cost			0.001***
			(0.0001)
Train-Time			0.031***
			(0.005)
Train-Comfort			-0.013*
			(0.008)
Nighttrain-Cost			0.001***
			(0.0001)
Nighttrain.-Time			0.014***
			(0.005)
Nighttrain-Comfort			-0.002
			(0.005)
Car-Cost			0.001**
			(0.0002)

Car-Time			0.012**
			(0.005)
Flight-ICOs * Biospheric Env. Concern[a]		0.0001	0.004
		(0.012)	(0.012)
Flight-ICOs * Altruistic Env. Concern[a]		0.004	0.002
		(0.012)	(0.012)
Flight-ICOs * Egoistic Env. Concern[a]		0.003	0.002
		(0.011)	(0.011)
Observations	7,326	7,326	7,326
Adjusted R^2	-0.199	-0.200	-0.139
F Statistic	2.818* (df = 1; 6104)	0.917 (df = 4; 6101)	22.581*** (df = 15; 6090)

Notes: Total N = 7326, entities = 1221, T = 6. ICOs = integrated carbon offsets. Standard errors in parentheses, clustered and corrected for heteroskedasticity and autocorrelation. Heteroskedasticity for model 2 confirmed by the Breusch-Pagan test and White test, for model 3 confirmed by the Breusch-Pagan test. All regressions include fixed effects on entities.

[a] Biospheric, Altruistic and Egoistic Env. Concern are centered.

*p<0.1; **p<0.05; ***p<0.01

G Appendix

Effect of rebound effect on net emissions

X = number of flights

E = CO_2e emissions per flight

Marginal probability effects of ICO = 1.2%-point

Y = effectively compensated CO_2e emissions

Total emissions with ICO = Total emissions without offsets

$$\mathrm{X} \times (1 + 0.012) \times \left(\mathrm{E} \times (1 - \mathrm{Y})\right) = \mathrm{E} \times \mathrm{X}$$

$$\mathrm{Y} = 0.011857708 \approx 1.2\%$$

If all flight emissions will be effectively compensated for 1.2%, then the rebound effect of 1.2%-point will not increase net emissions. All compensations above that threshold will reduce net emissions.