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MEASURING CHANGE IN BEHAVIOR: STATED CHOICE EXPERIMENTS IN TRANSPORTATION

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To my wife, family and friends

ABSTRACT

This thesis is motivated by the desire to understand how to effectively measure and predict changes of individual mode choice behavior in the realm of transportation. The demand for passenger transport is derived from our travel behavior, which in essence boils down to the choices (to travel) we make and hence inherently links our preferences to behavior. Transport planners not only rely on revealed preference (observed) data to estimate travel demand models but often use stated preference data to do so in response to a fast changing transport environment. Within that context, this thesis employs two key methods in order to investigate how people change their behavior in the light of hypothetical mode choice scenarios: stated choice experiments and choice models.

For the purpose of this work, a web-based approach to implement and conduct such experiments was developed. The framework should not only be helpful to researchers and practitioners in the transport planning community, but generally to everyone undertaking stated choice experiments.

Each of the chapters in this thesis approached a unique aspect of mode choice by applying those two methods.

A first case study examined how choice behavior would change if a long-distance bus service were introduced in Switzerland, competing with cars and public transportation. According to the findings, and given the assumption of a liberalised Swiss transport market, such a service would be difficult establish, but even more to sustain due to an inelastic demand pattern. The bus market share was estimated at around 8.5%, which likely represents an upper bound based on the dense bus stop network assumed. The estimated value of travel time for the bus is similar to the car, but higher than for public transportation, which indicates that the participants prefer the comfort level of the latter over the bus. Furthermore, long-distance buses mainly attract younger individuals who are particularly price-sensitive.

The second case study investigated the preferences for the use of urban ridepooling in Hamburg, Germany, exemplified by MOIA, a subsidiary of Volkswagen Group. The key drivers in choosing a ridepooling service like MOIA are primarily travel cost, travel time, trip purpose and distance. While for commutes, in terms of value of travel time, MOIA can not compete with public transport and cars, the results indicated similar values for MOIA and public transport for leisure trips of distances up to 6 km, which can

be attributed to comfort-related effects. For longer distances, however, this effect vanished and got compensated by comparatively higher travel costs, leading to increasing values. An important finding for MOIA, as the results support the main use case of MOIA in Hamburg, although only for shorter distances.

The last case study delved into the idea of a Tradable Mobility Credit Scheme in the city of Munich, Germany, and how it could help to promote the shift to more sustainable modes and internalize external costs. On top of the usual (internal) travel costs, a monthly mobility budget in the form of MobilityCoins was hypothetically introduced, which accounted for both the external costs and benefits associated with the modes under consideration. With respect to these coins, the results indicated that respondents showed greater cost sensitivity the lower the remaining budget was and the fewer days they were into a given month. Regarding the values of travel time, the largest variance in the values was observed for cars, presumably induced by higher external costs that were imposed and influenced the perceived overall cost, potentially shifting users away from using it. However, the approach did not allow an investigation into real-world trading of these MobilityCoins in the market.

ZUSAMMENFASSUNG

Diese Dissertation hat das Ziel zu verstehen, wie Veränderungen im individuellen Verkehrsverhalten effektiv gemessen und vorhergesagt werden können. Die Nachfrage nach Verkehr ergibt sich aus unserem Mobilitätsverhalten, welches im Grunde auf den Entscheidungen basiert, die wir täglich treffen. Dadurch lassen sich unsere Präferenzen vom Verhalten herleiten. Die Verkehrsplanung stützt sich nicht nur auf tatsächlich beobachtete Daten, um Verkehrsnachfrage-Modelle zu schätzen, sondern nutzt vermehrt auch sogenannte „stated preference“ Daten. In diesem Kontext werden zwei bekannte Methoden angewendet, um zu untersuchen, wie Menschen ihr Verhalten in hypothetischen Verkehrsmittelwahl-Szenarien ändern: Stated-Choice-Experimente und diskrete Entscheidungsmodelle.

Für diese Arbeit wurde eigens ein online-basiertes Verfahren entwickelt, um solche Experimente zu implementieren und durchzuführen. Dieser Ansatz soll nicht nur Forschern und Fachleuten aus der Verkehrsbranche helfen, sondern allgemein allen, die solche Experimente durchführen.

Die erwähnten Methoden wurden im Rahmen von drei Fallstudien im Bereich der Verkehrsmittelwahl angewendet.

Die erste Fallstudie untersuchte, wie sich das Wahlverhalten verändert, wenn ein Fernbus-Service im schweizerischen Fernverkehr eingeführt würde, der mit Autos und dem öffentlichen Verkehrs konkurriert. Den Ergebnissen zufolge wäre es schwierig einen solchen Service zu etablieren, trotz der Annahme eines liberalisierten Marktes. Der Marktanteil des Busses wurde auf etwa 8.5% geschätzt, was aufgrund des angenommenen, dichten Bushaltestellen-Netzwerk eine obere Grenze darstellen dürfte. Aufgrund einer unelastischen Nachfrage wäre es vermutlich aber noch schwieriger, die Martkanteile zu erhöhen. Die geschätzten Zeitwerte für den Bus sind vergleichbar mit dem Auto, aber höher als für den öffentlichen Verkehr, was darauf hindeutet, dass die Teilnehmer den Komfort des ÖV dem Bus und Auto vorziehen. Der angenommene Fernbus-Service zieht im Vergleich zum Auto und dem öffentlichen Verkehr aber vor allem jüngere und preissensible Menschen an.

Die zweite Fallstudie untersuchte die Präferenzen für die Nutzung von Ridepooling am Beispiel von MOIA (einer Tochtergesellschaft des deutschen Volkswagen Konzerns) in der Stadt Hamburg, Deutschland. Die Hauptkriterien bei der Wahl eines Ridepooling-Dienstes wie MOIA sind

in erster Linie die Reisekosten, die Reisezeit, der Reisezweck sowie die Distanz des Weges. Während für Pendelfahrten die Zeitwerte von MOIA nicht mit öffentlichen Verkehrsmitteln und Autos konkurrieren kann, wurden für Freizeitfahrten bis zu 6 km vergleichbare Werte für MOIA und den öffentlichen Nahverkehr festgestellt, was auf komfortbedingte Effekte zurückzuführen ist. Für längere Strecken verschwand dieser Effekt jedoch und wurde durch vergleichsweise höhere Reisekosten kompensiert, was zu steigenden Reisezeitwerten führte. Ein wichtiges Ergebnis für MOIA, welches die Bestrebungen von MOIA in Hamburg bekräftigt, eine valable Alternative zum Auto zu werden.

Die letzte Fallstudie beschäftigte sich mit der Idee eines handelbaren Mobilitätskredits in der Stadt München, Deutschland, und wie dieses Konzept dazu beitragen könnte, den Wechsel zu nachhaltigeren Verkehrsmitteln zu fördern und externe Kosten zu internalisieren. Zusätzlich zu den üblich anfallenden Reisekosten wurde ein monatliches Mobilitätsbudget in Form von MobilityCoins hypothetisch eingeführt, das sowohl die externen Kosten als auch Nutzen der zu Verfügung stehenden Verkehrsmittel berücksichtigt. Mit Bezug auf das monatliche Budget zeigten die Ergebnisse, dass die Befragten preissensibler wurden je niedriger das verbleibende Budget war und je weniger Tage sie in einem bestimmten Monat waren. Damit konnte gezeigt werden, dass sich die Teilnehmenden rational verhielten im Kontext dieses Experiments. Mit Bezug auf die Zeitwerde wurde die grösste Varianz in den Werten für Autos beobachtet, was vermutlich auf die unterstellten, höheren externen Kosten und damit die höher wahrgenommenen Gesamtkosten zurückzuführen ist. Dieses Ergebnis impliziert daher, dass heutige Autonutzer in Zukunft auf nachhaltigere Verkehrsmittel wechseln könnten, weil es zu teuer ist. Allerdings muss erwähnt werden, dass der angewendete Ansatz keine Untersuchung des Handels mit MobilityCoins auf dem realen Markt zulässt.

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It was six years ago when I finished my master's thesis under your guidance. In the last meeting, we had agreed that I would support Basil with his work, as a Hiwi. Little did I know I was going to embark on a PhD just two months later... but here I am, handing in my dissertation. I would never have achieved this milestone without those who encouraged, supported and challenged me on my journey.

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Joe, even though you showed me how academia, proper googling and coding works, I still don't know how to efficiently stomp through hip-deep snow. Anyways, you have inspired me, my friend. Basil, your mentorship throughout the years has been instrumental in my understanding of surveys, experimental designs, and choice modeling. I will always remember the fun we had together.

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DECLARATION OF PERSONAL CONTRIBUTION

Chapter 1 is based on Schatzmann et al. (2023). The paper is accepted for publication in Transportation Research Procedia. Joseph Molloy initially came up with the idea to load a picture, which is stored on an external storage server, within the survey software Qualtrics. Thomas Schatzmann developed, coded and currently maintains a full working example of the proposed approach. The authors acknowledge the help of Daniel Heimgartner in coding functions to generate images in R. Thomas Schatzmann prepared the manuscript. Joseph Molloy and Kay W. Axhausen edited the manuscript.

Chapter 2 is a revised and extended version of Schatzmann and Axhausen (2022). The literature review was done by Thomas Schatzmann. He developed and conducted both revealed and stated preference surveys, as well as the stated choice experiment. He also conducted the analysis. Basil Schmid helped with the initial modeling approach and helped interpreting the results. The current mode choice model and its analysis are first published in this thesis. Thomas Schatzmann prepared the manuscript. Basil Schmid and Kay W. Axhausen edited the manuscript.

Chapter 3 is a revised and extended version of Schatzmann et al (2023). Felix Zwick provided data and helped with the literature review. Together with Basil Schmid, Thomas Schatzmann developed and conducted both revealed and stated preference surveys, as well as the stated choice experiment. Thomas Schatzmann conducted the analysis, added new content, and prepared the manuscript. Felix Zwick and Kay W. Axhausen edited the manuscript.

Chapter 4 builds on Schatzmann et al (2024). The paper is accepted for presentation at the 103rd Annual Meeting of the Transportation Research Board in Washington, D.C.. Allister Loder, Lisa Hamm and Thomas Schatzmann developed the survey and experimental design. Thomas Schatzmann conducted the survey and estimated the choice models. Together with Santiago Álvarez-Ossorio Martínez, Thomas Schatzmann did the research for the literature review, conducted the analysis and prepared the manuscript. Allister Loder, Kay W. Axhausen and Klaus Bogenberger edited the manuscript.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOTATION

ABBREVIATIONS

API	Application Programming Interface
ARE	Swiss Federal Office for Spatial Development
BFS	Swiss Federal Statistical Office
CHF	Swiss Franc (monetary unit)
DCE	Discrete Choice Experiment
EUR	Euro (monetary unit)
KM	Kilometer (distance unit)
MATSim	Multi-Agent Transport Simulation
MiD	German Mobility Census
MTMC	Swiss Mobility and Transport Microcensus
PT	Public Transport
RP	Revealed Preference
SBB	Swiss Federal Railways
SC	Stated Choice
SCE	Stated Choice Experiment
SP	Stated Preference
VTT	Value of Travel Time
WTP	Willingness-to-pay

1

INTRODUCTION

All models are wrong, some are useful.
— George Box

1.1 BACKGROUND AND CONTEXT

> "Economic growth seems to have generated levels of demand exceeding the capacity of most transport facilities. Long periods of under-investment in some modes and regions have resulted in fragile supply systems which seem to break down whenever something differs slightly from average conditions. These problems are not likely to disappear in the near future. Sufficient time has passed with poor or no transportation planning to ensure that a major effort in improving most forms of transport, in urban and inter-urban contexts, is necessary. Given that resources are not unlimited, this effort will benefit from careful and considered decisions oriented towards maximising the advantages of new transport provision while minimising their money costs and undesirable side-effects." (Ortúzar and Willumsen, 2011, p. 3)

This quote highlights the major challenges that transport planners face when trying to enhance transportation in consideration of our environment. Given the ongoing population growth[1] and the escalating climate crisis (Fischer *et al.*, 2023), that quote has certainly gained importance, not only in the realm of transportation, but more generally for the sake of our well-being when it comes to making careful decisions.

How should we maximise those advantages of transport? In other words, what makes for a good transport system? Levinson *et al.* (2017) have adapted a famous quote by Theodore Dobzhansky and try to provide an answer to that question: "Nothing in cities makes sense except in the light of accessibility". In their book, the authors very intuitively define the underlying goal of transport as getting people to activities and opportunities, and

1 https://www.databank.worldbank.com/, last accessed: 10/01/2023

goods to market - a concept referred to as accessibility, which goes back to the idea of Hansen (1959). In essence, accessibility measures the ease of reaching destinations and can be mathematically calculated as the product of the number and quality of destinations that can be reached given the generalised costs (time, money, and other factors) of reaching them.

It is the people and the places where they engage in activities that define accessibility to a large extent. Despite the recurring patterns in our mobility behavior, it is still truly diverse. The demand for transport is derived from our travel behavior and needs, and is not an end in itself. It is highly differentiated over time and space and very dynamic, which makes it not only difficult to assess in the first place, but even more so to predict (Ortúzar and Willumsen, 2011). Transport supply is understood as a service to move people and goods which depends on infrastructure itself, its suppliers, service operators, manpower, vehicles, etc., and exhibits external costs (i.e., costs not borne by the users themselves) that are associated with the production of it. The main challenge is related to the fact that a transport service must be consumed when and where it is produced as otherwise its benefit is lost. Hence, for transport planners, it is essential to monitor, measure and forecast how people intend to adjust their mobility behavior in order to save resources by tailoring the supply of transport services to it.

Despite the growing adoption of activity- and agent-based transport modeling frameworks like MATSim (Horni *et al.*, 2016), which are employed for modeling and analyzing travel demand, many transport planners continue to adhere to the traditional four-step model. Within this modeling framework, mode choice corresponds to the third step and is concerned with the mode of travel that we choose. As such, the issue of mode choice is crucial in transport planning and policy-making, significantly impacting travel efficiency and resource consumption. For instance, numerous cities strive to steer their modal split in favor of more sustainable and space-efficient modes, as opposed to cars. As such, transport policies aim to directly affect the modal split. Seen as an aggregate problem, mode shares can be explained very well with observable measures of accessibility (Levinson *et al.*, 2017). In practice, however, investigating individual mode choices in response to a changing world requires a set of methods which can help to disentangle and focus on single aspects if needed.

As such, the work in this thesis is motivated by the desire to understand how to effectively measure, explain and predict changes of individuals' mode choices.

1.1.1 *Mode choice in a changing world*

The sudden onset of the Covid-19 pandemic in early 2020 dramatically changed travel behavior around the world. As new measures were continually imposed, reinforced, and relaxed, people had to adapt their daily routines. Switzerland faced severe restrictions during the first wave, although its lockdown measures were comparatively less stringent than those in neighboring countries. Based on a large GPS tracking study, Molloy *et al.* (2021b) documented unprecedented shifts in average daily distance travelled by mode. Notably, cycling saw a substantial increase, exceeding 100% in some weeks compared to the pre-pandemic baseline. In contrast, public transport usage experienced a sharp decline, and its recovery was comparatively slower in the aftermath of the pandemic. Working from home, which was a requirement during the pandemic, might have a more permanent impact on the modal split and peak-hour phenomena in the future. However, it remains to be seen to what extent it will be encouraged by the employers and governments, and what it implies for transport policy.

The climate crisis has profoundly influenced mode choice in transportation. As concerns about environmental sustainability grow, cities such as Paris and Amsterdam have implemented policies to promote eco-friendly modes, including building extensive cycling lanes, improving pedestrian infrastructure, pricing strategies to compensate for carbon dioxide emissions, and investing in efficient public transit systems. There have also been efforts to reduce the popularity of private car usage due to its environmental impact. Nevertheless, Switzerland is yet to achieve the goals set in this regard (BAFU, 2023a,b). The challenges have intensified, particularly after the Covid-19 crisis, with economic and geopolitical uncertainties further complicating the adherence to these objectives.

The impact of shared mobility services and automated vehicles on mode choice has been discussed extensively in recent years. Becker (2020) investigated the introduction of automated vehicles for the canton of Zurich, Switzerland, using a revealed and stated preference survey. The results indicated significant shifts from mass transit and traditional cars to automated modes, with the decrease in traditional car usage being nearly twice as large. Schmid (2019) explored the values of travel time in Austria for car-sharing and car-pooling in a post-car world. Using an advanced choice model, he found a generally higher value of travel time for shared modes compared to privately owned cars, indicating greater discomfort. Interestingly, even without private cars in the picture, those shared modes are unlikely to expand significantly due to inelastic demand patterns. With regards to micro-mobility, Reck (2021) examined the use of shared and personal e-scooters and e-bikes for the city of Zurich using GPS data and choice models. While both shared modes mostly replace walking, cycling and public transit, personal e-scooters and e-bikes replace car-based modes substantially more often, generally leading to less CO_2 emissions emitted than the transport mix they replace.

Technological advances have not only fostered the development of more energy-efficient vehicles, and new transport services, but also new data collection methods such as GPS-based travel diaries. For example, Molloy (2021b) used a GPS-based tracking application for a mobility pricing study undertaken in Switzerland (Mobility in Switzerland; MOBIS) and the monitoring of the Covid-19 pandemic (MOBIS:COVID-19). Clearly, these data provide a much more detailed and comprehensive replication of peoples' daily schedule compared to traditional travel diaries, but are currently still restricted to the existing transport environment.

Therefore, traditional data sources such as stated preference surveys will likely remain a key component of transport planning. This thesis specifically focuses on employing two methods within the realm of stated preferences.

1.1.2 *Stated choice experiments and discrete choice models*

In essence, measuring behavior boils down to understanding the choices one makes (to travel) which inherently link our preferences to behavior (Hausman, 2012; Samuelson, 1948).

According to Louviere *et al.* (2003, p. 1), "choosing manifests itself in many ways such as supporting one outcome and rejecting others, expressed through active responses, or through passive responses, such as supporting particular views. Individuals' choices are influenced by habit, inertia, experience, environmental constraints, accumulated opinion, household and family constraints, etc.". To investigate choices, analysts commonly use preference data, categorized into revealed and stated preference (RP & SP) data. RP data reflect the world as it is now, offering the possibility to examine preferences within an existing market and technological structure. In contrast, SP data explore hypothetical scenarios, shedding light on decision-making and the underlying preferences. However, the reliability of SP data depends on participants' understanding, commitment, and ability to respond effectively to the given tasks. Economists typically prefer observed data as they have been skeptical about relying on what consumers say they will do compared with what they actually do. Despite this skepticism, there are situations in which there might be no choice but to trust consumers.

In the context of transport planning and this dissertation, one such situation could be a scenario where a new mode is introduced to an existing transport system, or a the impact of a proposed new transport policy. In a fast changing world, there will always be a need to estimate demand for new alternatives or existing ones with new attributes or features. In that sense, SP data are (more) useful for forecasting changes in behavior than their RP counterpart, but may be limited by the imposed (lack of) realism of the choice context. Albeit the relative strengths of both data types, there can be significant value in combining them. An approach that is being used in this thesis as well.

SP surveys can generate data that are consistent with economic theory, enabling the estimation of econometric models. The question is not whether obtaining SP data is possible or advisable, but rather whether the models derived from SP data offer accurate insights and predictions regarding actual market behavior. Preference and choice measures are part of a broader category known as dominance measures. In simple terms, "dominance" measures are any form of numerical assignment enabling analysts to determine if one or more measured objects are equally preferred or if they are more or less preferred relative to one another. There are various types of dominance measures which are, or can be transformed to be, consistent with Random Utility Theory (RUT) (Luce and Suppes, 1965). For instance, these measures can include discrete choices from a set of options, yes or no decisions, rankings, or the expression of preferences using rating scales. However, when dealing with discrete choices, the data can only be weakly ordered, and it is not possible to establish a complete preference ordering from only one observation of an individual. More choices per individual and more individuals are needed in order to evaluate changes in choices in response to changes in the attributes of a mode, the transport system, characteristics of individuals or the general environment.

As such, stated choice (SC) data are generated by some systematic and planned design process in which the variable attributes and their levels are varied to elicit preferences or choices. "A designed experiment is therefore a way of manipulating attributes and their levels to permit rigorous testing of certain hypotheses of interest" (Louviere *et al.*, 2003, p. 84). An excellent review on the literature on experimental design theory can be found in ChoiceMetrics (2021), and current state-of-the-art designs are discussed in Rose and Bliemer (2009, 2014). The theory of discrete choice models contains elements of traditional microeconomic theory of consumer behavior, such as the formal definition of rational choice as well as other assumptions of traditional preference theory. Discrete choice models are statistical models of situations where a decision maker is facing a choice between a finite number of discrete and mutually exclusive alternatives (Ben-Akiva and Lerman, 1985; Train, 2009). Given a set of possible alternatives (the choice set), the model gives the probability that any alternative within the choice set is chosen. Two elements are fundamental: a function that relates the probability of an outcome to the utility associated with each alternative, and a function that relates the utility of each alternative to a set of attributes. Together with the estimated parameters and a random term, these functions determine the level of utility of each alternative. The underlying behavioral assumption is that of a rational, utility maximising decision maker.

Two paradigms have evolved over the past years when it comes to the elicitation of preferences: conjoint analysis (CA) and stated choice experiments (SCE) (Louviere *et al.*, 2010). Both academics and practitioners seem to confuse these paradigms such that they claim applying CA, but are actually using SCE. CA originates from the field of psychology and relies on mathematical axioms that only have a very restrictive relationship to utility theory. Furthermore, there is no error theory associated with conjoint measurement which allow the theory to be represented as testable statistical models. This has important implications for economic evaluation (e.g., the value of travel time in transport planning) as data collected by CA do not readily translate into choices on which RUT relies. It is the error components used in SC environments which distinguishes SCE from CA, and play key roles in determining parameter estimates and welfare measures derived from SCE data collection. Hence, it is the application and modeling approach (i.e. discrete choice modeling) that defines why transport planners should use the term "SCE" (although many also use "DCE"; discrete choice experiment).

In the context of transport planning, discrete choice models are perhaps most often used to better understand mode choices. These models are a mathematical representation of the decision process, and hence provide behavioral insights into the underlying preferences. Two key outputs of choice models are the valuation of attributes and elasticities of choice. Perhaps the most important number in transport planning is the value of travel time (VTT), calculated as the marginal rate of substitution between travel time and cost. The VTT resembles the willingness-to-pay for reduced travel times (or vice versa, the willingness-to-accept slower but cheaper travel times) and is a key input for project appraisal, as travel time savings form the biggest part in user-benefits in most transport related cost-benefit analyses (Wardman and Lyons, 2016). Furthermore, elasticities of choice help to assess the effectiveness of different scenarios (i.e., transport policies) by examining how market shares respond to changes in the attributes of alternatives. In combination with the model estimates and fit, these are important outcomes in the process of modeling that need to be considered.

1.2 THESIS OUTLINE AND OBJECTIVES

This thesis is concerned with practical and methodological aspects of measuring change in mode choice behavior in transportation.

Chapter 2 presents a framework for conducting web-based stated choice experiments using a combination of R, Amazon Web Services, and the survey software Qualtrics. It aims to address an existing gap in current practice in this context. Two ways of displaying a choice task to respondents are explained and discussed in detail, highlighting the advantages and limitations of each respectively. The chapter includes a link to a publicly available and fully reproducible working example on GitHub. The framework presented should not only be helpful to researchers and practitioners in the transport planning community, but generally to everyone implementing and conducting stated choice experiments.

Each of the following chapters approaches a unique aspect of mode choice by applying stated choice experiments and advanced discrete choice models. Chapters 3 and 4 stem from collaborative projects with industry partners, while Chapter 5 is an academic collaboration.

Chapter 3 examines how choice behavior would change if a long-distance bus service were introduced in Switzerland, competing with cars and public transportation. The main objective is to identify the key factors influencing individuals' decision-making process to use this service. Two online surveys (RP & SP) were conducted to gather the relevant data. By utilizing a comprehensive stated choice experiment that includes a dense bus stop network, and advanced choice models, the study offers new insights into trade-offs people consider when choosing between these modes. The chapter concludes by discussing the findings, how the underlying assumptions affect them, and potential extensions of the approach.

In Chapter 4, the preferences for the use of urban ridepooling in Hamburg, Germany, are explored. Using MOIA[2] as a case study, the chapter investigates how the introduction of ridepooling affects mode choice behavior within a multimodal urban environment. A combined RP-SP survey was conducted, integrating ridepooling-specific service attributes into the choice design. The data gathered were analyzed using discrete choice models to investigate the impact of ridepooling on travel decisions. The findings presented underpin the current challenges for the provision of a large-scale ridepooling service like MOIA. Given the complexity of the experiment, limitations, assumptions and improvements of the approach are discussed.

Chapter 5 delves into the idea of a Tradable Mobility Credit Scheme in the city of Munich, Germany, and how it could help to promote the shift to more sustainable modes and internalize external costs. An online SP survey containing two experiments was conducted: one resembling mode choice in the status quo, and the other one where the new paradigm was introduced. This chapter contributes with an elaborated choice design, first insights into the heterogeneity of choice behavior in such a regime, and concludes with a discussion on the modeling approach applied, the findings and their implications for future work, and whether this policy could convey the desired effects, given the assumptions made.

The final Chapter 6 provides a summary of the experience gained from employing stated choice methods to effectively measure shifts in mode choice behavior. It outlines the challenges faced, acknowledges the limitations, and explores potential avenues for future research.

2 https://www.moia.io/

2

IMPLEMENTING WEB-BASED STATED CHOICE EXPERIMENTS

The chapter is based on the following paper:

– Schatzmann, T., J. Molloy and K.W. Axhausen (2023) Implementing web-based discrete choice experiments in transportation, paper accepted for publication in *Transportation Research Procedia*.

2.1 INTRODUCTION

Travel behavior has been studied for as long as people began to agglomerate in order to benefit from their proximity and needs. These are determined by life itself and hence are truly diverse in nature, essentially resulting in activities undertaken by everyone in our society. Work, leisure and health are amongst the most prominent needs and define our mobility patterns to a large extent. The demand for passenger transport as such is therefore derived from personal needs and varies over time and space in a dynamic environment (Ortúzar and Willumsen, 2011). However, in the end it is the choices we make to travel that are observable by analysts and thus inherently link our preferences and needs to behavior. It comes as no surprise that transport researchers have developed various ways to collect data to analyse and predict the demand for travel.

Surveys have been the classical way to obtain a travel diary in order to gather information on people's mobility (e.g., stages, trips, tours, mode and route choice), sociodemographic characteristics and attitudes towards the environment, style of living and so forth. Such travel diaries serve as a source to forecast demand patterns for future scenarios in response to transport policy. A particular branch within transport research not only examines revealed preference data (RP; i.e., observed), but delves into hypothetical market scenarios, commonly referred to as stated preference data (SP). An example of such scenarios includes the introduction of a new mode into an existing transportation network. Discrete choice models are often used in the realm of transport planning to measure preferences, choices and decision environments regarding the choice of modes and routes. The underlying Random Utility Theory (RUT) enables the researcher to compare and combine these various sources of preference data to make inferences about behavioral processes (Louviere *et al.*, 2003). In general, the inclusion of SP data in the estimation of a choice model presumes some kind of a stated choice experiment (SCE; in the literature also referred to as discrete choice experiment (DCE)) in the travel survey. While web-based SCE have become the standard in the past years, the existing literature falls short in documenting the implementation nuances of these experiments. This chapter seeks to bridge this gap by presenting a web-based approach tailored for conducting SCE.

2.2 TRANSPORT SURVEYS

Louviere *et al.* (2003) define the term "survey" as any form of data collection involving the elicitation of preferences and/or choices from a sample of respondents. A survey can be conducted in various ways ranging from purely analog to fully digital. Analog surveys refer to interviews in person, the classical paper and pencil type of questionnaires, sent out and received by post, or such conducted by telephone only. With the advent of new software, for example SurveyEngine, Qualtrics, LimeSurvey, SurveyMonkey, Sawtooth or Sosci, there has been a shift towards web-based surveys during the last decade not only in the transport domain, but in many other fields of research (e.g., marketing, health, psychology, etc). At the Institute for Transport Planning and Systems (IVT) we have been using web-based survey tools for more than 10 years and many projects. However, it was only 3 years ago that we started to implement SCE fully online.

2.2.1 *Stated choice experiments*

Stated preference (SP) and stated choice (SC) data are generated by some systematic and planned design process in which the variable attributes and their levels are varied to elicit preferences or choices. "A designed experiment is therefore a way of manipulating attributes and their levels to permit rigorous testing of certain hypotheses of interest." (Louviere *et al.*, 2003). With regard to transport planning, many hypotheses evolve around testing the introduction of a new mode and/or route in a current or hypothetical system. The difficulty in implementing any SCE in transportation, apart from finding the most suitable experimental design, arises from the underlying preference data source and the context of the application (refer to Rose and Bliemer (2009); ChoiceMetrics (2021) for an overview of processes to generate SCE). In particular, an experiment that relies on RP data usually makes use of individualised reference values for the experimental choice design as opposed to one that is solely based on SP data with pre-defined attribute levels. This may result in a survey process that is divided into two phases: a first one with an initial survey to collect the relevant data, and a second one with a follow up survey that includes the actual SCE (refer to recent online studies carried out by IVT (Dubernet, 2019; Molloy *et al.*, 2020; Schatzmann and Axhausen, 2022)). A two-phase survey structure is a challenge in general, not only for traditional paper-based approaches, but also for online ones as it usually increases the response burden by design and thus might decrease the response rate (Schmid and Axhausen, 2019).

2.2.2 *Web-based survey tools*

There is a wide variety of web-based survey tools available to researchers. Many are even available at no cost, but at the same time often restrict the user to either basic question features or a limited number of active surveys or responses. For simple feedback surveys it should not make a difference which survey tool is used as most of them come with a similar set of standardised questionnaires and question types. However, conducting fully web-based stated choice experiments requires a flexible tool. For example, the option to add web services within a survey proved to be very convenient. Survey tools like SurveyEngine, Qualtrics, LimeSurvey, SurveyMonkey, Sawtooth or Sosci all offer the option to add customised JavaScript code in order to retrieve externally stored data like a choice design or pictures through an application programming interface (API). Furthermore, they all accept PHP, HTML or CSS code to change the appearance of the survey or even to create new features (e.g., new question types). The goal here is not to review the tools mentioned before. In our experience, the optimal survey tool should balance convenience of use, cost and reproducibility. The survey tool provided by Qualtrics Experience Management (XM) meets the requirements to conduct complex SCE best. Note that Qualtrics also provides an add-on for conjoint analysis which is costly and not flexible enough. Weber (2021) published an automated step-by-step procedure to implement SCE in Qualtrics which includes a full working example. It is suitable for standardised SCE that are based on SP data, but at the moment does not seem to work at all with RP based experiments.

2.3 A WEB-BASED APPROACH

Since Qualtrics surveys are hosted on a survey engine called JavaScript Form Engine (JFE), custom coding features using JavaScript enable for more advanced functionality (e.g., custom question types, API calls). However, the more one has to engage with custom coding, the more technically involved the process of implementing a SCE becomes. The primary goal is a relatively fast and convenient approach to get a smoothly working SCE and a decent survey experience for the respondent.

2.3.1 *Displaying choice situations*

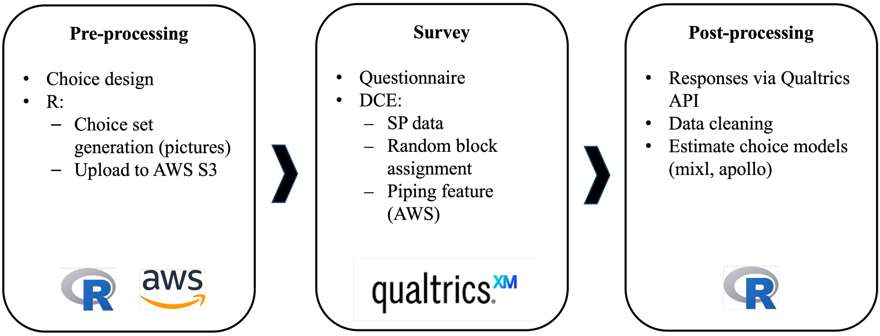
Generating a stated choice experimental design is not a straightforward task and is the theoretical backbone of the experiment and subsequent statistical modeling. At this point, we assume that such a design was already generated (for example using NGene (ChoiceMetrics, 2021)). The output of any design essentially is a data frame with choice situations (sometimes also referred to as choice tasks) as rows and attributes of each alternative as columns. The cells are filled with the attribute's levels which are usually balanced between all choice situations, depending on the type of the experiment. Blocks of choice situations (i.e., subsets) might be present if the total number needed for an efficient or orthogonal design is too large to give to a single respondent. However, a participant is faced with a certain number of choice situations where he or she has to choose one out of several alternatives. This chapter proposes two ways of how the information is displayed to the respondent. This could either be a picture of a table for each choice situation of the experimental design, or a matrix table (which is a question type in Qualtrics) that is filled with the corresponding information. The general approach builds around a couple of scripts written in R (R Core Team, 2020) to generate such pictures or the corresponding data that can be loaded in to matrix tables within Qualtrics.

2.3.1.1 *Experiments based on stated preference data*

The examples presented in this section are taken from a working example that can be freely accessed on GitHub (see `https://github.com/th0schA/dce_sp`). The example survey can also be found here. It contains all the R code which is mentioned below and a Qualtrics survey template. As mentioned in Section 2.2, the particular type of a SCE, or more specifically its preference data source, determines the complexity of the implementation.

Figure 2.1 shows a diagram of the pipeline for SCE based on SP data and pre-defined attribute levels in the choice design.

FIGURE 2.1: Pipeline for SP based SCE



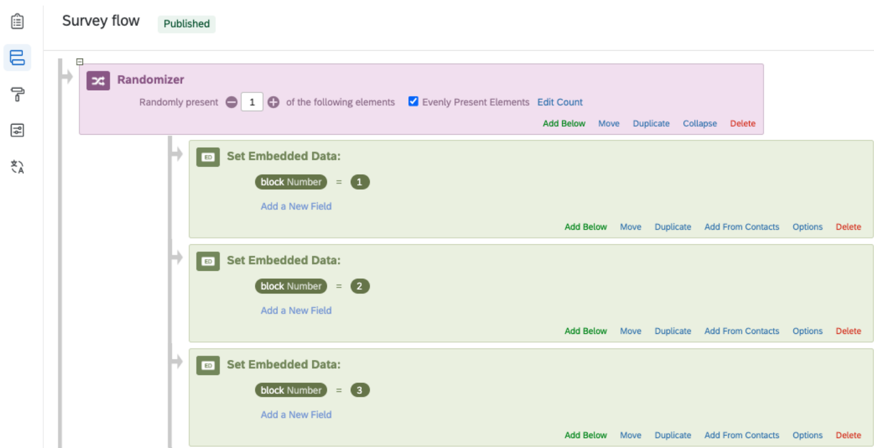
Creating pictures: Before the actual survey is conducted with Qualtrics, pictures of each choice situation of the experimental design have to be generated in R (Auguie and Antonov, 2017) and uploaded to a cloud storage server on AWS (e.g., S3). Uploading the pictures can be done using the R package "aws.s3" (Leeper *et al.*, 2020) or the AWS command line interface. The latter is recommended if a large number of pictures (i.e., thousands) needs to be uploaded as it is much faster. The crucial part is that all the pictures are saved with names that identify the block, choice situation and possible further specifications like language or purpose (e.g., *"block_1_cs_1.png"* or *"block_1_cs_2_purpose_leisure.png"*). The AWS permission settings need to be set to "public access" for the bucket (folder) that contains the pictures. The actual implementation in Qualtrics as a next step is straightforward. For each choice situation in a block the question type "multiple choice" is used with as many choice options as alternatives are present in the choice design with answer type "allow one answer". In order to load the corresponding picture stored on AWS in the description of the question, the *publicly accessible URL-link* from AWS is entered in HTML view as shown in Figure 2.2.

Two other features in Qualtrics called *"piped text"* and *"embedded data"* are needed to load the pictures. Embedded data is extra information stored in addition to the responses that can be displayed as piped text in questions once it has been added. These two features make it possible to dynamically

FIGURE 2.2: Loading a choice situation as picture in Qualtrics

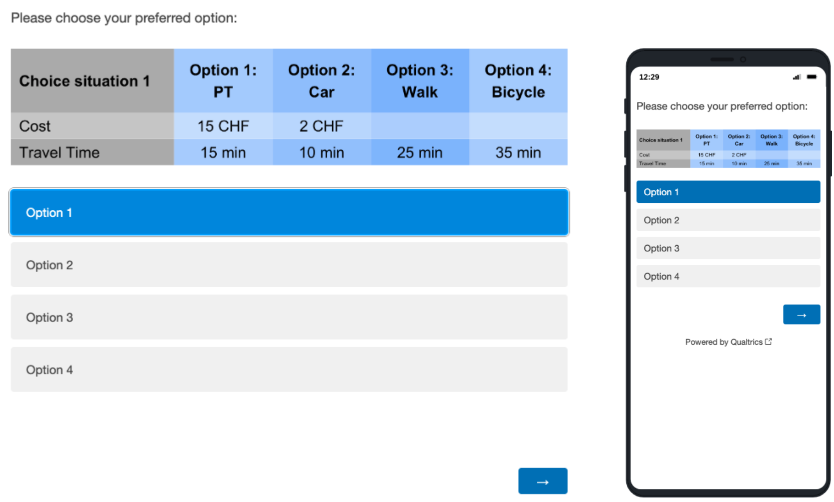
load a picture for the corresponding block and choice situation. Figure 2.2 shows where the relevant part (*"$e://Field/block"*) of the URL is exchanged with embedded data as piped text. In many SCE, participants are randomly assigned to a block of choice situations. Figure 2.3 shows how it can be done in Qualtrics' survey flow.

FIGURE 2.3: Random block assignment in Qualtrics



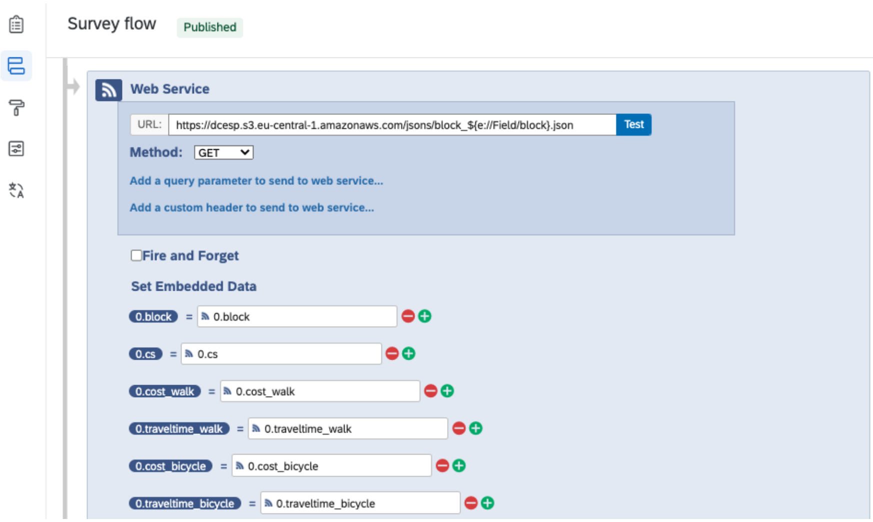
It is easy to randomize the order of the alternatives while creating the pictures within a block of a choice design in R. In that case, the ordering has to be saved in the pipeline as well and must be matched again for each respondent in the post-processing in the end. Furthermore, it requires to display the alternatives as numbered options in each choice situation. After proper implementation, the respondent experiences a simple and clean representation of a choice situation as shown in Figure 2.4. Note the numbered options as explained above. It is recommended to use a vertical alignment of choice options for a better mobile phone experience when filling out the survey. However, a drawback of using pictures is that on mobile devices these will be scaled down accordingly by Qualtrics to fit the screen size. Thus, on mobile phones, too many alternatives in a choice situation will result in a less easily readable picture unless the device is held horizontally.

FIGURE 2.4: Displayed user experience with a picture



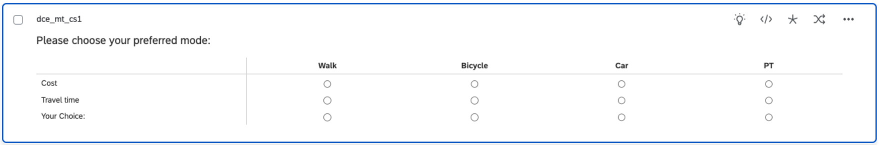
Qualtrics matrix tables: The picture-based approach presented above comes with two disadvantages. First, pictures may not scale nicely when displayed on a mobile device. Second, and dependent on the experimental design, hundreds or even thousands of pictures must be produced which makes this task burdensome. Using matrix tables within Qualtrics circumvents these issues. The main idea is to transfer the information for each choice situation in a block to Qualtrics, save it as embedded data and feed it as such into a matrix table. Instead of creating pictures, for every block in the design the data of all choice situations is saved in JavaScript Object Notation (JSON) format. Again, these files should be saved with names that identify the block (e.g., *"block_1.json"*) and uploaded to the same cloud storage server on AWS. In Qualtrics, the next step is to set up a web service (see Qualtrics help page for more detailed information) in the survey flow that gets all information from a JSON file and saves all values as embedded data. Figure 2.5 shows how to make a request to a designated URL.

FIGURE 2.5: A web service in Qualtrics



For each choice situation in a block the question type "matrix table" is used, where alternatives correspond to scale points (i.e., columns of the table) and attributes to statements (i.e., rows of the table). The basic mechanism is to "misuse" a likert matrix table in a way that text is displayed instead of radio buttons for all rows in the table, except for the choice row. For each cell in the table, the radio button is being hidden and the corresponding embedded data is piped in as text. This can easily be done with a few lines of JavaScript for each question. Please refer to the Qualtrics survey template on GitHub for detailed information. In the end, Figure 2.7 shows how a choice situation may look like when using a matrix table in combination with JavaScript code. The beauty of a matrix table is that it is highly flexible if needed. Conditional display logic of columns and rows can be used if alternatives and/or attributes might not be available in certain situations according to the choice design. In addition, random ordering of alternatives and/or attributes can also easily be set up by using scale point and statement randomization respectively.

FIGURE 2.6: A likert matrix table in Qualtrics

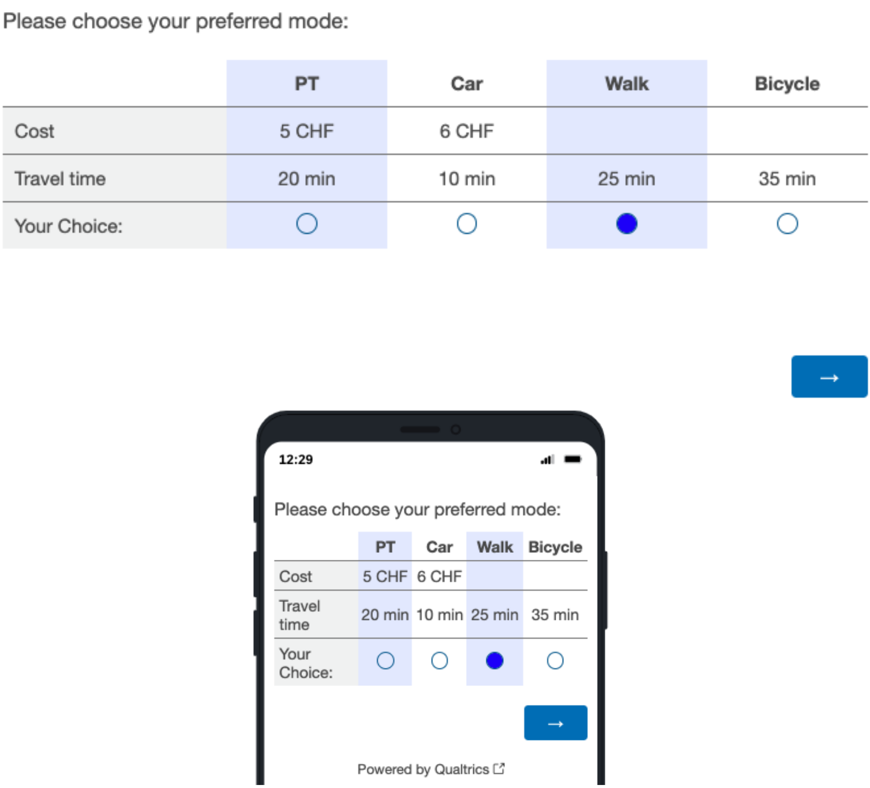


Once the survey is finished and all responses are gathered, there are two ways to extract the data from Qualtrics depending on the license acquired: 1) If access to the Qualtrics API is included, a convenient way to download the responses directly within R is using the package called "qualtRics" which handles the required API calls in the background given the corresponding Qualtrics survey ID (Silge and Ginn, 2021). Furthermore, the package comes with a couple of functions and options to shape the data based on the question type and its choice options defined by the user. 2) In case of no access to the API, a simple export to *.csv* or *.txt* files does the job. In a final step, proper data cleaning and the estimation of the choice models is done in R as well. As for the data cleaning, Qualtrics provides a very intuitive way of setting proper labels for each question with various recoding options for all answers. It is recommended to use a sound labelling strategy for convenient and fast data cleaning. After all, the goal is a properly formatted data set as input for the statistical modeling. At IVT, most choice models are then estimated in R using our own package called "mixl", or the "apollo" package that was developed by colleagues at Leeds University (Molloy *et al.*, 2021a; Molloy, 2021a; Hess and Palma, 2019; Hess *et al.*, 2022). Note that also the "Biogeme" package in Python is a great alternative to estimate choice models (Bierlaire, 2020; van Rossum, 1995).

2.3.1.2 *Experiments based on revealed preference data*

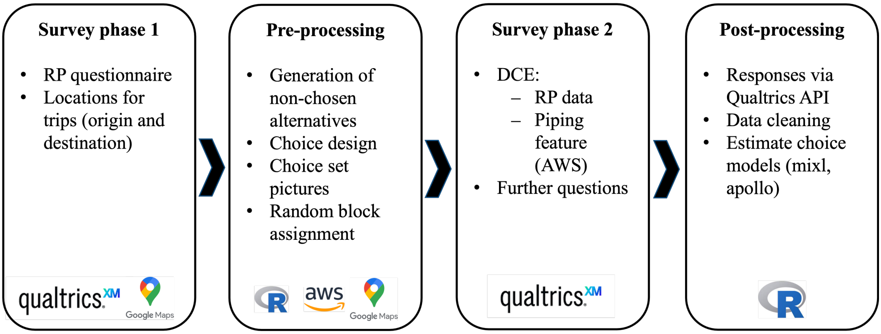
Many mode and route choice experiments though rely on trips that were reported (i.e., revealed) by participants. It is often easier for them to identify with a given choice situation in an experiment as it represents a more

Figure 2.7: Displayed user experience with a matrix table



realistic scenario. It is well known from recent literature that people tend to show less inertia in SP experiments since they are not mentally restricted to their own trip when choosing an alternative (Louviere *et al.*, 2010). Furthermore, random component variances are often smaller for SP than RP data because the former are obtained under well-controlled circumstances where respondents focus on fairly specific decision and choice tasks that encourage them to ignore omitted factor and/or assume that they are constant. The fact that we use a picture or matrix table-based approach has implications for the implementation of RP based SCE such that the survey is separated into two phases (i.e., two surveys), as shown in Figure 2.8:

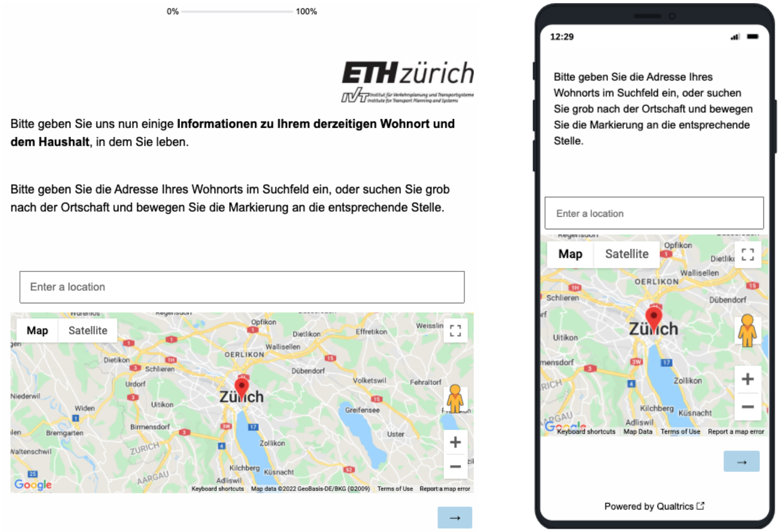
FIGURE 2.8: Pipeline for RP based SCE



A first survey captures the respondent's travel behavior by asking them to report trips for different purposes. These trips then serve as reference trips for the experimental design. Depending on data privacy regulations, the way to ask for details about the trips might differ substantially, going from simple text entry question types to fully embedded interactive maps where respondents can indicate trip origin and destination location. An example using a Google map embedded in Qualtrics is presented in Figure 2.9. The description and code can be accessed here. Note that a valid Google API key is required and access to the Maps and Places API should be enabled to render maps in Qualtrics. Each request under the pay-as-you-go pricing is charged 0.005 USD once the total cost exceeds a monthly credit (free tier). The coordinates for each location are stored directly like a normal question answer and can be downloaded in the same manner as explained above.

RP based mode and route SCE require the generation of individualised choice situations for each respondent and reference trip. As a consequence, this results in as many pictures or JSON files as the sample size times the defined number of choice situations per individual. The next major task in preparing the actual experiment is the generation of non-chosen alternatives. For example, imagine a mode choice experiment with three alternatives consisting of car, public transport and bicycle: If a participant chose car for a specific trip asked in survey phase one, it is the analyst's task to calculate the trip attributes for all other alternatives (i.e., available modes) presented in the experiment. This can be done using the Google API. It is crucial to perform consistency checks on the routed trips in order to have a valid and

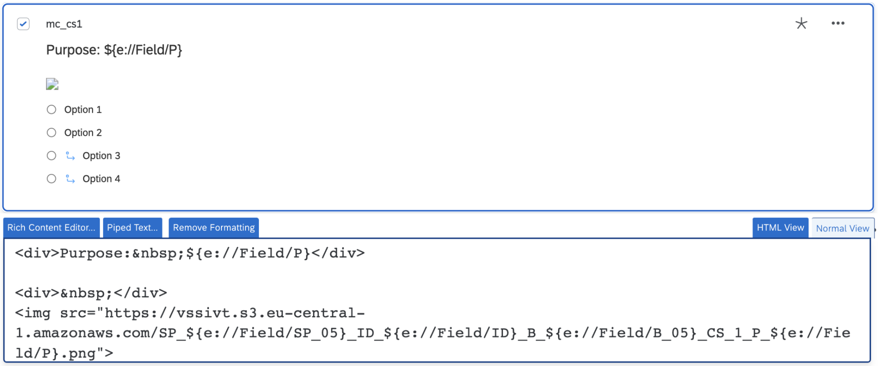
FIGURE 2.9: Retrieving trip details



realistic experiment. However, calculating the trip costs often imposes a bigger challenge than generating travel time related attributes, especially for public transport which heavily depends on season ticket ownership. Once non-chosen alternatives are generated, all pictures or JSON files have to be produced. Different to the process explained in section 2.3.1.1, there are now individualised choice situations and hence pictures/JSON files for each respondent. Again, the trick is to use names that link a picture not only to the block and number of choice situation, but also to the individual (usually a unique ID is assigned to the participants of the sample).

In the end, the second survey contains the actual SCE and is conducted in phase 2. It is important to mention how the respondents are invited such that the proposed approach will work. If e-mail addresses are not available prior to survey phase 1, they will have to be collected in the first survey. The respondents are then invited by e-mail to the second one with a personal invitation link attached, either sent through the Qualtrics Mailer or a third party (i.e., own) solution. These invitation links are generated by the analyst and contain additional information appended to the end of the survey URL which comes from Qualtrics - so called query strings. The information is stored in the query string and is captured by the survey

FIGURE 2.10: Loading the RP based choice situation as picture in Qualtrics



when it reads the URL. Once passed, the data can be saved as embedded data within the survey (see here for detailed information about the set up in Qualtrics). Finally, this ensures that the correct choice situations will be displayed based on the embedded data that are entered as piped text in the picture URL or web service.

Again, once all the responses are gathered, the same post-processing procedure applies as mentioned in Section 2.3.1.1. Last but not least, data cleaning is an important task in order to have a proper data set for the subsequent statistical modelling. Qualtrics in combination with R greatly facilitates that process if proper question labels are set in the survey.

2.4 CONCLUSION

Web-based SCE have been used frequently over the past years in many disciplines and seem to challenge or even replace traditional paper-based ways of conducting such experiments. Yet, there is still little research available on how to implement such work. In transportation, many studies that involve web-based surveys mainly report on the tools that were used to create and conduct SCE. As always in research, there are many different tools that may be used and various ways to get to the desired outcome.

This chapter presents an approach to conduct web-based SCE using R, Qualtrics and Amazon Web Services in two ways. The main idea is to create a picture or JSON file for each choice situation of an experimental design in

R, store it on AWS and access it from Qualtrics on the fly when a respondent fills out the survey. Obviously, just creating pictures and adding them to Qualtrics is nothing new. For a simple experiment with only a few pictures AWS cloud storage does not even need to be considered. However, the implementation effort in Qualtrics becomes tedious the more pictures need to be generated. For example in the case of an experimental design that contains many choice tasks or if there are multiple designs for one experiment (i.e., for many trip distance classes and/or for considering mobility tool ownership). The proposed approach greatly reduces the implementation effort for an analyst by using three features in Qualtrics:

1. A flexible URL to load any picture or JSON file stored in a publicly accessible repository, using
2. embedded data and
3. piped text.

It essentially means that only as many multiple choice questions or matrix tables need to be implemented in Qualtrics as a single respondent is faced with in the experiment, if set up correctly. However, the analyst still has to be able to code a routine to generate the pictures programmatically. For that reason, a full working example for SP based SCE is provided on GitHub. It contains all necessary steps and code in R and AWS as well as a Qualtrics survey template. A fully implemented survey can be filled out using this link. Furthermore, this chapter suggests suitable packages in R to facilitate the download of responses via Qualtrics API. The presented framework is not only helpful for researchers in the transport survey methods community, but generally for everyone conducting experiments.

3

PREFERENCES FOR A NEW LONG-DISTANCE BUS SERVICE IN SWITZERLAND

The chapter is adapted from the following publication:

– Schatzmann, T. and K.W. Axhausen (2022) Long-distance buses in Switzerland: An examination of their substitution effects for long-distance travel, paper presented at the *101st Annual Meeting of the Transport Research Board (TRB 2022)*, Washington, D.C.

3.1 INTRODUCTION

In recent years, long-distance buses have become an increasingly popular mode of transport. The most prominent example in Europe is FlixBus. They offer low priced international bus trips that appeal particularly to young, price-sensitive travelers and tourists. Moreover, an increasing number of older people take advantage of their service as travel times are not that important to them when choosing their mode of transport. FlixBus claims that a single vehicle of the latest generation is already more eco-friendly than an average sized car (Kurth, 2018). However, it remains an open question whether their service actually contributes to lowering the negative external costs produced with regards to greenhouse gas emissions. Whereas in many European countries long-distance bus markets are almost completely liberalised (e.g. UK, Germany, France, Italy), Switzerland's market is heavily restricted due to international and national regulations. For example, a current law called "Kabotageverbot" prohibits international bus service providers to transport Swiss residents within Switzerland. On top of that, any private company requires a concession issued by the federal government to run a bus service and hence prevents competition between train and bus services. In 2018, the Federal Office of Transport (FOT) granted the first concession to a national bus provider called "Eurobus Swiss-Express" to operate three publicly accessible bus lines which were embedded in the Swiss public transport (PT) schedule. After one and a half years they were forced to shut down their service due to a lack of demand. Since then, there has not been another application for a concession. This raised the question of who would use such a bus service if it was competitive enough in the case of a liberalised Swiss transport market and, if so, what would be the main drivers in the decision making process to use it.

The remainder of this chapter is structured as follows. Section 3.2 summarises recent literature on long-distance travel and defines the context of this paper. Section 3.3 presents the methodological framework used to examine long-distance travel behavior in Switzerland for three alternatives: long-distance bus, car and public transport. The main part describes the set-up of the discrete choice experiment, its experimental design and the underlying hypothetical bus network. Section 3.3.3 presents the modeling approach applied to estimate different discrete choice models. In Section 3.4.2, a descriptive analysis investigates the study sample, choice frequencies and (non-)trading behavior between the alternatives. Multinomial and Mixed Multinomial Logit models are estimated to calculate demand elasticities and valuation indicators for the different modes considered. Section 3.5 summarizes the main findings, puts them into the Swiss context and discusses potential improvements as well as limitations of the reported work.

Importantly, and although the term "long-distance coach" is commonly used in the UK and US, this chapter uses the terms "bus" as well as "long-distance bus" interchangeably.

3.2 LITERATURE REVIEW

Long-distance travel has substantially increased in recent decades mainly due to economic growth and technological innovation. The latter has led to improvements in transport infrastructure and reduced transport costs as well as times (Arbués *et al.*, 2016). However, in transport research there is no uniform definition of "long-distance travel", which makes it difficult to compare such studies in general. In the universe of movements the definition varies for different policy interests and thus a number of criteria may be used. The most important ones are trip distance, trip duration, trip purpose and combinations of these (Axhausen, 2004). Spatial definitions may vary between countries or regions and use different thresholds for distance. For example, the European DATELINE survey defines long-distance trips as trips of 100km or more whereas in the US, the Bureau of Transportation Studies uses 80km or more (50 miles) (Van Acker *et al.*, 2020). The duration of a trip often relates to a temporal definition in terms of overnight stays.

For purpose-based definitions, work, leisure or personal travel can be distinguished even though there might still be no clear separation with regards to short and long-distance movements. Of course, this has implications for long-distance travel surveys and their scope as particular care has to be taken in choosing the reporting period and level of detail of all relevant movements. For long-distance travel diaries in particular, people seem to under-report the number of long-distance journeys as showed by Janzen *et al.* (2018), who compared results from a national travel survey to mobile phone data for the case of France.

While long-distance trips only represent a small share of all trips, they account for a high share of total distance travelled (Aamaas *et al.*, 2013). Depending on the definition of "long-distance", its share in terms of total passenger-km travelled varies between 20% to 55% in European countries (Van Acker *et al.*, 2020). Even though air travel has been the fastest growing mode across the globe for distances longer than 400km, car travel accounts for the highest share of long-distance travel for trips between 100-400km. International PT has increased recently with new high-speed rail connections, especially in Europe. Still, it is only for a few corridors in Europe (e.g. France and Spain or Switzerland and Italy) where PT may be considered as a competitive mode to air and car travel. As such, long-distance buses have started to become relatively attractive after a recent market liberalisation in some West European countries, which might actually change modal split of long-distance travel substantially. In their work, Kuhnimhof *et al.* (2009) showed that transport policies affect modal splits significantly, especially when it comes to countries with a high-quality PT network as for example Switzerland. Before the liberalisation of bus markets, many West European countries had a legislation in place that protected their national railway companies until buses started to challenge railway as the then dominant mean of transport, mainly on less frequently used routes (Schiefelbusch, 2013). After the UK, which was the first country that abandoned such legislation in 1980, it was only until a couple of larger countries followed its example and completely deregulated their bus markets (e.g. Sweden, Norway and Italy between the 1990s and 2000s, Germany in 2013 and France in 2015; Van de Velde, 2009, 2013). A major change that helped FlixBus becoming the largest bus service provider in Europe at the time and growing bus ridership in general. This implies that within deregulated bus markets, FlixBus is allowed to sell both international and domestic tickets to all clienteles, irrespective of their residency status. A service that remains infeasible in Switzerland due to extant regulatory frameworks mandating the acquisition of a concession for such operations.

Due to limited availability of data there is relatively little research focusing on long-distance travel compared to daily mobility behavior (Kuhnimhof *et al.*, 2009; Frei *et al.*, 2010). National travel surveys (NTS) are predominantly used to collect and analyse data in that context. Since long-distance trips occur less frequently than for example regular commuting or short-distance leisure travel, NTS usually contain less detailed information on such trips. As mentioned above, they are usually more difficult to capture in travel diary surveys (Axhausen, 2004). Many NTS therefore have additional modules that specifically focus on long-distance trips (e.g. the Swiss Mobility and Transport Microcensus conducted by the Federal Office for Spatial Development in collaboration with the Swiss Federal Statistical Office, or the French/UK NTS and German MiD, etc.). With the rapid improvement of technology, but lately also propelled by the onset of the COVID-19 pandemic, other data sources as for example mobile phone data have become available to researchers. Though, because of privacy reasons these data are often anonymised such that preferences for different modes are difficult to investigate. For Europe, there are only few travel surveys that exclusively focused on long-distance travel (e.g. INVERMO for Germany in between 1999 and 2002, DATELINE in 2001 and 2002 for 15 EU-countries, MEST/TEST for France, Portugal, Sweden and UK in 1996 and 1997, KITE for Switzerland, Czech Republic and Portugal in 2008 and 2009). They were conducted to examine peoples' preferences for modal choices and what factors affect it in the context of long-distance travel.

Van Acker *et al.* (2020) provide an excellent overview on recent literature in that regard and distinguish between typical socio-economic, demographic, trip-specific and spatial characteristics. They conclude that income is one of the most important factors. On the one hand, low-income households in both Europe and the US tend to make less long-distance trips and are more car dependent than other income groups (Reichert and Holz-Rau, 2015; Llorca *et al.*, 2018). High-income households, on the other one, are more prone to use faster modes such as airplanes. A fact that can partly be associated with differences in employment status, which subsequently leads to different values of travel time between the income groups (Mackie *et al.*, 2003; Hess *et al.*, 2018). In addition, Limtanakool *et al.* (2006) in their analysis of the 1998 Dutch NTS found that said income effects in particular exist for leisure related long-distance trips, with low-income groups being more likely to use trains rather than cars. However, this might not necessarily hold for the case of Switzerland. With regards to differences between gender in mode choice for long-distance trips, women still seem to undertake fewer trips, as opposed to shorter trips where their daily travel pattern are becoming more similar to those of men (Kuhnimhof *et al.*, 2012). Findings with respect to the impact of age are not conclusive. Younger individuals, frequently constituting students, tend to exhibit a preference for railway and buses over private cars and air travel options. However, the outcomes in relation to elder age groups yield equivocal findings. Mobility tool ownership is another important factor. Having access to a car in the household increases the likelihood to use cars for long-distance trips and discourages the use of PT (Van Acker *et al.*, 2020). As for trip-specific characteristics, travel cost and time, as expected, yield substantial influence on mode choice decisions for long-distance travel. In general, an increase of either one for a given mode is associated with decreasing demand. The magnitude of the effects mostly depend on the competition between cars and PT and thus differ between countries. When comparing the effect of travel time between short- and long-distance trips, Moeckel *et al.* (2015) find that travel time seems to be a less dominating factor, as an additional minute of travel time often was found to have a bigger impact on the perception of time for shorter distances. Last but not least, spatial characteristics also influence modal choices of long-distance trips. Reichert and Holz-Rau (2015) report that easy access to train stations providing inter-city connections increase the chances to generally participate in any long-distance travel, but apparently even more for trips by train and air. Furthermore, Limtanakool *et al.* (2006) found that the denser the urban area at the origin or destination, the more likely the train or coach is used.

Dedicated RP and SP surveys often help to further investigate relevant factors in the decision making process in order to understand the use of long-distance buses. Only few studies focusing on buses exist and often address specific corridors where buses compete with other means of transport such as cars and rail. They mainly examine the VTT, or components of it, as well as other level-of-service attributes such as comfort, safety, and so on. In their literature review, Van Acker *et al.* (2020) highlight that in almost all recent SP studies, travel times and costs were found to be highly significant for long-distance bus transport. Access to and from transit stations were considered to be crucial when opting for or against PT. Two studies conducted in China (Wang *et al.*, 2017; Yao and Morikawa, 2005) report lower in-vehicle VTT for buses compared to train due to potential intangible factors such as additional leg-room and Wi-fi. Clearly, this finding depends heavily on the existing PT and car network in China. While RP data is limited to observed behavior, existing transport infrastructure and mode-specific attributes, DCE may help to understand the influence of comfort features as mentioned before. Van Acker *et al.* (2020) and Lannoo *et al.* (2018) both leveraged a SP survey to examine the effect of extra leg-space, the availability of on-board Wi-fi and further comfort features on the choice between inter-city trips by bus in Belgium. They conclude that besides an attractive pricing strategy, the provision of additional services could make a case for bus service providers and stimulate travelers to start using buses. However, their findings are limited by the fact that they did not account for any other mode in such a competitive transport market.

For the case of Switzerland, and to the best of our knowledge, there has only been one study which looked into the attractiveness of long-distance buses. Based on KITE data mentioned above, De Lapparent *et al.* (2013) investigated the VTT of long-distance buses by applying Mixed Multinomial Logit models (MMNL). They specifically focused on different distributional assumptions for the random parameters and the subsequent differences in the VTT that arise thereof. Depending on that assumption, they found average in-vehicle VTT for long-distance buses between 40 and 70 Euro per hour, and average WTP values for access/eggress travel time to and from the mainmode between 70 and 115 Euro per hour. Albeit these are the only existing VTT values for long-distance buses in Switzerland, it is worthwhile to compare the results in this work with them. However, De Lapparent *et al.* (2013) also highlight that it is important to test different distributional assumptions as the results and hence the gained insights depend on them.

Note that based on the discussion above on the definition of "long-distance", and given the size of Switzerland, we defined a long-distance trip to be 50 kilometers or longer.

Apparently, the particular context of this study is restricted by current regulatory restrictions and the focus on long-distance travel within Switzerland. Nevertheless, this work contributes to the literature by examining the preferences for a new long-distance bus service that competes with the two dominating modes in terms of modal split - cars and public transportation, i.e., intercity trains. It not only accounts for trip- and person-specific attributes, but also comfort features such as increased leg-space in the bus as well as WiFi-availability. Furthermore, it tests for different distributional assumptions when applying Mixed Multinomial Logit models in order to estimate the corresponding VTT values.

3.3 METHODOLOGY

3.3.1 *Survey*

The study was based on two web-based surveys. In the first one, we captured the respondents' travel behavior in the French- and German-speaking part of Switzerland (see Appendix A.1 for the complete survey). In the main part of that questionnaire we asked respondents to report typical commuting and long-distance trips within the last two months inside Switzerland at the point of filling out the survey. The reason for that was to increase peoples' awareness of the difference between typical commuting and irregular long-distance trips. In order to keep the response burden within reasonable limits, we required detailed answers only for one long-distance trip, broken down by stages (including start and destination, departure and arrival times, purpose of the journey, comfort features, activities during travel and at the destination, costs, overnight stays and so forth). However, we could observe that people experienced difficulties in reporting their journeys at such detailed level. Furthermore, we asked for standard sociodemographic information on personal and household level in order to be as consistent as possible with the Swiss Mobility and Transport Microcensus 2015 for comparability and sample weighting reasons (ARE and FSO, 2017).

The second survey focused on the respondents' preferences and willingness to-pay for different means of transport. Given their stated journey in the first one, we constructed a discrete choice experiment to explore the trade-offs that respondents make between three long-distance alternatives (long-distance bus, car and public transport) by varying the travel time of the main mode, access/egress and waiting times, number of transfers, two comfort features (leg space and Wi-Fi availability) and travel costs. Note that we defined inter-city or inter-regional trains to be the main mode for public transport connections. Hence, local buses in cities could still be used as access and egress mode to inter-city trains. We use the terms "bus" and "long-distance bus" interchangeably in this study.

Based on the collected data we estimated demand models (Multinomial Logit (MNL) and Mixed Multinomial Logit (MMNL)) which allowed us to examine if respondents have strong preferences about their options and to reveal how sensitive individuals react to changes in attributes. In addition, we specifically focused on willingness-to-pay indicators for the different alternatives.

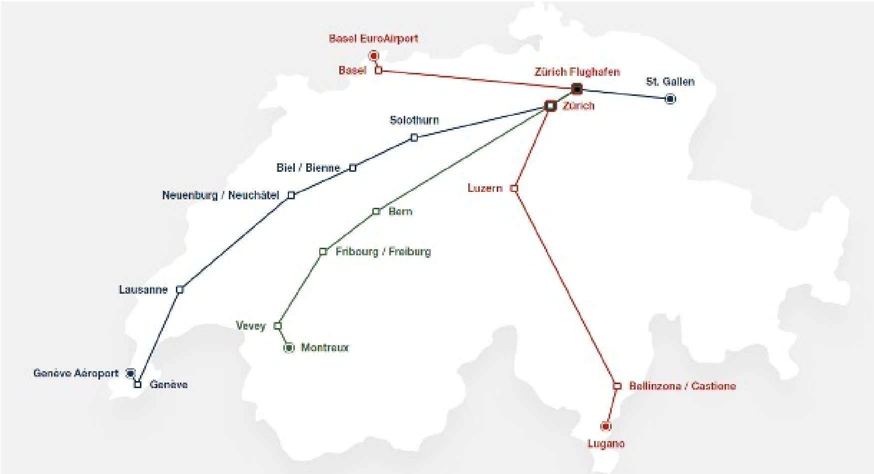
3.3.2 *Stated choice experiment*

The focus of this study involved the experimental design of the mode choice experiment presented to the respondents in the second survey, and specifically, the design of the underlying bus network. The idea was to use the reported trips of the participants as reference to construct an experiment as realistic as possible. Due to the high quality of the Swiss public transport network and the recent failure of a nationwide bus service, we constructed a fictional bus network which is assumed to be as competitive as possible in order to gain insights into the trade-offs people would make between car, long-distance bus and public transport (inter-city trains as the main mode) in such a setting.

3.3.2.1 *Bus network*

At the time of writing, there was no nationwide bus service in place that is directly embedded in the Swiss public transport schedule. The short-lived Eurobus (2018-2019) was established with three bus lines servicing a total of 18 bus stations along the Eastwest and Northsouth corridors in Switzerland (see Figure 3.1). The stations were mainly located at existing bus terminals that were close to train stations (e.g. Zurich, Geneva, Basel, Lucerne, Lausanne, St. Gallen), but also close to access and egress points of highways (e.g. Bern). Switzerland's major airports in Zurich, Geneva and Basel were also covered. Flixbus with its international bus line service was still providing bus connections with the onset of the COVID-19 pandemic in March 2020, even though at reduced frequency. In Switzerland, they only offered 19 out of 42 destinations until a complete shutdown in operation later on in 2020 (FlixBus has started servicing again in early 2021). In contrast to Eurobus they also serviced stops in smaller cities and villages in Switzerland. As a starting point for the bus station network, we georeferenced these bus stations. We then expanded it further to improve its competitiveness to the PT network, by adding a station in every Swiss city with more than 20'000 inhabitants that was not already serviced by either Eurobus or FlixBus, and some stations in specific Swiss municipalities without access to inter-city / inter-regional train connections. We assumed those extra bus stations to be within a reasonable walking distance (400 meters) of train stations. In the end, we constructed a bus network with 76 bus stations covering the most important Swiss cities, airports and bus stations (see Figure 3.2).

FIGURE 3.1: Eurobus service network in 2019



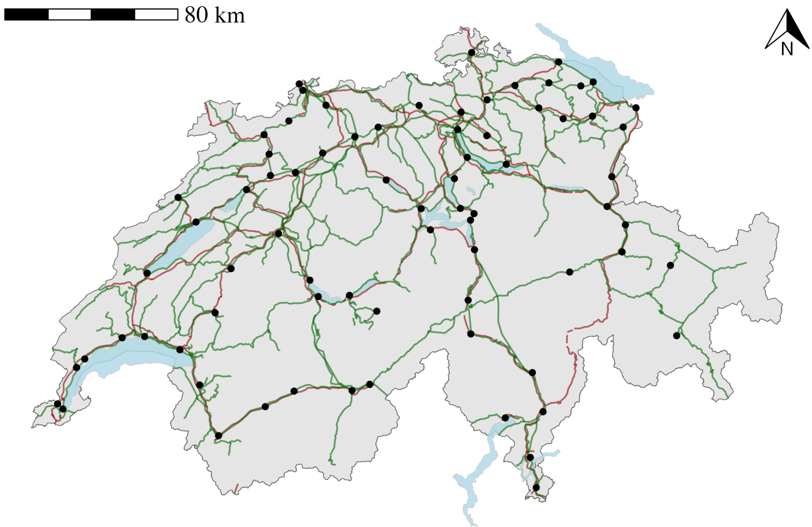
3.3.2.2 *Generation of non-chosen alternatives*

A major task in any discrete choice experiment is the generation of non-chosen alternatives. For example, if a respondent would have reported a long-distance trip by car from Zurich to Geneva, it's the analyst's task to calculate trip attributes (e.g. travel time, cost) for the same trip by a non-chosen mode. In our setting this would have been the generation of the corresponding trip attributes for bus and PT in order to construct a mode choice experiment with three alternatives available to every participant.

Since we had specific details of the respondents' long-distance trip (main mode, start and end location (i.e., the respondents could indicate the start and end location on a Google map), time of departure, weekday), we used these information to route all trips via Google API. While it seems straight forward to just let Google do the routing, it is necessary to mention a few assumptions that we made in that respect:

– Car routing: If eligible to drive, we assumed that respondents had a car available at the start location or in very close distance to it and that they would have a parking space available at the destination.

FIGURE 3.2: Assumed bus station network



- PT routing: We focused on PT connections with inter-city / inter-regional trains as main mode when it was available in order to get the fastest connection, even though people might have preferred a different route (the same holds for car routing). Access and egress modes could be any means of public transport (e.g., tram, trolley bus, regional train).
- Bus routing: We did not assume a specific bus schedule since this is not implemented in the Google API as a separate mode. Instead, for each trip, we matched the closest bus station to its start and end location, which results in a trip with three stages:
    1. Access to the bus start station from the trip start location.
    2. The actual bus trip from the bus start to the bus end station, routed as if it was car.
    3. Egress from the bus end station to the trip end location.

  Furthermore, we assumed walk and public transport modes as access and egress mode for the bus alternative and a specific bus headway in the experimental design. On the one hand, we acknowledge the limitation of this definition as it neglects car sharing/pooling options or simply a friends' or relatives' drop-off service. On the other hand, FlixBus claims that at least in Germany approximately 80% of their customers access bus stations by using means of public transport, which supports our assumption as Switzerland provides a great PT network (Kurth, 2018).

For a small number of trips it was not possible to get trip attributes with the collected data for different reasons:

– Start and/or end location was specified incorrectly on the Google map in the questionnaire (e.g. pin placed on water/on a mountain, etc.)

– No connection was found at the time of departure on a specified day of the week

– Due to the COVID-19 pandemic, certain PT connections were closed down and not available at the time of routing the trips (e.g., mostly regional bus connections for the long-distance bus (access and egress to it) and PT alternative)

To overcome this problem, we corrected falsely specified locations and time of departure issues manually. We changed such locations up to a point as close as possible where a connection could be found with Google API. For the departure time issue we tried to find a connection in the morning, afternoon or evening on the same day of week. Given the small number of such trips, such minor changes should not have significant impact on the preferences of participants.

3.3.2.3 *Experimental design*

A major goal of the study was to construct a personalised discrete choice experiment (DCE). Such a DCE is based on reported trips and makes use of individualised reference values as opposed to a standardised DCE that is based on a trip pre-defined by the analyst. We observed that approximately 73% of the participants in the first survey reported a long-distance trip (see Table 3.3 for a detailed overview). Another finding was that from 896 reported trips only 598 could be used for a personalised experiment, because those had a start and end location inside Switzerland, main mode was car/bus/PT and were longer than 50 kilometers crowfly distance.

Therefore, we decided to conduct a personalised and a standard DCE to achieve the envisaged sample size of 1,000.

In order to investigate peoples' preferences in choosing a mode for long-distance travelling it was necessary to take actual mobility tool ownership into account when constructing the DCE. We assumed that all three alternatives (bus, car and PT) were always available to all participants, but with different cost structures dependent on their mobility tools. If respondents had access to a car in their household (or upon consultation with a car owner in their household) we assumed marginal costs per kilometer of 0.27 CHF for a standard example car based on TCS (2020). Note that the marginal cost increased to 0.32 CHF in 2023 due to higher fuel costs. If no car was available, we assumed that people could rent a car for their trip with Mobility (2020) according to their pricing scheme which includes a variable time and a fixed distance component. Regarding PT ticket ownership, we distinguished between national season ticket (GA), half-fare ticket (HT) and full ticket prices for a specific trip. For the season ticket costs we followed ARE (2017) who converted a yearly cost of a GA into an average price per kilometer of 0.10 CHF, which we adjusted to current prices of about 0.12 CHF per kilometer. Full and half-fare costs as well as PT frequencies for each trip were calculated using the Multi-Agent Transportation Simulation (MATSim, (Horni *et al.*, 2016)) framework, which includes a module to calculate PT prices and frequencies. As we assumed three stages for a bus trip in our setting, the final price for a bus trip was given by a mixture of PT and bus prices. We inferred an average bus cost per kilometer of 0.10 CHF from bus tickets for different trips that were sold under the "Eurobus Swiss-Express" regime in the two previous years (Eurobus cooperated with FlixBus and used its online ticketing platform to sell tickets). This is in line with an assumption made by Von Arx *et al.* (2017) who analysed the potential of a national long-distance bus service in Switzerland in their report to the Swiss Federal Council. Since the "Eurobus Swiss-Express" was embedded in the Swiss PT schedule, GA owners could use the service for free (HT owners for half the price), but with a seat reservation for 5 CHF. We did account for that fee and added it to the final bus cost. Refer to Table 3.1 for an overview of the different cost structures assumed.

We implemented a D-efficient pivot design (Rose and Bliemer, 2009) for each experiment type in NGene (ChoiceMetrics, 2021). As mentioned above, the main difference between the two types is that the personal experiment is based on actual trips made by the participants whereas for the standard one we routed an example trip for five distance classes according to the

TABLE 3.1: Travel cost overview

Alternative	Mobility tool	Travel costs
Car	Own	0.27 CHF/km
Car	Rented	0.55 CHF/km (distance component)
		Best price (time component)*
PT	GA	0.12 CHF/km
PT	HT	Routed trip half-fare price
PT	-	Routed trip full price
Bus	-	0.10 CHF/km
Bus (access & egress)	PT: GA,HT,full	PT pricing scheme

* see Mobility (2020)

distance quantiles of observed trips in our survey sample. Both experiments account for car availability and PT season ticket ownership. Table 3.2 shows an overview of the main attributes and their levels used in our framework. In general, all travel time attributes (travel/access and egress/waiting) were calculated as described in Section 3.3.2.2. In order to present realistic choice situations to each participant, we applied a few restrictions:

– Since we did not assume a specific bus schedule, we defined four bus headway levels: Every 1, 2, 3 and 4 hours. This was a strong assumption, but can be seen as a competitive service level in comparison to the bus schedule that Eurobus had set up with two buses running per day for each line and direction (and a couple of direct city-to-city connections).

– We added 15 minutes to the waiting time at the start and end of the trip to account for possible delays due to lower bus speeds, but restricted the total waiting time to a maximum of 60 minutes.

The availability of Wi-Fi and more leg space (additional space of 10 cm) are incorporated as binary variables.

In summary, a respondent was faced with three alternatives in each choice situation - a car, a long-distance bus and a public transport connection. As mentioned above, for the PT alternative, the main mode was an inter-city

TABLE 3.2: Design specification and attributes

	Experiment	
Specification	P	NP
Choice situations	32	40
Blocks	4	5
Choices per respondent	8	8

	Experiment		Alternatives			Levels		
Attributes	P	NP	Bus	Car	PT	-	base	+
Cost (CHF)	x	x	x	x	x	-33%	0%	+33%
Travel time (h)	x	x	x	x	x	-33%	0%	+33%
Access & egress time (h)	x	x	x		x	-33%	0%	+33%
Waiting time (h)	x	x	x		x	-33%	0%	+33%
PT headway (h)	x	x			x	-33%	0%	+33%
Bus headway (h)	x	x	x				1-4	
Number of transfers (Nr.)	x	x	x		x	-1	0	+1
Wi-Fi (dummy)	x	x	x		x		0, 1	
More leg space (dummy)	x	x	x				0, 1	
Distance class (km)		x	x	x	x		1-5	

Note: P = personalized DCE, NP = non-personalized DCE

train. For both the PT and the bus alternative, walk and regional public transport (tram, métro, regional bus or train) were considered as access and egress modes to/from either a bus or train station.

3.3.3 *Modeling approach*

In the MMNL model formulation, the utility equations $V_{i,n,m,t}$ for alternative $i \in \{PT, C, B\}$ individual $n \in \{1, 2, ..., N\}$ in model component $m \in \{\text{RP, SP}\}$ and choice task $t \in \{1, 2, ..., T_n\}$ are given by:

$$\begin{aligned} V_{PT,n,RP,t} = & -\psi_{n,t} \log\Big(x^{tc}_{PT,n,RP,t} + x^{tt}_{PT,n,RP,t} VTT_{PT,n,t} + \\ & X^{LOS}_{PT,n,RP,t} WTP^{LOS}_{PT} \Big) \end{aligned} \tag{3.1}$$

$$\begin{aligned} V_{C,n,RP,t} = & \; \alpha_{C,RP} + S_{n,t}\kappa_{\alpha_C} + \eta_{\alpha_C,n} - \\ & \psi_{n,t} \log\Big(x^{tc}_{C,n,RP,t} + x^{tt}_{C,n,RP,t} VTT_{C,n,t} + \\ & X^{LOS}_{C,n,RP,t} WTP^{LOS}_{C} \Big) \end{aligned} \tag{3.2}$$

$$\begin{aligned} V_{PT,n,SP,t} = & \; \omega_{SP} \Big(-\psi_{n,t} \log\Big(x^{tc}_{PT,n,SP,t} + x^{tt}_{PT,n,SP,t} VTT_{PT,n,t} + \\ & X^{LOS}_{PT,n,SP,t} WTP^{LOS}_{PT} \Big) \Big) \end{aligned} \tag{3.3}$$

$$\begin{aligned} V_{C,n,SP,t} = & \; \omega_{SP} \Big(\alpha_{C,SP} + S_{n,t}\kappa_{\alpha_C} + \eta_{\alpha_C,n} - \\ & \psi_{n,t} \log\Big(x^{tc}_{C,n,SP,t} + x^{tt}_{C,n,SP,t} VTT_{C,n,t} + \\ & X^{LOS}_{C,n,SP,t} WTP^{LOS}_{C} \Big) \Big) \end{aligned} \tag{3.4}$$

$$\begin{aligned} V_{B,n,SP,t} = & \; \omega_{SP} \Big(\alpha_{B,SP} + S_{n,t}\kappa_{\alpha_B} + \eta_{\alpha_B,n} - \\ & \psi_{n,t} \log\Big(x^{tc}_{B,n,SP,t} + x^{tt}_{B,n,SP,t} VTT_{B,n,t} + \\ & X^{LOS}_{B,n,SP,t} WTP^{LOS}_{B} \Big) \Big) \end{aligned} \tag{3.5}$$

with:

- ω_m: Parameter to account for scale differences (error variance) between the two model components in pooled estimation (Hensher *et al.*, 1998); (RP = reference; ω_{RP} = 1)
- $\alpha_{i,m}$: Alternative-specific constant (PT = reference; $\alpha_{PT,RP}$ & $\alpha_{PT,SP}$ = 0)
- $S_{n,t}$: Vector of trip-specific and sociodemographic attributes as a shift on the ASC's
- κ_{α_i}: Vector of parameters for $S_{n,t}$
- $\eta_{\alpha_i,n}$: Random error component
- ψ_n: Scale parameter WTP attributes (see Equation 3.6)
- $x^{tc}_{i,n,m,t}$: Travel cost
- $x^{tt}_{i,n,m,t}$: In-vehicle travel time
- $VTT_{i,n}$: Vector of VTT parameters (see Equation 3.7)
- $X^{LOS}_{i,n,m,t}$: Vector of other level-of-service attributes (LOS), e.g., access and egress time, wait time, headway, number of transfers, WiFi availability and additional leg space
- WTP^{LOS}_i: Vector of WTP parameters

The pooled RP/SP model assumes a multiplicative error specification $U(V,\epsilon) = V \cdot \epsilon$ as defined in (Fosgerau and Bierlaire, 2009) and thereby allows for heteroscedastic errors across alternatives. The multiplicative specification can be written in the random utility framework with an additive error specification, where V (or part of it) is replaced by a logarithmic form $log(.)$. As in the additive case, identification requires the normalization of a parameter. In this framework, the parameter of travel cost $x^{tc}_{i,n,m,t}$ is normalized to -1 (Sillano and Ortúzar, 2005; Train and Weeks, 2005; Train, 2009) so that the other coefficients can be interpreted as willingness-to-pay indicators (i.e., mode-specific travel times $x^{tt}_{i,n,m,t}$ and a row vector of other LOS attributes $x^{LOS}_{i,n,m,t}$). $s_{n,t}$ is a row vector of sociodemographic characteristics and trip-specific attributes with an alternative-specific parameter vector $\kappa_{\alpha_{i,m}}$.

The scale coefficient is defined as the following function

$$\psi_n = exp\left(a_{log(\beta^{scale})} + b_{log(\beta_n^{scale})} r_U\right) \tag{3.6}$$

and accounts for individual heterogeneity in the error variance of the VTT and WTP parameters. It follows a log-uniform distribution according to $\beta^{scale} = exp(a + br_U)$ with uniform random draws $r_U \sim U(0, 1)$.

Based on a partworth analysis (Winkelmann and Boes, 2006) to evaluate the relative importance of each attribute in the utility function (see Figure 3.8), we focus on the modeling of unobserved heterogeneity in the value of travel time (VTT). The VTT is given by

$$\begin{aligned} VTT_{i,n} = exp\left(a_{log(\beta_i^{VTT})} + b_{log(\beta_{i,n}^{VTT})} r_U\right) \left(\frac{inc_n}{\overline{inc}}\right)^{\delta_{inc}} \\ \prod_z \left((\kappa_{i,z}^{VTT}) p_{z,n} + (1 - p_{z,n})\right) \end{aligned} \tag{3.7}$$

and follows a log-uniform distribution according to $\beta_i^{VTT} = exp(a + br_U)$ with uniform random draws $r_U \sim U(0, 1)$. The non-linear interaction allows the VTT to vary with a person's income according to parameter δ_{inc}. We expect a positive δ_i^{VTT}, indicating that the VTT marginally increase with higher personal income. Moreover, we incorporate person- and purpose-specific multipliers z on the VTT, $\kappa_{i,z}^{VTT}$ times a dummy for each $p_{z,n}$, to account for differences between two trip purposes (e.g., leisure, business and not-stated) and user characteristics (gender, age, and education). The WTP coefficients for all mode-specific LOS attributes are fixed across respondents and, as the VTT, also interacted with income.

The error components $\eta_{\alpha_i,n}$ account for unobserved heterogeneity in the errors between individuals and alternatives. Note that based on Walker and Ben-Akiva (2002), for identification reasons one error component (PT in our case) is normalized to zero.

Assuming that the random coefficients $\beta_{i,n}$ and η_{α_i} are mutually independent, $\epsilon_{i,n,m,t}$ is i.i.d. extreme value type I and θ is a set of fixed parameters, the likelihood of the sequence of choices for individual n is given by $L_n(\Omega, \Phi, \theta)$ (see Equation 3.8). This implies that sensitivities may vary across individuals, but stay constant within. The MMNL model is estimated by means of Maximum Simulated Likelihood (MSL) where the simulated log-likelihood (SLL, see Equation 3.11) is the probability of reproducing each choice in the sample. $\beta_{r,n}$ and $\eta_{r,n}$ give the r^{th} draw from $f(\beta|\Omega)$ and

$f(\eta|\Phi)$ for individual n. $i^*_{n,m,t}$ represents the individual's chosen alternative i in model component m and choice task t.

$$L_n(\Omega, \Phi, \theta) = \int_\beta \int_\eta \prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t}\left(i^*_{n,m,t}|\beta, \eta, \theta\right) f(\beta|\Omega)\, g(\eta|\Phi)\, d\beta\, d\eta \tag{3.8}$$

$$L(\Omega, \Phi, \theta) = \prod_{n=1}^{N} \int_\beta \int_\eta \left[\prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t}\left(i^*_{n,m,t}|\beta, \eta, \theta\right)\right] f(\beta|\Omega)\, g(\eta|\Phi)\, d\beta\, d\eta \tag{3.9}$$

$$LL(\Omega, \Phi, \theta) = \sum_{n=1}^{N} ln \left(\int_\beta \int_\eta \left[\prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t}\left(i^*_{n,m,t}|\beta, \eta, \theta\right)\right] f(\beta|\Omega)\, g(\eta|\Phi)\, d\beta\, d\eta\right) \tag{3.10}$$

$$SLL(\Omega, \Phi, \theta) = \sum_{n=1}^{N} ln \left(\frac{1}{R} \sum_{r=1}^{R} \left[\prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t}\left(i^*_{n,m,t}|\beta_{r,n}, \eta_{r,n}, \theta\right)\right]\right) \tag{3.11}$$

The models were estimated with 1'000 Sobol draws using R (version 4.2.0) and the Apollo package (version 0.2.9) on ETH's Euler compute cluster (Sobol, 1967; R Core Team, 2020; Hess and Palma, 2019).

3.4 RESULTS

3.4.1 *Study participation*

The first survey was conducted online using Qualtrics from September to December 2019, including two reminders for participants that had not filled it out after the first invitation by letter. The addresses were bought from a Swiss direct marketing provider following a sampling plan that accounted for a similar age and gender distribution of people living in the French- and German speaking regions according to the Swiss Federal Statistical Office (FSO). 1'231 people indicated to participate, which corresponds to a participation rate of 10.8% and was anticipated because of a relatively high response burden (approximately 1,450 with no prior recruitment of participants and an incentive of 10 CHF for completing both phases) according to Schmid and Axhausen (2019). In the main part we asked the participants to report a trip within the last two months at the time of filling out the survey, that was above 50 kilometer and inside Switzerland. 73% of 1'231 (896) respondents did make and report such a trip. However, as already mentioned in Section 3.3.2.3 we observed that 298 out of 896 trips did not meet these requirements. Hence, we could not present them a personalized discrete choice experiment (DCE). Therefore, we invited 598 participants for a personalized and 633 for a non-personalized DCE.

Table 3.3: Study participation

		Language:	German		French		Total	
Phase 1	Invitations		7,612	100%	3,804	100%	11,416	100%
	Responses		1,102		639		1,741	
	Participation		793	10.4%	438	11.5%	1,231	10.8%
	Long-distance trip reported	Yes	586	7.7%	310	8.2%	896	7.9%
		No	207	2.7%	128	3.3%	335	2.9%
Phase 2	Invitations	P	377		221		598	
		NP	416		217		633	
	Responses	P	353		174		527	
		NP	308		162		470	
	Participation		671	8.8%	336	8.8%	997	8.8%

Note: P = personalized DCE, NP = non-personalized DCE

The second survey was conducted from June to September 2020. Participants receiving a personalized DCE were specifically framed in a way that they knew the experiment was based on their trip and that a long-distance bus was introduced. An issue was the onset of the COVID-19 pandemic that hit Switzerland in March 2020 and could have affected peoples choices in the experiment probably towards the car alternative. We thought of explicitly framing the respondents such that they should try to not let their choice depend on the risk of being infected on a bus or on a train. Instead, we decided to not do so as it could introduce a change in behavior that we can and do not want to account for.

In the end we achieved the desired sample size of 997 respondents that completed both surveys, corresponding to an overall participation rate of 9%.

3.4.2 *Descriptive analysis*

Table 3.4 shows a comparison between the survey sample and the representative MCMT 2015 data as reference, which we filtered for participants living in French- and German-speaking cantons and trips longer than 50 kilometers. In general, our sample over-represents the youngest age cohort between 19 and 30 years of age, females and one-person households, while the other variables show similar shares. Note that there were participants that did not provide their personal income, which is why we imputed it using an Ordered Logit (OL) approach. In order to account for the slightly biased sample composition, we weighted model outcomes such as the VTT and elasticities post-estimation using Iterative Proportional Fitting (IPF) and the following variables: gender, age, household income, national season ticket ownership (GA), half-fare card (HT), driving license, household size and education level (Batley *et al.*, 2019).

Table 3.4: Sample comparison to the Swiss MTMC 2015

Variable	Value	% MCMT	% Sample
Age	19-30 years	21.2	28.3
	31-40 years	16.2	15.0
	41-49 years	21.8	16.7
	51-65 years	27.3	25.1
	66-81 years	13.5	14.9
Gender	female	41.1	48.9
	male	58.2	51.1
Education	compulsory education	14.9	4.7
	further education	52.0	67.3
	university	33.0	27.8
Occupation	employed	63.6	60.2
	student/apprentice	2.8	5.0
	unempl./household duties	30.5	11.0
	searching for job	0.7	2.8

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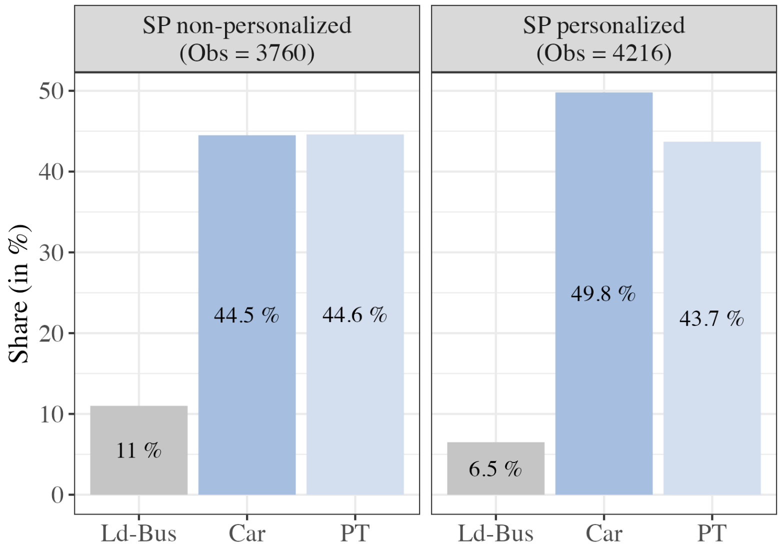
Table 3.4 – *Continued from previous page*

Variable	Value	% MCMT	% Sample
	retired	2.2	17.6
Drivers licence	yes	91.0	91.9
	no	9.0	8.1
PT season ticket (GA)	yes	19.8	17.4
	no	80.2	82.6
PT half-fare ticket (HT)	yes	39.2	52.8
	no	60.8	47.2
Household size	1	15.8	53.3
	2	37.8	18.1
	3	16.9	12.4
	4	20.5	10.8
	5	6.7	4.3
	>5	2.2	1.1
Household income	under 2,000 CHF	1.0	0.8
	2,001 - 4,000 CHF	5.5	5.5
	4,001 - 6,000 CHF	13.6	11.5
	6,001 - 8,000 CHF	15.6	18.3
	8,001 - 10,000 CHF	13.7	14.6
	10,001 - 12,000 CHF	12.1	13.3
	12,001 - 14,000 CHF	7.0	8.3
	14,001 - 16,000 CHF	6.3	6.8
	more than 16,000 CHF	10.3	8.6
	not provided	15.0	12.1

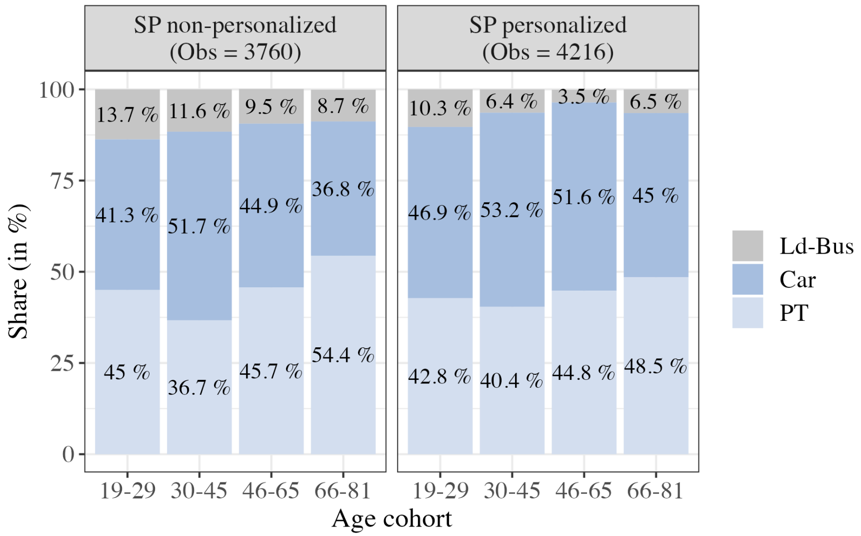
Figure 3.3 shows an overview of the overall choice frequencies by experiment type. In both experiment types the bus alternative was chosen the least, indicating a market share of 6.5% and 11% in the personalized and non-personalized settings respectively, and 8.5% overall. Car and PT were chosen equally often in the non-personalized experiment compared to a slightly increased choice frequency for car in favour of the bus in the personalized experiment. This suggests that cars and PT act more like substitutes for long-distance travelling than bus and PT. Note that the shares presented are an artifact of the experimental design and should always be treated with caution.

FIGURE 3.3: Choice frequencies by experiment type



However, looking at different age cohorts (Figure 3.4) and levels of personal income (Figure 3.5) provide first insights into the respondents' preferences. As expected, and already pointed out by Von Arx *et al.* (2017) in their analysis, young and low income people were more prone to choose a bus in their settings than older and richer respondents. Again, these effects seem to be more pronounced in the non-personalized experiment. It is noticeable that the car was the most chosen mode of transportation across all age cohorts, except for the oldest participants. This pattern is not apparent when it comes to the influence of income. For both experiment types, the lowest income group chose PT more often than car.

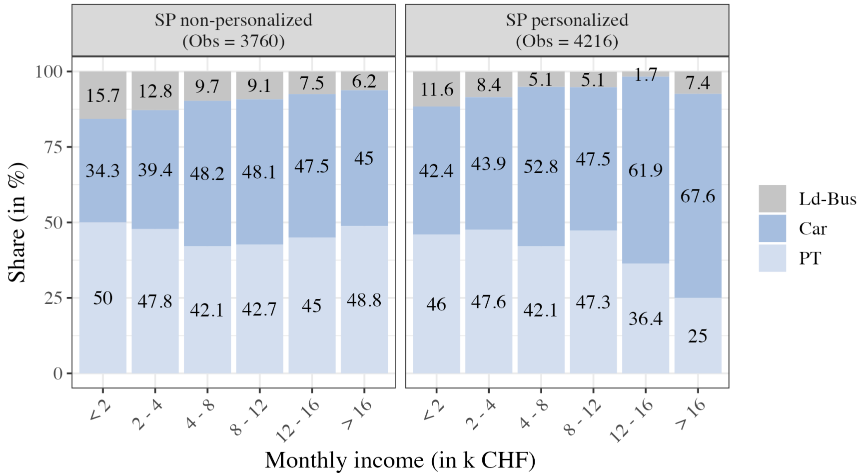
FIGURE 3.4: Choice frequencies by age cohort and experiment type



In general, in the standard experiment the participants showed a substantially greater willingness-to-trade between the alternatives (32.1% vs. 18.8%) as can be inferred from Figure 3.6. Approximately a third of all participants chose all three available alternatives at least once in 8 choice situations, compared to 18% with personal experiments. This result is in line with findings in the literature where people show less inertia in experiments that are not based on revealed-preference (RP) data since they are not restricted to their own trip when choosing an alternative. This might be a reason why people chose bus more frequently in the non-personalized experiment. A closer look at the personal setting offers a more distinguished way to examine changes in the choice behavior.

Figure 3.7 shows that people who reported a car trip in phase one in general show a lower willingness to choose other modes in the SP experiment. 34% of RP car users always chose car compared to 23% of RP PT users that always chose PT in the experiment. Interestingly, RP PT users tend to choose bus more often for four and more times than RP car users. They also show greater willingness to choose a car than car users

Figure 3.5: Choice frequencies by income group and experiment type



do to choose PT. To examine the influence of non-trading (i.e., inconsistent behavior) on the model results, we estimated initial MNL models for only traders and all respondents correspondingly. In the end we decided to not exclude non-traders for the following reasons. First, the model performance was not substantially different between both models, although slightly better when excluding non-traders. However, we could observe smaller market shares for bus. Second, the differences in the VTT were only minor. Last but not least, the order of the VTT among the alternatives did not change, indicating stable preference relations.

FIGURE 3.6: Trading behavior of alternatives by experiment type

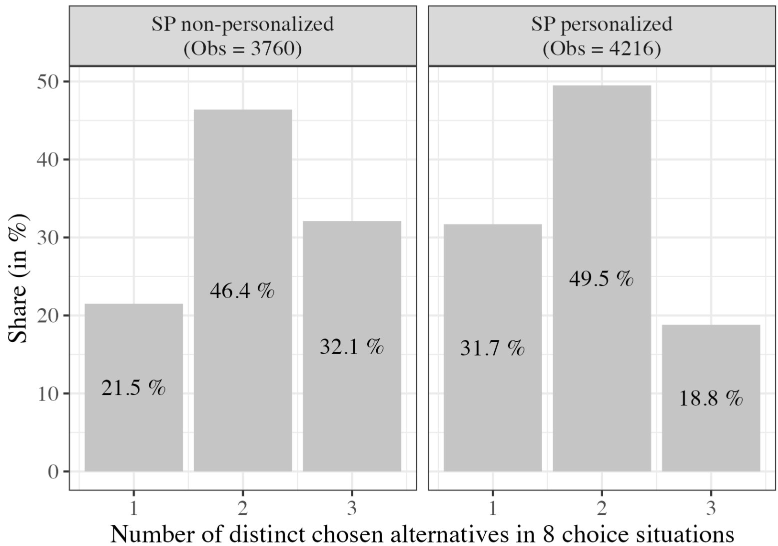
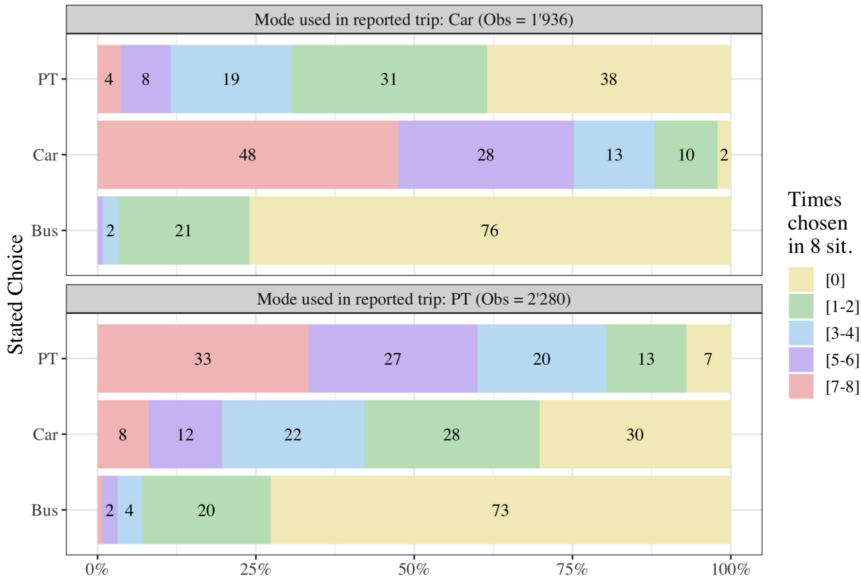


FIGURE 3.7: Trading behavior in the personal experiment



3.4.3 *Model results and discussion*

To investigate the importance of each choice attribute in the utility function, a partworth analysis was conducted based on a simple MNL model (estimated in preference space and not shown in Table 3.5) that only includes the main effects of the attributes presented in Section 3.3.2.3 and a scale parameter specific to each experiment type. The average partworth of choice attribute $X_{k,i}$ is defined as

$$VI_{k,i} = |\widehat{\theta}_{k,i}| \cdot \overline{X}_{k,i} \tag{3.12}$$

where the absolute value of the estimated parameter $|\widehat{\theta}_{k,i}|$ is multiplied with the sample mean of the corresponding variable, $\overline{X}_{k,i}$. Figure 3.8 shows that the mode-specific travel times exhibit the highest importance in explaining choice behavior, closely followed by travel costs (generic parameter; averaged over alternatives). This was an important criterion before specifying the utility functions of the more complex models, such that we mainly focus on the modeling of deterministic and random heterogeneity in the VTT (and, of course, the ASC and scale coefficient). Furthermore, it shows that the remaining LOS attributes (access and egress time, headway, transfers and waiting time) for bus tend to show a slightly higher partworth than for PT, indicating that ceteris paribus, the bus features were perceived as more important in the decision process. WiFi availability in both modes is perceived as the least important attribute, which can be also explained by the nowadays widely available, relatively cheap flat rate data packages.

Figure 3.8: Partworth analysis based on a simple MNL

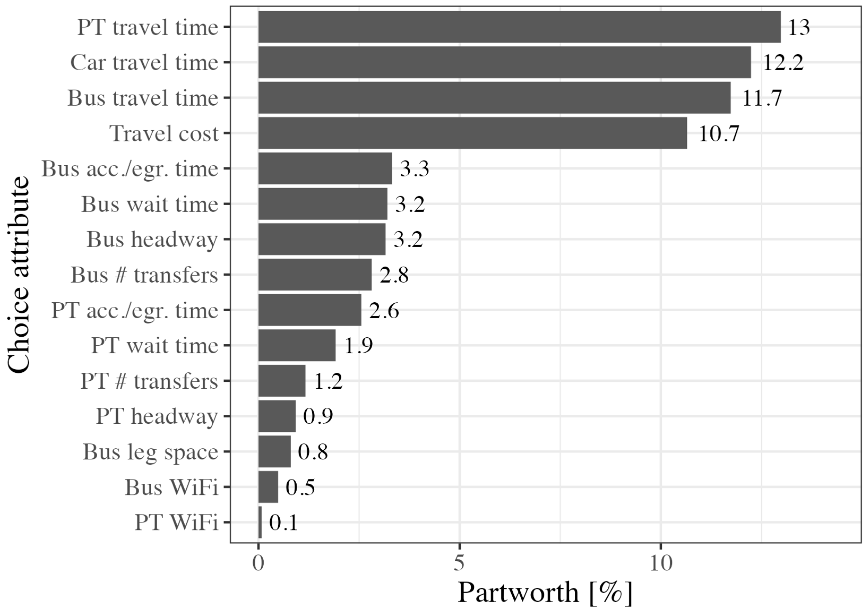


Table 3.5: Estimation results

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Scale model component						
SP ω_{SP}	0.981	(−0.192)	1.802	(3.938)	1.782	(3.941)
ASC, EC and ASC shift						
ASC car $\alpha_{C,RP}$ (fixed)	0.145	(0.428)				
ASC car $\alpha_{C,SP}$ (fixed)	1.308	(3.749)				
ASC car $\mu_{log(\alpha_{C,RP})}$			−0.741	(−1.898)	−0.782	(−2.018)
ASC car $\mu_{log(\alpha_{C,SP})}$			0.269	(0.734)	0.231	(0.627)
EC car η_{α_C}			1.110	(7.938)	1.159	(8.457)
ASC car shift business	−0.080	(−0.481)	1.307	(1.981)	1.098	(1.548)
ASC car shift trip-na	0.281	(2.166)	0.085	(0.238)	0.029	(0.071)
ASC car shift sub-urban	0.327	(2.472)	0.397	(2.950)	0.404	(2.883)
ASC car shift rural	0.324	(2.259)	0.285	(2.096)	0.295	(2.135)
ASC car shift male	0.385	(3.381)	0.158	(0.377)	0.345	(0.943)
ASC car shift age mid	−0.102	(−0.853)	−0.277	(−0.820)	−0.263	(−0.741)
ASC car shift age high	−0.580	(−2.640)	0.136	(0.248)	0.099	(0.157)

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Table 3.5 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
ASC car shift unemployed	0.233	(1.322)	0.238	(1.343)	0.219	(1.213)
ASC car shift inc. high	0.300	(1.617)	0.373	(1.918)	0.361	(1.896)
ASC car shift french	0.008	(0.073)	0.066	(0.625)	0.073	(0.683)
ASC bus $\alpha_{B,SP}$ (fixed)	−0.110	(−0.160)				
ASC bus $\mu_{log(\alpha_{B,SP})}$			−0.442	(−0.712)	−0.572	(−1.070)
EC bus η_{α_B}			−0.615	(−2.941)	−0.646	(−3.725)
ASC bus shift business	−0.005	(−0.022)	0.297	(0.706)	0.123	(0.252)
ASC bus shift trip-na	0.241	(1.438)	−0.213	(−0.535)	−0.232	(−0.569)
ASC bus shift sub-urban	0.033	(0.182Z	0.085	(0.593)	0.100	(0.683)
ASC bus shift rural	0.278	(1.511)	0.250	(1.748)	0.269	(1.854)
ASC bus shift male	0.029	(0.199)	−0.191	(−0.625)	−0.152	(−0.481)
ASC bus shift age mid	−0.496	(−2.944)	−0.393	(−1.165)	−0.368	(−1.044)
ASC bus shift age high	−0.465	(−1.239)	0.909	(1.752)	0.899	(1.734)
ASC bus shift unemployed	−0.107	(−0.361)	0.034	(0.158)	0.025	(0.120)
ASC bus shift inc. high	0.103	(0.380)	0.094	(0.467)	0.110	(0.542)
ASC bus shift french	0.239	(1.569)	0.252	(2.118)	0.259	(2.168)

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Table 3.5 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
VTT & multipliers						
PT β^{VTT} (fixed)	17.800	(11.296)				
PT $\mu_{log(\beta^{VTT})}$			3.164	(20.846)		
PT $\sigma_{log(\beta^{VTT})}$			0.267	(6.969)		
PT $a_{log(\beta^{VTT})}$					2.718	(15.035)
PT $b_{log(\beta^{VTT})}$					0.907	(6.519)
PT multiplier business			0.812	(−1.400)	0.865	(−0.890)
PT multiplier trip-na			1.177	(1.110)	1.204	(1.210)
PT multiplier male			1.154	(1.170)	1.118	(0.980)
PT multiplier age mid			1.126	(0.820)	1.107	(0.720)
PT multiplier age high			0.832	(−1.000)	0.818	(−1.220)
PT multiplier educ. high			0.996	(−0.050)	0.990	(−0.110)
Car β^{VTT} (fixed)	31.255	(12.711)				
Car $\mu_{log(\beta^{VTT})}$			3.446	(27.441)		
Car $\sigma_{log(\beta^{VTT})}$			0.128	(1.847)		
Car $a_{log(\beta^{VTT})}$					3.363	(16.569)
Car $b_{log(\beta^{VTT})}$					0.150	(0.500)

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Table 3.5 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Car multiplier business			1.494	(1.440)	1.444	(1.230)
Car multiplier trip-na			1.052	(0.440)	1.041	(0.330)
Car multiplier male			1.030	(0.200)	1.081	(0.570)
Car multiplier age mid			0.989	(−0.090)	0.984	(−0.120)
Car multiplier age high			1.160	(0.760)	1.125	(0.520)
Car multiplier educ. high			1.103	(1.260)	1.094	(1.120)
Bus β^{VTT} (fixed)	24.805	(5.291)				
Bus $\mu_{log(\beta^{VTT})}$			3.373	(13.140)		
Bus $\sigma_{log(\beta^{VTT})}$			−0.429	(−4.335)		
Bus $a_{log(\beta^{VTT})}$					2.661	(13.719)
Bus $b_{log(\beta^{VTT})}$					1.385	(5.255)
Bus multiplier business			0.980	(−0.080)	0.935	(−0.270)
Bus multiplier trip-na			0.933	(−0.350)	0.935	(−0.340)
Bus multiplier male			1.034	(0.210)	1.015	(0.090)
Bus multiplier age mid			1.134	(0.610)	1.129	(0.560)
Bus multiplier age high			1.844	(1.820)	1.801	(1.690)
Bus multiplier educ. high			1.003	(0.030)	0.990	(−0.080)

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Table 3.5 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Income elasticity VTT δ_{inc}	0.092	(2.356)	0.105	(2.423)	0.108	(2.564)
WTP LOS attributes						
PT access/egress time	15.623	(6.150)	24.155	(8.181)	24.237	(8.032)
PT wait time	15.698	(4.734)	23.202	(6.524)	23.231	(6.330)
PT headway	0.479	(0.209)	1.678	(0.682)	1.411	(0.568)
PT # transfers	0.579	(1.183)	1.449	(2.566)	1.389	(2.505)
PT WiFi availability	−1.893	(−2.384)	−1.782	(−2.141)	−1.756	(−2.100)
Bus access/egress time	22.507	(3.620)	29.379	(4.842)	28.030	(5.548)
Bus wait time	19.364	(2.638)	21.747	(2.933)	21.552	(2.972)
Bus headway	3.648	(3.263)	3.882	(4.280)	3.749	(4.349)
Bus # transfers	7.494	(3.572)	7.278	(4.446)	7.044	(4.230)
Bus WiFi availability	−2.353	(−1.001)	−0.895	(−0.390)	−0.700	(−0.327)
Bus leg space	−7.116	(−2.876)	−6.341	(−2.701)	−6.079	(−2.831)
Scale parameter VTT & WTP						
β^{scale} (fixed)	−4.509	(−9.898)				

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Table 3.5 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
$\mu_{log(\beta^{scale})}$			1.407	(12.753)		
$\sigma_{log(\beta^{scale})}$			0.475	(9.337)		
$a_{log(\beta^{scale})}$					0.629	(4.165)
$b_{log(\beta^{scale})}$					1.551	(9.135)
LL(0,RP)	-365.289		-365.289		-365.289	
LL(final,RP)	-277.066		-283.283		-283.121	
LL(0,SP)	-8762.532		-8762.532		-8762.532	
LL(final,SP)	-5447.598		-4503.189		-4501.665	
LL(0,model)	-9127.820		-9127.820		-9127.820	
LL(final,model)	-5724.664		-4757.811		-4756.410	
Adj. rho squared (model)	0.373		0.479		0.479	
# respondents	997		997		997	
# observations	8503		8503		8503	
# parameters	43		67		67	
# draws	0		1000		1000	

Three models are presented in Table 3.5. The first model (MNL) contains all mode-specific attributes and user characteristics as shifts on the ASC. The second model (MMNL 1) adds all random parameters, i.e., random continuous coefficients as well as random error components. While MMNL 1 assumes log-normally distributed WTP and scale parameters, the third model (MMNL 2) assumes log-uniformly distributed ones as explained in Section 3.3.3. Many model specifications were tested at the beginning. The most promising specification in terms of model fit and VTT was the multiplicative error specification. It exhibits the best fit as well as interesting differences in the VTT values between the modes, which will be discussed below. To account for potential nesting structures between the three alternatives, we tested Cross-Nested MNL and MMNL specifications. Importantly, we could not find significant evidence for any nesting structure. Taking random heterogeneity into account shows a significant improvement in model fit ($LL(0, model)$) increases more than 900 units going from MNL to either of the two MMNL models), which indicates that a substantial amount of the heterogeneity in behavior is related to unobserved factors as all random parameters are significant, but for the spread in the car VTT ($b_{log(\beta^{VTT})}$, MMNL 2). In order for the MMNL models to converge successfully and consistently, we used the starting value search algorithm proposed by Bierlaire *et al.* (2009) that was implemented in the Apollo package by Hess and Palma (2019).

We included mode- and person-specific shifts on the ASC in order to account for deterministic heterogeneity in the models (see section *ASC, EC and ASC shift* in Table 3.5). For shifts on the car ASC, we observe positive effects on the probability to choose a car for respondents living in rural and sub-urban municipalities. It seems intuitive as people more often rely on cars in areas where PT does not provide as good of a service. Also, male and high income (earning more than 9'000 CHF/month) individuals were more prone to choose a car relative to PT. As for shifts on the bus ASC, the only positive and significant effects can be seen for people living in rural municipalities and such that speak French. The latter might be related to the fact the PT network in the French-speaking part of Switzerland generally is not as well as established compared to the German-speaking part according to the Swiss Federal railways. However, this finding should be treated with caution since there are French-speaking people living in the German-speaking part of Switzerland and vice versa. The error components included in the utilities for both car and bus show that there also is random heterogeneity present in the error terms. As such, this simply suggests that omitted factors influence the decision process as well.

For all models presented, the coefficients of LOS attributes (see section *WTP LOS attributes* in Table 3.5) show the expected signs and are consistent (i.e., have the same signs) between them. Except for PT headway and Bus WiFi availability, all coefficients are statistically significant at the 5% level. However, for both PT and bus, access/egress time and wait time increase substantially in the MMNL models. The fact that the WTP for bus access/egress time is higher than for PT might be related to the assumed bus station network. Since we assumed much more sparsely distributed bus stations compared to the generally dense Swiss PT network, access/egress to and from a bus station takes comparatively longer. People may tend to be more sceptical with the bus service, such that the attributes need to exhibit a substantial improvement in order to be chosen. Interestingly, the difference between the estimates for PT access and egress time and the mean VTT in MNNL 2 (in-vehicle time) is smaller for PT than for bus (PT: 2.5 CHF/h; bus: 7.5 CHF/h). This might be pinned down to the fact that for the bus alternative we assumed PT as the access and egress mode. As such, the difference between the estimates mentioned before could be explained due to the perceived differences in the assumed modes for access and egress (PT) and in-vehicle time (bus). At least for the bus, this finding contradicts De Lapparent *et al.* (2013), who found WTP estimates for access and egress times being at least as large as VTT estimates for in-vehicle travel times in their paper about international long-distance travel. When comparing the headway of PT to bus in MMNL 2, we observe a higher WTP for the latter (bus: 3.7 CHF/h; PT: 1.4), which intuitively makes sense. Even though we assumed a competitive bus service, the headway levels for PT are obviously lower, given the high quality of the Swiss PT network. Similarly, the PT transfers are valued substantially lower than for bus (1.4 CHF/h vs. 7.0 CHF/h). The WTP for WiFi availability is only significant for PT (1.7 CHF), while additional leg space (i.e., increased comfort) in the bus is valued by about 6.1 CHF.

The scale coefficients β^{scale} are significant in all models presented (see section *Scale parameter VTT & WTP* in Table 3.5). For both MMNL models, we observe significant random scale heterogeneity. An interaction with distance was tested, but turned out to have no substantial effect, and was insignificant as well, probably because of the multiplicative error specification that already accounts for the range in the trip distances modeled.

To examine the mode-specific VTT and multipliers (see section *VTT & multipliers* in Table 3.5), we used the unconditional posterior distribution that includes the draws and hence accounts for uncertainty around the mean, instead of using the conditional posterior means which ignores part of the heterogeneity. By definition, the value of travel time is the extra cost that a person would be willing to incur to save one unit of time (Train, 2009). A higher VTT generally indicates a larger discomfort when traveling with that mode if user effects (i.e., sociodemographic effects) are controlled for. Figure 3.9 shows the distribution of the derived VTT for all modes. We then used sample enumeration in order to get a meaningful population weighted average for the VTT as shown in Table 3.6 (Batley *et al.*, 2019).

TABLE 3.6: Summary of VTT values for each model

MNL								
Mode	W. mean	Mean	Sd	P0	P25	P50	P75	P100
Bus	24.04	24.10	2.23	18.54	23.32	24.45	25.22	27.38
Car	30.29	30.37	2.81	23.36	29.39	30.81	31.78	34.50
PT	17.25	17.30	1.60	13.30	16.74	17.54	18.10	19.65
MMNL 1								
Mode	W. mean	Mean	Sd	P0	P25	P50	P75	P100
Bus	75.85	37.93	20.65	3.34	23.72	33.19	46.71	384.68
Car	72.45	36.22	9.58	12.99	29.84	34.62	40.71	105.00
PT	54.28	27.14	9.24	5.43	20.49	25.77	32.27	112.71
MMNL 2								
Mode	W. mean	Mean	Sd	P0	P25	P50	P75	P100
Bus	35.53	35.52	17.37	9.42	21.96	31.75	45.42	117.10
Car	35.82	35.81	8.25	20.22	30.84	34.41	39.22	70.15
PT	26.69	26.79	8.74	9.23	20.06	25.42	32.47	62.11

In the simple MNL model, there is a clear order and difference in the VTT between PT, bus and car. PT exhibits the lowest VTT (17.3 CHF/h), followed by bus (24.0 CHF/h) and car (30.29 CHF/h). As already mentioned before, in comparison to a model without multiplicative errors (not shown in Table 3.5), these values were all very close to each other at about 30 CHF/h. However, once we account for random heterogeneity in individual sensitivities, only the median VTT for bus and cars seem to be more similar, and definitely higher compared to the MNL model (see Subfigure (b) in Figure 3.9). The VTT for PT increased as well. Apparently, when looking at Subfigure (a) in Figure 3.9, the spread in the VTT for MMNL 1 and 2 shows that there is substantial heterogeneity in all mode-specific VTT, which on top highly depends on the distributional assumption taken. Assuming log-normally distributed VTT in MMNL 1 lead to very high valuations for all modes, which is most pronounced for the bus and seems unreasonably high for some observations. Log-uniformly distributed VTT in MMNL 2 do not show such high valuations in general, but also show that the range in VTT for bus is much bigger, similarly to MMNL 1. Another issue that arises when comparing VTT distributions is that if only medians (see *P50* in Table 3.6) were compared, one could conclude that there is not much of a difference between the two MMNL models, since the median is more robust to outliers than the mean. In fact, the weighted mean of the VTT reveals substantial differences. The valuations for all modes are more than twice as high in MMNL 1 compared to MMNL 2 (see *W. mean* in Table 3.6), whereas for the latter weighting only barely affects the VTT. Interestingly, and as pointed out above, there does not seem to be random heterogeneity associated with the VTT for car in MMNL 2, while there is for MMNL 1, although rather small. A possible reason might be that for log-uniformly distributed VTT, extreme valuations for car were not estimated and hence there is not enough evidence for random heterogeneity.

These results have three important implications: (i) Similar to many recent studies that found a considerably high mode effect (i.e. positive VTT difference between car and PT; see e.g. VSS Norm (2009), Bogenberger *et al.* (2021) and Schmid *et al.* (2021)), our findings indicate that this also seems to be the case for long-distance travel within Switzerland. The weighted mean VTT for PT is roughly 9 CHF/h smaller than the one for car and bus. The mode effects often found in favor of PT – either due to a relatively high perception of comfort, the possibility to use travel time productively or strategic/self-selection issues – seem to persist under the given circumstances. Nevertheless, there are also studies that did not find such mode effects (while also including shorter trips than 50km). For example the German valuation study from 2012 (VTT car: 5.8 CHF/h; VTT PT: 6 CHF/h;

Axhausen *et al.* (2014)), the Dutch study in 2010 (car: 11.8 CHF/h; bus: 8.9 CHF/h; train: 12.1 CHF/h; Kouwenhoven *et al.* (2014)) as well as the most recent Swiss valuation study in 2015 (car: 13.2 CHF/h; PT: 12.2 CHF/h; Weis *et al.* (2021)).[1] (ii) While many previous studies have shown increasing VTT for longer distances (in the case of Switzerland, see VSS Norm, 2009; ARE, 2017; Axhausen, 2004; Weis *et al.*, 2017, 2021), this is not the case when focusing on long-distance trips. However, we observe a positive income elasticity on the VTT and WTP ($\delta_{inc} = 0.108$). (iii) The hypothetically introduced bus service is perceived worse than PT, but similar to car in terms of VTT and hence shows no improved quality/perception of travel compared to PT.

Mode- and user-specific multipliers (Hess *et al.*, 2017) are included in the MMNL models to account for differences in VTT between men/females, different age cohorts, high education levels as well as leisure/business trips. Even though the multipliers are very similar and consistent between the two models, none of the coefficients is significant at the 5% significance level, which simply shows that there is uncertainty present. Still, they show differences in VTT for the modes considered. With respect to the bus VTT, we observe higher valuations for people between 30 – 64 (+ 13%) and 65 – 81 (+ 80%) years of age using 19 – 29 as the base, while there is no substantial difference between male and female respondents. Business trips are valued 7.5% lower than leisure trips. For the car VTT, however, business trips are valued substantially higher than leisure trips (+ 44%).

The own- and cross-elasticities ($E_{i,k}$ and $E_{ji,k}$) for the MMNL 2 model presented in Table 3.7 show the average responsiveness of choice probabilities (i.e., %-changes) to a change in choice attribute $X_{k,i}$ while keeping all other attributes fixed (see e.g. Winkelmann and Boes, 2006). We approximate the derivative of the choice probability with respect to a variable of interest by taking the difference between the simulated a-priori ($\overline{P}_{i,k}$) and ex-post ($\overline{P}_{i,k^*}$) probabilities after an increase in that variable, conditional on the estimated parameters.

$$E_{i,k} = \frac{\text{\%-change in } P_i}{\text{\%-change in } X_{k,i}} = \frac{\dfrac{\overline{P}_{i,k^*} - \overline{P}_{i,k}}{(\overline{P}_{i,k} + \overline{P}_{i,k^*})/2}}{\dfrac{\overline{X}_{k^*,i} - \overline{X}_{k,i}}{(\overline{X}_{k,i} + \overline{X}_{k^*,i})/2}} \tag{3.13}$$

1 Inflation-adjusted 2015 prices; 1 CHF = 0.83 Euro.

As already indicated in the partworth analysis, Table 3.7 shows that mode-specific travel time and cost exhibit the largest elasticities. Except for bus travel time ($E_{i,k}$ = −1.45), however, all own elasticities are below one indicating an inelastic response pattern. In other words, travel time tends to be the most critical factor when introducing an new long distance bus service in Switzerland, being primarily attractive in case of higher relative speeds. When looking at the elasticities in the SP dataset (where the new bus service is introduced), all values for car and PT are consistent with the RP dataset but tend to be higher, which may be related to the hypothetical setting. Clearly, while SP data should not be used for real-world forecasting (e.g. Glerum *et al.*, 2013), results give insights into respondents' trade-off behavior after the introduction of a bus as a new mode alternative for long-distance travel.

FIGURE 3.9: Overall VTT distribution (a) and zoom-in (b)

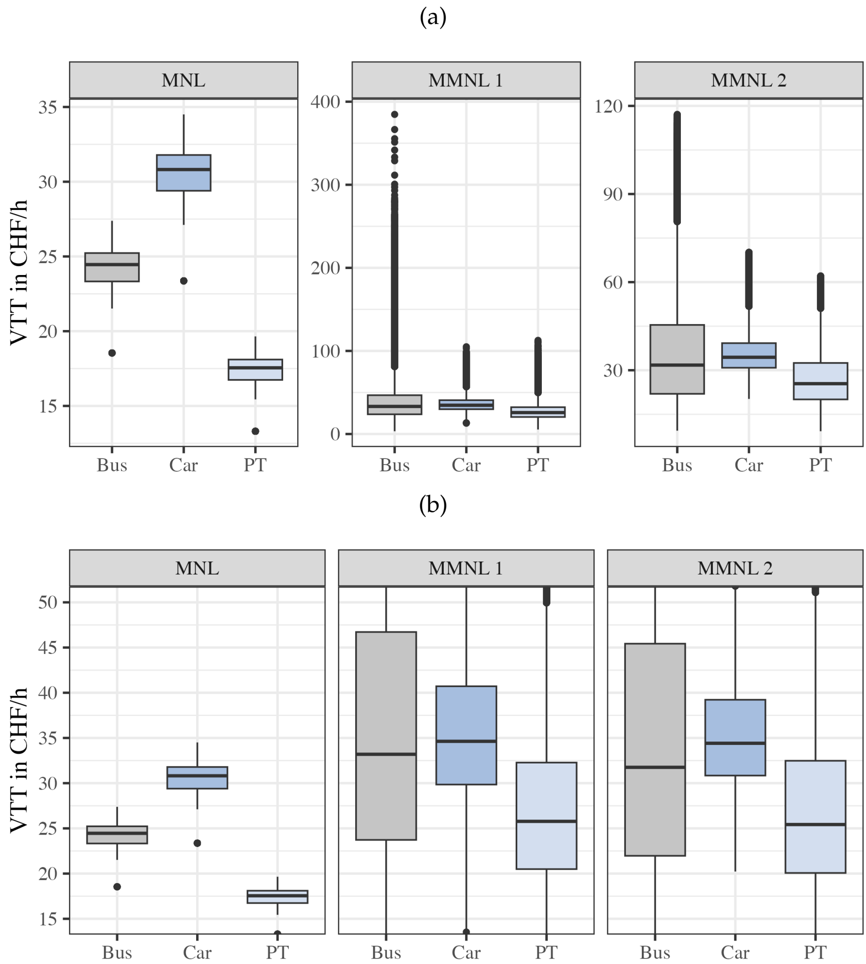

TABLE 3.7: Elasticities $E_{i,k}$ and $E_{ji,k}$ (MMNL 2)

Variable	Model component	Bus	Car	PT
Car travel time	RP		−0.83	0.74
Car travel cost	RP		−0.54	0.48
PT travel time	RP		0.57	−0.52
PT access/egress time	RP		0.17	−0.16
PT wait time	RP		0.13	−0.12
PT # transfers	RP		0.06	−0.05
PT travel cost	RP		0.43	−0.39
Variable	Model component	Bus	Car	PT
Bus travel time	SP	−1.45	0.12	0.17
Bus access/egress time	SP	−0.38	0.03	0.04
Bus wait time	SP	−0.30	0.03	0.04
Bus travel cost	SP	−0.78	0.07	0.09
Car travel time	SP	0.91	−0.91	0.81
Car travel cost	SP	0.63	−0.60	0.53
PT travel time	SP	0.95	0.55	−0.82
PT access/egress time	SP	0.15	0.13	−0.18
PT wait time	SP	0.12	0.09	−0.13
PT # transfers	SP	0.06	0.05	−0.07
PT travel cost	SP	0.68	0.40	−0.59

3.5 CONCLUSION

This chapter presents a comprehensive investigation of peoples' mode choice preferences for long-distance travel in Switzerland. It aims to examine the change in choice behavior if there was a competitive long-distance bus service within a liberalised Swiss transport market where car and PT traditionally are the dominating modes.

Based on the assumptions made, the choice model applied estimates a hypothetical market share of approximately 8.5% for such a bus service. However, given the Swiss context and the regulatory restrictions, a bus provider with a similar level of service as assumed in this study would probably never be given a concession by the Federal Office of Transport since it would be deemed as a direct competition for PT rather than a complement. Moreover, the study does not account for travel time reliability of such a bus service and neglects the lower speed of those vehicles. The inelastic demand pattern underpins the challenge for a new bus provider to enter the market, even with a dense bus station network and a dedicated schedule. Consequently, it is reasonable to conclude that the estimated market share likely represents an upper limit.

The MMNL model contributes valuable insights into preferences concerning the choice between a car, PT and a long-distance bus. It confirms prior research findings indicating that long-distance buses mainly attract younger individuals who are particularly price-sensitive. On the one hand, the descriptive results suggest that current PT users are more willing to choose a bus compared to current car users, which would imply potential substitution effects between bus and PT. On the other one, the derived VTT show clear mode-effects in favour of PT. While there is substantial unobserved heterogeneity associated with the VTT of bus and PT, the valuation of car seems to be unaffected. Nonetheless, the VTT for bus seems to be primarily influenced by unobserved heterogeneity among the three modes. Furthermore, the observed VTT values for long-distance travel appear to be generally higher compared to the findings of other value of time studies conducted in Switzerland, which predominantly focus on shorter trip distances. However, when examining journeys exceeding 50 km within Switzerland, distance was not found to have a significant influence on these estimates.

In line with many other studies, in-vehicle travel time and travel cost were found to be the main drivers in the decision to choose a mode. For both the bus and PT, the access and egress time as well as wait time play a bigger role than the corresponding headway and number of transfers. The WTP for all those factors is generally higher for the bus, which can be attributed to the high quality of the Swiss PT network and the fact that people are more familiar with the quality of an existing rather than a hypothetical alternative. Concerning the comfort features included for bus, additional leg-space is valued similarly to having one transfer less on the trip.

Of course, every study comes with limitations, and so does this one. The study does not account for tourists and hence presumably lacks an important share of demand for a long-distance bus service. With respect to other comfort features, crowding in PT was not accounted for, but is known to have an influence on the VTT. Thus, the mode-effect in favor of PT might not be as large as estimated. The scope of the study is confined to Switzerland, and the results can clearly not be generalized to other countries or international long-distance travel in general.

For future work, the study design presented could easily be extended to Europe, for example, and could also include other modes such as airplanes. In terms of modeling, it would be very interesting to account for personal attitudes towards the different modes, different transport policies and how they affect mode choice under these circumstances.

4

INVESTIGATING THE PREFERENCES FOR THE USE OF URBAN RIDEPOOLING

The chapter is adapted from the following publication:

– Schatzmann, T., F. Zwick and K.W. Axhausen (2023) Investigating the preferences for the use of urban ridepooling, paper presented at the *11th Symposium of the European Association for Research in Transportation (hEART)*, Zurich, Switzerland.

4.1 INTRODUCTION

Urban ridepooling has emerged as a promising solution to the challenges of urban mobility. Leveraging advanced technology and algorithms, ridepooling services optimize urban travel by enabling multiple passengers traveling in the same direction to share a single vehicle. One of the primary advantages of ridepooling is its potential to reduce traffic congestion and alleviate the strain on urban transport infrastructure. By maximizing vehicle occupancy, ridepooling may reduce the number of vehicles on the road, consequently lowering noise, greenhouse gas emissions and promoting eco-friendly transportation. Furthermore, it may offer a more affordable way to travel short to medium distances (Shaheen and Cohen, 2018; Zwick *et al.*, 2021). It enhances the concept of shared mobility, aligning with the growing trend towards collaborative consumption and reducing individual reliance on private vehicles. Additionally, ridepooling services offer convenient mobile apps, allowing users to book rides, track vehicles in real-time, and make cashless payments, increasing the overall user experience.

However, ridepooling also comes with limitations. One significant challenge lies in optimizing routes and ensuring timely pickups and drop-offs for multiple passengers, which can lead to longer travel times, especially during peak-hours. The success of ridepooling depends on public participation, and it may face resistance from individuals who prefer the privacy and convenience of private transportation. It remains to be seen how well ridepooling integrates with public transportation and whether it can be operated cost-efficiently in a city. With the advent of automated driving, ridepooling is expected to have a greater potential to disrupt the transport industry in the future as automated vehicles would reduce fleet operating costs substantially.

MOIA is a subsidiary of Volkswagen Group and currently operates the largest fleet in Europe with up to 500 fully-electric vehicles in the cities of Hamburg and Hanover, Germany. The vehicles can carry up to six passengers and provide enough room for privacy. More than 900 drivers work in shifts to service all the booking requests coming in. Since launching the service in 2019, over 7.8 million passengers were transported in total, and more than 252,000 in August 2023[1]. Trips can be booked via their intuitive mobile application, which uses an advanced pooling algorithm dispatching users to vehicles while maximizing the pooling rate. In Hamburg, MOIA's algorithm incorporates over 12,000 virtual stops, some of which are shared with the local public transit network. MOIA currently reports a pooling rate of 60%, meaning that there is a 60% chance of another user joining the same vehicle once a trip has started. The recent expansion of services to a larger area (270 km² instead of 200 km², as depicted in Figure 4.3), the inclusion of wheelchair-accessible vehicles, and the tariff integration into the public transport system, provided the opportunity for a comprehensive scientific evaluation. This chapter is part of funded project and forms the basis for the work conducted in this context.

This study extends the findings of earlier research conducted by the Karlsruhe Institute of Technology and TU Munich during 2019-2021 (Kagerbauer *et al.*, 2021). For a comprehensive understanding of not just MOIA's service but also recent developments in the literature on ridepooling, the interested reader is referred to the detailed review provided by Zwick (2022).

In their study, Kostorz *et al.* (2021) presented findings from a survey involving over 12,000 MOIA users and non-users in 2019. The results indicated MOIA's diverse user base, spanning all age groups and genders, and showcased its role in promoting multimodal travel behavior. In contrast to their approach, this study employs a RP-based stated choice experiment. The aim is to not only investigate the intermodal use of MOIA's ridepooling service descriptively, but by incorporating it in the choice design and model. The issue of intermodality was also explored by Diebold *et al.* (2021) using the example of ioki in Hamburg. Unlike MOIA, ioki operates differently, providing customers with transportation to the nearest railway station

1 https://www.moia.io/, last accessed: 09/15/2023

within a 15 km^2 service area for a small fee of 1 Euro in addition to a public transit ticket. Consequently, it is not surprising that they reported a remarkably high 72% share of intermodal trips. Additionally, the average age of ioki users is relatively young at 34, attracting a demographic of price-sensitive travelers.

This chapter investigates the preferences for the use of urban ridepooling on the example of the MOIA service in Hamburg. We contribute to the literature on ridepooling by examining the preferences for the use of urban ridepooling, and identifying the factors that influence individuals' willingness-to-pay to use such a service. The presented findings can help to inform policy-makers and urban transportation planners in their efforts to promote sustainable and efficient transportation systems through new digital and smart mobility services.

The remainder of this chapter is structured as follows. Section 4.2 presents the survey set up used to collect the relevant data, and the experimental design developed to investigate the choices Section 4.2.3 presents the modeling approach applied to estimate different discrete choice models. In Section 4.3.2, a descriptive analysis investigates the study sample, choice frequencies and (non-)trading behavior between the alternatives. Multinomial Logit models are estimated to calculate valuation indicators and elasticities for the different modes considered. Section 4.4 summarizes the main findings and discusses potential improvements as well as limitations of the reported work.

4.2 METHODOLOGY

This section outlines the methodological approach to explore peoples' mode choices and attributes that drive their decisions when trading-off between different means of transport in a multimodal city context.

4.2.1 *Survey*

The study employed an online two-stage approach using a combination of revealed and stated preference surveys (RP & SP), which were administered to participants. RP data provide valuable information about mode choices in real markets, but often lack in variability of the underlying variables to construct appropriate models and forecasts (Ortúzar and Willumsen, 2011). To better comprehend the trade-off confronted by individuals in choosing between multiple modes, SP methods such as stated choice experiments (SCE) have been used as these are often richer in trade-off information by design (Louviere *et al.*, 2003; Train, 2009).

The goal of the RP survey was twofold: First, all relevant information was obtained from the participants which serve as input for the mode choice experiment in the SP part. Second, selected questions from an earlier study in 2019 by KIT & TUM (Kagerbauer *et al.*, 2021) were integrated as part of an update on MOIA (non-) users and their usage of the ridepooling service. Therefore, the web-based questionnaire comprised batteries of questions concerning (see Appendix A.2 for the complete RP survey):

1. Sociodemographic profile on personal and household level (e.g., age, gender, education, occupation, household composition/-income, etc.)
2. Mobility tool ownership and behavior:
   - Tools: Public transport subscription, driver's license, car ownership and availability
   - Behavior: Typical commute and/or leisure trip (e.g., start and end location, main mode of trip, start time, etc.)
   - Mobility impairment
3. MOIA assessment:
   - Membership
   - Last trip booked (e.g., purpose, start and end location, weekday, intermodality, etc.)

  - Rating of MOIA service
  - Reasons for non-usage

Whenever possible, the questions were standardized according to the most recent German mobility census, "Mobilität in Deutschland", for sample comparability and weighting reasons (Nobis and Kuhnimhof, 2018). The last part was specifically devoted to MOIA's ridepooling service, asking the respondents whether they had used it already, and if so, detailed information of their last trip booked. In part two, each participant was asked for a typical commuting and/or leisure trip by indicating three locations using interactive Google Maps:

1. Home location of the household
2. Work or education location, if a participant is working/going to an educational institution outside of home at least once in a regular week
3. A frequently visited leisure location, either shopping or meeting with friends

These locations were then used to infer a reference trip for each participant in the mode choice experiment.

4.2.2 *Stated choice experiment*

In order to have a complete choice set, all alternative modes that are considered and were available, but not chosen for the inferred trip, need to be generated. It is relatively convenient to query the Google API to obtain reliable travel times for walking, cycling, car and PT, while ridepooling (i.e., MOIA) needs to be constructed. Figure 4.1 presents an example trip where public transportation was the main mode reported (top left) and hence walking, cycling, driving a car (top right) and MOIA (bottom row) were non-chosen modes. A typical ride with MOIA can be characterized as a sequence of three stages: walking to the pick-up location, traveling in a MOIA vehicle and walking from the drop-off location to the final destination. To simulate this process, MOIA's internal virtual stop network with over 12,000 stops was utilized to route these trips. However, this procedure comes with a couple of limitations. The reconstructed trips might be overly optimistic: (1) It is not always the closest stop to the home and the activity location reported that is serviced by MOIA, (2) the routed in-vehicle travel time (car travel time) is likely to be higher due to possible pooling and thus longer routes, (3) wait time for the vehicle as well as scheduled delays in the arrival time are not accounted for and (4) the booking process (e.g., a rejected booking request) is neglected. Nevertheless, some of these limitations can be addressed in the choice experiment by using hypothetical scenarios where such trip characteristics are displayed to the participants.

Figure 4.1: Generation of non-chosen alternatives

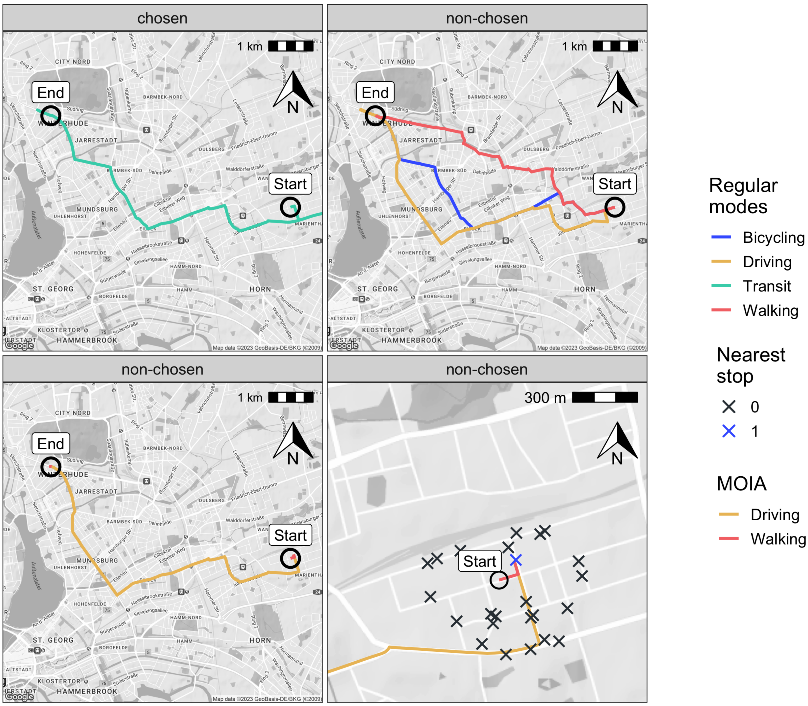

Table 4.1 shows the assumptions made on the cost of each alternative, differentiated by ownership of the corresponding mobility tool. For MOIA, their internal pricing scheme was applied to calculate the cost of each ride. It accounts for varying demand price factors dependent on the start time and location of the trip, as well as different base fees. For respondents who own a monthly or yearly public transport subscription, we assumed zero costs, while for the rest we accounted for Hamburgs public transportation

zones and applied a cost of 0.25 Euro per kilometer for trips taking place outside the zones.

TABLE 4.1: Travel cost overview

Mode	Mobility tool	Price	Source
Walk	-	-	-
Bicycle	Owner	-	-
Bicycle	Shared service	0.125 €/km	-
Car	Owner	0.70 €/km	ADAC
Car	Company	RP: -	-
Car	Company	SP: 1 €	-
Car	Shared service	0.20 €/km & 0.30 €/min	Wheego
Taxi	Ride	base fee: 4.50 € & 0-4 km: 2.65 €/km 4-9 km: 2.45 €/km 9+ km: 1.75 €/km	Taxi Rechner
PT	Owner season ticket	-	-
PT	Ride	0.25 €/km	Pro Bahn
MOIA	Ride	internal pricing scheme	MOIA (undisclosed)

Six D-efficient pivot designs were implemented using NGene (Rose and Bliemer, 2009; ChoiceMetrics, 2021). The mode choice experiment includes up to seven alternatives displayed to a respondent: walking, cycling, car, taxi, PT, MOIA, and MOIA combined with PT. Dependent on the trip distance, trip purpose, driver's license ownership and car availability, each one is assigned to a block of eight choice situations of one of those experimental designs. Table 4.2 gives an overview of the alternatives, attributes and corresponding pivoting levels available in the design. For example, if a participant owned a driver's license, had a car available and reported a trip of 2 km, choice design number 1 would be applied, and six alternatives would be displayed in all choice situations. Figure 4.2 shows an example of a choice situation that could have been presented to that particular participant.

Table 4.2: Design specification and attributes

	Available alternatives							Distance
Design	**Walk**	**Bicycle**	**Car**	**PT**	**Taxi**	**MOIA**	**PT & MOIA**	**Class (km)**
1	✓	✓	✓	✓	✓	✓		0.4-4
2	✓	✓		✓	✓	✓		0.4-4
3		✓	✓	✓	✓	✓	✓	5-10
4		✓		✓	✓	✓	✓	5-10
5			✓	✓	✓		✓	10-30
6				✓	✓		✓	10-30

	In alternative							Levels		
Attributes	**Walk**	**Bicycle**	**Car**	**PT**	**Taxi**	**MOIA**	**PT & MOIA**	**-**	**ref**	**+**
Travel cost		✓	✓	✓	✓	✓	✓	25%	RP	25%
Travel time main mode	✓	✓						5%	RP	5%
Travel time main mode			✓	✓	✓	✓	✓	20%	RP	20%
Travel time access (MOIA)							✓	20%	RP	20%
Access/egress time (Walk)				✓		✓	✓	20%	RP	20%
Access/egress time (Car)			✓					4	10	16
Wait time vehicle					✓	✓	✓	0	3	8
Wait time transfers				✓			✓	20%	RP	20%
Transfers				✓			✓	-1	RP	+1
Time window at arrival						✓		5	10	20

Figure 4.2: Example mode choice task

	Zu Fuß	Fahrrad	Auto	ÖPNV	Taxi	MOIA
Fahrtzeit Hauptverkehrsmittel	19 min	6 min	5 min	3 min	5 min	7 min
Fahrtkosten		0,00 €	1,60 €	1,80 €	8,80 €	6,70 €
Zu- & Abgangszeit (zu Fuß)			4 min	10 min		3 min
Wartezeit vor Fahrtantritt					3 min	3 min
Wartezeit Umstiege				2 min		
Umstiege				0 mal		
Zeitfenster Ankunftszeit						10 min
Ihre Wahl	○	○	○	○	○	○

Note that in the RP data, ridepooling is only available if all obtained coordinates were within MOIA's operating area as of 2022. The choice experiment accounts for virtual stops and operating area that recently was increased (border in black) as shown in Figure 4.3. As mentioned above, some ridepooling-specific characteristics were added in the experiment. For example, the arrival time uncertainty that might arise due to pooling or wait time for the vehicle to arrive. In order to present a ridepooling alternative to all participants in the SP even when no trip was inferred, the missing attributes were imputed based on OLS-regressions (Ordinary Least Squares). Furthermore, and based on the premise that ridepooling could complement public transportation in urban areas, a hypothetical, intermodal alternative was also included in the choice experiment for trips between 10 - 30 km of length and within the city boundaries. As such, MOIA was assumed to be the access and egress mode to public transport as the main mode. We assumed the total travel time of said alternative to be a simple mixture of the corresponding PT and car travel times as it would have been to complex to assume specific routes and transfer locations.

Figure 4.3: MOIA's new service area (border in black)

4.2.3 *Modeling approach*

The data gathered allowed for the estimation of pooled RP-SP MNL models. In the MNL model formulation, the utility equations $V_{i,n,m,t}$ for alternative $i \in \{W, B, C, T, PT, M, MPT\}$, individual $n \in \{1, 2, ..., N\}$ in model component $m \in \{\text{RP, SP}\}$ and choice task $t \in \{1, 2, ..., T_n\}$ are given by:

$$V_{W,n,RP,t} = x^{tt}_{W,n,RP,t}\ f^{tt}_i(x^{dist}_n, x^{purp}_n) \tag{4.1}$$

$$\begin{aligned} V_{B,n,RP,t} = {} & \alpha_{B,RP} + S_{n,t}\kappa_{\alpha_B} + \\ & x^{tt}_{B,n,RP,t}\ f^{tt}_i(x^{dist}_n, x^{purp}_n) \end{aligned} \tag{4.2}$$

$$\begin{aligned} V_{C,n,RP,t} = {} & \alpha_{C,RP} + S_{n,t}\kappa_{\alpha_C} + \\ & x^{tt}_{C,n,RP,t}\ f^{tt}_i(x^{dist}_n, x^{purp}_n) + x^{tc}_{C,n,RP,t}\ f^{tc}(x^{dist}_n, x^{purp}_n) \end{aligned} \tag{4.3}$$

$$\begin{aligned} V_{T,n,RP,t} = {} & \alpha_{T,RP} + S_{n,t}\kappa_{\alpha_T} + \\ & x^{tt}_{T,n,RP,t}\ f^{tt}_i(x^{dist}_n, x^{purp}_n) + x^{tc}_{T,n,RP,t}\ f^{tc}(x^{dist}_n, x^{purp}_n) \end{aligned} \tag{4.4}$$

$$\begin{aligned} V_{PT,n,RP,t} = {} & \alpha_{PT,RP} + S_{n,t}\kappa_{\alpha_{PT}} + \\ & x^{tt}_{PT,n,RP,t}\ f^{tt}_i(x^{dist}_n, x^{purp}_n) + X^{LOS}_{PT,n,RP,t}\ \beta^{LOS}_{PT} + \\ & x^{tc}_{PT,n,RP,t}\ f^{tc}(x^{dist}_n, x^{purp}_n) \end{aligned} \tag{4.5}$$

$$\begin{aligned} V_{M,n,RP,t} = {} & \alpha_{M,RP} + S_{n,t}\kappa_{\alpha_M} + \\ & x^{tt}_{M,n,RP,t}\ f^{tt}_i(x^{dist}_n, x^{purp}_n) + X^{LOS}_{M,n,RP,t}\ \beta^{LOS}_{M} + \\ & x^{tc}_{M,n,RP,t}\ f^{tc}(x^{dist}_n, x^{purp}_n) \end{aligned} \tag{4.6}$$

$$V_{W,n,SP,t} = x^{tt}_{W,n,SP,t}\, f^{tt}_i(x^{dist}_n, x^{purp}_n) \tag{4.7}$$

$$\begin{aligned} V_{B,n,SP,t} = \omega_{SP}\Big(&\alpha_{B,SP} + S_{n,t}\kappa_{\alpha_B} + \\ &x^{tt}_{B,n,SP,t}\, f^{tt}_i(x^{dist}_n, x^{purp}_n) + x^{tc}_{B,n,SP,t}\, f^{tc}(x^{dist}_n, x^{purp}_n)\Big) \end{aligned} \tag{4.8}$$

$$\begin{aligned} V_{C,n,SP,t} = \omega_{SP}\Big(&\alpha_{C,SP} + S_{n,t}\kappa_{\alpha_C} + \\ &x^{tt}_{C,n,SP,t}\, f^{tt}_i(x^{dist}_n, x^{purp}_n) + x^{tc}_{C,n,SP,t}\, f^{tc}(x^{dist}_n, x^{purp}_n)\Big) \end{aligned} \tag{4.9}$$

$$\begin{aligned} V_{T,n,SP,t} = \omega_{SP}\Big(&\alpha_{T,SP} + S_{n,t}\kappa_{\alpha_T} + \\ &x^{tt}_{T,n,SP,t}\, f^{tt}_i(x^{dist}_n, x^{purp}_n) + x^{tc}_{T,n,SP,t}\, f^{tc}(x^{dist}_n, x^{purp}_n)\Big) \end{aligned} \tag{4.10}$$

$$\begin{aligned} V_{PT,n,SP,t} = \omega_{SP}\Big(&\alpha_{PT,SP} + S_{n,t}\kappa_{\alpha_{PT}} + \\ &x^{tt}_{PT,n,SP,t}\, f^{tt}_i(x^{dist}_n, x^{purp}_n) + X^{LOS}_{PT,n,SP,t}\, \beta^{LOS}_{PT} + \\ &x^{tc}_{PT,n,SP,t}\, f^{tc}(x^{dist}_n, x^{purp}_n)\Big) \end{aligned} \tag{4.11}$$

$$\begin{aligned} V_{M,n,SP,t} = \omega_{SP}\Big(&\alpha_{M,SP} + S_{n,t}\kappa_{\alpha_M} + \\ &x^{tt}_{M,n,SP,t}\, f^{tt}_i(x^{dist}_n, x^{purp}_n) + X^{LOS}_{M,n,SP,t}\, \beta^{LOS}_{M} + \\ &x^{tc}_{M,n,SP,t}\, f^{tc}(x^{dist}_n, x^{purp}_n)\Big) \end{aligned} \tag{4.12}$$

$$\begin{aligned} V_{MPT,n,SP,t} = \omega_{SP}\Big(&\alpha_{M,SP} + S_{n,t}\kappa_{\alpha_M} + \\ &x^{tt}_{M,n,SP,t}\, f^{tt}_i(x^{dist}_n, x^{purp}_n) + X^{LOS}_{M,n,SP,t}\, \beta^{LOS}_{M} + \\ &x^{tc}_{M,n,SP,t}\, f^{tc}(x^{dist}_n, x^{purp}_n)\Big) \end{aligned} \tag{4.13}$$

with:

- ω_m: Parameter to account for scale differences (error variance) between the two model components in pooled estimation (Hensher *et al.*, 1998); (RP = reference; ω_{RP} = 1)

- $\alpha_{i,m}$: Alternative-specific constant (PT = reference; $\alpha_{PT,RP}$ & $\alpha_{PT,SP}$ = 0)
- $S_{n,t}$: Vector of trip-specific and sociodemographic attributes as a shift on the ASC's
- κ_{α_i}: Vector of parameters for $S_{n,t}$
- $x^{tt}_{i,n,m,t}$: Travel time
- $f^{tt}_i(x^{dist}_n, x^{purp}_n)$: Travel time parameters (see Equation 4.14)
- $x^{tc}_{i,n,m,t}$: Travel cost
- $f^{tt}_i(x^{dist}_n, x^{purp}_n)$: Travel cost parameters (see Equation 4.15)
- $X^{LOS}_{i,n,m,t}$: Vector of other level-of-service attributes (LOS) for PT and MOIA, e.g., access/egress time, wait time for transfers, wait time for the vehicle, number of transfers, arrival time uncertainty
- β^{LOS}_i: Vector of LOS parameters

Furthermore, we include a continuous distance elasticity on travel times and cost as well as trip purpose-specific shifts to additionally allow for deterministic taste heterogeneity,

$$f^{tt}_i(x^{dist}_n, x^{purp}_n) = (\beta^{tt}_i + \beta^{tt,purp}_i \; x^{purp}_n)\left(\frac{x^{dist}_n}{8\ km}\right)^{\lambda^{tt,dist}_i} \tag{4.14}$$

$$f^{tc}(x^{dist}_n, x^{purp}_n) = (\beta^{tc} + \beta^{tc,purp} \; x^{purp}_n\left(\frac{x^{dist}_n}{8\ km}\right)^{\lambda^{cost,dist}} \tag{4.15}$$

where x^{purp}_n is a dummy for individual n and the λ's represent the elasticity coefficients.

Assuming that all error terms of the utility, $\epsilon_{i.n,m,t}$, are distributed *iid* and follow a type I extreme value distribution, the choice probability for alternative i, individual n, model component m and choice task t is given by Equation 4.16. θ is a vector combining all model parameters, $V_{j,n,m,t}$ refers to the observed part of the utility and $a_{j.n,m,t}$ takes the value of 1 if alternative j is available, and 0 otherwise. The contribution by indivudial n to the likelihood function is then given by Equation 4.17. The MNL model is estimated by means of Maximum Likelihood (ML) where the log-likelihood (LL, see Equation 4.18) is the probability of reproducing each choice in the sample.

$$P_{i,n,m,t}(\theta) = \frac{a_{i,n,m,t} \cdot e^{V_{i,n,m,t}}}{\sum_{j=1}^{J} a_{j,n,m,t} \cdot e^{V_{j,n,m,t}}} \tag{4.16}$$

$$L_n(\theta) = \prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t}\left(i^{*}_{n,m,t} | \theta\right) \tag{4.17}$$

$$LL(\theta) = \sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{m=1}^{M} P_{n,m,t}\left(i^{*}_{n,m,t} | \theta\right) \tag{4.18}$$

Since an intermodal alternative was introduced in the choice experiment, where MOIA is assumed to be an access mode to PT (even though that this might already be a use case for MOIA in reality, the RP survey did not capture it), two model specifications were tested. While MNL 1 treated the in-vehicle travel times for MOIA as separate effects (main mode: $\beta_{M,tt}$ and access or egress mode: $\beta_{MPT,M,tt}$), MNL 2 estimated these two effects jointly in $\beta_{M,tt}$ (see Table 4.4). As a consequence, this affects the VTT for MOIA, which is discussed in the next section. The proposed modeling approach accounts for the impact of trip purpose and distance, various LOS and sociodemographic attributes on mode choice in the presence of ridepooling.

The models were estimated in preference space, using R and the Apollo package (R Core Team, 2020; Hess and Palma, 2019).

4.3 RESULTS

4.3.1 *Study participation*

Given that MOIA operates predominantly in the city of Hamburg, we focused on participants residing in the city and the agglomeration. The recruitment process included two distribution channels, with current MOIA members being internally recruited by MOIA's marketing department and other respondents being externally sourced via two regional panel providers. All respondents were invited by E-Mail. While no incentives were paid for respondents recruited by MOIA, both panel providers did pay small incentives for successful participation. On average, the participants spent

16 minutes to fill out the RP survey, and 8 minutes for the SP survey. The targeted total sample size was 4,500 respondents with approximately one third (1,500) recruited by the panel providers. Unfortunately, we encountered significant challenges in recruiting participants through one of the two panel providers. Furthermore, the spatial focus on Hamburg proved to be a challenging endeavor for both recruitment partners. Ultimately, the sample size for the RP survey amounted to 4,167 individuals. Comprehensive data cleaning and participants not filling out the experiment reduced the sample size to 3,823 individuals for the SP survey. Both surveys were conducted using the survey software Qualtrics.

4.3.2 *Descriptive analysis*

An analysis of the sample in comparison with the German MiD, which was restricted to Hamburg, uncovered two noteworthy observations: First, the sample was representative in terms of gender and holders of a driver's license. Second, it demonstrated a slight inclination towards younger participants, as well as an over-representation of individuals with a high degree of education (university or diploma) and high-income households (more than 6,500 Euro per month). Consequently, post-estimation re-weighting was necessary for the measures of interest using sample enumeration. The German MiD 2017 served as reference sample to generate the weights using Iterative Proportional Fitting (IPF) for the following variables: age, education, occupation, PT season ticket ownership, household size and income. Nevertheless, we would like to emphasize that the sample will not be fully representative due to the unbalanced sample composition induced by the recruitment strategy.

Table 4.3: Sample comparison to the German MiD 2017 (Hamburg)

		MiD 2017	Sample		
		Hamburg	All	MOIA	
				Users	Non-users
Age	0-15 years	11.1	-	-	-
	16-20 years	4.0	1.4	0.8	2.9
	21-30 years	8.7	16.2	15.7	12.6
	31-40 years	13.0	26.2	26.7	16.4
	41-49 years	14.0	23.6	24.9	17.9
	51-65 years	23.6	26.7	26.8	38.7
	66-86 years	24.5	5.9	6.1	11.5
	87-101 years	1.1	-	-	-
Gender	female	51.2	52.4	52.4	52.4
	male	48.8	47.6	47.6	47.6
	divers	-	0.1	0.1	-
Education	none	13.7	0.1	0.1	0.4
	Volks-/Hauptschule	11.2	1.8	1.3	6.0
	Mittlere Reife	19.5	8.1	7.1	16.2
	Fachhochschulreife	19.7	39.3	37.7	52.4
	University	36.0	50.6	53.8	25.0
	other	1.6	-	-	-
	not provided	0.4	-	-	-
Occupation	employed	48.5	84.8	87.5	63.0
	unemployed	2.2	1.5	0.9	6.0
	retired	27.5	8.5	7.3	19.0
	student/apprentice	14.6	3.6	3.2	6.9
	at home	7.2	1.6	1.2	5.1
	not provided	1.8	-	-	-
Driver's license	yes	87.6	89.7	90.4	83.6

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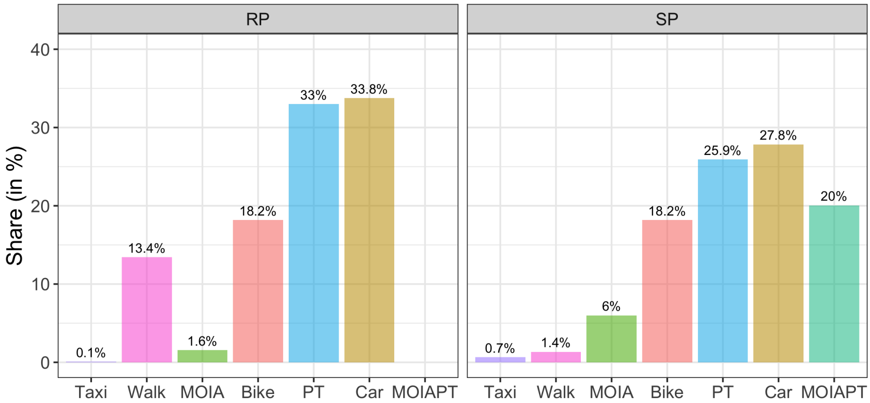
Table 4.3 – *Continued from previous page*

		MiD 2017	Sample		
		Hamburg	All	MOIA	
				Users	Non-users
	no	12.4	10.3	9.6	16.4
PT season ticket	yes	25.2	40.0	40.2	38.3
	no	74.8	60.0	60.0	61.7
Household size	1	16.0	29.5	29.1	32.5
	2	44.6	43.5	44.8	33.0
	3	16.9	14.2	13.6	19.0
	4	17.1	10.3	10.1	12.2
	5 and more	5.4	2.6	2.5	3.3
Household income	under 500 €	0.2	0.4	0.2	2.2
	500 - 899 €	0.8	1.1	0.6	5.3
	900 - 1,499 €	3.9	3.7	2.5	13.5
	1,500 - 1,999 €	6.6	6.3	5.5	13.5
	2,000 - 2,999 €	21.7	18.1	17.7	21.2
	3,000 - 3,999 €	22.2	15.6	15.3	18.6
	4,000 - 4,999 €	18.6	14.0	14.2	12.2
	5,000 - 5,999 €	12.3	11.7	12.6	4.4
	6,000 - 6,999 €	7.2	7.8	8.5	1.5
	7,000 € and more	6.5	12.3	13.3	3.5
	not provided	-	9.0	9.6	4.0

In the sample, 90% of participants (3,715) responded affirmatively to having booked a ride with MOIA within the past year, which might be an artefact of the recruitment process, but also demonstrates the popularity of MOIA's ridepooling service in Hamburg. The sample's sociodemographic profile in general is very similar compared to the work done in 2019 by Kagerbauer *et al.* (2021). MOIA users are on average 44 years old, well-educated and mostly live in one-person, high-income households. With regard to their last trip booked, two insights were relevant for the choice experiment. It was found that 60% of the participants reported their last trip as being for leisure, 12.9% for travel to a train station or the airport, and 10.6% for work. Additionally, 14% of the trips were combined with other modes of transportation, with 70% of those including PT. This indicated the necessity of incorporating and testing an intermodal alternative in the SCE, also because the survey did not differentiate between a combination with short- and long-distance public transportation.

Figure 4.4 shows the choice frequencies (market shares) divided by model component. Examining the RP data, car and PT were the most commonly chosen alternatives (33.8% and 33% respectively), followed by bike and walk (18.2% & 13.4%). MOIA exhibits a market share of 1.6%, which is higher than MOIA's actual share of roughly 0.1%. This might be related to the large proportion of MOIA users in the sample. The SP data illustrates a decrease in car, PT and walk market shares, in favor of the intermodal alternative and MOIA. Taxi was the least chosen mode with 0.1% and 0.7% market shares in the RP and SP data, respectively. This is unsurprising as taxis are not often the first choice for commutes or frequent leisure trips. It is important to note that the SP modal splits presented here are an artefact of the experimental design and the associated distance classes, and should not be compared to real-world modal splits (Glerum *et al.*, 2013). A detailed investigation of non-trading and lexicographic choice behavior revealed that in 32% of all choice tasks the least expensive option was chosen, which either indicates a highly price-sensitive sample or an experimental design that transparently exposed all fares. However, this can be attributed to the assumption of zero costs for PT season ticket subscribers. On an individual level, 18% of all participants always (i.e., 8 times) chose the least expensive mode. As a result, in terms of cost, both PT and the intermodal alternative were viable options, which could explain the observed popularity of the latter in particular. With regards to travel times, even though the fastest option was chosen in 24% of all choice tasks, this could not be attributed to the choice of a single mode that always was the fastest. On individual level, only 2% of the respondents always chose the fastest option. As discussed by Hess *et al.* (2010), there are three ways to deal with these kind of issues: (1) treating the data as is, (2) removing all respondents affected by the phenomena, or (3) discriminating between consistent and inconsistent responses. Given the assumptions made in the experimental design, and the fact that we filtered out respondents rushing through the experiment (i.e., potentially not engaging enough with it), we considered the responses gathered to be consistent with the random utility model applied.

FIGURE 4.4: Choice frequencies



4.3.3 *Model results and discussion*

The model estimates are presented in Table 4.4. The units of the temporal variables are minutes, while those of the costs are Euros. Building upon the recommendations of Wasserstein *et al.* (2019), the table does not present associated p-values. Thus, researchers should recognize the presence of uncertainty and should not assume that effects exist simply due to the statistical significance or lack thereof. The model fit, $Adj.\rho^2$, of both models is almost equal, although slightly higher for MNL 1, which likely is a consequence of not pooling the travel time attribute for MOIA of the intermodal alternative ($\beta_{MPT,tt,com}$). Anyway, the VTT differ between the two models, as shown in Figures 4.5 and 4.6, and will be discussed in detail further below. The scale coefficient for the model component is not significantly different from one as indicated by the t-ratio of ω_{SP}.

Given the sample composition, the most substantial shifts on the ASC were observed for being a ridepooling (non-) user ($\delta_{M,SP,nonuser}$) in the SP data, which highlights the importance to distinguish between them and shows that non-users were less prone to choose MOIA and the intermodal alternative. Furthermore, it is important to also account for trip purpose related shifts on the ASC as they influence the subsequent calculation of the VTT. Noteworthy findings concerning the user characteristics considered are the following: With respect to gender, a substantial effect was only observed for the choice of bicycles. Men were more likely to do so than women. An effect for high income households was only apparent for private cars. As such, this does not seem to be the case for choosing a ridepooling service like MOIA. The strongest impact among all variables was observed for education. While a high education degree (i.e., university or diploma) has a positive impact on the probability of choosing a bicycle, it has negative one for all other modes. This finding might be related to the fact that cycling is a more sustainable way of traveling compared to motorized modes and thus might appeal more to well-educated people.

Table 4.4: Estimation results

Reference: Walk	MNL 1		MNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Scale model component				
SP ω_{SP}	1.053	(0.982)	1.034	(0.657)
ASC and ASC shift trip purpose (RP & SP)				
ASC bike $\alpha_{B,RP}$	−1.712	(−2.038)	−1.727	(−2.053)
ASC bike shift leisure $\kappa_{B,RP,leis}$	−0.904	(−1.609)	−0.922	(−1.644)
ASC car $\alpha_{C,RP}$	−2.442	(−2.961)	−2.538	(−3.069)
ASC car shift leisure $\kappa_{C,RP,leis}$	−0.121	(−0.212)	−0.079	(−0.139)
ASC PT $\alpha_{PT,RP}$	−1.455	(−1.765)	−1.509	(−1.831)
ASC PT shift leisure $\kappa_{PT,RP,leis}$	−0.597	(−1.053)	−0.552	(−0.976)
ASC taxi $\alpha_{T,RP}$	−5.499	(−7.951)	−5.616	(−8.203)
ASC MOIA $\alpha_{M,RP}$	−3.253	(−3.557)	−3.237	(−3.526)
ASC MOIA shift leisure $\kappa_{M,RP,leis}$	−0.044	(−0.070)	−0.579	(−0.931)
ASC MOIA shift non-user $\kappa_{M,RP,nonuser}$	−1.495	(−1.456)	−1.487	(−1.443)
ASC bike $\alpha_{B,SP}$	−1.268	(−1.476)	−1.266	(−1.469)
ASC bike shift leisure $\kappa_{B,SP,leis}$	0.296	(0.491)	0.267	(0.443)

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Table 4.4 – *Continued from previous page*

Reference: Walk	MNL 1		MNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio
ASC car $\alpha_{C,SP}$	−2.729	(−3.236)	−2.814	(−3.320)
ASC car shift leisure $\kappa_{C,SP,leis}$	0.364	(0.601)	0.437	(0.725)
ASC PT $\alpha_{PT,SP}$	−1.796	(−2.134)	−1.845	(−2.189)
ASC PT shift leisure $\kappa_{PT,SP,leis}$	0.259	(0.434)	0.314	(0.524)
ASC taxi $\alpha_{T,SP}$	−3.154	(−5.944)	−3.250	(−6.210)
ASC MOIA $\alpha_{M,SP}$	−0.846	(−0.921)	−0.832	(−0.902)
ASC MOIA shift leisure $\kappa_{M,SP,leis}$	0.182	(0.286)	−0.329	(−0.526)
ASC MOIA shift non-user $\kappa_{M,SP,nonuser}$	−1.571	(−4.100)	−1.592	(−4.165)
ASC MOIA & PT $\alpha_{MPT,SP}$	−3.275	(−3.760)	−2.672	(−3.080)
ASC MOIA & PT shift leisure $\kappa_{MPT,SP,leis}$	1.119	(1.741)	0.737	(1.150)
ASC MOIA & PT shift non-user $\kappa_{MPT,SP,nonuser}$	−0.781	(−5.017)	−0.777	(−4.915)
ASC shift sociodemographic's (pooled)				
ASC bike shift male $\kappa_{B,male}$	0.157	(1.012)	0.157	(1.006)
ASC bike shift age mid $\kappa_{B,age31-65}$	0.072	(0.360)	0.075	(0.375)
ASC bike shift age high $\kappa_{B,age66-86}$	−0.412	(−1.082)	−0.422	(−1.098)
ASC bike shift educ high $\kappa_{B,educhigh}$	0.189	(1.178)	0.195	(1.207)

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Table 4.4 – *Continued from previous page*

Reference: Walk	MNL 1		MNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio
ASC bike shift inc mid $\kappa_{B,inc1.7-5.5k}$	0.059	(0.134)	0.060	(0.135)
ASC bike shift inc mid $\kappa_{B,inc6.5k+}$	0.163	(0.350)	0.163	(0.346)
ASC car shift male $\kappa_{C,male}$	−0.037	(−0.254)	−0.037	(−0.252)
ASC car shift age mid $\kappa_{C,age31-65}$	0.232	(1.243)	0.236	(1.260)
ASC car shift age high $\kappa_{C,age66-86}$	0.187	(0.522)	0.179	(0.499)
ASC car shift educ high $\kappa_{C,educhigh}$	−0.514	(−3.438)	−0.523	(−3.487)
ASC car shift inc mid $\kappa_{C,inc1.7-5.5k}$	0.566	(1.344)	0.561	(1.321)
ASC car shift inc high $\kappa_{C,inc6.5k+}$	0.650	(1.455)	0.645	(1.434)
ASC PT shift male $\kappa_{PT,male}$	−0.047	(−0.319)	−0.051	(−0.341)
ASC PT shift age mid $\kappa_{PT,age31-65}$	−0.026	(−0.139)	−0.027	(−0.145)
ASC PT shift age high $\kappa_{PT,age66-86}$	−0.191	(−0.536)	−0.213	(−0.598)
ASC PT shift educ high $\kappa_{PT,educhigh}$	−0.288	(−1.910)	−0.294	(−1.942)
ASC PT shift inc mid $\kappa_{PT,inc1.7-5.5k}$	−0.112	(−0.272)	−0.122	(−0.295)
ASC PT shift inc high $\kappa_{PT,inc6.5k+}$	−0.430	(−0.978)	−0.443	(−1.002)
ASC MOIA shift male $\kappa_{M,male}$	−0.044	(−0.251)	−0.048	(−0.270)
ASC MOIA shift age mid $\kappa_{M,age31-65}$	0.139	(0.655)	0.149	(0.692)
ASC MOIA shift age high $\kappa_{M,age66-86}$	0.917	(1.431)	0.964	(1.469)

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Table 4.4 – *Continued from previous page*

Reference: Walk	MNL 1		MNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio
ASC MOIA shift educ high$\kappa_{M,educhigh}$	−0.638	(−3.627)	−0.639	(−3.588)
ASC MOIA shift inc mid $\kappa_{M,inc1.7-5.5k}$	0.047	(0.084)	0.053	(0.093)
ASC MOIA shift inc high $\kappa_{M,inc6.5k+}$	0.007	(0.012)	0.003	(0.005)
ASC MOIA & PT shift male $\kappa_{MPT,male}$	−0.153	(−0.984)	−0.157	(−0.998)
ASC MOIA & PT shift age mid $\kappa_{MPT,age31-65}$	0.290	(1.458)	0.295	(1.473)
ASC MOIA & PT shift age high $\kappa_{MPT,age66-86}$	0.490	(1.303)	0.490	(1.297)
ASC MOIA & PT shift educ high $\kappa_{MPT,educhigh}$	−0.497	(−3.127)	−0.508	(−3.179)
ASC MOIA & PT shift inc mid $\kappa_{MPT,inc1.7-5.5k}$	0.105	(0.256)	0.093	(0.226)
ASC MOIA & PT shift inc high $\kappa_{MPT,inc6.5k+}$	0.029	(0.066)	0.015	(0.035)
Attributes & shifts				
Travel cost β_{tc}	−0.292	(−14.970)	−0.301	(−15.438)
Travel cost shift leisure $\beta_{tc,leis}$	0.127	(7.165)	0.139	(7.809)
Travel time walk $\beta_{W,tt}$	−0.130	(−7.736)	−0.133	(−7.842)
Travel time walk shift leisure $\beta_{W,tt,leis}$	0.009	(0.476)	0.010	(0.567)
Travel time bike $\beta_{B,tt}$	−0.144	(−12.704)	−0.148	(−13.089)
Travel time bike shift leisure $\beta_{B,tt,leis}$	0.016	(1.382)	0.022	(1.875)

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Table 4.4 – *Continued from previous page*

Reference: Walk	MNL 1		MNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Travel time car $\beta_{C,tt}$	−0.037	(−3.537)	−0.035	(−3.327)
Travel time car shift leisure $\beta_{C,tt,leis}$	−0.014	(−1.420)	−0.014	(−1.384)
Access/egress time car $\beta_{C,aet}$	−0.086	(−12.696)	−0.087	(−12.828)
Travel time $\beta_{PT,tt}$	−0.061	(−10.903)	−0.062	(−11.107)
Travel time PT shift leisure $\beta_{PT,tt,leis}$	0.019	(2.608)	0.022	(3.116)
Access/egress time PT $\beta_{PT,aet}$	−0.052	(−9.911)	−0.053	(−10.085)
Travel time taxi $\beta_{T,tt}$	−0.015	(−0.686)	−0.012	(−0.571)
Travel time taxi shift leisure $\beta_{T,tt,leis}$	−0.016	(−0.559)	−0.018	(−0.604)
Travel time MOIA $\beta_{M,tt}$	−0.087	(−8.255)	−0.092	(−8.893)
Travel time MOIA shift leisure $\beta_{M,tt,leis}$	0.025	(1.791)	0.057	(5.079)
Access/egress time MOIA $\beta_{M,aet}$	−0.022	(−2.309)	−0.018	(−1.819)
Arrival time uncertainty MOIA $\beta_{M,latewin}$	−0.039	(−7.818)	−0.039	(−7.810)
Travel time MOIA as feeder $\beta_{MPT,M,tt}$	−0.018	(−2.823)		
Wait time (pooled) $\beta_{waittime}$	−0.020	(−2.532)	−0.019	(−2.362)
Nr. of transfers (pooled) β_{trans}	−0.269	(−12.445)	−0.268	(−12.350)
Wait time vehicle (pooled) $\beta_{waitveh}$	−0.021	(−4.934)	−0.022	(−5.000)

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Table 4.4 – *Continued from previous page*

Reference: Walk	MNL 1		MNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Distance elasticities				
Cost $\lambda_{cost,dist}$	-0.531	(-14.592)	-0.502	(-14.057)
Travel time walk $\lambda_{W,tt,dist}$	-0.212	(-2.780)	-0.206	(-2.684)
Travel time bike $\lambda_{B,tt,dist}$	-0.276	(-6.043)	-0.270	(-5.891)
Travel time car $\lambda_{C,tt,dist}$	-0.254	(-3.311)	-0.216	(-1.987)
Travel time PT $\lambda_{PT,tt,dist}$	-0.077	(-0.777)	-0.033	(-0.325)
Travel time taxi $\lambda_{T,tt,dist}$	0.357	(1.146)	0.373	(1.097)
Travel time MOIA $\lambda_{M,tt,dist}$	0.090	(1.074)	0.017	(0.220)
LL(0,RP)	-8147.19		-8147.19	
LL(final,RP)	-4728.96		-4724.12	
LL(0,SP)	-34631.63		-34631.63	
LL(final,SP)	-23942.47		-23967.60	
LL(0,model)	-42778.82		-42778.82	
LL(final,model)	-28671.43		-28691.72	
Adj. rho squared (model)	0.327		0.325	

Continued on next page

Table 4.4 – *Continued from previous page*

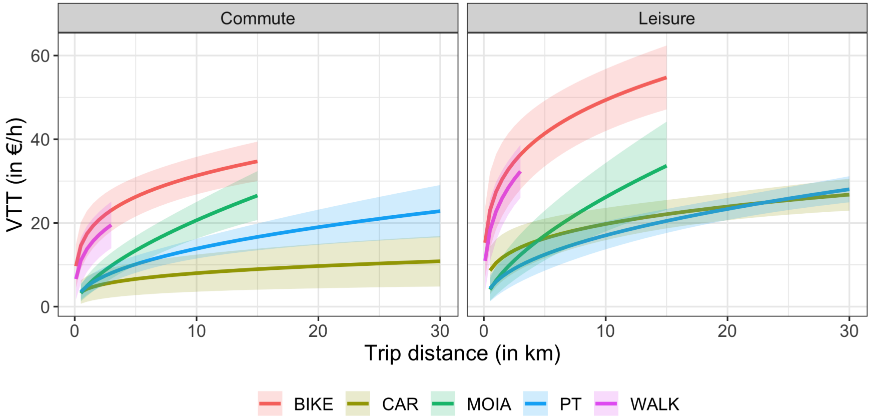
Reference: Walk	MNL 1		MNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio
# respondents	3823		3823	
# observations	28907		28907	
# parameters	83		82	

Figures 4.5 and 4.6 present the VTT for the main modes of both models by trip purpose. As can be inferred from the corresponding legend, the VTT for the intermodal alternative is not displayed since the main mode is PT, whose parameter was jointly modeled with the PT alternative. Moreover, the VTT are only modeled for the range of distance the modes were available in the data. The Delta method was used to derive weighted VTT values and their 95%-confidence interval (Daly *et al.*, 2012). Despite a very similar pattern of VTT for commute trips, contrastingly, the two models yield notable differences in the VTT for leisure trips. That difference in VTT among the modes is primarily the result of the different travel time parameters and their corresponding shifts in combination with the cost coefficient as well as the distance elasticities. Interestingly, for bicycle, public transport, and MOIA, leisure travel time sensitivities are less negative compared to their commutes, suggesting that participants find the time spent using these modes more enjoyable. This manifests even more in MNL 2, where the VTT for MOIA is much lower due to the joint estimation of MOIA as a main and feeder mode. In addition, the distance elasticitiy of travel time for MOIA is positive (but not significant), indicating that travel time sensitivity for it is barely influenced by distance. In both models, the cost sensitivity for commute trips (β^{tc}) is more negative compared to leisure due to the positive shift coefficient ($\beta_{tc,leis}$). The distance elasticity on cost is higher in absolute terms in comparison with the mode-specific travel times. Note that we also tested for income effects on cost sensitivity, but eventually did not find any substantial effect. Furthermore, the travel time coefficient for taxi turned out be small as well as statistically insignificant at the 10% significance level. Unsurprisingly, there were too few observations as taxi was very rarely chosen.

In summary, for MNL 1, the model results suggest that the leisure-specific VTT for MOIA is comparatively more driven by a comfort effect for shorter distances (0.5-6 km) in relation to other modes. However, for longer distances (6km +), travel cost seems to affect the VTT more strongly than travel time. For MNL 2, the leisure effect induced by pooling the travel time parameters seemed to affect the VTT more strongly than cost, resulting in a substantially lower value over the whole range of observed trip distances. This might also be a result of the intermodal alternative being difficult to understand or process in the context of the experiment, and needs further investigation in the future. In addition, it should be emphasized that the 95%-confidence interval for the MOIA VTT is increasing with distance in

MNL 1, which implies greater uncertainty in the VTT value for longer distances.

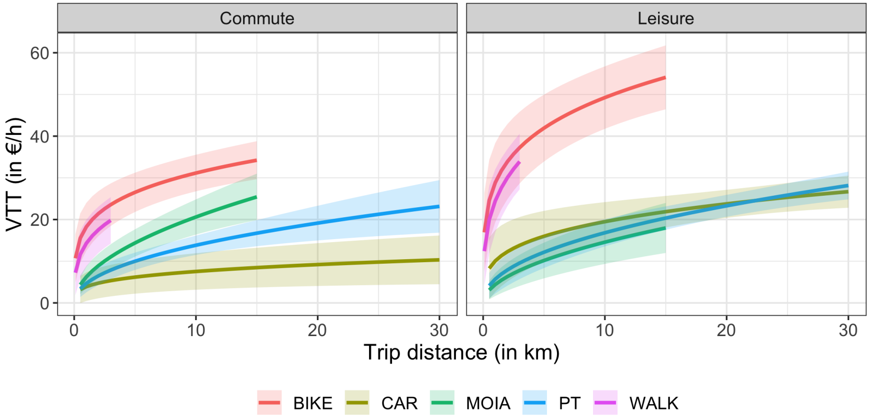
FIGURE 4.5: Values of travel time by Beeline-distance (MNL 1)



In the context of ridepooling, three other findings are of interest: First, uncertainty about the arrival time (e.g., postponed arrival time at destination due to pooling with other users) is perceived twice as bad than waiting for the vehicle after booking or accessing, egressing it. Second, the access and egress time (i.e., walking) to and from the MOIA vehicle seems to be more convenient in contrast to public transport. This is an intuitive finding since MOIA's virtual stop network entails more than 12,000 stops that are used by the pooling algorithm to dispatch users, vehicles and locations. Third, an additional transfer has a substantial and negative impact on the choice probability. However, this only affects MOIA in the case of the multimodal alternative which combines ridepooling and PT. Still, it is an important insight in the light of MOIA's service seen as a complement to PT.

The own- and cross-elasticities ($E_{i,k}$ and $E_{ji,k}$) for the MNL 1 model presented in Table 4.5 show the average responsiveness of choice probabilities (i.e., %-changes) to a change in choice attribute $X_{k,i}$ while keeping all other attributes fixed (see e.g. Winkelmann and Boes, 2006). We approximate the derivative of the choice probability with respect to a variable of interest by taking the difference between the simulated a-priori ($\overline{P}_{i,k}$) and ex-post ($\overline{P}_{i,k^*}$) probabilities after an increase in that variable, conditional on the estimated parameters.

FIGURE 4.6: Values of travel time by Beeline-distance (MNL 2)



$$E_{i,k} = \frac{\text{\%-change in } P_i}{\text{\%-change in } X_{k,i}} = \frac{\dfrac{\overline{P}_{i,k^*} - \overline{P}_{i,k}}{(\overline{P}_{i,k} + \overline{P}_{i,k^*})/2}}{\dfrac{\overline{X}_{k^*,i} - \overline{X}_{k,i}}{(\overline{X}_{k,i} + \overline{X}_{k^*,i})/2}} \tag{4.19}$$

The elasticities presented in Table 4.5 generally show higher values for the SP model component, which can be explained by the fact that the SP data contains more and richer trade-off information than the RP counterpart. Apparently, in-vehicle travel time and travel cost show larger elasticities compared to other LOS attributes as for example access and egress or wait time. Also, according to the magnitude of the cross-elasticities, PT and car show greater substitution effects in contrast to MOIA as a ridepooling service. Interestingly, when looking at the cross-elasticities for car travel time and cost, the RP data shows a higher increase in the choice probability of MOIA compared to PT. However, this should be treated with great caution, as the influence of potential pooling is not accounted for in the RP data. This pattern is not visible anymore in the SP data, where further ridepooling-specific attributes such as arrival time uncertainty were introduced.

TABLE 4.5: Elasticities $E_{i,k}$ and $E_{ji,k}$ (MNL 1)

Variable (+1%)	Model component	Walk	Bike	Car	PT	MOIA
Walk travel time	RP	−1.22	0.33	0.17	0.13	0.13
Bike travel time	RP	0.17	−1.72	0.42	0.41	0.53
Car travel time	RP	0.06	0.18	−0.33	0.21	0.26
Car travel cost	RP	0.09	0.36	−0.62	0.37	0.41
PT travel time	RP	0.02	0.23	0.26	−0.43	0.45
PT access/egress time	RP	0.04	0.14	0.14	−0.25	0.24
PT wait time	RP	0.01	0.02	0.02	−0.03	0.03
PT travel cost	RP	0.04	0.14	0.14	−0.25	0.19
MOIA travel time	RP	0.01	0.02	0.02	0.03	−1.12
MOIA access/egress time	RP	0.01	0.01	0.01	0.01	−0.06
MOIA travel cost	RP	0.01	0.04	0.03	0.04	−2.06

Variable (+1%)	Model component	Walk	Bike	Car	PT	MOIA
Walk travel time	SP	−2.82	0.13	0.02	0.03	0.03
Bike travel time	SP	0.80	−1.58	0.35	0.42	1.05
Car travel time	SP	0.04	0.11	−1.00	0.41	0.16
Car access/egress time	SP	0.05	0.07	−0.29	0.11	0.09
Car travel cost	SP	0.10	0.25	−1.12	0.44	0.34
PT travel time	SP	0.04	0.18	0.46	−1.20	0.29
PT access/egress time	SP	0.06	0.11	0.18	−0.50	0.14
PT wait time	SP	0.01	0.02	0.04	−0.09	0.02
PT travel cost	SP	0.06	0.09	0.12	−0.30	0.10
MOIA travel time	SP	0.01	0.13	0.07	0.08	−1.10
MOIA access/egress time	SP	0.01	0.01	0.01	0.01	−0.07
MOIA wait time vehicle	SP	0.01	0.01	0.01	0.01	−0.06
MOIA arrival time uncertainty	SP	0.02	0.04	0.02	0.03	−0.33
MOIA travel cost	SP	0.11	0.25	0.10	0.13	−1.83

4.4 CONCLUSION

This chapter presents a comprehensive investigation of mode choice preferences in the presence of ridepooling for the city of Hamburg, Germany. MOIA is a subsidiary of the Volkswagen Group and provides an on-demand ridepooling service operating a fleet of more than 250 fully electric vehicles, which is considered to be the largest in Europe. While existing research almost exclusively focused on RP data, the study presented in this chapter employed an RP and SP survey approach to examine the effect of sociodemographic characteristics and level-of-service attributes on the choice between walking, cycling, car, PT, taxi, MOIA and an intermodal alternative for commute and leisure trips.

The results of the RP survey conducted in this study confirmed findings from previous research on MOIA in 2019. The main use case for MOIA's ridepooling service was found to be related to leisure activities. While the majority of the obtained trips with MOIA were unimodal, 10% were combined with public transportation, which strengthened the need to include an intermodal alternative in the choice experiment as well. These insights were then used, tested and incorporated in the subsequent mode choice experiment and modeling approach.

The MNL models applied provide novel insights into mode choice preferences in a multimodal transport context, and the derived VTT distribution for the modes considered. The key drivers in choosing a ridepooling service like MOIA are primarily travel cost, travel time, trip purpose as well as distance. However, there are notable differences in the VTT for MOIA between commuting and leisure travel. For the latter, we found similar VTT values for MOIA in comparison with PT for trip lengths up to 6km, which can be attributed to comfort-related effects. For longer distances, this effect vanished and got compensated by comparatively higher travel costs, leading to increasing VTT values. This is an important finding for transport policy as the results support the main use case of MOIA in Hamburg, although only for shorter distances. With regards to other LOS attributes, the presented results might not only help MOIA, but also other ridepooling providers. When opting for ridepooling, arrival time uncertainty plays the biggest role in the decision process in comparison with accessing/egressing to or from the vehicle or waiting for it. This highlights one of the main challenges of providing a cost-efficient ridepooling service. It is the trade-off between maximising the pooling rate and providing a cost-efficient, convenient, but fast service.

The study has a couple of limitations that need to be addressed. First, despite re-weighting the data and controlling for ridepooling usage in the model, the sample might be biased towards ridepooling-friendly respondents and thus the model potentially suffers from sample selection effects. The same study is currently being conducted again, where we aim for a fully random sample. Second, the results regarding the intermodal alternative should be treated with great caution. The way it was incorporated and introduced to the respondents in the experiment was simple from a design perspective, but required a lot of attention to actually process all the information. Third, the study area is confined to Hamburg, Germany, and hence it is difficult to generalize the results to other cities. However, this one of the first studies to investigate preferences for the use of urban ridepooling in Europe and these kind of surveys are expensive to conduct. Thus, these insights might be taken as a starting point in order to assess ridepooling in a multimodal city. Similar to Chapter 3, the approach presented could be further refined and applied to other areas.

For future research, it would definitely be interesting to extend the modeling approach to Mixed Multinomial or Nested Logit models in order to examine unobserved taste heterogeneity and nesting structures between the modes. Furthermore, accounting for attitudes towards the different modes or transport policies in place could deepen our understanding of peoples' preferences in the context of ridepooling.

5

MODE CHOICE PREFERENCES IN A TRADABLE MOBILITY CREDIT SCHEME

The chapter is adapted from the following publication:

– Schatzmann, T., S. Álvarez-Ossorio Martínez, A. Loder, K.W. Axhausen and K. Bogenberger (2024) Investigating mode choice preferences in a Tradable Mobility Credit Scheme, paper accepted for presentation at the *103rd Annual Meeting of the Transportation Research Board (TRB 2024)*, Washington, D.C.

5.1 INTRODUCTION

Over the past century, the transport sector has become a key economic activity providing countless benefits to society and sustaining millions of jobs worldwide. However, mobility-related activities also have significant negative impacts on human life and the ecosystem, such as their contribution to global warming, air and water pollution, accidents, and sprawl (European Commission, 2020a). The prominence of the effects of climate change and the growing social demands to address them are pushing governments to develop ambitious plans to radically reduce the externalities of the transport sector, In the case of the European Union, the recent Sustainable and Smart Mobility Strategy (European Commission, 2020b) vows to reduce the dependence on fossil fuels and cut greenhouse gas emissions by at least 55% by 2030 (and more than 90% by 2050). It also aims to promote the shift to more sustainable transport modes, and internalize external costs, thus ensuring that the full cost of their transport is borne by the users rather than by the society as a whole (European Commission, 2020b).

5.2 LITERATURE REVIEW

In urban areas, a wide variety of strategies have been proposed and implemented to mitigate the environmental impacts of transport, reduce traffic congestion, and enhance liveability. These strategies include informative, regulative, and economic measures. The latter categories are particularly promising and can be subdivided into two groups: price control measures and quantity control measures. Congestion charging, for example, is a price control mechanism that consists of charging travelers an amount equal to the marginal externalities they impose on society (Shirmohammadi *et al.*, 2013; FHWA, 2016; Eliasson *et al.*, 2009; Lehe, 2019). Conversely, quantity control measures, such as Tradable Credits Schemes (TCS), aim at influencing individual demand for motorized trips and regulating traffic flows by limiting the allowed production of externalities.

TCS are cap-and-trade policy instruments that originated in the field of environmental economics for pollution control (Dales, 1968). They consist of the introduction of property rights for the aforementioned production of externalities, which are valued and circulated in a market to achieve optimal allocation. To the present date they have been applied in numerous fields, such as in the EU Emissions Trading System (Skjærseth and Wettestad, 2009). In the urban transportation field, Verhoef *et al.* (1997) and Goddard (1997) were among the first to investigate the possibilities of TCS to reduce emissions and mitigate congestion. As an example, we illustrate the fundamentals of TCS based on the so-called *MobilityCoins* system, a TCS proposed by Bogenberger *et al.* (2021) – and further developed by Hamm and Bogenberger (2022); Hamm *et al.* (2022); Blum *et al.* (2022) – in which this research is framed.

In a nutshell, in the *MobilityCoins* system eligible users receive periodically a credit budget, which accounts for a given amount of transport externalities (e.g., CO2 equivalent emissions). When a user undertakes a trip, the corresponding credit amount is subtracted from her budget. This amount is decided by the agency issuing the coins depending on the transport mode, engine type, route, and period of the day of the trip. Thus, active mobility modes are not charged or might be even slightly rewarded. Importantly, the usual ownership and operational costs (e.g., lease, fuel, vehicle maintenance, and public transport tickets) are paid as normal with coins on top. If users require additional credits to meet their mobility needs, or if they have a credit surplus, they can trade with other citizens on the *MobilityCoins* market. As a distinctive aspect with respect to other proposed credit schemes, the *MobilityCoins* system incentivizes the shift to active-mobility modes by rewarding bicycle trips with a small amount of credits (i.e., substantially lower than the credit charge for an equivalent motorized trip, but high enough to influence mode choice). Trips by foot are excluded of this incentive as this would require digital tracking and processing of all pedestrian movements, as well. Additionally, the *MobilityCoins* system introduces the novel idea of giving the users the possibility to invest their remaining credits on infrastructure improvements through crowdfunding, e.g., to build additional cycle lanes or to increase the frequency of a given bus line. Thus, the public's role in the transport planning process shifts from *passive* to *active*, and a balancing mechanism is introduced between the transportation demand and supply sides (Blum *et al.*, 2023).

Numerous publications have discussed the strengths of TCS in comparison to alternative travel demand management measures such as congestion pricing or license plate rationing (Dogterom *et al.*, 2018b; Fan and Jiang, 2013). First, TCS do not only reduce the attractiveness of using motorized vehicles, but they also provide direct incentives to users of sustainable modes (i.e., citizen who travel sustainably will have credit surplus, which can be sold on the market). Besides, TCS outperform congestion pricing in terms of social justice, since they avoid imposing a high tax burden on the poor while only marginally affecting the wealthy, and equity, as the revenue generated within the system is redistributed among the users. Interestingly, advocates of TCS argue that these schemes could enjoy greater social acceptance due to their government budget-neutrality (i.e., the credits circulate directly between users without mediation by the authorities) and the initial free allocation of credits (Krabbenborg *et al.*, 2021). Finally, a crucial key strength of TCS is that they allow a better quantity control of the system's goal –e.g., the overall emissions– in a context of uncertainty over the agent's price response functions (Raux, 2004; OECD, 2001). On the downside, the complexity of the system is one of the main drawbacks of TCS, making them difficult to implement and hard for the public to any concerns about the necessary computing infrastructure of the users (Krabbenborg *et al.*, 2020). In particular, the unfamiliarity with credit-based schemes and with trading have been identified as major issues. Furthermore, TCS entail high administrative and information costs, although these could be minimized by using digital technologies and information services, e.g., to collect user travel data and to facilitate the trading of credits (Fan and Jiang, 2013; Blum *et al.*, 2022).

Existing literature on TCS has mostly focused on aspects such as the pricing of credits and the influence on emissions (Xu and Grant-Muller, 2016; Meng and Grant-Muller, 2016), market design (Chen *et al.*, 2023), modeling of user and market equilibrium Wang *et al.* (2012), and public acceptance and equity aspects of such schemes Krabbenborg *et al.* (2020, 2021); Di Wu *et al.* (2012). The interested reader is referred to (Fan and Jiang, 2013) for a comprehensive review of different schemes and to (Provoost *et al.*, 2023) for a framework guiding their practical implementation. However, the empirical behavior of the users within a TCS has remained largely unstudied. Among the exceptions, Dogterom *et al.* (2018a,b) conducted surveys in Beijing and the Netherlands to analyze the likelihood of changing car use in response to a TCS. Similarly, Zanni *et al.* (2013) studied if, and how much, citizens would reduce their carbon footprint by modifying their transport choices under a personal carbon credit scheme. Finally, Aziz *et al.* (2015) implemented a real-time experimental game to study travel decisions (route choice) and market behavior within a carbon mobility budget. Recently, Geng *et al.* (2023) provided the first real-life evidence of TCS's ability to manage actual scheduling decisions. As illustrated, existing research lacks a disaggregated analysis of the potential impacts of TCS on mode choice. In this paper, we seek to address this gap by presenting the results of a stated mode choice (SC) experiment conducted to examine the trade-offs between travel time, private and external travel costs, and other level-of-service attributes in a multimodal TCS.

The remainder of this chapter is organized as follows: Section 5.3 provides an exposition of the methodology and modeling framework employed to investigate the disparities in mode choice preferences in a situation where a TCS is absent or present. Section 5.4 presents a summary of the findings from a Mixed Multinomial Logit (MMNL) model and examines the sensitivity of external travel costs as well as the corresponding values of travel time (VTT). Lastly, Section 5.5 provides a conclusion that highlights the novel insights gained, limitations of the proposed method, and future research directions.

5.3 METHODOLOGY

This section outlines the methodological approach to investigate peoples' mode choices and attributes that drive their decisions when trading-off between different means of transport for various trip purposes. With regards to the challenges the transport sector has been confronted with, many hypotheses evolve around the choice of a mode not only in an existing, but rather hypothetical transport system, such as TCS for example. SP surveys therefore often contain a stated choice (SC) experiment, which allows to introduce and test the effect of such a scenario on mode choice. As such, SP data are rich in attribute trade-off information and hence useful for forecasting changes in behavior, but may be limited by the imposed (lack of) realism of the choice context (Louviere *et al.*, 2003). The main features of the survey discussed in this paper are two experiments - the first one resembles the choice of modes in a status quo scenario (SQ), the second accounts for the introduction of the mobility budget and TCS to understand the differences between these regimes.

5.3.1 *Survey*

The survey software (Qualtrics) was used to implement and conduct the survey online (this includes mobile phones). The questionnaire was divided into six parts (see Appendix A.3 for the complete survey):

1. Socio-demographic profile on personal and household level (e.g., age, gender, education, occupation, household composition/-income, residential location, etc.)
2. Mobility tool ownership and behavior:
   - Tools: Public transport subscriptions, driver's license, car ownership and availability
   - Behavior: Simplified travel diary, distance classes for work or education, leisure, errands
3. Attitudes and personality
4. Mode choice experiment 1 (status quo; SQ)
5. Introduction of TCS:
   - Mobility budget and allocation
   - Willingness-to-pay (WTP) and willingness-to-sell (WTS)
6. Mode choice experiment 2 (TCS)

In part 1-3, the respondents gave information about personal attributes and the status quo travel behavior. Personal data was gathered (e.g., sociodemographic variables, socioeconomic status, etc.), and questions on mobility tool ownership and mode usage were included. Each respondent was asked for a simplified travel diary (mode choice, number of trips and trip length) for three trip purposes (work/education, leisure and errands) in a typical week of the year. As the residential location of each respondent was not be asked directly because of privacy concerns, respondents were asked about their home district and the availability of transport services within a five-minute walking distance around their residential location.

A further set of questions captured their attitudes towards risk, societal equity and environment. In part 4 the participants were faced with the first mode choice experiment. In part 5, the TCS framework was introduced formally and user preferences as well as behavioral responses to a TCS were measured. It included questions on designs of the initial credit allocation (mobility budget) and the WTP/WTS for extra/excess credits (see Hamm and Bogenberger (2022) for detailed results). Last but not least, the respondents were then presented with another mode choice experiment, similar to part 4, but under the constraint of a mobility budget for external costs.

5.3.1.1 *Experimental design*

As previously mentioned, the survey contained two experiments in order to account for the existence of different scales of choices (i.e., variance in choices) between the two regimes. Therefore, two sets of designs were created. For each regime there are 8 designs according to 4 trip distance classes (0-3, 3-6, 6-12 and longer than 12 kilometers) and the respondent's car availability (i.e., ownership of a driver's license and actual household car availability). Furthermore, and based on the distance class, 4 alternatives were available or not: walking, cycling, car, and public transport (PT). The variation of attribute levels increased with the underlying length of a reference trip to create reasonable trade-offs between the alternatives, and to have trip lengths that slightly overlap. Moreover, three trip purposes were distinguished: work/education, errands, and other leisure activities. These are so-called "scenario" variables and were not explicitly included as an attribute since they were constant between different choice tasks of an individual, but varied between them.

In the end, 16 D-efficient pivot designs were implemented using NGene (Rose and Bliemer, 2009; ChoiceMetrics, 2021). Weak priors were used for travel time and cost attributes. Each design was divided into 4 to 5 blocks. In total, a respondent was faced with 12 choice tasks - 6 mode choice tasks in each regime. Table 5.1 shows an overview of the available alternatives, distance classes, level variations, and attributes considered in each design and regime.

TABLE 5.1: Design specification and attributes

Design	Available alternatives				Distance class	Levels
Nr.	Walk	Bicycle	Car	PT	(km)	(- | +)
1	✓	✓	✓	✓	0-3	-10% | +10%
2	✓	✓		✓	0-3	-10% | +10%
3	✓	✓	✓	✓	3-6	-15% | +15%
4	✓	✓		✓	3-6	-15% | +15%
5		✓	✓	✓	6-12	-20% | +20%
6		✓		✓	6-12	-20% | +20%
7		✓	✓	✓	12+	-25% | +25%
8		✓		✓	12+	-25% | +25%

	In alternative				
Attributes	Walk	Bicycle	Car	PT	In regime
Internal travel cost			✓	✓	Status-quo & TCS
External travel cost			✓	✓	TCS
External travel gain		✓			TCS
Mobility coin budget		✓	✓	✓	TCS
Days into month		✓	✓	✓	TCS
Travel time	✓	✓	✓	✓	Status-quo & TCS
Access & eggress time				✓	Status-quo & TCS
Frequency				✓	Status-quo & TCS
Nr. of transfers				✓	Status-quo & TCS
Bike lane quality		✓			Status-quo & TCS
Weather	✓	✓	✓	✓	Status-quo & TCS

Design assignment: While filling in the survey, the following information was gathered and stored for each respondent:

– district of the residential location

– being "employed" or "in education" and working/studying out of home at least one day in a normal week

– car availability

The participants were assigned to one block of an experimental design for each regime. However, in order to have an approximately even distribution of trip lengths over the whole sample, the trip distance class was chosen randomly for each respondent. The trip purpose assignment was partially random, but dependent on the employment status. Only designs with a car alternative available could be assigned to respondents actually owning a driver's license and having access to a car in their household.

Design of reference values in a TCS system: For both studied regimes, reasonable values for the private costs as well as a reasonable TCS design must be presented to the respondents in order to obtain meaningful choices. Thus, the following assumptions are made:

– TCS scheme is implemented in the city of Munich. Hence, the following values are assumed: average travel distance of 40 kilometers per day and 3.2 trips per day. The modal share in terms of kilometers is 56% private transport, 36% public transport, 5% cycling, and 3% walking Follmer and Belz (2019). The kilometer cost for private transport is 0.5 Euro, 1.30 Euro for public transport trips shorter than 1.5 kilometers, and 2.50 Euro for public transport trips longer than 1.5 kilometers.

– The target of the scheme is to reduce car travel in terms of kilometers by 15%.

– A monthly budget is set at 1,000 credits for every citizen, divided by the monthly total travel production, this results in approximately 5/6 credits per travel-km.

– The assigned budget suffices to make all trips using public transport during a month without buying any additional credits on the market.

– A ratio of 2:1 is set between the credit charges for cars and public transport trips based on their external costs in Munich (Schröder *et al.*, 2023).

Then, the following steps are taken to generate the reference values for the attribute levels in the designs. First, representative trips between the 25 city districts of Munich are queried using Google's directions web service. For every trip, the mode alternatives walking, cycling, driving, and public transport are requested and their values stored. Second, the reference travel time attribute levels are defined as the values obtained from the web service, while the reference levels for the private cost attributes are calculated using the trip distance and the assumed values (see above). Third, the trip credit charges as well as market prices are calculated as follows:

(i) the target per-capita travel production (i.e., modal share) is computed based on the 15% reduction factor for car travel, assuming that half of the reduction is shifted to cycling and half to public transport;

(ii) the credit charges for all public transport trips obtained from Google's directions web service are set to the trip distance times 5/6 credits per travel-km, i.e., the initial 1,000 monthly credit budget divided by the monthly travel production per capita to ensure that all public transport travel does not require any additional credits.

(iii) the charges for car trips are computed by using the assumed 2:1 ratio. The charges for bicycle trips, in this case subsidy, are set to 10% of the public transport charge. The charges for walking trips are set to zero.

(iv) the market price for credits is obtained using a discrete mode choice model built using values for Munich and the German value of time, where the credit charges enter the generalized cost of travel through their market price and the value of time (Moeckel, 2023; Dubernet, 2019). We then search for each origin-destination pair for the credit market price where the observed credit spending equals the available budget, i.e., market clearing balance. This leads to a distribution of market prices with an average market price of around 0.5 Euro per credit. To account for the possibility of varying market prices, the price was pivoted as well. As such, three market price levels were implemented: 0.25, 0.5 (reference price), and 1.25 Euros per credit. The market price is not listed in Table 5.1 as it was not explicitly shown in a given choice task.

Furthermore, two attributes with respect to the mobility budget in a TCS are of interest: the remaining budget of *MobilityCoins* (in percentage) in a given month and the number of days into a month. Both are likely to have an impact on cost sensitivity in the decision-making process and should therefore be controlled for. For example, the decision to use a car in a TCS, given the travel cost and other level-of-service attributes, might be taken differently if one is already 25 days into a month with a remaining mobility budget of 25% (250 *MobilityCoins*) compared to a situation where someone is 15 days into a month and still has 75% of the budget left. In this sense, we expect that –ceteris paribus– the disincentive to use credit-demanding modes (i.e., car and PT) is stronger as the remaining budget decreases and more days of the month are left. The levels of the remaining share of budget left at a given day into a month were 25, 50, and 75%, while those for the days into month attribute were 15, 20, and 25 days.

Figure 5.1 presents an example choice task for both the status quo and the TCS regime to illustrate the outcome of an experimental design.

5.3.1.2 *Sample recruitment*

In the survey, we contacted a representative sample of 10,000 inhabitants of Munich, Germany. Their postal addresses were provided by Munich's registry office, and each of them received an invitation letter with a unique code they could use to access an online form. Upon completion of the survey, respondents received a 15 EUR voucher as an incentive. The sample was restricted to residents aged between 18 and 80 years old and having their official residence within the city boundaries. To evaluate the survey design, 500 individuals were invited to participate in a pre-test survey in June 2022, achieving a 14, 6% response rate (Hamm and Bogenberger, 2022). Subsequently, we implemented some minor improvements in the design and invited the remaining 9,500 individuals. The data collection spanned between July and October 2022 and, including the pre-test, a total of 1,349 individuals completed the survey (13, 5% response rate). The response rate was slightly lower from what could be expected according to a response burden score of 865, and experience from prior surveys conducted at the IVT (Schmid and Axhausen, 2019).

FIGURE 5.1: Example mode choice tasks for (a) the status quo and (b) TCS regime

(a)

You travel for the following purpose: **Errand**.
Your average trip distance is **3 to 5.99 km**.
The weather is **rainy**.

Scenario 1	Option 1: Walk	Option 2: Car	Option 3: Bicycle	Option 4: PT
Travel time	48 min	12 min	18 min	8 min
Access & egress time				16 min
Frequency				every 15 min
Transfers				2 x
Travel cost		2,9 €		2,5 €
Quality of cycle lane			medium	

(b)

You travel for the following purpose: **Errand**.
Your average trip distance is **3 to 5.99 km**.

It's day **15** of the month and you have a remaining budget of **25 %** .
The weather is **sunny**.

Scenario 1	Option 1: Walk	Option 2: Car	Option 3: PT	Option 4: Bicycle
Travel time	1h 6 min	14 min	7 min	18 min
Access & egress time			14 min	
Frequency			every 15 min	
Transfers			0 x	
Travel cost		2,9 €	2,5 €	
MobilityCoin expense		14,25 €	5,25 €	
MobilityCoin revenue				0,5 €
Quality of cycle lane				bad

5.3.2 *Modeling approach*

The following model formulation represents the MMNL model applied to the data at hand. In Section 5.4 we present the results of both our MNL and MMNL models.

Each alternative i for an individual n in model component m and choice task t is associated with a utility $U_{i,n,m,t} = V_{i,n,m,t} + \epsilon_{i,n,m,t}$ with $V_{i,n,m,t} = f(\beta)$ referring to the observed and $\epsilon_{i,n,m,t}$ to the random (unobserved) part of it. The observed part $V_{i,n,m,t}$ relates to a vector of parameters β that is estimated based on the attributes given in the choice experiment and sociodemographic variables of the respondents. The random utility terms are distributed identically and independently (iid) across alternatives and respondents using the type 1 extreme value distribution. Since the value of $\epsilon_{i,n,m,t}$ is not known, only the probability of choosing an alternative can be calculated. Whereas in MNL β is fixed across individuals, in MMNL the coefficients vary over decision makers and therefore might reveal random heterogeneity across decision-makers. β_n resembles an unobserved vector taste parameters for individual n. For the MMNL, to account for the random heterogeneity across decision-makers, we assume $\beta_n \forall n$ with density $f(\beta|\Omega)$, where Ω is a vector of parameters of this distribution (i.e., its mean and variance). Since we have multiple choices per individual, the likelihood of the sequence of choices for individual n is given by $L_n(\Omega)$ (see Equation 5.1), assuming that sensitivities vary across individuals, but stay constant within. $i^*_{n,m,t}$ represents the individual's chosen alternative i in model component m and choice task t. Since the likelihood is given by an integral without a closed-form solution, we need simulation to approximate it. The MMNL model is estimated by means of Maximum Simulated Likelihood (MSL) where the simulated log-likelihood (SLL, see Equation 5.4) is the probability of reproducing each choice in the sample and $\beta_{r,n}$ gives the r^{th} draw from $f(\beta|\Omega)$ for individual n. θ resembles the set of fixed parameters.

$$L_n(\Omega) = \int_\beta \prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t}\left(i^*_{n,m,t}|\beta,\theta\right) f(\beta|\Omega)\, d\beta \tag{5.1}$$

$$L(\Omega) = \prod_{n=1}^{N} \int_\beta \left[\prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t}\left(i^*_{n,m,t}|\beta,\theta\right)\right] f(\beta|\Omega)\, d\beta \tag{5.2}$$

$$LL(\Omega) = \sum_{n=1}^{N} ln \left(\int_{\beta} \left[\prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t} \left(i^{*}_{n,m,t} | \beta, \theta \right) \right] f(\beta|\Omega) \, d\beta \right) \tag{5.3}$$

$$SLL(\Omega) = \sum_{n=1}^{N} ln \left(\frac{1}{R} \sum_{r=1}^{R} \left[\prod_{t=1}^{T} \prod_{m=1}^{M} P_{n,m,t} \left(i^{*}_{n,m,t} | \beta_{r,n}, \theta \right) \right] \right) \tag{5.4}$$

We estimate a pooled MMNL model parametrized in willingness-to-pay (WTP) space. The term "pooled" refers to parameters that are calibrated jointly across both model components for robustness reasons (e.g., the alternative-specific constants (ASC) and level-of-service (LOS) attributes such as travel time, travel cost, access & egress time). The utility equations $V_{i,n,m,t}$ are given by:

$$\begin{aligned} V_{W,n,SQ,t} = {} & \alpha_W + S_{n,t}\kappa_{\alpha_W} + \\ & \psi_{n,t}\left(x^{tc}_{W,n,SQ,t} + x^{tt}_{W,n,SQ,t} VTT_{W,n,t} \right) + V_{SQ,t}\gamma_W \end{aligned} \tag{5.5}$$

$$\begin{aligned} V_{B,n,SQ,t} = {} & \alpha_B + S_{n,t}\kappa_{\alpha_B} + \\ & \psi_{n,t}\left(x^{tc}_{B,n,SQ,t} + x^{tt}_{B,n,SQ,t} VTT_{B,n,t} \right) + V_{SQ,t}\gamma_B \end{aligned} \tag{5.6}$$

$$\begin{aligned} V_{C,n,SQ,t} = {} & \alpha_C + S_{n,t}\kappa_{\alpha_C} + \\ & \psi_{n,t}\left(x^{tc}_{C,n,SQ,t} + x^{tt}_{C,n,SQ,t} VTT_{C,n,t} \right) + V_{SQ,t}\gamma_C \end{aligned} \tag{5.7}$$

$$\begin{aligned} V_{PT,n,SQ,t} = {} & \psi_{n,t}\Big(x^{tc}_{PT,n,SQ,t} + x^{tt}_{PT,n,SQ,t} VTT_{PT,n,t} + \\ & X_{PT,n,SQ,t} WTP_{PT} \Big) \end{aligned} \tag{5.8}$$

$$\begin{aligned} V_{W,n,TCS,t} = \omega_{TCS}\Big(&\alpha_W + S_{n,t}\kappa_{\alpha_W} + \\ &\psi_{n,t}\left(x^{tc}_{W,n,TCS,t} + x^{tt}_{W,n,TCS,t}VTT_{W,n,t}\right) + V_{TCS,t}\gamma_W\Big) \end{aligned} \tag{5.9}$$

$$\begin{aligned} V_{B,n,TCS,t} = \omega_{TCS}\Big(&\alpha_B + S_{n,t}\kappa_{\alpha_B} + \\ &\psi_{n,t}\left(x^{tc}_{B,n,TCS,t} + x^{tt}_{B,n,TCS,t}VTT_{B,n,t}\right) + \\ &x^{mb}_{B,n,TCS,t}\iota^{mb}_{TCS} + V_{TCS,t}\gamma_B\Big) \end{aligned} \tag{5.10}$$

$$\begin{aligned} V_{C,n,TCS,t} = \omega_{TCS}\Big(&\alpha_C + S_{n,t}\kappa_{\alpha_C} + \\ &\psi_{n,t}\left(x^{tc}_{C,n,TCS,t} + x^{tt}_{C,n,TCS,t}VTT_{C,n,t}\right) + \\ &x^{mc}_{C,n,TCS,t}\tau^{mc}_{TCS} + V_{TCS,t}\gamma_C\Big) \end{aligned} \tag{5.11}$$

$$\begin{aligned} V_{PT,n,TCS,t} = \omega_{TCS}\Big(&\psi_{n,t}\Big(x^{tc}_{PT,n,TCS,t} + x^{tt}_{PT,n,TCS,t}VTT_{n,t} + \\ &X_{PT,n,TCS,t}WTP_{PT}\Big) + x^{mc}_{PT,n,TCS,t}\tau^{mc}_{TCS}\Big) \end{aligned} \tag{5.12}$$

with:

- ω_m: Parameter to account for scale differences (error variance) between the two model components in pooled estimation (Hensher *et al.*, 1998); $m \in \{SQ, TCS\}$ (SQ = reference; $\omega_{SQ} = 1$)
- α_i: Alternative-specific constant (PT = reference; $\alpha_{PT} = 0$)
- $S_{n,t}$: Vector of trip-specific and sociodemographic attributes as a shift on the ASC's
- κ_i: Vector of parameters for $S_{n,t}$
- $\psi_{n,t}$: Scale parameter of VTT & WTP attributes (see Equation 5.13)
- $x^{tc}_{i,n,m,t}$: Private travel cost
- $x^{tt}_{i,n,m,t}$: Travel time
- $VTT_{i,n,t}$: VTT parameter (see Equation 5.14)

- $X_{PT,n,m,t}$: Vector of trip-specific PT attributes (e.g., access & egress time, number of transfers, frequency; excluding PT private travel costs and travel time)
- WTP_{PT}: Vector of PT-related WTP parameters
- $x^{mc}_{i,n,TCS,t}$: *MobilityCoin* expense (external travel cost for car and PT)
- τ^{mc}_{TCS}: Parameters for $x^{mc}_{i,n,TCS,t}$
- $x^{mb}_{B,n,TCS,t}$: *MobilityCoin* revenue (external travel incentive for bicycle)
- ι^{mb}_{TCS}: Parameters for $x^{mb}_{B,n,TCS,t}$
- $V_{m,t}$: Vector of scenario attributes (e.g., weather, bike lane quality)
- γ_i: Vector of parameters for $V_{m,t}$.

For models parametrized in WTP, the overall model scale is a product of the scale parameter of the extreme value distribution and, as in our case, the private cost parameter. Therefore, the effect of scale heterogeneity, which is shared across coefficients, can not be separated from heterogeneity in individual coefficients when using univariate distributions (Train and Weeks, 2005; Hess and Rose, 2012). The scale coefficient is then defined as a function (Equation 5.13) that accounts for heterogeneity in all VTT-related attributes. It follows a negative log-normal distribution according to $\beta^{scale} = -exp(\mu + \sigma r_N)$ with $r_N \sim N(\mu, \sigma)$. The non-linear interaction term with distance $dist_{n,t}$ ($\overline{dist}$ is the sample average) additionally allows for heterogeneity with respect to the trip length. We expect a negative δ_{scale}, indicating that for longer distances, potentially relevant but unobservable features may gain in relative importance, which are omitted in the utility function.

$$\psi_{n,t} = -exp\left(\mu_{log(\beta^{scale})} + \sigma_{log(\beta^{scale})} r_N\right)\left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\delta^{scale}} \tag{5.13}$$

$VTT_{i,n,t}$ (Equation 5.14) follows a log-normal distribution according to $\beta^{VTT}_{i,n} = exp(\mu_i + \sigma_{i,n} r_N)$ with $r_N \sim N(\mu, \sigma)$ and thereby accounting for random individual-related heterogeneity in VTT parameters. Again, the non-linear interaction term with distance $dist_{n,t}$ additionally allows for heterogeneity with respect to the trip length. We expect a positive δ^{VTT}, indicating that VTTs marginally increase for longer trip distances. Moreover, we incorporate purpose-specific multipliers z on the VTT, $\kappa_{i,z}^{VTT}$ times a dummy for each $p_{z,n}$, to account for differences between the three trip purposes mentioned in Section 5.3.

$$VTT_{i,n,t} = exp\left(\mu_{log(\beta_i^{VTT})} + \sigma_{log(\beta_{i,n}^{VTT})} r_N\right)\left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\delta^{VTT}} \prod_z \left((\kappa_{i,z}^{VTT})p_{z,n} + (1 - p_{z,n})\right) \quad (5.14)$$

Note that only β parameters in $\psi_{n,t}$ and $VTT_{i,n,t}$ are random in our specification. The models were estimated using R (version 4.2.0) and the Apollo package (version 0.2.9) on ETH's Euler compute cluster (R Core Team, 2020; Hess and Palma, 2019).

5.4 RESULTS

This section presents the results of the choice model mentioned above and discusses the implied effects on mode choice preferences. Special focus is given to the cost sensitivity of *MobilityCoin* expenses and VTT estimates.

5.4.1 *Study participation*

A total of 1,349 complete responses were collected in 2022. A comparison of the sample composition with the most recent mobility census from 2017 in Germany filtered for Bavaria (Nobis and Kuhnimhof, 2018) as well as local data for Munich revealed two noteworthy differences: our sample over-represents younger age cohorts (18-30 & 30-40 years of age) and people holding a university degree (see Table 5.2). In order to have representative results it is therefore necessary to re-weight the model outcome to population level to account for those differences. We used iterative proportional fitting (IPF) to calculate weights for all individuals in the sample based on the marginal distributions of gender, age cohort, highest education level, mobility tool ownership, and household size. The resulting weights range from 0.2 to 5.

5.4.2 *Descriptive analysis*

Non-trading in choice behavior can be an issue in SC experiments as discussed in Hess *et al.* (2010). It generally refers to the situation where a respondent always chooses the same alternative across choice tasks for different reasons: extreme preferences, heuristic decision-making, and political or strategic behavior. In addition, SP data might exhibit further behavioral bias such as the social desirability or lack of consequentiality bias (Tsoleridis *et al.*, 2022). We observed non-trading behavior for 296 individuals in our sample. After comprehensive testing, we decided to remove these for the following reasons. First, many of those respondents rushed through the survey having an experiment duration time of less than 5 minutes. Second, a substantial share failed the exam question at the end of the survey concerning the purpose of a TCS, which indicates that they did not understand the basic principles of such a scheme. Last but not least, the MNL models tested with only traders gave more reliable results in terms of parameter estimates, model fit, and corresponding VTT values.

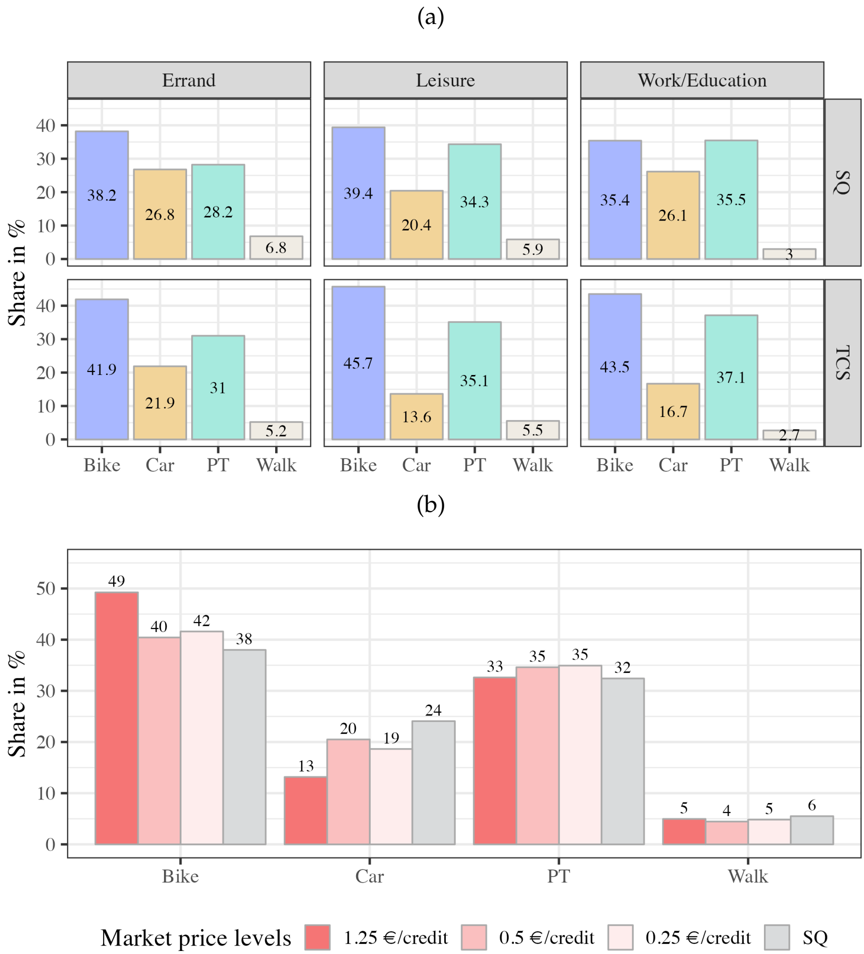
Figure 5.2 presents an overview of the choice frequencies for different trip purposes and regimes, and *MobilityCoin* price levels. The modal split in Subfigure (a) shows a high cycling share across trip purposes and regimes, which might either be related to the mobility behavior of the sample or to the experimental design. Regarding the former possibility, the simplified travel diary of the survey revealed that more than 40% of the participants ride their bicycle almost daily and another 20% on 2-3 days per week. Albeit these are high values, Munich and other comparable European cities have seen a substantial increase in cycling usage in the last years (OpenDataPortal, 2023). Furthermore, due to the recruitment strategy of our study, the sample of participants consists exclusively of residents of the city of Munich, presumably with higher accessibility to services and jobs and lower needs to commute by car, and excludes those of the metropolitan area. This would explain the low car shares observed in the SC experiment.

Despite the discussed cycling trend and the use of efficient choice designs, we can not rule out the presence of other biases affecting the behavior of the participants. Nevertheless, the effect of introducing a TCS is clearly visible across all trip purposes and price levels. Trips with work/education purposes experience the strongest reduction in car share (almost 10%) and consequent growth of the bike mode, with a lower observed increase of public transport. Conversely, for errand activities, we observe the smallest reduction in car share, which is distributed evenly between car and public transport. This difference is intuitive as public transport, and bikes in particular, are poor substitutes of cars for the transport of loads (e.g., groceries). Overall, there seem to be only small increases between the regimes for PT, whereas walking is barely affected. Regarding the market price in Subfigure (b), introducing the TCS leads to a significant reduction of car share for all price levels, but this reduction is strongest for the high market price level. Interestingly, public transport share experiences a slight increase for low and medium market price levels, but falls back to the status quo level for the high market price. A possible explanation is that, for this market level, PT becomes too expensive and its utility degrades excessively in relation to that of the bike mode. Thus, with a high market price level, all the reduction in car share is shifted to bike.

Table 5.2: Sample comparison to the German MiD 2017 (Munich)

Variable	Value	% MiD	% Sample
Age	18-30 years	21.8	26.0
	31-40 years	20.5	24.8
	41-50 years	17.8	16.2
	51-65 years	21.6	23.7
	66-90 years	18.3	9.3
gender	female	50.1	49.3
	male	49.9	50.7
education	no education	0.1	0.1
	elementary school	30.7	1.6
	mittlere reife	26.2	6.9
	university of a.s.	13.2	26.0
	university	26.2	56.9
	other	2.6	8.2
drivers licence	yes	93.6	91.9
	no	6.4	8.1
PT season ticket	no	84.2	56.2
	weekly	3.8	1.8
	monthly/yearly	7.4	34.2
	semester	4.6	7.8
household size	1	18.1	24.2
	2	40.7	42.8
	3	17.6	15.0
	4	16.5	13.3
	>5	6.9	4.5
personal income	under 900 Euro	-	10.0
	900 - 1,599 Euro	-	10.2
	1,600 - 2,599 Euro	-	20.8
	2,600 - 3,599 Euro	-	25.6
	3,600 - 4,599 Euro	-	11.7
	4,600 - 5,999 Euro	-	7.2
	more than 6,000 Euro	-	7.6

FIGURE 5.2: Choice frequencies by (a) trip purpose and regime (b) market price levels



5.4.3 *Model results and discussion*

The model estimates are presented in Table 5.3. The discussion focuses on the MMNL 2 model and follows the segmentation used in Table 5.3. The units of the temporal variables are minutes while those related to costs are Euros. Building upon the recommendations of Wasserstein *et al.* (2019), the table does not present associated p-values. Thus, researchers should recognize the presence of uncertainty and should not assume that effects simply exist due to the statistical significance or lack thereof.

TABLE 5.3: Estimation results

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Scale model component						
TCS (ω_{TCS})	0.973	(−0.810)	0.975	(−0.620)	0.975	(−0.640)
ASC						
Car (α_C)	−1.370	(−1.988)	−1.865	(−1.754)	−1.886	(−1.462)
Car shift errand (κ_C)	0.558	(1.702)	0.211	(0.514)	0.366	(0.759)
Car shift leisure (κ_C)	−0.397	(−1.144)	0.040	(0.099)	0.269	(0.621)
Car shift male (κ_C)	0.330	(3.049)	0.478	(3.011)	0.462	(2.847)
Car shift divers (κ_C)	1.777	(2.186)	2.913	(1.866)	3.462	(2.052)
Car shift age (κ_C)	0.057	(2.342)	0.096	(2.817)	0.090	(2.480)
Car shift age sq. (κ_C)	−0.001	(−2.514)	−0.001	(−3.044)	−0.001	(−2.691)
Car shift high educ. level (κ_C)	−0.343	(−2.922)	−0.387	(−2.216)	−0.374	(−2.145)
Bike (α_B)	−3.873	(−7.165)	−5.134	(−6.290)	−5.174	(−5.375)
Bike shift errand (κ_B)	0.200	(0.762)	0.252	(0.673)	0.323	(0.615)
Bike shift leisure (κ_B)	0.101	(0.398)	−0.606	(−1.848)	−0.411	(−1.097)
Bike shift male (κ_B)	0.177	(1.956)	0.370	(2.840)	0.368	(2.766)

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Table 5.3 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Bike shift divers (κ_B)	0.140	(0.124)	1.223	(0.685)	1.913	(0.992)
Bike shift age (κ_B)	0.060	(3.217)	0.098	(3.462)	0.094	(3.269)
Bike shift age sq. (κ_B)	−0.001	(−2.994)	−0.001	(−3.443)	−0.001	(−3.270)
Bike shift high educ. level (κ_B)	−0.009	(−0.087)	−0.003	(−0.021)	0.024	(0.164)
Walk (κ_W)	−2.612	(−2.193)	−2.855	(−1.858)	−2.639	(−1.480)
Walk shift errand (κ_W)	0.275	(0.323)	0.456	(0.430)	1.199	(0.936)
Walk shift leisure (κ_W)	0.032	(0.037)	−0.358	(−0.343)	0.122	(0.099)
Walk shift male (κ_W)	−0.193	(−1.045)	−0.148	(−0.609)	−0.169	(−0.649)
Walk shift divers (κ_W)	2.187	(3.131)	2.220	(1.737)	2.771	(2.319)
Walk shift age (κ_W)	0.049	(1.483)	0.094	(1.828)	0.058	(1.145)
Walk shift age sq. (κ_W)	−0.000	(−0.817)	−0.001	(−1.278)	−0.000	(−0.560)
Walk shift high educ. level (κ_W)	0.131	(0.663)	0.256	(0.969)	0.261	(0.949)
MobilityCoin expense / revenue						
Cost sensitivity (τ^{mc}_{TCS}), with:						
75% budget left, 15 days into month	−0.037	(−3.510)	−0.049	(−3.827)	−0.049	(−3.817)
75% budget left, 20 days into month	−0.013	(−1.434)	−0.041	(−3.333)	−0.042	(−3.399)

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Table 5.3 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
75% budget left, 25 days into month	−0.010	(−0.950)	−0.028	(−2.138)	−0.026	(−1.891)
50% budget left, 15 days into month	−0.080	(−4.541)	−0.098	(−5.089)	−0.100	(−5.120)
50% budget left, 20 days into month	−0.013	(−1.068)	−0.063	(−3.489)	−0.063	(−3.493)
50% budget left, 25 days into month	−0.014	(−1.028)	−0.039	(−2.219)	−0.038	(−2.165)
25% budget left, 15 days into month	−0.081	(−5.975)	−0.127	(−7.613)	−0.128	(−7.555)
25% budget left, 20 days into month	−0.053	(−4.276)	−0.096	(−5.678)	−0.097	(−5.643)
25% budget left, 25 days into month	−0.058	(−4.166)	−0.081	(−5.291)	−0.080	(−5.075)
Distance elasticity ($\delta_{TCS}^{mc,dist}$)	−0.785	(−7.881)	−0.902	(−12.328)	−0.898	(−12.024)
Income elasticity ($\delta_{TCS}^{mc,inc}$)	−0.302	(−2.766)	−0.215	(−2.326)	−0.200	(−2.179)
Revenue/incentive sensitivity (ι_{TCS}^{mb})	0.199	(2.003)	0.291	(2.279)	0.286	(2.247)
Scale parameter						
Mean scale ($\mu_{log(\beta^{scale})}$)	−0.149	(−8.009)	−1.731	(−14.345)	−1.725	(−13.248)
Sd scale ($\sigma_{log(\beta^{scale})}$)			0.133	(1.814)	0.166	(1.102)
Distance elasticity scale ($\delta_{TCS}^{tc,dist}$)	−0.715	(−6.514)	−0.654	(−9.394)	−0.680	(−9.765)

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Table 5.3 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
VTT (mean & sd) & WTP indicators						
Mean VTT PT ($\mu_{log(\beta_{PT}^{VTT})}$)	0.402	(5.084)	−1.281	(−5.089)	−1.099	(−3.135)
Mean VTT Car ($\mu_{log(\beta_{C}^{VTT})}$)	0.296	(2.822)	−0.855	(−2.605)	−0.903	(−2.532)
Mean VTT Bike ($\mu_{log(\beta_{B}^{VTT})}$)	0.411	(5.283)	−0.483	(−3.236)	−0.487	(−2.902)
Mean VTT Walk ($\mu_{log(\beta_{W}^{VTT})}$)	0.540	(3.451)	−0.288	(−1.180)	−0.417	(−1.295)
Sd VTT PT ($\sigma_{log(\beta_{PT}^{VTT})}$)			−1.000	(−10.286)	−0.862	(−5.903)
Sd VTT Car ($\sigma_{log(\beta_{C}^{VTT})}$)			−1.218	(−8.821)	−1.161	(−7.662)
Sd VTT Bike ($\sigma_{log(\beta_{B}^{VTT})}$)			0.625	(14.423)	0.612	(13.566)
Sd VTT Walk ($\sigma_{log(\beta_{W}^{VTT})}$)			0.459	(7.343)	0.447	(7.286)
Multiplier PT leisure ($\kappa_{PT,leisure}^{VTT}$)	0.893	(4.944)	1.152	(5.148)	0.993	(4.838)
Multiplier PT errand ($\kappa_{PT,errand}^{VTT}$)	0.628	(3.949)	1.459	(4.796)	1.294	(3.295)
Multiplier Car leisure ($\kappa_{C,leisure}^{VTT}$)	0.443	(1.461)	1.263	(3.747)	1.359	(3.787)
Multiplier Car errand ($\kappa_{C,errand}^{VTT}$)	0.444	(1.548)	0.647	(3.722)	0.727	(3.786)
Multiplier Walk leisure ($\kappa_{W,leisure}^{VTT}$)	0.731	(3.514)	0.716	(4.559)	0.767	(3.578)
Multiplier Walk errand ($\kappa_{W,errand}^{VTT}$)	0.755	(3.234)	0.793	(4.640)	0.955	(3.557)
Multiplier Bike leisure ($\kappa_{B,leisure}^{VTT}$)	0.853	(6.598)	0.687	(9.509)	0.730	(7.239)

Continued on next page

Table 5.3 – *Continued from previous page*

Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
Multiplier Bike errand ($\kappa^{VTT}_{B,errand}$)	0.693	(5.568)	1.062	(9.114)	1.052	(6.321)
Distance elasticity VTT	0.541	(4.011)	0.047	(0.810)	0.067	(1.054)
Income elasticity VTT			0.018	(0.501)	0.017	(0.425)
WTP PT access/eggress time	0.118	(1.799)	0.231	(3.272)	0.227	(2.552)
WTP PT frequency	0.064	(1.344)	0.160	(3.274)	0.156	(2.900)
WTP PT transfers	0.713	(3.418)	1.101	(4.352)	1.057	(3.885)
Scenario variables (normalized for rain and bad bike lane quality)						
Bike lane medium quality ($\gamma_{medium\ q.,t}$)	0.763	(10.974)	1.125	(12.087)	1.127	(12.040)
Bike lane good quality ($\gamma_{good\ q.,t}$)	0.942	(13.870)	1.477	(15.040)	1.475	(14.945)
Car sunny weather ($\gamma_{C\ sun,t}$)	−0.381	(−4.511)	−0.770	(−7.326)	−0.767	(−7.263)
Bike sunny weather ($\gamma_{B\ sun,t}$)	2.829	(29.240)	3.884	(26.571)	3.882	(26.538)
Walk sunny weather ($\gamma_{W,t}$)	2.107	(12.732)	2.873	(12.020)	2.866	(11.981)
LL(0,SQ)	-6283.166		-6283.166		-6283.166	
LL(final,SQ)	-4594.511		-4184.881		-4181.870	
LL(0,TCS)	-6539.372		-6539.372		-6539.372	
LL(final,TCS)	-4738.993		-4329.226		-4328.746	

Continued on next page

Table 5.3 – *Continued from previous page*

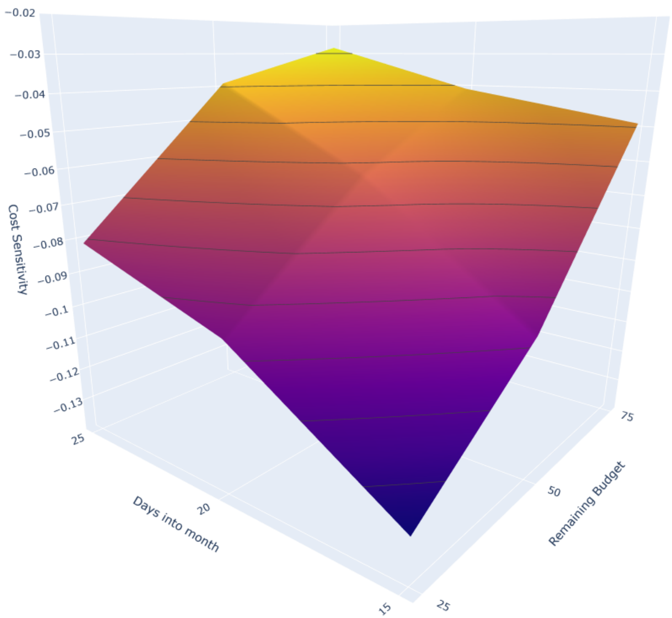
Reference: PT	MNL		MMNL 1		MMNL 2	
	Est.	Rob. t-ratio	Est.	Rob. t-ratio	Est.	Rob. t-ratio
LL(0,model)	-12822.537		-12822.537		-12822.537	
LL(final,model)	-9333.504		-8106.550		-8110.860	
Adj. rho squared (model)	0.272		0.367		0.367	
# respondents	1053		1053		1053	
# observations	11172		11172		11172	
# parameters	72		78		78	
# draws	0		500		1000	

The scale parameter of the TCS model component ω_{TCS} is not significantly different from one, which shows that we cannot reject equal error variances between the two experiments. However, it is still important to control for it.

The ASC represent the mean of unobserved factors in the model. For identification reasons, one has to be normalized to zero, which is the one for PT in our case. The same principle holds for categorical variables, where one level is set as reference to the others. For each alternative, we include shifts on the ASC for different trip purposes and sociodemographic variables. To start, all the purpose-specific shifts included are not significantly different from zero, but show the expected sign. The coefficients of the non-linear specification for age suggest that –ceteris paribus– walking, bike, and car are preferred over PT for younger ages, but the latter two become less attractive than PT after retirement age. With regard to car, male and divers people (0.462; 3.462) are more likely than females to choose car over PT. In contrast, highly educated individuals holding a University degree (-0.374) are less prone to do so than people with a lower education. Similar –although slightly lower– effects were found for male and divers people (0.368; 1.913) with respect to bike. However, higher education does not seem to significantly influence the choice to ride a bike compared to lower education levels (0.024) and relative to PT. With respect to the ASC for car, neither the base ASC nor any shift turned out to be significant. However, in general, it is still important to control for these effects when deriving VTT values.

The external-cost coefficients for different remaining budgets and days into the month (τ_{TCS}^{mc}) are all negative and significant. As shown in Figure 5.3, for a given budget at the mean trip distance and monthly household income, the sensitivity to the *MobilityCoins* charge is higher the more days are left until the end of the month, as individuals need to distribute their remaining budget within more days. Conversely, for a given day in the month, individuals are less sensitive to the external costs the larger their remaining budget is. Albeit intuitive, both observations confirm that the participants understood the complexity of TCS and seem to behave rationally by incorporating it into their decision-making process. They also reveal that the same *MobilityCoins* charge could have different impacts on mode choice at different moments in time within a month. Moreover, we found that the cost sensitivity marginally decreases with longer trip distances and higher monthly household income. While the effect of the latter is lower in absolute magnitude (-0.2 vs. -0.898), it is interesting that we found no income effect on all the VTT values (see Section 5.4.3.1), which in our framework only depend on private travel costs. As expected, a *MobilityCoins* incentive ι_{TCS}^{mb} positively affects the probability to choose a bike.

FIGURE 5.3: External-cost-sensitivity for different remaining budgets and day of the month



The scale was specified as a random continuous parameter in MMNL 2 to possibly reveal scale heterogeneity in the VTT values. Interestingly, there does not seem to be random scale heterogeneity as the estimated standard deviation $\sigma_{log(\beta^{scale})} = 0.166$ is not significant (t-ratio $= 1.102$). $-exp(\sigma_{log(\beta^{scale})}) = -0.178$ shows that the parameter is very similar to MNL estimate of -0.149. The distance elasticity on the scale parameter yields a decreasing marginal effect for longer trip distances (-0.680), which again is comparable to -0.715 in the MNL model and further confirms our hypothesis from Section 5.3.2. This indicates that the VTT values presented in Section 5.4.3.1 to a large extent are driven by randomness in the individual sensitivities.

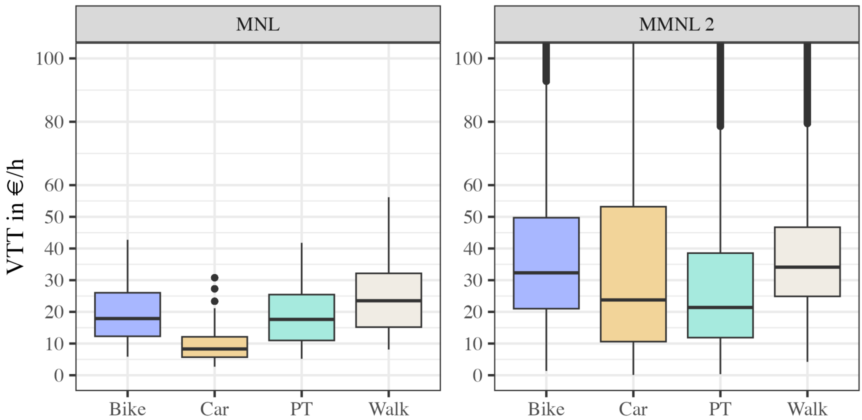
By definition, the value of travel time is the extra cost that a person would be willing to incur to save one unit of time (Train, 2009). A higher VTT generally indicates a larger discomfort when traveling with that mode if user effects (i.e., sociodemographic effects) are controlled for. The VTT estimates presented in the next part of Table 5.3 were also specified as random continuous parameters as explained in Section 5.3.2. As with the scale parameters, it is important to mention that the estimates can not be directly compared between the MNL and MMNL 2 model, as the latter are given by the logarithm of it and need back-transformation to do so. We discuss the resulting VTT values in Section 5.4.3.1. For now, we observe that there is significant random individual heterogeneity in the VTT estimates for all alternatives, with the largest std. deviation for cars (see $\sigma_{log(\beta_i^{VTT})}$). Except for the distance and income elasticity estimates on the VTT, all parameters are statistically significant on the 5% significance level. In contrast to the scale parameter, the VTT values are only barely affected by trip distance and household income. Nevertheless, both show a slightly positive influence and hence partially confirm our expectation from Section 5.3.2. In addition, the alternative-specific multipliers on the VTT yield important differences between the modes. Whereas the VTT between commute/education and leisure-related PT trips is not significantly different (0.993 vs. 1), the VTT for errands is almost 30% higher (1.294), which is often associated with higher discomfort (i.e., mode effect). With regard to the car VTT values, we observe a higher value for leisure (35%, 1.359) and a lower one for errands (0.727) compared to commute/education trips. The VTT value for leisure seems somewhat counter-intuitive and might have picked up unobserved factors (i.e., we did not control for) given that the estimate in the MNL model is lower. With respect to walking, the VTT for leisure is lower (0.767, approx. 24%) compared to commute/education whereas there is no visible difference to errand related trips (0.995).

When looking at the scenario variables, we observe very intuitive and significant estimates. Medium and very good cycling lane qualities (a very simplified proxy in the SC experiment for cycling infrastructure) show positive effects on the probability to choose a bike (1.127 & 1.475). Furthermore, sunny weather has a negative influence on choosing a car in comparison to rainy weather and relative to PT (-0.767), while it is associated with substantial positive effects on cycling (3.882) and walking (2.866). As the estimates show, it is important to at least approximate the influence of weather when including active modes in an SC experiment.

5.4.3.1 *VTT distributions across alternatives and models*

In order to present a meaningful comparison between the VTT values across alternatives, trip purposes, and models, we applied sample enumeration, which essentially calculates values for each observation in the data. We used the unconditional posterior distributions that include the draws and hence account for uncertainty around the mean, instead of using the conditional posterior means which ignores part of the heterogeneity. Figure 5.4 summarizes the resulting VTT distributions (in €/hour) for each alternative and model, and Table 5.4 presents the corresponding numbers.

FIGURE 5.4: VTT comparison between the models



In the case of the MNL model, the median car VTT is lowest (8.3), followed by PT (17.6), bike (17.9), and walk (23.5). In many VTT studies, the values for active modes such as walking or cycling tend to be higher compared to car and PT since they actually resemble physical activity. Note that the median VTT value for PT is relatively high, which might be due to the fact that we do not account for crowding, for example. In the context of a city like Munich this could be important. Furthermore, we assumed zero private travel costs for persons owning a PT subscription to account for mobility tool ownership effects. The median car VTT value observed might (still) be attributed to a general preference for cars in Munich even though we removed non-traders from the sample. However, as explained

TABLE 5.4: Summary of VTT values for each model

MNL				
Mode	W. mean	Mean	Median	IQR
Bike	19.42	19.01	17.88	13.74
Car	9.52	9.53	8.29	6.42
PT	18.65	18.41	17.61	14.47
Walk	24.99	24.22	23.51	16.97

MMNL 2				
Mode	W. mean	Mean	Median	IQR
Bike	39.50	39.50	32.31	28.69
Car	41.73	40.62	23.17	40.32
PT	29.41	30.86	21.35	26.58
Walk	38.02	38.00	34.11	21.82

in Section 5.3.1.1, we decided to have evenly distributed trip distances in the SC experiment, leading to a higher mean of trip distances compared to current data and hence higher means of VTT values.

Looking at the VTT values derived from MMNL 2, and taking random heterogeneity into account, we generally observe higher mean values as well as a larger spread across alternatives. This can be related to our assumption of log-normally distributed VTT parameters, which often exhibit longer tails on the right side of the distribution, and might translate into unrealistically high values (Hess *et al.*, 2017). Therefore, Figure 5.4 is truncated at values of 100 €/hour. However, the larger variance in VTT values for bike, car and PT indicate that external travel costs or incentives play an important role. This effect is particularly noticeable in the case of car, further reinforcing the conjecture that a portion of the random heterogeneity captured by the model is associated with the presumed TCS scenario. This supposition finds support in the generally heightened levels of sensitivity regarding external costs within MMNL 2 when contrasted with the comparatively simpler

MNL model. Based on these results, a TCS regime will likely increase the perceived VTT value for car and might shift users away from using it.

The own- and cross-elasticities ($E_{i,k}$ and $E_{ji,k}$) for the MMNL 2 model presented in Table 5.5 are population weighted and show the average responsiveness of choice probabilities (i.e., %-changes) to a change in choice attribute $X_{k,i}$ while keeping all other attributes fixed (see e.g. Winkelmann and Boes, 2006). For all attributes, a 1%-increase in their levels was assumed.

$$E_{i,k} = \frac{\text{\%-change in } P_i}{\text{\%-change in } X_{k,i}} = \frac{\dfrac{\overline{P}_{i,k^*} - \overline{P}_{i,k}}{(\overline{P}_{i,k} + \overline{P}_{i,k^*})/2}}{\dfrac{\overline{X}_{k^*,i} - \overline{X}_{k,i}}{(\overline{X}_{k,i} + \overline{X}_{k^*,i})/2}} \tag{5.15}$$

In both model components (i.e., regimes) travel time seems to have stronger effects than internal (and external) travel cost. When looking at the TCS component specifically, it should be highlighted that for both car and PT, an 1%-increase in internal or external travel cost yield very similar changes in the corresponding choice probabilities. This is an interesting finding indicating that external travel costs influence mode choice as strongly as internal travel costs under the given assumptions of this study. Although on a rather low level, for the car, the own- and cross-elasticities regarding a change in external costs are higher compared to PT, which is intuitive as we assumed comparatively higher costs for cars. Furthermore, and based on the magnitude of elasticities, there seem to be greater substitution effects between car and PT compared to walk and bike despite the incentive for the latter and the modal split presented in Section 5.4.2.

5.5 CONCLUSION

This chapter presents first findings concerning mode choice preferences within the framework of a Tradable Credit Scheme in the city of Munich, Germany. The main objective of the TCS is twofold: Firstly, to curtail the usage of less sustainable transportation modes, and secondly, to promote more sustainable alternatives by implementing a monthly mobility budget in the form of *MobilityCoins*. These coins account for both the external costs and benefits associated with the modes under consideration. To investigate heterogeneity of choice behavior in such a context, we conducted a survey that contained two SC experiments. One resembling the choice between

Table 5.5: Elasticities $E_{i,k}$ and $E_{ji,k}$ (MMNL 2)

Variable (+1%)	Model component	Walk	Bike	Car	PT
Walk travel time	SQ	−2.43	0.15	0.08	0.11
Bike travel time	SQ	0.61	−0.67	0.32	0.45
Car travel time	SQ	0.11	0.09	−0.43	0.19
Car internal travel cost	SQ	0.06	0.06	−0.28	0.12
PT travel time	SQ	0.14	0.17	0.20	−0.36
PT internal travel cost	SQ	0.06	0.04	0.06	−0.10

Variable (+1%)	Model component	Walk	Bike	Car	PT
Walk travel time	TCS	−2.40	0.15	0.10	0.11
Bike travel time	TCS	0.66	−0.63	0.38	0.53
Bike travel incentive	TCS	−0.02	0.03	−0.02	−0.03
Car travel time	TCS	0.09	0.07	−0.45	0.15
Car internal travel cost	TCS	0.05	0.05	−0.31	0.10
Car external travel cost	TCS	0.06	0.05	−0.30	0.09
PT travel time	TCS	0.13	0.16	0.23	−0.37
PT internal travel cost	TCS	0.06	0.04	0.07	−0.10
PT external travel cost	TCS	0.06	0.05	0.06	−0.12

walking, cycling, car, and PT in a status quo regime, and one where we hypothetically introduced the TCS paradigm.

A descriptive analysis of the data gathered revealed that the implementation of a TCS leads to significantly lower car shares for all considered trip purposes and credit market price levels. The bicycle share experiences the largest increase, whereas PT only slightly gains and walking remains unaffected. We estimated a Mixed Multinomial (MMNL) choice model to investigate sensitivities to external travel costs and to derive values of travel time for each mode considered. First, and with respect to the external travel costs, the respondents showed greater cost sensitivity the lower the remaining budget was and the fewer days they were into a given month. Given the complexity of the experiment, we can conclude that the respondents showed rational choice behavior when confronted with mobility budget constraints. Second, the derived mean VTT values are higher across all modes when accounting for random heterogeneity. However, we observed the largest variance in VTT values for cars, presumably induced by higher external costs that influence the perceived overall cost.

This chapter aims to fill a current gap in the literature by presenting the first SC experiment and mode choice model considering a TCS regime. The study leverages an elaborated choice design and relies on a thorough sample recruitment plan. As with everything, there are limitations to our work. First and foremost, our approach did not allow an investigation into real-world trading of *MobilityCoins* in the market. Secondly, the scope of the study is confined to the city of Munich. Lastly, the choice model applied is based on the assumption of log-normally distributed parameters, which can lead to VTT estimates that are not necessarily supported by the data. For future work, it would be of interest to conduct a paired SC and market-trading experiment, and explore feasible TCS design parameters in combination with macroscopic and agent-based models.

6

DISCUSSION AND OUTLOOK

The objective of this thesis is to investigate and synthesize different key features to successfully apply stated choice experiments and discrete choice models in the realm of mode choice. This discussion consolidates the knowledge gained not only within the scope of this thesis but throughout the entire doctoral journey. It emphasizes the challenges, limitations, and potential avenues for future research.

The framework for implementing and conducting web-based stated choice experiments, outlined in Chapter 2, served as a fundamental foundation for the research in Chapters 3 to 5, and was employed in numerous other projects as well. The main reason to develop it was due to the complexity of most experiments in transportation research, which often involve several experimental designs instead of only one. Moreover, the literature on stated choice methods and experimental design theory lacks a step-by-step guide on how to implement them in practice. Just recently, however, SurveyEngine[1] announced the integration of NGene into their survey software tool, which provides new opportunities to conduct behavioral research more efficiently. Albeit the update, it remains to be seen whether and how well the software is able to cope with more complex designs. The approach relies on the survey software Qualtrics, which brings both advantages and disadvantages. Researchers using Qualtrics for surveys appreciate its user-friendly web-based interface, providing a convenient experience for respondents on both computers and mobile devices. However, like many licensed products, it comes with associated costs. While the picture-based approach described in this chapter can be utilized with the free version of Qualtrics, the more advanced matrix table-based approach requires the use of the licensed version, incurring additional expenses. Apart from this limitation, the proposed framework worked very well for the purpose of this thesis and all other related projects.

Utilizing RP and SP surveys to gather relevant data represents a fundamental step in studying choice behavior. The development of all questionnaires presented in Chapters 3 to 5 was based on extensive literature

1 https://surveyengine.com/7446-2/, last accessed: 10/02/2023

reviews, experience gained from similar projects at the Institute of Transport Planning (ETHZ), and close collaboration with the project partners. One of the main challenges in developing a questionnaire relates to the trade-off between the number and complexity of the entailed questions, the sample recruitment process, and expected response rates. In general, the higher the associated response burden score of a questionnaire is, the lower the expected response rates are (Schmid and Axhausen, 2019). The surveys conducted in Chapters 3 to 5 confirmed this relationship, although with notable differences that need to be addressed. The incentives offered to respondents significantly affected response rates. In Chapters 3 and 5, respondents received incentives for successful participation, leading to comparatively higher response rates. However, in the survey on ridepooling preferences in Chapter 4, excluding participants recruited through online panel providers, no incentives were paid. Consequently, response rates were significantly lower, despite similar response burden scores. The collaboration with one of the online panel providers for the ridepooling project proved unsatisfactory, with response rates during the field phase nearly nonexistent, despite a thorough pre-test where no issues were encountered. This underscores the importance of pre-tests not only when conducting surveys but also in regard of stated choice experiments. They help to find and correct for possible mistakes, unclear questions, and general inconsistencies.

Conducting surveys online offers several advantages over traditional methods like paper-and-pencil surveys and telephone interviews. Firstly, it allows convenient control over the completeness and formal quality of the responses, if implemented properly. Qualtrics' API access facilitates data download and subsequent cleaning. Part of the success of this thesis is due to the (formal) quality of the data collected. Secondly, web-based surveys can easily scale up for large sample sizes. Additionally, built-in indicators, such as survey duration measurement, help identify and remove low-quality responses. Respondents rushing through a survey in less than two to three minutes can severely compromise response quality, unfortunately, a phenomenon that was observed across all surveys in this thesis. These responses need to be deleted to maintain data integrity. However, a downside of using web-based surveys can be attributed to the fact that people are left out from participation which are unfamiliar with this technology. Although this demographic, primarily older people, might decrease in the future, this limitation perhaps needs more consideration in future work.

The samples recruited in this thesis were largely representative of the population under consideration. In Chapters 3 and 5, postal addresses were bought according to a dedicated sampling plan. However, these samples exhibited slight demographic differences compared to the national transport and mobility census. To ensure meaningful and representative inference about the observed choice behavior, outputs from the applied choice models (such as valuation indicators and choice elasticities) were re-weighted using census-based weights. Chapter 4 employed a different sampling approach. Part of the sample was internally recruited by the project partner, while the other part was recruited by an online panel provider, ensuring representative sampling through quotas. Nevertheless, this approach led to an over-representation of "ridepooling-friendly" individuals in the sample, potentially influencing the findings, despite controlling for ridepooling usage in the model and re-weighting the model outputs. For future work, modeling methods that account for sample- and self-selection effects should be tested and applied in order to address and mitigate such problems consistently.

The stated choice experiments carried out in this thesis were thoroughly planned and designed. The approach used in all chapters involved a pivot design. In Chapters 3 and 4, individual RP trips were utilized to create personalized choice scenarios, whereas Chapter 5 employed a more aggregated approach based on a set of representative trips. Data privacy regulations did not allow for a RP-based approach. Ultimately, for each experiment, standard D-efficient designs were generated, incorporating weak parameter priors, some of which were adjusted after the pre-test. While more intricate experimental designs exist, the ones utilized in this thesis were found to be suitable. Future work could benefit from Bayesian efficient designs which account for uncertainty about the true parameter priors, using random rather than fixed priors.

This thesis employed a consistent modeling approach using advanced discrete choice models in order to investigate mode choice behavior and possible changes induced by hypothetical scenarios. In each chapter, non-trading and lexicographic choice behavior was assessed. Such behavior refers to the situation where a respondent always chooses the same alternative across choice tasks for different reasons: extreme preferences, heuristic decision-making, and political or strategic behavior. How to deal with these issues ultimately depends on the fact whether the responses, and hence observed behavior, is consistent with the assumptions of random utility. The context of a Tradable Mobility Credt Scheme as introduced in Chapter 5 is very political and presumably influenced by attitudes which were not considered. As a consequence, and in combination with quality control measures and attention questions, the affected responses were excluded in the analysis. In addition, the distribution and ordering of the derived values of travel time when including those observations was far from reality. Albeit the existence of strong preferences towards a single or fast mode within the choice tasks, no responses were excluded in Chapters 3 and 4.

In all chapters, many different model specifications were tested in order to get meaningful behavioral insights. For the case of long-distance travel in Switzerland, Chapter 3, the multiplicative error specification had a substantial and significant impact on the obtained values of travel time. Especially for public transport, the VTT was lower compared to the ones of car and long-distance bus, which was not the case without multiplicative errors, generating very similar values for all three modes. Mixed Multinomial choice models were applied in order to not only account for deterministic but also random taste heterogeneity in choice behavior. Chapter 3 showcased the implications of the distributional assumptions for random parameters in that regard. Log-uniformly distributed values of travel time exhibited substantially less extreme values than log-normally distributed ones, which is a consequence of the longer tail of the log-normal distribution. Something that would have been worthwhile to test in Chapter 5. For future work, the application of hybrid choice models could eventually bring more behavioral insights when modeling mode choice, as they are able to account for latent processes and constructs such as for example attitudes towards the environment, transport policies or mobility tool ownership.

In summary, the work in this thesis makes valuable contributions to the application of stated choice experiments and discrete choice models, specifically in the context of understanding the determinate in various mode choice scenarios.

A

APPENDIX

A.1 PREFERENCES FOR A NEW LONG-DISTANCE BUS SERVICE IN SWITZERLAND

A.1.1 *RP survey print*

SBB Fernbus RP

Start of Block: Herzlich willkommen

Q1.2 Willkommen bei unserer Mobilitätserhebung und vielen Dank, dass Sie mitmachen!

Mit Ihrer Teilnahme helfen sie uns sehr, ein möglichst genaues Abbild des Verkehrsverhaltens der Bevölkerung zu erstellen und die Verkehrsmittelwahl für Fernreisen innerhalb der Schweiz zu analysieren.

Die Studie besteht aus zwei Teilen: Einem Fragebogen (1. Teil) zu Ihrem sozio-demographischen Hintergrund, allgemeinem Verkehrsverhalten wie Pendeln und Fernreisen sowie einem Wahlexperiment (2. Teil). Nach dem ersten Teil erhalten Sie eine E-Mail als Bestätigung für das Ausfüllen des Fragebogens. Danach brauchen wir drei bis vier Wochen Zeit um die gesammelten Daten zu verarbeiten und das Experiment für den zweiten Teil zu erstellen. Die Einladung dazu wird an die im ersten Teil registrierte E-Mail Adresse verschickt.

Für die Teilnahme an der gesamten Studie (Fragebogen und Wahlexperiment) erhalten Sie nach Abschluss als Dank 10 Franken per Post.

Alle Ihre Angaben werden streng vertraulich behandelt. Die Eintragungen dienen ausschliesslich Forschungszwecken und statistischen Auswertungen an der ETH Zürich. Alle mit der Erhebung beauftragten Personen sind zur Verschwiegenheit verpflichtet.

Für Ihre Fragen stehe ich Ihnen gerne unter **thomas.schatzmann@ivt.baug.ethz.ch** oder **044 633 30 88** zu Verfügung.

Q1.3
Bevor Sie mit dem Ausfüllen des Fragebogens beginnen, möchten wir Sie bitten, sich die Informationen zur Studie aufmerksam durchzulesen und anschliessend die folgende Einverständniserklärung zu akzeptieren:
Ich nehme an dieser Studie freiwillig teil und kann jederzeit ohne Angabe von Gründen meine Zustimmung zur Teilnahme widerrufen, ohne dass mir deswegen Nachteile entstehen. Ich wurde schriftlich über die Ziele, den Ablauf der Studie, über mögliche Vor- und Nachteile sowie über eventuelle Risiken informiert. Ich habe die zur oben genannten Studie abgegebenen schriftlichen Informationen zur Studie gelesen. Meine Fragen im Zusammenhang mit der Teilnahme an dieser Studie sind mir zufriedenstellend beantwortet worden. Ich hatte genügend Zeit, um meine Entscheidung zu treffen. Ich bin einverstanden, dass die zuständigen Untersuchenden und/oder Mitglieder der Ethikkommission zu Prüf- und Kontrollzwecken meine Originaldaten einsehen dürfen, jedoch unter strikter Einhaltung der Vertraulichkeit.

- ○ Ja, ich möchte teilnehmen. (1)
- ○ Nein, ich möchte nicht teilnehmen. (0)

Display This Question:
If intro_yesno = Nein, ich möchte nicht teilnehmen.

Q1.4 Sind Sie sicher?

Ihre Angaben und Antworten sind für unsere Studie essenziell und wir wären für Ihre Teilnahme sehr dankbar! Sind Sie sicher, dass Sie an der Befragung nicht teilnehmen möchten?

- ○ Ja, ich möchte **nicht teilnehmen**. (1)
- ○ Nein, ich möchte doch teilnehmen. (0)

End of Block: Herzlich willkommen

Start of Block: Adressen

Q2.1 Stimmt Ihre Wohnadresse mit derjenigen auf dem Einladungsbrief überein?

- ○ Ja (1)
- ○ Nein (0)

Display This Question:
If intro_addresscorrect = Nein

Q2.2 Bitte geben Sie Ihre korrekte Wohnadresse an.

○ Strasse (1) ____

○ Hausnummer (2) ____

○ PLZ (3) ____

○ Ort (4) ____

Q2.3 Bitte geben Sie Ihre E-Mail Adresse an. Diese brauchen wir, um Sie für die zweite Phase der Studie einzuladen.

○ E-Mail Adresse (1) ____

Q2.4 Bitte validieren Sie Ihre E-Mail Adresse (geben Sie diese ein zweites Mal ein).

○ E-Mail Adresse (1) ____

End of Block: Adressen

Start of Block: Haushalt

Q3.1 **Um Ihre Antworten besser interpretieren zu können, bitten wir Sie im Folgenden um allgemeine Angaben zu Ihrem Haushalt und Ihrer Person.**

Q3.2 Wie viele Personen leben in Ihrem Haushalt? (Sie selbst eingeschlossen)

	0 (0)	1 (1)	2 (1)	3 (3)	4 (4)	5 (5)	> 5 (6)
Kleinkinder (< 6 Jahre) (hh_size_kk)	○	○	○	○	○	○	○
Kinder (6-12 Jahre) (hh_size_k)	○	○	○	○	○	○	○
Jugendliche (13-18 Jahre) (hh_size_j)	○	○	○	○	○	○	○
Erwachsene (> 18 Jahre) (hh_size_erw)	○	○	○	○	○	○	○

Q3.3 Wie hoch ist das Brutto-Einkommen pro Monat des gesamten Haushalts? (vor Steuern / in CHF)

- ○ Kein Einkommen (0)
- ○ < 2'000 (1)
- ○ 2'001 - 4'000 (2)
- ○ 4'001 - 6'000 (3)
- ○ 6'001 - 8'000 (4)
- ○ 8'001 - 10'000 (5)
- ○ 10'001 - 12'000 (6)
- ○ 12'001 - 14'000 (7)
- ○ 14'001 - 16'000 (8)
- ○ > 16'000 (9)
- ○ Keine Angabe (-98)

Q3.4 Wie viele der folgenden Verkehrsmittel besitzt Ihr Haushalt?

	0 (1)	1 (2)	2 (3)	3 (4)	4 (5)	5 (6)	> 5 (7)
Personenwagen (hh_mobtools_car)	○	○	○	○	○	○	○
Motorrad (hh_mobtools_moto)	○	○	○	○	○	○	○
Fahrrad (hh_mobtools_bike)	○	○	○	○	○	○	○
E-Bikes (hh_mobtools_ebike)	○	○	○	○	○	○	○

End of Block: Haushalt

Start of Block: Person

Q4.1 Geburtsjahr

- ○ Jahr (z.B. 1985) (1) ____

Q4.2 Geschlecht

- weiblich (1)
- männlich (0)
- divers (2)

Q4.3 Wie gross sind Sie?

- < 165 cm (1)
- 166 - 170 cm (2)
- 171 - 175 cm (3)
- 176 - 180 cm (4)
- 181 - 185 cm (5)
- 186 - 190 cm (6)
- 191 - 195 cm (7)
- 196 - 200 cm (8)
- > 200 cm (9)

Q4.4 Welche Staatsbürgerschaft haben Sie? (Doppelbürger/innen kreuzen bitte beide an)

- ☐ Schweizer/-in (1)
- ☐ Andere, und zwar (2) ____
- ☐ Weitere, und zwar (3) ____

Q4.5 Welchen Zivilstand haben Sie?

- Ledig (1)
- Verheiratet (2)
- Verheiratet, in Trennung lebend (3)
- Eingetragene Partnerschaft (4)
- Aufgelöste, eingetragene Partnerschaft (5)
- Geschieden (6)
- Verwitwet (7)

Q4.6 Was ist Ihr höchster Ausbildungsabschluss?

- ○ keine Ausbildung abgeschlossen (1)
- ○ Obligatorische Schule (2)
- ○ Gymnasiale Maturität (3)
- ○ Berufsmaturität (4)
- ○ Berufsabschluss / Lehre (5)
- ○ Fachhochschule / Universität (6)
- ○ Andere, und zwar (7) ____

Q4.7 Wie ist Ihre aktuelle berufliche Situation?

- ▢ berufstätig (1)
- ▢ in Ausbildung (2)
- ▢ im eigenen Haushalt beschäftigt (3)
- ▢ auf Arbeitssuche (4)
- ▢ nicht erwerbstätig (5)
- ▢ in Rente (6)

Display This Question:

If p_occup = berufstätig

Or If

p_occup = berufstätig

And p_occup = in Ausbildung

Q4.8 Wo führen Sie Ihre Arbeit hauptsächlich aus?

- ○ Ausserhaus (1)
- ○ Zuhause (2)

Display This Question:

If p_occup = berufstätig

Or If

p_occup = berufstätig

And p_occup = in Ausbildung

Q4.9 Arbeiten Sie derzeit in einem Schichtbetrieb?

- ○ Ja (1)
- ○ Nein (0)

Display This Question:

If p_workloc = Ausserhaus

Q4.10 Wie lautet die Adresse Ihrer hauptsächlichen Arbeitsstätte ausserhaus?

- ○ Strasse (1) ____
- ○ Hausnummer (2) ____
- ○ PLZ (3) ____
- ○ Ort (4) ____

Display This Question:

If p_occup = in Ausbildung

Or If

p_occup = in Ausbildung

And p_occup = berufstätig

Q4.11 Wo führen Sie Ihre Ausbildung hauptsächlich aus?

- ○ Ausserhaus (1)
- ○ Zuhause (2)

Display This Question:

If p_educloc = Ausserhaus

Q4.12 Wie lautet die Adresse Ihrer hauptsächlichen Ausbildungsstätte ausserhaus?

- ○ Strasse (1) ____
- ○ Hausnummer (2) ____
- ○ PLZ (3) ____
- ○ Ort (4) ____

Page Break

Q4.13 Haben Sie einen Führerausweis für Personenwagen? (Kategorie B)

- Ja (1)
- Nein (2)

Q4.14 Wie oft steht Ihnen ein Personenwagen zur Verfügung?

- immer verfügbar (1)
- nicht verfügbar (2)
- nach Absprache verfügbar (3)
- weiss nicht (4)

Q4.15 Sind Sie Mitglied einer Carsharing Organisation oder als Nutzer(in) registriert auf einer solchen Plattform? (z.B. Mobility)

- Ja (1)
- Nein (0)

Display This Question:

If p_carshmember = Ja

Q4.16 Bei welcher Organisation sind Sie Mitglied oder als Nutzer(in) registriert? (Alle zutreffenden ankreuzen)

- Mobility Carsharing (1)
- Sharoo Carsharing (2)
- Uber (3)
- Andere, und zwar (4) ____

Display This Question:

If p_carshmember = Ja

Q4.17 Grob geschätzt, wie oft benutzen Sie das Angebot pro Monat?

- ○ < 1 (0)
- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ 4 (4)
- ○ 5 (5)
- ○ > 5 (6)

Display This Question:

If p_carshorg = Mobility Carsharing

Q4.18 Welches Angebot von Mobility nutzen Sie?

- ○ Mobility-Return (1)
- ○ Mobility-One-Way (2)
- ○ Mobility-Go (3)
- ○ Mobility-Carpool (4)

Q4.19 Besitzen Sie eines oder mehrere der folgenden ÖV-Abonnemente? (Alle zutreffenden ankreuzen)

- ☐ General-Abonnement 1. Klasse (18)
- ☐ General-Abonnement 2. Klasse (19)
- ☐ Halbtax-Abonnement (20)
- ☐ Strecken-Abonnement (21)
- ☐ Verbundkarte (z.B. ZVV) (22)
- ☐ Métro (23)
- ☐ Gleis 7 (24)
- ☐ Mehrfahrtenkarte (25)
- ☐ Keines (26)

Q4.20 Wer hat Ihr Abonnement finanziert? Falls Sie mehrere haben, wer hat das teurere Abonnement finanziert?

- ○ Sie selber (1)
- ○ Ihr Arbeitgeber (2)
- ○ Ihr/-e Ausbilder/-in (3)
- ○ Sie und Ihr Arbeitgeber/Ausbilder zusammen (4)
- ○ Andere, und zwar (5) ____

Q4.21 Welche(n) Mobilfunkanbieter nutzen Sie? (Alle zutreffenden ankreuzen)

- ☐ Swisscom (1)
- ☐ Sunrise (2)
- ☐ Salt (3)
- ☐ UPC-Cablelom (4)
- ☐ Migros-Budget Mobile (5)
- ☐ Coop Mobile (6)
- ☐ Mucho (7)
- ☐ Wingo Mobile (8)
- ☐ Lycamobile (9)
- ☐ Einen anderen (10)
- ☐ Weiss nicht (11)

Q4.22 Wie hoch ist das **persönliche** Brutto-Einkommen pro Monat? (vor Steuern / in CHF)

- Kein Einkommen (0)
- < 500 (1)
- 500 - 2'000 (10)
- 2'001 - 4'000 (2)
- 4'001 - 6'000 (3)
- 6'001 - 8'000 (4)
- 8'001 - 10'000 (5)
- 10'001 - 12'000 (6)
- 12'001 - 14'000 (7)
- 14'001 - 16'000 (8)
- > 16'000 (9)
- Keine Angabe (-98)

End of Block: Person

Start of Block: Pendeln_Intro

Q5.1 **In den nächsten Fragen geht es um Ihr Pendelverhalten. Wir nehmen dabei an, dass Sie Ihre typische Pendelfahrt vom Wohnort aus starten.**

Q5.2 An wie vielen Tagen unter der Woche pendeln Sie zu Ihrer Arbeits- respektive Ausbildungsstätte?

- 0 (36)
- 1 (29)
- 2 (30)
- 3 (31)
- 4 (32)
- 5 (33)
- 6 (34)
- 7 (35)

Skip To: End of Block If com_nrofdays = 0

End of Block: Pendeln_Intro

Start of Block: Pendeln

Q6.1 Welches ist das Hauptverkehrsmittel, das Sie für eine typische Pendel-Hinfahrt benützen?

Wählen Sie das Verkehrsmittel, mit dem Sie die grösste Distanz zurücklegten.

- Zu Fuss (72)
- Fahrrad (73)
- E-Bike (74)
- Motorrad (75)
- Bus (76)
- Tram (77)
- Métro (78)
- Bahn (79)
- Auto (Fahrer/-in) (80)
- Auto (Mitfahrer/-in) (81)

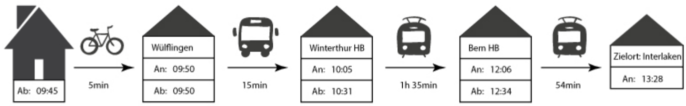
Q6.2 Pendeln Sie üblicherweise weiter als 50km zu Ihrer Arbeits- oder Ausbildungsstätte?

- Ja (1)
- Nein (0)

Q6.3 Wie viele Male steigen Sie auf einer typischen Pendel-Hinfahrt um?

Beispiel für eine Pendel-Hinfahrt mit dem Hauptverkehrsmittel Auto - 0 Mal umsteigen entspricht 1 Etappe

Beispiel mit dem Hauptverkehrsmittel Bahn - 3 Mal umsteigen entspricht 4 Etappen



▼ 0 ... 9

Q6.4 Pendeletappen Hinfahrt

Pendeletappen Hinfahrt

	Column Options	Column Options		Column Options		Column Options	Column Options
	Verkehrsmittel	Ist es die Etappe mit dem Hauptverkehrsmittel?		Etappen-		Ungefähre Abfahrtszeit für diese Etappe	Ungefähre Ankunftszei diese Etappe
		Ja	Nein	Startort	Zielort	(z.B. 08:05)	(z.B. 08:15)
Etappe 1		○	○				
Etappe 2		○	○				
Etappe 3		○	○				
Etappe 4		○	○				
Etappe 5		○	○				
Etappe 6		○	○				
Etappe 7		○	○				
Etappe 8		○	○				
Etappe 9		○	○				
Etappe 10		○	○				

Display This Question:

If com_outmainmode = Bus

Or com_outmainmode = Tram

Or com_outmainmode = Métro

Or com_outmainmode = Bahn

Or com_outmainmode = Auto (Mitfahrer/-in)

Q6.5 Was haben Sie auf der auf der Hinfahrt während der Etappe mit dem Hauptverkehrsmittel gemacht? (Alle zutreffenden ankreuzen)

- ▢ Arbeiten (1)
- ▢ Lesen (2)
- ▢ Essen (3)
- ▢ Entspannen (4)
- ▢ Sich unterhalten (5)
- ▢ Aussicht geniessen (6)
- ▢ Ich musste stehen und hatte keinen Sitzplatz (7)
- ▢ Anderes (8) ____

Display This Question:

If com_outmainmode = Bus

Or com_outmainmode = Tram

Or com_outmainmode = Métro

Or com_outmainmode = Bahn

Or com_outmainmode = Auto (Mitfahrer/-in)

Q6.6 Wie schätzen Sie den Komfort ein auf der Hinfahrt während der Etappe mit dem Hauptverkehrsmittel ?

Display This Choice:

If com_outmainmodeactivity != Ich musste stehen und hatte keinen Sitzplatz

Display This Choice:

If com_outmainmodeactivity != Ich musste stehen und hatte keinen Sitzplatz

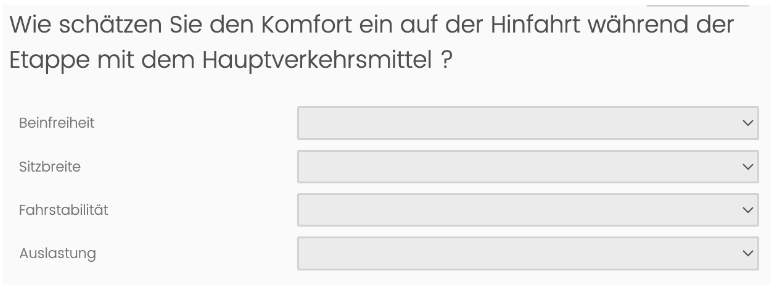
Display This Choice:

If com_outmainmode = Bus

Or com_outmainmode = Tram

Or com_outmainmode = Métro

Or com_outmainmode = Bahn



Q6.7 Pendeln Sie auf Ihrer Pendel-Rückfahrt auf der gleichen Route wie auf der Hinfahrt?

- ○ Ja (1)
- ○ Nein (2)

End of Block: Pendeln

Start of Block: Pendeln_Rückfahrt

Q7.1 Sie haben angegeben, dass Sie für eine typische Pendel-Rückfahrt auf einer anderen Route reisen.

Q7.2 Welches ist das Hauptverkehrsmittel, das Sie für eine typische Pendel-Rückfahrt benützen?

Wählen Sie das Verkehrsmittel, mit dem Sie die grösste Distanz zurücklegten.

- ○ Zu Fuss (72)
- ○ Fahrrad (73)
- ○ E-Bike (74)
- ○ Motorrad (75)
- ○ Bus (76)
- ○ Tram (77)
- ○ Métro (78)
- ○ Bahn (79)
- ○ Auto (Fahrer/-in) (80)
- ○ Auto (Mitfahrer/-in) (81)

Q7.3 Wie viele Male steigen Sie auf einer typischen Pendel-Rückfahrt um?

▼ 0 (52) ... 9 (51)

Q7.4 Pendeletappen Rückfahrt

Pendeletappen Rückfahrt

	Column Options	Column Options		Column Options		Column Options	Column Options
	Verkehrsmittel	Ist es die Etappe mit dem Hauptverkehrsmittel?		Etappen-		Ungefähre Abfahrtszeit für diese Etappe	Ungefähre Ankunftszeit diese Etappe
		Ja	Nein	Startort	Zielort	(z.B. 17:05)	(z.B. 17:15)
Etappe 1		○	○				
Etappe 2		○	○				
Etappe 3		○	○				
Etappe 4		○	○				
Etappe 5		○	○				
Etappe 6		○	○				
Etappe 7		○	○				
Etappe 8		○	○				
Etappe 9		○	○				
Etappe 10		○	○				

Display This Question:

If com_retmainmode = Bus

Or com_retmainmode = Tram

Or com_retmainmode = Métro

Or com_retmainmode = Bahn

Or com_retmainmode = Auto (Mitfahrer/-in)

Q7.5 Was haben Sie auf der auf der Rückfahrt während der Etappe mit dem Hauptverkehrsmittel gemacht? (Alle zutreffenden ankreuzen)

- ☐ Arbeiten (1)
- ☐ Lesen (2)
- ☐ Essen (3)
- ☐ Entspannen (4)
- ☐ Sich unterhalten (5)
- ☐ Aussicht geniessen (6)
- ☐ Ich musste stehen und hatte keinen Sitzplatz (7)
- ☐ Anderes (8) ____

Display This Question:

If com_retmainmode = Bus

Or com_retmainmode = Tram

Or com_retmainmode = Métro

Or com_retmainmode = Bahn

Or com_retmainmode = Auto (Mitfahrer/-in)

Q7.6 Wie schätzen Sie den Komfort ein auf der Rückfahrt während der Etappe mit dem Hauptverkehrsmittel?

Display This Choice:

If com_retmainmodeactivity != Ich musste stehen und hatte keinen Sitzplatz

Display This Choice:

If com_retmainmodeactivity != Ich musste stehen und hatte keinen Sitzplatz

Display This Choice:

If com_retmainmode = Bahn

Or com_retmainmode = Bus

Or com_retmainmode = Tram

Or com_retmainmode = Métro

Wie schätzen Sie den Komfort ein auf der Rückfahrt während der Etappe mit dem Hauptverkehrsmittel?

Beinfreiheit	
Sitzbreite	
Fahrstabilität	
Auslastung	

End of Block: Pendeln_Rückfahrt

Start of Block: Pendeln_Kombi

Q8.1 Bitte geben Sie an, falls Sie den Arbeitsweg mit dem Ausbildungsweg kombinieren.

- ○ Keine Kombination (1)
- ○ Kombination (aber Zusatzweg von maximal 1km notwendig) (2)
- ○ Kombination (aber Zusatzweg von 1-5 km notwendig) (3)
- ○ Kombination (aber Zusatzweg von 5-20 km notwendig) (4)
- ○ Kombination (aber Zusatzweg von 20-50 km notwendig) (5)
- ○ Kombination (aber Zusatzweg von mehr als 50km notwendig) (6)

Q8.2 An wie vielen Tagen einer Woche können Sie den Arbeitsweg mit dem Ausbildungsweg kombinieren?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)

End of Block: Pendeln_Kombi

Start of Block: Fernreise_intro

Q9.1 **In diesem Teil befragen wir Sie zu Fernreisen innerhalb der Schweiz, die Sie in den letzten 8 Wochen getätigt haben und über 50km lang waren.**

Zum Beispiel Freizeit- oder Geschäftsreisen. Dabei geht es nicht um das Pendeln, zu welchem Sie vorher schon geantwortet haben.

Q9.2 Haben Sie innerhalb der letzten 8 Wochen eine oder mehrere Fernreisen gemacht?

- Ja (1)
- Nein (0)

End of Block: Fernreise_intro

Start of Block: Fernreise

Q10.1 **Denken Sie nun an die letzte Fernreise, die Sie innerhalb der Schweiz gemacht haben und länger als 50km war.**

Zu dieser Fragen wir Sie detaillierte Fragen. Zu allfälligen weiteren Fernreisen möchten wir nur allgemeine Informationen.

Q10.2 An welchem Wochentag fand die Reise statt?

▼ Montag (1) ... Sonntag (7)

Q10.3 Was war der Grund Ihrer Reise?

- ○ Freizeit (1)
- ○ Arbeit/Ausbildung (2)

Q10.4
Bitte geben Sie den Start Ihrer Reise an.

Bewegen Sie den Pin **möglichst genau an Ihren Startort** oder **geben Sie die Adresse ein**.

Enter a location

Q10.5
Bitte geben Sie das Ziel Ihrer Reise an.

Bewegen Sie den Pin möglichst genau an Ihren Zielort oder geben Sie die Adresse ein.

Q10.6 War der Reiseablauf für die Hin- und Rückfahrt schon im Voraus geplant?

- Ja (1)
- Nein (2)

Q10.7 Haben Sie auf Ihrer Reise auswärts übernachtet?

- Ja (1)
- Nein (2)

End of Block: Fernreise

Start of Block: Fernreise_Hinfahrt

Q11.1 Welches war das Hauptverkehrsmittel, das Sie für Ihre Hinfahrt benutzt haben?

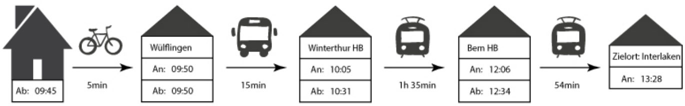
Wählen Sie das Verkehrsmittel, mit dem Sie die grösste Distanz zurücklegten.

- Fahrrad (178)
- E-Bike (179)
- Bus / Fernbus (180)
- Bahn (181)
- Motorrad (182)
- Auto (Fahrer/-in) (183)
- Auto (Mitfahrer/-in) (184)
- Flugzeug (185)

Q11.2 Wie viele Male sind Sie auf Ihrer Hinfahrt umgestiegen?

Beispiel für eine Hinfahrt der Fernreise mit dem Hauptverkehrsmittel Auto - 0 Mal umsteigen entspricht 1 Etappe

Beispiel mit dem Hauptverkehrsmittel Bahn - 3 Mal umsteigen entspricht 4 Etappen



▼ 0 (52) ... 9 (51)

Q11.3 Fernreiseetappen Hinfahrt

Fernreiseetappen Hinfahrt

	Column Options	Column Options		Column Options		Column Options	Column Options
	Verkehrsmittel	Ist es die Etappe mit dem Hauptverkehrsmittel?		Etappen-		Ungefähre Abfahrtszeit für diese Etappe	Ungefähre Ankunftszei diese Etappe
		Ja	Nein	Startort	Zielort	(z.B. 07:05)	(z.B. 07:15)
Etappe 1		○	○				
Etappe 2		○	○				
Etappe 3		○	○				
Etappe 4		○	○				
Etappe 5		○	○				
Etappe 6		○	○				
Etappe 7		○	○				
Etappe 8		○	○				
Etappe 9		○	○				
Etappe 10		○	○				

Display This Question:

If ldj_outmainmode = Bus / Fernbus

Or ldj_outmainmode = Bahn

Or ldj_outmainmode = Auto (Mitfahrer/-in)

Q11.4 Was haben Sie auf der Hinfahrt während der Etappe mit dem Hauptverkehrsmittel gemacht? (Alle zutreffenden ankreuzen)

- ▢ Arbeiten (1)
- ▢ Lesen (4)
- ▢ Essen (5)
- ▢ Entspannen (6)
- ▢ Sich unterhalten (7)
- ▢ Aussicht geniessen (8)
- ▢ Ich musste stehen und hatte keinen Sitzplatz (10)
- ▢ Anderes (9) ____

Display This Question:

If ldj_outmainmode = Bus / Fernbus

Or ldj_outmainmode = Bahn

Or ldj_outmainmode = Auto (Mitfahrer/-in)

Q11.5 Wie schätzen Sie den Komfort ein auf der Hinfahrt während der Etappe mit dem Hauptverkehrsmittel?

Display This Choice:

If ldj_outmainmodeactivity != Ich musste stehen und hatte keinen Sitzplatz

Display This Choice:

If ldj_outmainmodeactivity != Ich musste stehen und hatte keinen Sitzplatz

Display This Choice:

If ldj_outmainmode = Bahn

Or ldj_outmainmode = Bus / Fernbus

Wie schätzen Sie den Komfort ein auf der Hinfahrt während der Etappe mit dem Hauptverkehrsmittel ?

Beinfreiheit	⌄
Sitzbreite	⌄
Fahrstabilität	⌄
Auslastung	⌄

Display This Question:

If Idj_outmainmode = Bus / Fernbus

Q11.6 Sind Sie auf Ihrer Hinfahrt mit dem Eurobus "Swiss-Express" gereist?

- ○ Ja (1)
- ○ Nein (2)

Display This Question:

If Idj_outmainmode = Bus / Fernbus

And Idj_outmainmodeldbus = Ja

Q11.7 Wie sind Sie zum Einsteigeort für den Fernbus gekommen?

- ○ Öffentliches Verkehrsmittel (Bahn/Bus/Tram/Métro) (1)
- ○ Fahrer/in in privatem Verkehrsmittel (2)
- ○ Mitfahrer/in in privatem Verkehrsmittel (3)
- ○ Anderes, und zwar: (4) ____

Display This Question:

If Idj_outmainmode = Bus / Fernbus

And Idj_outmainmodeldbus = Ja

Q11.8 Wie sind vom Aussteigeort zu Ihrem Zielort gekommen?

- ○ Öffentliches Verkehrsmittel (Bahn/Bus/Tram/Métro) (1)
- ○ Fahrer/in in privatem Verkehrsmittel (2)
- ○ Mitfahrer/in in privatem Verkehrsmittel (3)
- ○ Anderes, und zwar: (4) ____

Display This Question:

If ldj_outmainmode = Bahn

Q11.9 In welcher Klasse reisten Sie auf Ihrer Hinfahrt?

- ○ 1. Klasse (1)
- ○ 2. Klasse (2)

Display This Question:

If ldj_outmainmode = Bahn

And p_ptmobtools != General-Abonnement 1. Klasse

And p_ptmobtools != General-Abonnement 2. Klasse

Or If

ldj_outmainmode = Bus / Fernbus

Or ldj_outmainmode = Flugzeug

Q11.10 Wie viel haben die Tickets der Hinfahrt insgesamt gekostet? (in CHF)

____

Display This Question:

If ldj_outmainmode = Motorrad

Or ldj_outmainmode = Auto (Fahrer/-in)

Or ldj_outmainmode = Auto (Mitfahrer/-in)

Q11.11 Wie viel hat die Hinfahrt insgesamt gekostet? (in CHF)

____

Display This Question:

If ldj_outmainmode = Bahn

And p_ptmobtools != General-Abonnement 1. Klasse

And p_ptmobtools != General-Abonnement 2. Klasse

Or If

ldj_outmainmode = Bus / Fernbus

Or ldj_outmainmode = Motorrad

Or ldj_outmainmode = Auto (Fahrer/-in)

Or ldj_outmainmode = Auto (Mitfahrer/-in)

Or ldj_outmainmode = Flugzeug

Q11.12 Wer hat für Ihre Hinfahrt bezahlt?

▼ Sie selber (19) ... Sonstige Person (23)

Q11.13 Wie stark haben Sie...

	nicht stark (1)	mittel (2)	stark (3)
sich an die geplanten Abfahrtszeiten auf der Hinfahrt gehalten? (4)	○	○	○

Q11.14 Was war für Sie...

○ die optimale Ankunftszeit am Zielort? (z.B. 12:00) (1) ________________

○ die späteste mögliche Ankunftszeit am Zielort? (z.B. 12:30) (2) ________________

Q11.15 Wie wichtig war es für Sie...

	nicht wichtig (1)	wichtig (2)	sehr wichtig (3)
vor der spätesten möglichen Ankunftszeit am Zielort anzukommen? (4)	○	○	○

Q11.16 Was haben Sie am Zielort unternommen? (Alle zutreffenden ankreuzen)

- ☐ Geschäftstermin (1)
- ☐ Ausbildung (2)
- ☐ Shopping (3)
- ☐ Kulturveranstaltung (4)
- ☐ Religion (5)
- ☐ Ausflug / Ferien (6)
- ☐ Besuche (Verwandte, Bekannte, etc.) (7)
- ☐ Gastronomiebesuch (8)
- ☐ Aktiver Sport (Velofahren, Wandern, etc.) (9)
- ☐ Passiver Sport (Matchbesuch, etc.) (10)
- ☐ Anderes (11) ____

Q11.17 Wurden Sie auf Ihrer Hinfahrt von weiteren Personen begleitet?

- ○ Ja (1)
- ○ Nein (2)

Display This Question:

If ldj_outaccompany = Ja

Q11.18 Sie haben zuvor geantwortet, dass auf Ihrer Hinfahrt weitere Personen dabei waren.

Sie haben zuvor geantwortet, dass auf Ihrer Hinfahrt weitere Personen dabei waren.

	0	1	2	3	4	5	mehr als 5	Weiss nicht
Begleitpersonen								
Von wie vielen Personen wurden Sie auf Ihrer Hinfahrt begleitet?	○	○	○	○	○	○	○	○
Wie viele Ihrer Begleiter/innen gehören zur Familie?	○	○	○	○	○	○	○	○
Wie viele Ihrer Begleiter/innen sind Kinder unter 6 Jahren?	○	○	○	○	○	○	○	○
Für wie viele Ihrer Begleiter/innen haben Sie die Kosten der Hinfahrt übernommen?	○	○	○	○	○	○	○	○
Wie viele Begleiter/innen besitzen ein ÖV-Abonnement oder ein Auto?								
General-Abonnement	○	○	○	○	○	○	○	○
Halbtax-Abonnement	○	○	○	○	○	○	○	○
Auto	○	○	○	○	○	○	○	○

Display This Question:

If ldj_outaccompany = Ja

Q11.19 Waren Sie Entscheidungsträger für die Durchführung der Hinfahrt?

- ○ Ja, ich habe entschieden (1)
- ○ Teilweise, andere Begleitpersonen haben mitentschieden (2)
- ○ Teilweise, andere Personen ausserhalb Begleitpersonen haben mitentschieden (3)
- ○ Nein, eine oder mehrere andere Begleitpersonen haben entschieden (4)
- ○ Nein, andere Personen ausserhalb der Begleitpersonen haben entschieden (5)

Q11.20 Reisten Sie auf Ihrer Rückfahrt auf der gleichen Route wie auf der Hinfahrt?

- ○ Ja (1)
- ○ Nein (2)

Display This Question:

If ldj_outsameret = Ja

Q11.21 Waren auf Ihrer Rückfahrt dieselben Begleitpersonen dabei wie auf der Hinfahrt?

- ○ Ja (1)
- ○ Nein (2)

End of Block: Fernreise_Hinfahrt

Start of Block: Fernreise_Rückfahrt

Q12.1 **Sie haben angegeben, dass Sie auf Ihrer Rückfahrt der Fernreise auf einer anderen Route reisten.**

Q12.2 Welches war das Hauptverkehrsmittel, das Sie für Ihre Rückfahrt benutzt haben?

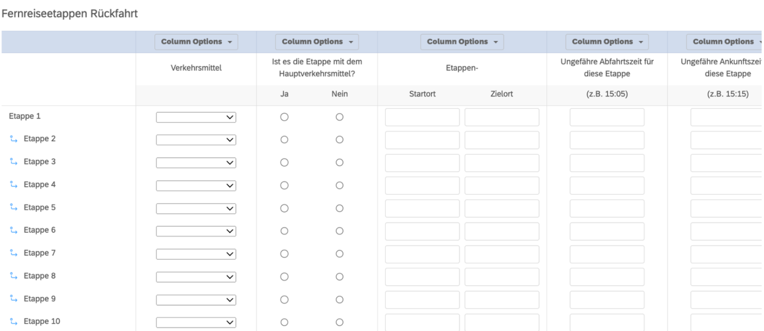
Wählen Sie das Verkehrsmittel, mit dem Sie die grösste Distanz zurücklegten.

- ○ Fahrrad (178)
- ○ E-Bike (179)
- ○ Bus / Fernbus (180)
- ○ Bahn (181)
- ○ Motorrad (182)
- ○ Auto (Fahrer/-in) (183)
- ○ Auto (Mitfahrer/-in) (184)
- ○ Flugzeug (185)

Q12.3 Wie viele Male sind Sie auf Ihrer Rückfahrt umgestiegen?

▼ 0 (52) ... 9 (51)

Q12.4 Fernreiseetappen Rückfahrt



Fernreiseetappen Rückfahrt

	Column Options	Column Options		Column Options		Column Options	Column Options
	Verkehrsmittel	Ist es die Etappe mit dem Hauptverkehrsmittel?		Etappen-		Ungefähre Abfahrtszeit für diese Etappe	Ungefähre Ankunftszei diese Etappe
		Ja	Nein	Startort	Zielort	(z.B. 15:05)	(z.B. 15:15)
Etappe 1		○	○				
Etappe 2		○	○				
Etappe 3		○	○				
Etappe 4		○	○				
Etappe 5		○	○				
Etappe 6		○	○				
Etappe 7		○	○				
Etappe 8		○	○				
Etappe 9		○	○				
Etappe 10		○	○				

Display This Question:

If ldj_retmainmode = Bus / Fernbus

Or ldj_retmainmode = Bahn

Or ldj_retmainmode = Auto (Mitfahrer/-in)

Q12.5 Was haben Sie auf der Rückfahrt während der Etappe mit dem Hauptverkehrsmittel gemacht? (Alle zutreffenden ankreuzen)

- ▢ Arbeiten (1)
- ▢ Lesen (4)
- ▢ Essen (5)
- ▢ Entspannen (6)
- ▢ Sich unterhalten (7)
- ▢ Aussicht geniessen (8)
- ▢ Ich musste stehen und hatte keinen Sitzplatz (10)
- ▢ Anderes (9) ____

Display This Question:

If ldj_retmainmode = Bus / Fernbus

Or ldj_retmainmode = Bahn

Or ldj_retmainmode = Auto (Mitfahrer/-in)

Q12.6 Wie schätzen Sie den Komfort ein auf der Rückfahrt während der Etappe mit dem Hauptverkehrsmittel?

Display This Choice:

If ldj_retmainmodeactivity != Ich musste stehen und hatte keinen Sitzplatz

Display This Choice:

If ldj_retmainmodeactivity != Ich musste stehen und hatte keinen Sitzplatz

Display This Choice:

If ldj_retmainmode = Bahn

Or ldj_retmainmode = Bus / Fernbus

Wie schätzen Sie den Komfort ein auf der Rückfahrt während der Etappe mit dem Hauptverkehrsmittel?

Beinfreiheit	
Sitzbreite	
Fahrstabilität	
Auslastung	

Display This Question:

If ldj_retmainmode = Bus / Fernbus

Q12.7 Sind Sie auf Ihrer Rückfahrt mit dem Eurobus "Swiss-Express" gereist?

- ○ Ja (1)
- ○ Nein (2)

Display This Question:

If ldj_retmainmode = Bus / Fernbus

And ldj_retmainmodeldbus = Ja

Q12.8 Wie sind Sie zum Einsteigeort für den Fernbus gekommen?

- ○ Öffentliches Verkehrsmittel (1)
- ○ Fahrer/in in privatem Verkehrsmittel (2)
- ○ Mitfahrer/in in privatem Verkehrsmittel (3)
- ○ Anderes, und zwar: (4) ____

Display This Question:

If ldj_retmainmode = Bus / Fernbus

And ldj_retmainmodeldbus = Ja

Q12.9 Wie sind Sie vom Aussteigeort zu Ihrem Zielort gekommen?

- ○ Öffentliches Verkehrsmittel (1)
- ○ Fahrer/in in privatem Verkehrsmittel (2)
- ○ Mitfahrer/in in privatem Verkehrsmittel (3)
- ○ Anderes, und zwar: (4) ____

Display This Question:

If ldj_retmainmode = Bahn

Q12.10 In welcher Klasse reisten Sie auf Ihrer Rückfahrt?

- ○ 1. Klasse (1)
- ○ 2. Klasse (2)

Display This Question:

If ldj_retmainmode = Bahn

And p_ptmobtools != General-Abonnement 1. Klasse

And p_ptmobtools != General-Abonnement 2. Klasse

Or If

ldj_retmainmode = Bus / Fernbus

Or ldj_retmainmode = Flugzeug

Q12.11 Wie viel haben die Tickets der Rückfahrt insgesamt gekostet? (in CHF)

____

Display This Question:

If ldj_retmainmode = Motorrad

Or ldj_retmainmode = Auto (Fahrer/-in)

Or ldj_retmainmode = Auto (Mitfahrer/-in)

Q12.12 Wie viel hat die Rückfahrt insgesamt gekostet? (in CHF)

____

Display This Question:

If ldj_retmainmode = Bahn

And p_ptmobtools != General-Abonnement 1. Klasse

And p_ptmobtools != General-Abonnement 2. Klasse

Or If

ldj_retmainmode = Bus / Fernbus

Or ldj_retmainmode = Motorrad

Or ldj_retmainmode = Auto (Fahrer/-in)

Or ldj_retmainmode = Auto (Mitfahrer/-in)

Or ldj_retmainmode = Flugzeug

Q12.13 Wer hat für Ihre Rückfahrt bezahlt?

▼ Sie selber (19) ... Sonstige Person (23)

Q12.14 Wie stark haben Sie...

	nicht stark (1)	mittel (2)	stark (3)
sich an die geplanten Abfahrtszeiten auf der Rückfahrt gehalten? (4)	○	○	○

Q12.15 Wurden Sie auf Ihrer Rückfahrt von weiteren Personen begleitet?

○ Ja (1)

○ Nein (2)

End of Block: Fernreise_Rückfahrt

Start of Block: Fernreise_Rückfahrt_Personen

Q13.1 **Sie haben zuvor geantwortet, dass auf Ihrer Rückfahrt weitere und / oder andere Personen dabei waren.**

Sie haben zuvor geantwortet, dass auf Ihrer Rückfahrt weitere und / oder andere Personen dabei waren.

	0	1	2	3	4	5	mehr als 5	Weiss nicht
Begleitpersonen								
Von wie vielen Personen wurden Sie auf Ihrer Rückfahrt begleitet?	○	○	○	○	○	○	○	○
Wie viele Ihrer Begleiter/innen gehören zur Familie?	○	○	○	○	○	○	○	○
Wie viele Ihrer Begleiter/innen sind Kinder unter 6 Jahren?	○	○	○	○	○	○	○	○
Für wie viele Ihrer Begleiter/innen haben Sie die Kosten der Rückfahrt übernommen?	○	○	○	○	○	○	○	○
Wie viele Begleiter/innen besitzen ein ÖV-Abonnement oder ein Auto?								
General-Abonnement	○	○	○	○	○	○	○	○
Halbtax-Abonnement	○	○	○	○	○	○	○	○
Auto	○	○	○	○	○	○	○	○

Q13.2 Waren Sie Entscheidungsträger für die Durchführung der Rückfahrt?

○ Ja, ich habe entschieden (1)

○ Teilweise, andere Begleitpersonen haben mitentschieden (2)

○ Teilweise, andere Personen ausserhalb Begleitpersonen haben mitentschieden (3)

○ Nein, eine oder mehrere andere Begleitpersonen haben entschieden (4)

○ Nein, andere Personen ausserhalb der Begleitpersonen haben entschieden (5)

End of Block: Fernreise_Rückfahrt_Personen

Start of Block: Fernreise_Einkaufen

Q14.1 Haben Sie auf Ihrer **letzten Reise (Hin- und / oder Rückfahrt)** in einem Bahnhof oder mehreren Bahnhöfen **Einkäufe getätigt oder Dienstleistungen bezogen**?

○ Ja (1)

○ Nein (2)

Display This Question:

If ldj_shopping = Ja

Q14.2 Was haben Sie unterwegs insgesamt gekauft oder bezogen? (Alle zutreffenden ankreuzen)

- ☐ Verpflegung: Take-away (1)
- ☐ Verpflegung: Café / Restaurant (2)
- ☐ Einkaufen: Lebensmittel (3)
- ☐ Einkaufen: Elektronik (4)
- ☐ Einkaufen: Kleider (5)
- ☐ Einkaufen: Toilettenartikel (6)
- ☐ Einkaufen: Sonstiges (Geschenke, Blumen, etc.) (7)
- ☐ Dienstleistungen: Post (Briefe, Pakete, etc.) (8)
- ☐ Dienstleistungen: Sonstiges (Arzt, Coiffeur, etc.) (9)
- ☐ Sanitäranlagen (McClean) (10)
- ☐ Schliessfächer (11)

Display This Question:

If ldj_shopping = Ja

Q14.3 Grob geschätzt, wie viel Geld haben Sie ausgegeben? (in CHF)

- ○ 0-10 (1)
- ○ 11-20 (2)
- ○ 21-50 (3)
- ○ 51-100 (4)
- ○ mehr als 100 (5)

Display This Question:

If ldj_shopping = Ja

Q14.4 In welchem Bahnhof oder welchen Bahnhöfen haben Sie dies gemacht? (maximal 3)

	Bahnhof 1 (1)	Bahnhof 2 (2)	Bahnhof 3 (3)
Ort (1)			

End of Block: Fernreise_Einkaufen

Start of Block: Fernreisen_weitere

Q15.1 Wie viele weitere Fernreisen innerhalb der Schweiz haben Sie noch gemacht in den letzten 8 Wochen?

- ○ 0 (66)
- ○ 1 (67)
- ○ 2 (68)
- ○ 3 (69)
- ○ 4 (70)
- ○ mehr als 4 (72)

Display This Question:

If ldj_nrofmorejourneys = 1

Or ldj_nrofmorejourneys = 2

Or ldj_nrofmorejourneys = 3

Or ldj_nrofmorejourneys = 4

Or ldj_nrofmorejourneys = mehr als 4

Q15.2 Für Ihre weitere Fernreise benötigen wir nur noch allgemeine Angaben. (maximal 4 weitere Fernreisen)

Für Ihre weitere Fernreise benötigen wir nur noch allgemeine Angaben. (maximal 4 weitere Fernreisen)

	Column Options		Column Options	Column Options		Column Options	Column Options
	Was war der Grund Ihrer Reise?		Wochentag der Reise	Fernreise-		Hauptverkehrsmittel auf der Hinfahrt	Hauptverkehrsmittel auf der Rückfahrt
	Freizeit	Arbeit / Ausbildung		Startort	Zielort		
Fernreise 2	○	○					
Fernreise 3	○	○					
Fernreise 4	○	○					
Fernreise 5	○	○					

End of Block: Fernreisen_weitere

Start of Block: Entscheidungskriterien und Reisekrankheiten

Q16.1 **Was sind für Sie relevante Entscheidungskriterien bei der Wahl für oder gegen ein Hauptverkehrsmittel bei Fernreisen über 50 Kilometer?**

Q16.2 Bitte nennen Sie maximal 3 Kriterien (z.B. Preis / Umweltfreundlichkeit / Fahrplanabhängigkeit / Freiheit usw.) und geben Sie deren Wichtigkeit an.

	Column Options	Column Options			Column Options	Column Options		
	Kriterium 1	Wichtigkeit Kriterium 1			Kriterium 2	Wichtigkeit Kriterium 2		
		Weniger wichtig	Wichtig	Sehr wichtig		Weniger wichtig	Wichtig	Sehr wichtig
Für die Bahn		○	○	○		○	○	○
Gegen die Bahn		○	○	○		○	○	○
Für den Fernbus		○	○	○		○	○	○
Gegen den Fernbus		○	○	○		○	○	○
Für das Auto		○	○	○		○	○	○
Gegen das Auto		○	○	○		○	○	○

Q16.3 **Wird es Ihnen bei Reisen im Auto, Fernbus oder in der Bahn übel?**

- ○ Ja, das kann vorkommen. (10)
- ○ Nein, es wird mir nie übel. (11)

Display This Question:

If illness_yesno = Ja, das kann vorkommen.

Q16.4 In welchen Fernreiseverkehrsmittel kann dies vorkommen?

- ▢ Bahn (Neigezug) (1)
- ▢ Bahn (Normaler Intercity-Zug) (2)
- ▢ Fernbus (3)
- ▢ Auto (Mitfahrer/in) (4)

Display This Question:

If illness_yesno = Ja, das kann vorkommen.

Q16.5 Bitte geben Sie uns genauere Angaben über mögliche Reisekrankheiten.

Display This Choice:

If illness_mode = Bahn (Neigezug)

Display This Choice:

If illness_mode = Bahn (Neigezug)

Display This Choice:

If illness_mode = Bahn (Neigezug)

Display This Choice:

If illness_mode = Bahn (Normaler Intercity-Zug)

Display This Choice:

If illness_mode = Bahn (Normaler Intercity-Zug)

Display This Choice:

If illness_mode = Bahn (Normaler Intercity-Zug)

Display This Choice:

If illness_mode = Fernbus

Display This Choice:

If illness_mode = Fernbus

Display This Choice:

If illness_mode = Fernbus

Display This Choice:

If illness_mode = Auto (Mitfahrer/in)

Display This Choice:

If illness_mode = Auto (Mitfahrer/in)

Display This Choice:

If illness_mode = Auto (Mitfahrer/in)

Bitte geben Sie uns genauere Angaben über mögliche Reisekrankheiten.

	Keine Übelkeit	Leichte Übelkeit	Starke Übelkeit
Bahn: Neigezug			
Normales mitfahren	○	○	○
Lesen	○	○	○
Arbeiten am Laptop	○	○	○
Bahn: Normaler Intercity-Zug			
Normales mitfahren	○	○	○
Lesen	○	○	○
Arbeiten am Laptop	○	○	○
Fernbus (z.B. Eurobus)			
Normales mitfahren	○	○	○
Lesen	○	○	○
Arbeiten am Laptop	○	○	○
Auto (Mitfahrer/in)			
Normales mitfahren	○	○	○
Lesen	○	○	○
Arbeiten am Laptop	○	○	○

End of Block: Entscheidungskriterien und Reisekrankheiten

Start of Block: Eurobus

Q17.1 Seit Juni 2018 bietet die Firma Eurobus in der Schweiz drei Fernbuslinien unter dem Namen "Swiss-Express" an, die komplementär zu den Öffentlichen Verkehrsmitteln in das Schweizer Verkehrsnetz eingebunden sind. Diese Fernbusse fahren hauptsächlich auf der Ost-West und Nord-Süd-Achse und damit nur innerhalb der Schweiz.

Quelle: Eurobus / Flixbus

Q17.2 Wussten Sie von diesem Fernbusangebot bereits vor dieser Umfrage?

- ○ Ja (1)
- ○ Nein (0)

Q17.3 Haben Sie bereits eine Reise in einem solchen Fernbus gemacht?

- ○ Ja (1)
- ○ Nein (0)

End of Block: Eurobus

A.2 INVESTIGATING THE PREFERENCES FOR THE USE OF URBAN RIDE-POOLING

A.2.1 *RP survey print*

MOIA RP

Start of Block: welcome

Display This Question:

If group = moia

Herzlich Willkommen!

Diese Umfrage ist Teil des Projekts "Auf dem Weg zum Hamburg-Takt" und wird vom Institut für Verkehrsplanung und Transportsysteme (IVT) der ETH Zürich im Auftrag von MOIA durchgeführt. Ihre Teilnahme erfolgt freiwillig.

Das Ziel der Umfrage ist es, Ihre Bedürfnisse im Kontext von MOIA und öffentlichen Verkehrsmitteln besser zu verstehen. Ihre Teilnahme ermöglicht es, das Angebot des ÖPNV in Hamburg zu verbessern. Die Umfrage kann sowohl auf dem Mobilgerät sowie im Browser (Apple Safari, Google Chrome, Microsoft Edge, Mozilla Firefox) ausgefüllt werden.

Sie besteht aus zwei Teilen (Dauer je ca. 10 - 15 Minuten):
Teil 1: Enthält Fragen zu Ihrem sozialen und demographischen Hintergrund, Ihrer Mobilität im Allgemeinen sowie zu spezifischen Reisezwecken.
Teil 2 (in ungefähr 3 Wochen): Enthält Fragen zu Ihrem Entscheidungsverhalten in Bezug auf die Verkehrsmittelwahl für verschiedene Reisezwecke wie Arbeit, Ausbildung und Freizeit. Dieses Wahlexperiment beruht auf Ihren Angaben im ersten Teil. Die Einladung dazu erfolgt per E-Mail.

Falls Sie Fragen oder Anmerkungen zur Studie haben, melden Sie sich bitte via E-Mail bei

moia-umfrage@ethz.ch

Herzlichen Dank für Ihre Teilnahme!

Mit freundlichen Grüssen

Das IVT Forschungsteam

Display This Question:

If group = nonmoia

Herzlich Willkommen!

Diese Umfrage ist Teil des Projekts "Auf dem Weg zum Hamburg-Takt" und wird vom Institut für Verkehrsplanung und Transportsysteme (IVT) der ETH Zürich im Auftrag von MOIA durchgeführt. Ihre Teilnahme erfolgt freiwillig.

Das Ziel der Umfrage ist es, Ihre Bedürfnisse im Kontext von MOIA und öffentlichen Verkehrsmitteln besser zu verstehen. Ihre Teilnahme ermöglicht es, das Angebot des ÖPNV in Hamburg zu verbessern. Die Umfrage kann sowohl auf dem Mobilgerät sowie im Browser (Apple Safari, Google Chrome, Microsoft Edge, Mozilla Firefox) ausgefüllt werden.

Sie besteht aus zwei Teilen (Dauer je ca. 10 - 15 Minuten):
Teil 1: Enthält Fragen zu Ihrem sozialen und demographischen Hintergrund, Ihrer Mobilität im Allgemeinen sowie zu spezifischen Reisezwecken.
Teil 2 (in ungefähr 3 Wochen): Enthält Fragen zu Ihrem Entscheidungsverhalten in Bezug auf die Verkehrsmittelwahl für verschiedene Reisezwecke wie Arbeit, Ausbildung und Freizeit. Dieses Wahlexperiment beruht auf Ihren Angaben im ersten Teil. Die Einladung dazu erfolgt per E-Mail.

MOIA-Neukunden erhalten als Entschädigung für die Teilnahme an beiden Teilen einen Gutschein im Wert von 10 Euro, der in der MOIA-App aktiviert werden kann.

Falls Sie Fragen oder Anmerkungen zur Studie haben, melden Sie sich bitte via E-Mail bei

moia-umfrage@ethz.ch

Herzlichen Dank für Ihre Teilnahme!

Mit freundlichen Grüssen

Das IVT Forschungsteam

Wichtige Information zum Datenschutz:

Als Dateneigner/in können Sie die Datenschutz_Informationen herunterladen und durchlesen. Mit der Teilnahme stimmen Sie den Datschutz Informationen zu.

Die wichtigsten Punkte sind hier zusammengefasst:
Zum zweiten Teil der Umfrage werden Sie in ungefähr 3 Wochen per E-Mail eingeladen. Daher fragen wir nach Ihrer E-Mail Adresse.
Für realistische Entscheidungssituationen bezüglich Ihrer Verkehrsmittelwahl (in Teil 2) sind die genauen Ortsangaben auf den gezeigten Karten in diesem Teil der Umfrage sehr wichtig. Die Angaben werden ausschliesslich für die Berechnung Ihrer Wege (Reisezeiten und -kosten, Route) verwendet.
Sie haben die Möglichkeit, die Löschung der erhobenen Daten nach der Teilnahme am zweiten Teil zu verlangen.
Während der Umfrage werden Cookies gespeichert. Diese ermöglichen es, die Umfrage zu pausieren und zu einem späteren Zeitpunkt fertig auszufüllen. Ihre Antwort wird mit einem reCAPTCHA Score versehen. Damit wir sichergestellt, dass Sie kein Roboter sind.

Wir freuen uns sehr, wenn Sie an der Studie teilnehmen. Es ermöglicht MOIA, Ihre Bedürfnisse besser zu verstehen und den angebotenen Service zu optimieren.

Möchten Sie an der Studie teilnehmen?

○ Ja, ich möchte mit der Studie beginnen.

○ Nein, ich möchte nicht an der Studie teilnehmen.

End of Block: welcome

Start of Block: consent_sure

Sind Sie sicher, dass Sie nicht an der Studie teilnehmen möchten? Wir freuen uns sehr, wenn Sie teilnehmen würden!

○ Ja, ich möchte definitiv nicht teilnehmen.

○ Nein, ich möchte doch teilnehmen.

End of Block: consent_sure

Start of Block: person_household

Vielen Dank für Ihre Bereitschaft, an der Studie teilzunehmen!

Die ersten Fragen beziehen sich auf Ihre Person, Ihren Haushalt und Ihre Mobilität allgemein.

Bitte geben Sie Ihr Geschlecht an.

- ○ männlich
- ○ weiblich
- ○ divers

Bitte geben Sie Ihr Geburtsjahr an. (Klicken Sie auf die Dropdown-Liste)

▼ 1940 ... 2005

Bitte geben Sie Ihren höchsten Bildungsabschluss an.

- ○ kein Abschluss
- ○ Haupt-/Volksschulabschluss
- ○ Mittlerer Abschluss (Mittlere Reife)
- ○ Fachhochschulreife/Allgemeine Hochschulreife
- ○ Abgeschlossene Berufsausbildung
- ○ Bachelor/Master/Diplom
- ○ Promotion

Bitte geben Sie die Größe Ihres Haushalts in Personen an (**Sie selbst mit eingeschlossen**).

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6 oder mehr

Display This Question:

If Bitte geben Sie die Größe Ihres Haushalts in Personen an (Sie selbst mit eingeschlossen). != 1

Leben Kinder in Ihrem Haushalt?

- ○ Ja
- ○ Nein

Display This Question:

If Leben Kinder in Ihrem Haushalt? = Ja

Wie viele Kinder leben in Ihrem Haushalt pro Alterskategorie?

Eine Antwort pro Spalte.

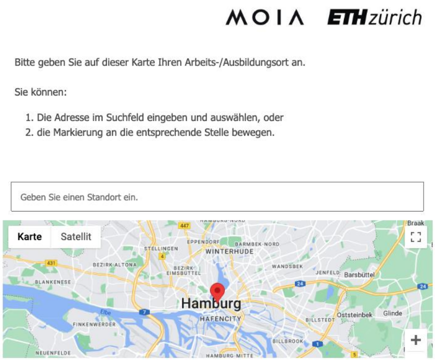
	0	1	2	3	4 und mehr
0-5 Jahre	○	○	○	○	○
6-13 Jahre	○	○	○	○	○
14-17 Jahre	○	○	○	○	○

Wie hoch ist das monatliche Netto-Einkommen Ihres Haushaltes insgesamt?

- ○ bis unter 500 €
- ○ 500 bis unter 900 €
- ○ 900 bis unter 1,500 €
- ○ 1,500 bis unter 2,000 €
- ○ 2,000 bis unter 3,000 €
- ○ 3,000 bis unter 4,000 €
- ○ 4,000 bis unter 5,000 €
- ○ 5,000 bis unter 6,000 €
- ○ 6,000 bis unter 7,000 €
- ○ 7,000 € und mehr
- ○ keine Angabe

Wir bitten Sie, auf dieser Karte Ihren Wohnort anzugeben.

Sie können: Ihre Adresse im Suchfeld eingeben und auswählen, oder die Markierung an die entsprechende Stelle bewegen. Beispiel:



End of Block: person_household

Start of Block: mobility

Sind Sie aus gesundheitlichen Gründen in Ihrer Mobilität eingeschränkt?

Mehrere Antworten möglich.

- ☐ ⊗ Nein
- ☐ Ja, aufgrund einer Gehbehinderung.
- ☐ Ja, aufgrund einer Sehbehinderung.
- ☐ Ja, aufgrund einer Hörbehinderung.
- ☐ ⊗ Keine Antwort

Display This Question:

If Sind Sie aus gesundheitlichen Gründen in Ihrer Mobilität eingeschränkt? Mehrere Antworten möglich. = Ja, aufgrund einer Gehbehinderung.

Benötigen Sie einen Rollstuhl in Ihrem Alltag? (Diese Frage ist wichtig für MOIA als Dienstleistungsunternehmen)

- ○ Ja
- ○ Nein

Besitzen Sie einen Führerschein für ein Auto (Klasse B)?

- ○ Ja
- ○ Nein

Wie viele Autos gibt es in Ihrem Haushalt?

Berücksichtigen Sie sowohl private Fahrzeuge als Dienstwagen.

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4 und mehr

Steht Ihnen im Allgemeinen ein Auto zur Verfügung?

Carsharing wird hier nicht dazugezählt.

Mehrere Antworten möglich.

- ☐ ⊗ Nein
- ☐ Ja, ich kann uneingeschränkt über einen Auto verfügen.
- ☐ Ja, ich kann nach Absprache innerhalb des Haushalts über einen Auto verfügen.
- ☐ Ja, ich kann nach Absprache mit Verwandten/Bekannten über einen Auto verfügen.

Display This Question:

If Steht Ihnen im Allgemeinen ein Auto zur Verfügung? Carsharing wird hier nicht dazugezählt. Mehrer... != Nein

Verfügen Sie über einen Dienstwagen, welchen Sie auch zu privaten Zwecken kostenlos (inkl. Treibstoff) nutzen können?

- ○ Nein
- ○ Ja

Besitzen Sie ein Abo für den öffentlichen Personennahverkehr (ÖPNV)?

Dazu zählen eine Monatskarte oder zum Beispiel ein HVV Abo.

- ○ Ja
- ○ Nein

Steht Ihnen ein Fahrrad zur Verfügung?

Bikesharing Anbieter wie z.B StadtRad oder Donkey Republic werden hier nicht dazugezählt.

Mehrere Antworten möglich.

- ☐ ⊗ Nein
- ☐ Ja, ein normales Fahrrad.
- ☐ Ja, ein E-Bike (bis 25 km/h)
- ☐ Ja, ein E-Bike (bis 45 km/h)

Steht Ihnen ein E-Scooter zur Verfügung?

E-Scootersharing Anbieter wie z.B. Tier, Lime, Voi oder Circ werden hier nicht dazugezählt.

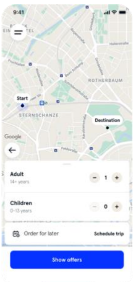
- ○ ⊗ Ja
- ○ Nein

End of Block: mobility

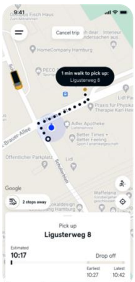
Start of Block: moia

Dieser Abschnitt befasst sich mit dem Thema Ridepooling:

Beim Ridepooling buchen Sie eine Fahrt via App auf Ihrem Smartphone und geben Start und Ziel an (Bild 1). Der Anbieter versucht Fahrtwünsche verschiedener Kunden, die in dieselbe Richtung fahren möchten, in einer gemeinsamen Fahrt zu bündeln. Sie steigen also in ein Auto, in dem bereits eine andere Person sitzt, oder das Fahrzeug in dem Sie sitzen, holt ggf. noch eine andere Person ab. Die Zuordnung zu den Fahrzeugen erfolgt durch Algorithmen. So wird für jede Person eine individuelle Fahr- und Ankunftszeit auf der gemeinsamen Route bestimmt (Bild 2). Ziel ist es, die Anzahl der eingesetzten Fahrzeuge zu reduzieren. Einer der Ridepooling-Anbieter ist MOIA (Bild 3).



(1) Start-Ziel-Eingabe



(2) Fahrtbestätigung



(3) MOIA Eindrücke

Kannten Sie MOIA bereits vor der Teilnahme an dieser Umfrage?

- ○ Ja, ich kannte MOIA und bin schon mindestens einmal mit MOIA gefahren.
- ○ Ja, ich kannte MOIA, bin aber bisher noch nicht mit MOIA gefahren.
- ○ Nein, ich habe bisher noch nichts von MOIA gehört.

Display This Question:

If Kannten Sie MOIA bereits vor der Teilnahme an dieser Umfrage? = Ja, ich kannte MOIA und bin schon mindestens einmal mit MOIA gefahren.

Haben Sie die Fahrt selber gebucht oder ein:e Bekannte:r?

- ○ Ja, ich habe sie selber gebucht.
- ○ Nein, ein:e Bekannte:r hat sie gebucht.

Display This Question:

If Kannten Sie MOIA bereits vor der Teilnahme an dieser Umfrage? = Ja, ich kannte MOIA und bin schon mindestens einmal mit MOIA gefahren.

Haben Sie bereits MOIA Fahrten mit oder für Kinder bis 13 Jahre gebucht?

- ○ Ja
- ○ Nein
- ○ Ich weiss nicht

Display This Question:

If Haben Sie bereits MOIA Fahrten mit oder für Kinder bis 13 Jahre gebucht? = Nein

Or Haben Sie bereits MOIA Fahrten mit oder für Kinder bis 13 Jahre gebucht? = Ich weiss nicht

Könnten Sie sich vorstellen, in Zukunft Fahrten mit oder für Kinder bis 13 Jahre zu buchen?

- ○ Ja
- ○ Nein

Display This Question:

If Haben Sie bereits MOIA Fahrten mit oder für Kinder bis 13 Jahre gebucht? = Nein

Or Haben Sie bereits MOIA Fahrten mit oder für Kinder bis 13 Jahre gebucht? = Ich weiss nicht

Wissen Sie, dass Kinder bis 13 Jahre mit Begleitpersonen kostenlos mit MOIA fahren und bei Alleinfahrten um 50% vergünstigt fahren?

- ○ Ja
- ○ Nein

End of Block: moia

Start of Block: moia_user

Bitte bewerten Sie folgende Komponenten Ihrer bisherigen Fahrt(en) mit MOIA.

Buchungsprozess in der App	☆	☆	☆	☆	☆
Wartezeit	☆	☆	☆	☆	☆
virtuelle Haltepunkte	☆	☆	☆	☆	☆
Fahrzeug (inkludiert WLAN, Infoscreen, etc.)	☆	☆	☆	☆	☆
Fahrer:innen	☆	☆	☆	☆	☆
Routenführung	☆	☆	☆	☆	☆
Geschwindigkeit / Reisezeit	☆	☆	☆	☆	☆
Pünktlichkeit	☆	☆	☆	☆	☆
Preis	☆	☆	☆	☆	☆
Zuverlässigkeit	☆	☆	☆	☆	☆
Verfügbarkeit	☆	☆	☆	☆	☆
Privatsphäre und Platzangebot im Fahrzeug	☆	☆	☆	☆	☆

Für welchen Wegezweck haben Sie MOIA zuletzt genutzt?

Ich habe MOIA zuletzt genutzt für einen Weg...

- ○ zur / von der Arbeit
- ○ zu / von einer dienstlichen oder geschäftlichen Angelegenheit
- ○ zur / von der Schule oder Hochschule
- ○ zum / vom Einkaufen
- ○ zu / von einer Freizeitgelegenheit
- ○ um jemanden abzuholen / zu bringen
- ○ zu / von einem Bahnhof oder Flughafen
- ○ sonstiges: ____

Sie haben angegeben, MOIA zuletzt für einen Weg **${moia_lastride_purp/ChoiceGroup/SelectedChoices}** genutzt zu haben.

War die Fahrt zu dieser Aktivität hin oder weg?

- ○ hin zur Aktivität
- ○ weg von der Aktivität

Display This Question:

If Sie haben angegeben, MOIA zuletzt für einen Weg ${q://QID63/ChoiceGroup/SelectedChoices} genutzt... = hin zur Aktivität

Sie haben angegeben, dass es die Fahrt **${moia_lastride_purp2/ChoiceGroup/SelectedChoices}** war.

Wo startete Ihre Fahrt?

- ○ Wohnort
- ○ anderer Ort

Display This Question:

If Sie haben angegeben, MOIA zuletzt für einen Weg ${q://QID63/ChoiceGroup/SelectedChoices} genutzt... = weg von der Aktivität

Sie haben angegeben, dass es die Fahrt **${moia_lastride_purp2/ChoiceGroup/SelectedChoices}** war.

Wo endete Ihre Fahrt?

- ○ Wohnort
- ○ anderer Ort

Wann haben Sie MOIA zuletzt genutzt?

- ○ Innerhalb der letzten Woche
- ○ Innerhalb des letzten Monats
- ○ Vor mehr als einem Monat
- ○ Vor mehr als einem halben Jahr

An welchem Wochentag haben Sie MOIA zuletzt genutzt?

- ○ Montag
- ○ Dienstag
- ○ Mittwoch
- ○ Donnerstag
- ○ Freitag
- ○ Samstag
- ○ Sonntag

Was war die ungefähre Abfahrtszeit?

Bitte geben Sie die ungefähre Stunde und Minute ein oder klicken Sie auf die Uhr:

Angenommen, MOIA hätte Ihnen für diesen letzten Weg nicht zur Verfügung gestanden, welches Verkehrsmittel hätten Sie alternativ genutzt?

- ○ Ohne MOIA hätte ich diesen Weg nicht zurückgelegt.
- ○ zu Fuß

Display This Choice:

If Steht Ihnen ein Fahrrad zur Verfügung? Bikesharing Anbieter wie z.B StadtRad oder Donkey Republic... != Nein

- ○ Privates Fahrrad
- ○ Bikesharing Angebot

Display This Choice:

If Steht Ihnen ein E-Scooter zur Verfügung? E-Scootersharing Anbieter wie z.B. Tier, Lime, Voi oder... = Ja

- ○ Privater E-Scooter
- ○ E-Scootersharing Angebot

Display This Choice:

If Besitzen Sie einen Führerschein für ein Auto (Klasse B)? = Ja

And Steht Ihnen im Allgemeinen ein Auto zur Verfügung? Carsharing wird hier nicht dazugezählt. Mehrer... != Nein

- ○ Privates Fahrzeug als Fahrer/in (inkl. Dienstwagen)
- ○ Privates Fahrzeug als Mitfahrer/in
- ○ Taxi
- ○ Carsharing Angebot
- ○ Bus
- ○ U-Bahn, S-Bahn, Straßenbahn
- ○ Sonstiges: ____

End of Block: moia_user

Start of Block: moia_nonuser

Weshalb haben Sie MOIA bisher nicht genutzt?

	Trifft voll zu	Trifft eher zu	Weder noch	Trifft weniger zu	Trifft gar nicht zu
Ich gehe lieber zu Fuß.	○	○	○	○	○
Ich fahre lieber Fahrrad.	○	○	○	○	○
Ich fahre lieber Auto.	○	○	○	○	○
Ich fahre lieber Bus und Bahn.	○	○	○	○	○
Ich fahre lieber Taxi.	○	○	○	○	○
Ich nutze lieber andere Anbieter für Ridepooling.	○	○	○	○	○
MOIA ist mir zu teuer.	○	○	○	○	○
Meine Start-/Zielpunkte liegen ausserhalb des Geschäftsgebiets.	○	○	○	○	○
MOIA war nicht verfügbar, als ich es brauchte.	○	○	○	○	○
MOIA fährt nicht zu meinen präferierten Servicezeiten.	○	○	○	○	○
Ich finde die Buchung via App zu umständlich.	○	○	○	○	○
Ich finde den Zugang zu den Haltepunkten zu weit/umständlich.	○	○	○	○	○
Ich möchte meine Fahrt nicht mit Mitfahrenden teilen.	○	○	○	○	○
Die Fahrt mit MOIA dauert mir zu lange.	○	○	○	○	○
Ich würde gerne mit einem autonomen/selbstfahrenden Fahrzeug fahren.	○	○	○	○	○
Sonstige Gründe:	○	○	○	○	○

End of Block: moia_nonuser

Start of Block: commuting

In diesem Abschnitt geht es um Ihren Beschäftigungsstatus und Ihr Reiseverhalten zum Arbeits-/Ausbildungsort.

Was ist Ihr derzeitiger Beschäftigungsstatus?

Mehrere Antworten möglich.

- ☐ angestellt
- ☐ selbständig tätig
- ☐ in Berufsausbildung
- ☐ Student/in
- ☐ pensioniert
- ☐ Hausfrau/-mann
- ☐ ⊗ arbeitslos

Display This Question:

If Was ist Ihr derzeitiger Beschäftigungsstatus? Mehrere Antworten möglich. = angestellt

Or Was ist Ihr derzeitiger Beschäftigungsstatus? Mehrere Antworten möglich. = selbständig tätig

Or Was ist Ihr derzeitiger Beschäftigungsstatus? Mehrere Antworten möglich. = in Berufsausbildung

Welche Art von Beschäftigung üben Sie aus?

- ○ Vollzeitbeschäftigung (100%)
- ○ Eine Teilzeitbeschäftigung
- ○ Mehr als eine Teilzeitbeschäftigung

Display This Question:

If Was ist Ihr derzeitiger Beschäftigungsstatus? Mehrere Antworten möglich. = angestellt

Or Was ist Ihr derzeitiger Beschäftigungsstatus? Mehrere Antworten möglich. = selbständig tätig

Or Was ist Ihr derzeitiger Beschäftigungsstatus? Mehrere Antworten möglich. = in Berufsausbildung

Or Was ist Ihr derzeitiger Beschäftigungsstatus? Mehrere Antworten möglich. = Student/in

Reisen Sie an mindestens einem Tag in einer regulären Woche zu Ihrem Arbeits-/Ausbildungsort (außerhalb von zu Hause)?

- ○ Ja
- ○ Nein

Display This Question:

If Reisen Sie an mindestens einem Tag in einer regulären Woche zu Ihrem Arbeits-/Ausbildungsort (auß... = Ja

Bitte geben Sie auf dieser Karte Ihren Arbeits-/Ausbildungsort an.

Sie können: Die Adresse im Suchfeld eingeben und auswählen, oder die Markierung an die entsprechende Stelle bewegen.

____

Display This Question:

If Reisen Sie an mindestens einem Tag in einer regulären Woche zu Ihrem Arbeits-/Ausbildungsort (auß... = Ja

Welche(s) Verkehrsmittel benutzen Sie üblicherweise für Ihren typischen Weg von zu Hause aus zum Arbeits-/Ausbildungsort?

Mehrere Antworten möglich.

- ☐ Öffentlicher Verkehr

Display This Choice:

If Besitzen Sie einen Führerschein für ein Auto (Klasse B)? = Ja

And Steht Ihnen im Allgemeinen ein Auto zur Verfügung? Carsharing wird hier nicht dazugezählt. Mehrer... != Nein

- ☐ Privates Fahrzeug als Fahrer/in (ink. Dienstwagen)
- ☐ Privates Fahrzeug als Mitfahrer/in
- ☐ Taxi
- ☐ MOIA
- ☐ Carsharing Angebot

Display This Choice:

If Steht Ihnen ein Fahrrad zur Verfügung? Bikesharing Anbieter wie z.B StadtRad oder Donkey Republic... != Nein

- ☐ Privates Fahrrad
- ☐ Bikesharing Angebot

Display This Choice:

If Steht Ihnen ein E-Scooter zur Verfügung? E-Scootersharing Anbieter wie z.B. Tier, Lime, Voi oder... = Ja

- ☐ Privater E-Scooter
- ☐ E-Scootersharing Angebot
- ☐ Zu Fuß

Display This Question:

If Reisen Sie an mindestens einem Tag in einer regulären Woche zu Ihrem Arbeits-/Ausbildungsort (auß... = Ja

Carry Forward Selected Choices from "Welche(s) Verkehrsmittel benutzen Sie üblicherweise für Ihren typischen Weg von zu Hause aus zum Arbeits-/Ausbildungsort?Mehrere Antworten möglich."

Welches der zuvor gewählten Verkehrsmittel ist das Hauptverkehrsmittel?

Im Hauptverkehrsmittel verbringen Sie die meiste Zeit auf Ihrem Weg.

○ Öffentlicher Verkehr

Display This Choice:

If Besitzen Sie einen Führerschein für ein Auto (Klasse B)? = Ja

And Steht Ihnen im Allgemeinen ein Auto zur Verfügung? Carsharing wird hier nicht dazugezählt. Mehrer... != Nein

○ Privates Fahrzeug als Fahrer/in (ink. Dienstwagen)

○ Privates Fahrzeug als Mitfahrer/in

○ Taxi

○ MOIA

○ Carsharing Angebot

Display This Choice:

If Steht Ihnen ein Fahrrad zur Verfügung? Bikesharing Anbieter wie z.B StadtRad oder Donkey Republic... != Nein

○ Privates Fahrrad

○ Bikesharing Angebot

Display This Choice:

If Steht Ihnen ein E-Scooter zur Verfügung? E-Scootersharing Anbieter wie z.B. Tier, Lime, Voi oder... = Ja

○ Privater E-Scooter

○ E-Scootersharing Angebot

○ Zu Fuß

Display This Question:

If Reisen Sie an mindestens einem Tag in einer regulären Woche zu Ihrem Arbeits-/Ausbildungsort (auß... = Ja

Zu welcher Uhrzeit legen Sie diesen Weg typischerweise zurück?

Bitte geben Sie die Stunde und Minute ein oder klicken Sie auf die Uhr:

____

End of Block: commuting

Start of Block: leisure

In diesem Abschnitt möchten wir mehr über Ihr Freizeit-Reiseverhalten erfahren.

Wie oft unternehmen Sie die folgenden Freizeitaktivitäten?

Dabei geht es um Aktivitäten, die Sie von zu Hause aus starten.

Eine Antwort pro Spalte.

	(fast) täglich	1-3 Mal pro Woche	1-3 Mal pro Monat	Weniger als 1 Mal pro Monat
Freunde/Familie treffen	○	○	○	○
Einkauf (Alltag)	○	○	○	○

End of Block: leisure

Start of Block: leisurelocation

Display This Question:

If purpose = Treffen

Bitte geben Sie auf dieser Karte einen von Ihnen häufig besuchten Freizeitort an, wo sie sich mit Leuten treffen. Zum Beispiel ein Restaurant, Sportzentrum oder Ausflugsziel.

Sie können: Die Adresse oder Ortschaft im Suchfeld eingeben und auswählen, oder die Markierung an die entsprechende Stelle bewegen.

____

Display This Question:

If purpose = Einkauf

Bitte geben Sie auf dieser Karte einen von Ihnen häufig besuchten Einkaufsort an. Zum Beispiel ein Supermarkt oder ein Einkaufszentrum.

Sie können: Die Adresse, Ortschaft oder den Einkaufsort im Suchfeld eingeben und auswählen, oder die Markierung an die entsprechende Stelle bewegen.

____

Display This Question:

If purpose = Treffen

Welche(s) Verkehrsmittel benutzen Sie üblicherweise für Ihren typischen Weg von zu Hause aus zum zuvor angegebenen Freizeitort?

Mehrere Antworten möglich.

- ☐ Öffentlicher Verkehr

Display This Choice:

If Besitzen Sie einen Führerschein für ein Auto (Klasse B)? = Ja

And Steht Ihnen im Allgemeinen ein Auto zur Verfügung? Carsharing wird hier nicht dazugezählt. Mehrer... != Nein

- ☐ Privates Fahrzeug als Fahrer/in (ink. Dienstwagen)
- ☐ Privates Fahrzeug als Mitfahrer/in
- ☐ Taxi
- ☐ MOIA
- ☐ Carsharing Angebot

Display This Choice:

If Steht Ihnen ein Fahrrad zur Verfügung? Bikesharing Anbieter wie z.B StadtRad oder Donkey Republic... != Nein

- ☐ Privates Fahrrad
- ☐ Bikesharing Angebot

Display This Choice:

If Steht Ihnen ein E-Scooter zur Verfügung? E-Scootersharing Anbieter wie z.B. Tier, Lime, Voi oder... = Ja

- ☐ Privater E-Scooter
- ☐ E-Scootersharing Angebot
- ☐ Zu Fuß

Display This Question:

If purpose = Treffen

Carry Forward Selected Choices from "Welche(s) Verkehrsmittel benutzen Sie üblicherweise für Ihren typischen Weg von zu Hause aus zum zuvor angegebenen Freizeitort?Mehrere Antworten möglich."

Welches der zuvor gewählten Verkehrsmittel ist das Hauptverkehrsmittel?

Im Hauptverkehrsmittel verbringen Sie die meiste Zeit auf Ihrem Weg.

○ Öffentlicher Verkehr

Display This Choice:

If Besitzen Sie einen Führerschein für ein Auto (Klasse B)? = Ja

And Steht Ihnen im Allgemeinen ein Auto zur Verfügung? Carsharing wird hier nicht dazugezählt. Mehrer... != Nein

○ Privates Fahrzeug als Fahrer/in (ink. Dienstwagen)

○ Privates Fahrzeug als Mitfahrer/in

○ Taxi

○ MOIA

○ Carsharing Angebot

Display This Choice:

If Steht Ihnen ein Fahrrad zur Verfügung? Bikesharing Anbieter wie z.B StadtRad oder Donkey Republic... != Nein

○ Privates Fahrrad

○ Bikesharing Angebot

Display This Choice:

If Steht Ihnen ein E-Scooter zur Verfügung? E-Scootersharing Anbieter wie z.B. Tier, Lime, Voi oder... = Ja

○ Privater E-Scooter

○ E-Scootersharing Angebot

○ Zu Fuß

Display This Question:

If purpose = Einkauf

Welche(s) Verkehrsmittel benutzen Sie üblicherweise für Ihren typischen Weg von zu Hause aus zum zuvor angegebenen Einkaufsort?

Mehrere Antworten möglich.

- ☐ Öffentlicher Verkehr

Display This Choice:

If Besitzen Sie einen Führerschein für ein Auto (Klasse B)? = Ja

And Steht Ihnen im Allgemeinen ein Auto zur Verfügung? Carsharing wird hier nicht dazugezählt. Mehrer... != Nein

- ☐ Privates Fahrzeug als Fahrer/in (ink. Dienstwagen)
- ☐ Privates Fahrzeug als Mitfahrer/in
- ☐ Taxi
- ☐ MOIA
- ☐ Carsharing Angebot

Display This Choice:

If Steht Ihnen ein Fahrrad zur Verfügung? Bikesharing Anbieter wie z.B StadtRad oder Donkey Republic... != Nein

- ☐ Privates Fahrrad
- ☐ Bikesharing Angebot

Display This Choice:

If Steht Ihnen ein E-Scooter zur Verfügung? E-Scootersharing Anbieter wie z.B. Tier, Lime, Voi oder... = Ja

- ☐ Privater E-Scooter
- ☐ E-Scootersharing Angebot
- ☐ Zu Fuß

Display This Question:

If purpose = Einkauf

Carry Forward Selected Choices from "Welche(s) Verkehrsmittel benutzen Sie üblicherweise für Ihren typischen Weg von zu Hause aus zum zuvor angegebenen Einkaufsort?Mehrere Antworten möglich."

Welches der zuvor gewählten Verkehrsmittel ist das Hauptverkehrsmittel?

Im Hauptverkehrsmittel verbringen Sie die meiste Zeit auf Ihrem Weg.

○ Öffentlicher Verkehr

Display This Choice:

If Besitzen Sie einen Führerschein für ein Auto (Klasse B)? = Ja

And Steht Ihnen im Allgemeinen ein Auto zur Verfügung? Carsharing wird hier nicht dazugezählt. Mehrer... != Nein

○ Privates Fahrzeug als Fahrer/in (ink. Dienstwagen)

○ Privates Fahrzeug als Mitfahrer/in

○ Taxi

○ MOIA

○ Carsharing Angebot

Display This Choice:

If Steht Ihnen ein Fahrrad zur Verfügung? Bikesharing Anbieter wie z.B StadtRad oder Donkey Republic... != Nein

○ Privates Fahrrad

○ Bikesharing Angebot

Display This Choice:

If Steht Ihnen ein E-Scooter zur Verfügung? E-Scootersharing Anbieter wie z.B. Tier, Lime, Voi oder... = Ja

○ Privater E-Scooter

○ E-Scootersharing Angebot

○ Zu Fuß

End of Block: leisurelocation

Start of Block: email

Schon fast fertig mit dem ersten Teil!

Damit wir Sie für den zweiten Teil der Umfrage per E-Mail einladen können, benötigen wir eine aktuelle E-Mail Adresse von Ihnen.

Bitte geben Sie Ihre E-Mail Adresse an.

Achten Sie darauf, dass keine Leerzeichen in der Antwort sind.

____

Bitte bestätigen Sie Ihre E-Mail Adresse.

____

Diese Umfrage wird in ungefähr einem Jahr wieder durchgeführt mit dem ZIel, Veränderungen in Ihrem Mobilitätsverhalten erfassen zu können. Wir freuen uns, wenn wir Sie dazu wieder per E-Mail einladen dürfen.

Möchten Sie auch an der nächsten Umfrage in einem Jahr teilnehmen?

○ Ja

○ Nein

End of Block: email

A.3 MODE CHOICE PREFERENCES IN A TRADABLE MOBILITY CREDIT SCHEME

A.3.1 *SP survey print*

MoCo RP and SP

Start of Block: Einstieg

Display This Question:

If Q_URL != https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G

And Q_URL != https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G?Q_CHL=qr

Herzlich Willkommen,

Sie sind Teil einer repräsentativen Stichprobe von Bewohnern der Stadt München, die wir im Rahmen des Forschungsprojekts „**MobilityCoins (MoCo) – Anreiz statt Gebühr**“ befragen wollen. Ziel ist es, herauszufinden, ob das Mobilitätsverhalten in München nachhaltiger werden könnte, wenn man platzsparende und emissionsarme Wege und Transportmittel finanziell belohnt, und für andere Wege etwas hinzuzahlt. Daher erforschen wir die Ausgabe von „Mobilitätsbudgets“.

Das Ausfüllen der Umfrage beansprucht circa 15-20 Minuten. Für Ihre vollständige Teilnahme bedanken wir uns mit **15 Euro** - Informationen dazu erhalten Sie am Ende der Befragung.

Die Umfrage wird vom Lehrstuhl für Verkehrstechnik der TU München in Zusammenarbeit mit der ETH Zürich durchgeführt.

Falls Sie Fragen oder Anmerkungen zur Studie haben, melden Sie sich bitte via E-Mail unter mobilitycoins.vtk@ed.tum.de

Herzlichen Dank für Ihre Teilnahme!

Mit freundlichen Grüßen

Das MobilityCoins-Forschungsteam

Display This Question:

If Q_URL = https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G

Or Q_URL = https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G?Q_CHL=qr

Herzlich Willkommen,

wir führen eine Studie im Rahmen des Forschungsprojekts „**MobilityCoins (MoCo) – Anreiz**

statt Gebühr“ durch. Ziel ist es, herauszufinden, ob das Mobilitätsverhalten in München nachhaltiger werden könnte, wenn man platzsparende und emissionsarme Wege und Transportmittel finanziell belohnt, und für andere Wege etwas hinzuzahlt. Daher erforschen wir die Ausgabe von „Mobilitätsbudgets“.

Das Ausfüllen der Umfrage beansprucht circa 15-20 Minuten.

Die Umfrage wird vom Lehrstuhl für Verkehrstechnik der TU München in Zusammenarbeit mit der ETH Zürich durchgeführt.

Falls Sie Fragen oder Anmerkungen zur Studie haben, melden Sie sich bitte via E-Mail unter mobilitycoins.vtk@ed.tum.de

Herzlichen Dank für Ihre Teilnahme!

Mit freundlichen Grüßen

Das MobilityCoins-Forschungsteam

Bevor Sie mit dem Ausfüllen des Fragebogens beginnen, möchten wir Sie bitten, sich die Informationen zur Studie durchzulesen und anschließend die folgende Einverständniserklärung zu akzeptieren.

Datenschutzregelung:

- Ihre personenbezogenen Daten werden streng vertraulich behandelt und ausschließlich zur Durchführung dieser Studie verwendet. Ihre personenbezogenen Daten werden spätestens nach Ende der Auswertung vollständig gelöscht.
- Die Auswertung erfolgt anonymisiert. Aus den zusammengeführten, unpersönlichen Ergebnissen der Studie werden keine Rückschlüsse auf einzelne Personen möglich sein.
- Sie haben das Recht, jederzeit von der Teilnahme an der Studie zurückzutreten und die Löschung sämtlicher über Sie erhobenen Daten zu verlangen.

Einverständniserklärung:

- Ich nehme an dieser Studie freiwillig teil und kann jederzeit ohne Angabe von Gründen meine Zustimmung zur Teilnahme widerrufen, ohne dass für mich deswegen Nachteile entstehen.
- Ich habe die Informationen zur Studie gelesen.
- Meine Fragen im Zusammenhang mit der Teilnahme an dieser Studie sind mir zufriedenstellend beantwortet worden.

○ Ja, ich möchte mit der Studie beginnen.

○ Nein, ich möchte nicht an der Studie teilnehmen.

End of Block: Einstieg

Start of Block: Consent 2

Sind Sie sicher, dass Sie nicht an der Studie teilnehmen möchten? Wir freuen uns sehr, wenn Sie teilnehmen würden!

○ Ja, ich möchte definitiv nicht teilnehmen.

○ Nein, ich möchte doch teilnehmen.

End of Block: Consent 2

Start of Block: Kontrollvariablen

Bitte geben Sie Ihr Geschlecht an

- ○ männlich
- ○ weiblich
- ○ divers

Bitte geben Sie Ihr Geburtsjahr an
Wählen...

▼ 1941 ... 2005

Sind Sie momentan erwerbstätig und/oder in Ausbildung/im Studium?

- ○ ja, erwerbstätig
- ○ ja, in Ausbildung / im Studium
- ○ ⨂ ja, beides
- ○ ⨂ nein

Bitte geben Sie Ihren höchsten Bildungsabschluss an.

- ○ kein Abschluss
- ○ Haupt-/Volksschulabschluss
- ○ Mittlerer Abschluss (Mittlere Reife)
- ○ Fachhochschulreife/Allgemeine Hochschulreife
- ○ Abgeschlossene Berufsausbildung
- ○ Bachelor/Master/Diplom
- ○ Promotion

Bitte geben Sie Ihr persönliches monatliches Nettoeinkommen (nach allen Abzügen) an.

- unter 900 Euro
- 900 bis 1599 Euro
- 1600 bis 2599 Euro
- 2600 bis 3599 Euro
- 3600 bis 4599 Euro
- 4600 bis 5999 Euro
- mehr als 6000 Euro
- keine Angabe

Bitte geben Sie die Größe Ihres Haushalts in Personen an (Sie selbst mit eingeschlossen).

- 1
- 2
- 3
- 4
- 5 oder mehr

Display This Question:

If Bitte geben Sie die Größe Ihres Haushalts in Personen an (Sie selbst mit eingeschlossen). != 1

Leben Kinder in Ihrem Haushalt?

- ja
- nein

Display This Question:

If Sind Sie momentan erwerbstätig und/oder in Ausbildung/im Studium? != nein

Fahren/laufen Sie an mindestens einem Arbeitstag zu Ihrem Arbeitsplatz (außerhalb von zuhause)?

- ja
- nein

Leben Sie in München?

○ ja

○ nein

Display This Question:

If Leben Sie in München? = ja

In welchem Stadtbezirk leben Sie?

▼ Allach-Untermenzing ... Untergiesing-Harlaching

End of Block: Kontrollvariablen

Start of Block: Mobilitätsparameter

Besitzen Sie einen Führerschein für ein Auto (Klasse B)?

○ ja

○ nein

Steht Ihnen ein Auto regelmäßig zur Nutzung zur Verfügung?

○ ja

○ nein

Nutzen Sie Abos für den öffentlichen Personennahverkehr (ÖPNV) des Münchner Verkehrsverbunds (MVV) und wenn ja, welche?

○ ⊗ Nein, ich habe innerhalb der letzten drei Jahre kein Abo genutzt.

○ Ich nutze aktuell kein Abo, habe aber innerhalb der letzten 3 Jahre ein Abo genutzt.

○ Ich nutze ein Wochenticket (z.B. IsarCard Wochenkarte)

○ Ich nutze ein Monatsabo (z.B. IsarCard Monatskarte, IsarCard 9 Uhr, IsarCard 65 Monatskarte)

○ Ich nutze ein Semesterticket (z.B. IsarCard Semester)

○ Ich nutze ein Jahresabo (z.B. IsarCard Abo, IsarCard 9 Uhr Abo, IsarCard 65 Abo, IsarCard Job, 365-Euro-Ticket)

Haben Sie für mindestens einen Monat das deutschlandweite 9€-Ticket erworben bzw. war dieses in Ihrem Verkehrsabo enthalten?

- ○ ja
- ○ nein

End of Block: Mobilitätsparameter

Start of Block: Wegetagebuch

Wie oft nutzen Sie die folgenden Verkehrsmittel in einer Woche durchschnittlich?

Bitte geben Sie pro Spalte eine Antwort an.

Display This Choice:
If car_availability = 1

	täglich	an 4-5 Tagen der Woche	an 2-3 Tagen der Woche	an 1 Tag der Woche	weniger als einmal wöchentlich	nie
Display This Choice: If car_availability = 1 Auto	○	○	○	○	○	○
Fahrrad	○	○	○	○	○	○
Öffentlicher Verkehr	○	○	○	○	○	○
Zu Fuß	○	○	○	○	○	○

An wie vielen Tagen einer Woche bewegen Sie sich durchschnittlich **von Ihrem Wohnort** zu den folgenden Orten?
Bitte geben Sie pro Spalte eine Antwort an.

Display This Choice:
If purpose_work = 1

	0	1	2	3	4	5 oder mehr
Display This Choice: If purpose_work = 1 Arbeit / Ausbildung	○	○	○	○	○	○
Freizeit (Sport, Kultur, etc.)	○	○	○	○	○	○
Einkauf	○	○	○	○	○	○

Wie viele Kilometer müssen Sie durchschnittlich zurücklegen, um folgende Orte von Ihrem Wohnort aus zu erreichen?
Bitte geben Sie pro Spalte eine Antwort an.

Display This Choice:
If purpose_work = 1

	0.1 bis 2.99 km	3 bis 5.99 km	6 bis 11.99 km	12 km oder mehr
Display This Choice: If purpose_work = 1 Arbeit / Ausbildung	○	○	○	○
Freizeit (Sport, Kultur, etc.)	○	○	○	○
Einkauf	○	○	○	○

End of Block: Wegetagebuch

Start of Block: Verfügbarkeiten Modi

Welche Verkehrsmittel stehen in einem Umkreis von 5 Gehminuten um Ihren Wohnort zur Verfügung?
Mehrere Antworten möglich.

- ▢ Tram
- ▢ Bus
- ▢ U-Bahn
- ▢ S-Bahn
- ▢ Verleihsysteme für Fahrrad, Elektro-Scooter, Elektro-Roller
- ▢ Car-Sharing (z.B. SixtShare, ShareNow) oder Ride-Hailing (z.B. Uber, Lyft)
- ▢ ⊗weiß nicht

End of Block: Verfügbarkeiten Modi

Start of Block: Politics & Personality

Wie schätzen Sie sich persönlich ein: Wie risikobereit sind Sie im Allgemeinen?

	1	2	3	4	5	6	7	
gar nicht risikobereit	○	○	○	○	○	○	○	sehr risikobereit

Für wie ernst halten Sie das Problem des Klimawandels aktuell?

	1	2	3	4	5	6	7	
Kein ernstzunehmendes Problem, bedarf keiner Handlung	○	○	○	○	○	○	○	Ein besonders ernstzunehmendes Problem das strikterer Handlung bedarf

Bitte beurteilen Sie die Aussage mithilfe der Skala:
Es ärgert mich, wenn es anderen unverdient besser geht als mir.

	1	2	3	4	5	6	
trifft überhaupt nicht zu	○	○	○	○	○	○	trifft voll und ganz zu

Es macht mir zu schaffen, wenn es mir unverdient besser geht als anderen.

	1	2	3	4	5	6	
trifft überhaupt nicht zu	○	○	○	○	○	○	trifft voll und ganz zu

End of Block: Politics & Personality

Start of Block: DCEnomoco

In den folgenden Fragen werden Ihnen 6 verschiedene Szenarien präsentiert.

Nehmen Sie bitte **für alle Szenarien** an, dass Sie sich für den Zweck **${e://Field/purpose_DE}** fortbewegen wollen und durchschnittlich zwischen **${e://Field/dc_show_DE}** zurücklegen.
Ihnen werden verschiedene **Wetterverhältnisse** angezeigt (sonnig, regnerisch).
Hier sehen Sie ein Beispiel eines Szenarios mit verschiedenen Verkehrsmitteln und damit verbundenen Eigenschaften:

Fahrtzeit: Die Zeit für die Nutzung eines Verkehrsmittels/ die Zeit die man zum Laufen benötigt.
Zu- & Abgangszeit: Die Zeit zu Fuß zur Starthaltestelle des öffentlichen Verkehrsmittels plus die Zeit von der Endhaltestelle zum Ziel.
Takt: Der Zeitabstand zwischen zwei verfügbaren ÖPNV-Verbindungen.
Umsteigen: Die Anzahl der Umstiege für die ÖPNV-Verbindung.
Fahrtkosten: Die Reisekosten für einen Weg im jeweiligen Verkehrsmittel.
Qualität Radweg: Eine allgemeine Einschätzung der Qualität des Radwegs (z.B. Sicherheit, vom Autoverkehr getrennter Weg usw.)

Bitte wählen Sie auf Basis aller gegebenen Informationen aus, für welches Verkehrsmittel Sie sich bevorzugt entscheiden würden.

Szenario 1	**Option 1: Auto**	**Option 2: Zu Fuß**	**Option 3: ÖPNV**	**Option 4: Fahrrad**
Fahrtzeit	8 min	36 min	7 min	12 min
Zu- & Abgangszeit			9 min	
Takt			alle 5 min	
Umsteigen			0 x	
Fahrtkosten	1,65 €		2,25 €	
Qualität Radweg				mittel

Sie führen die Fahrt aus folgendem Grund durch: **${e://Field/purpose_DE}**.
Sie legen dabei durchschnittlich **${e://Field/dc_show_DE}** zurück.
Das Wetter ist **${e://Field/mocono_cs1_weather_DE}**.

○ Option 1

○ Option 2

Display This Choice:
If walk_availability = 1
Or car_availability = 1

○ Option 3

Display This Choice:
If car_availability = 1
And walk_availability = 1

○ Option 4

Scenario 2-6 similar.

End of Block: DCEnomoco

Start of Block: Mobilitätsbudget

Die Stadt entscheidet sich, das **„MobilityCoin“** System einzuführen, um nachhaltige Mobilität zu fördern und die negativen Auswirkungen des motorisierten Verkehrs, wie z.B. Feinstaubbelastung, Flächenverbrauch, Unfälle und Lärm, zu reduzieren.

Jeder Bürger erhält monatlich kostenlos ein Mobilitätsbudget bestehend aus MobilityCoins. Von diesem Budget muss für die negativen Auswirkungen aller täglichen Wege bezahlt werden. Die zusätzlich anfallenden Kosten von Verkehrsmitteln (Tanken, Reparatur, Tickets, etc.) müssen unabhängig vom Mobilitätsbudget bezahlt werden. **Ein durchschnittliches Mobilitätsbudget reicht aus, um die negativen Auswirkungen einer täglichen Hin- und Rückfahrt mit dem ÖPNV im Stadtgebiet davon zu bezahlen.** Wenn Sie also z.B. nach der Hälfte des Monats noch 75% ihres Mobilitätsbudgets übrig haben und nur noch ÖPNV oder Fahrrad fahren, werden Sie am Ende des Monats Mobilitätsbudget übrig haben, dass Sie wiederum gegen Geld an andere Nutzer verkaufen können.

Autofahrten sind z.B. aufgrund des Platzverbrauchs und der verursachten Emissionen teurer als ÖPNV-Fahrten. Für Fahrten mit dem **Fahrrad** verdienen Sie sogar zusätzliche Coins für ihr Mobilitätsbudget, da keine negativen Auswirkungen verursacht werden. Als **Fußgänger** können Sie keine Coins verdienen - denn dies würde erfordern dass jeder einzelne Fußweg digital erfasst wird, was technischen und datenschutzrechtlichen Aufwand bedeuten würde. Sollten Sie einen Monat lang nur Fahrrad fahren und Zufuß gehen, können Sie am Ende des Monats Ihr gesamtes Mobilitätsbudget gegen Geld verkaufen.

Ist ihr Mobilitätbudget aufgebraucht (z.B. weil Sie sehr viel Auto fahren), können sie Coins gegen Geld auf der Marktplattform hinzukaufen. Überschüssige Coins können Sie gegen Geld verkaufen.

Sind Sie grundsätzlich dafür, dass die Höhe des persönlichen Mobilitätsbudgets nach individuellen Voraussetzungen angepasst wird? Ein Beispiel wäre, dass Menschen mit Mobilitätseinschränkung ein höheres Budget erhalten als Uneingeschränkte. Ein anderes Beispiel wäre, dass Menschen mit einer guten ÖPNV-Anbindung etwas weniger Budget erhalten als Menschen, die auf ihr Auto angewiesen sind.

- ○ ja
- ○ nein
- ○ weiß nicht

Display This Question:

If Sind Sie grundsätzlich dafür, dass die Höhe des persönlichen Mobilitätsbudgets nach individuellen... = ja

Or Sind Sie grundsätzlich dafür, dass die Höhe des persönlichen Mobilitätsbudgets nach individuellen... = weiß nicht

In welchen Fällen sollte das persönliche Mobilitätsbudget angepasst werden? Sortieren Sie die Gründe für eine Anpassung von eher relevant (ganz oben) bis weniger relevant (ganz unten). Sie können die Elemente der Liste nach oben und unten verschieben, indem sie darauf klicken und halten, und dann ziehen.

In welchen Fällen sollte das persönliche Mobilitätsbudget angepasst werden? Sortieren Sie die Gründe für eine Anpassung von eher relevant (ganz oben) bis weniger relevant (ganz unten). Sie können die Elemente der Liste nach oben und unten verschieben, indem sie darauf klicken und halten, und dann ziehen.

1. Höhe des Einkommens (mehr Budget für geringe Einkommen)
2. Mobilitätseinschränkung
3. Fürsorgepflicht für pflegebedürftige Personen
4. Verfügbarkeit von ÖPNV und Verleihsystemen
5. Anzahl und Distanz notwendiger Fahrten
6. Distanz zum Arbeitsort
7. Andere ____________

Display This Question:

If Sind Sie grundsätzlich dafür, dass die Höhe des persönlichen Mobilitätsbudgets nach individuellen... = ja

Or Sind Sie grundsätzlich dafür, dass die Höhe des persönlichen Mobilitätsbudgets nach individuellen... = weiß nicht

Stellen Sie sich vor, Bürger erhalten durchschnittlich ein MobilityCoin Budget im Wert von 100€ im Monat, das im Durchschnitt dafür ausreicht, für die Emissionen und den Platzverbrauch von zwei ÖPNV Fahrten pro Tag zu zahlen. Bitte geben Sie nun an, wie viel Geld Sie für die unten angegebenen Attribute **zusätzlich** an die betroffenen Personen verteilen würden.

	0 10 20 30 40 50 60 70 80 90 100	
Für Eltern: Pauschale pro Kind in Euro		62
Bei unterdurchschnittlich schlechter ÖPNV-Anbindung: Pauschale in Euro		34
Mobilitätseinschränkung: Pauschale in Euro		73
Geringverdienende: Pauschale in Euro		43
Pendler ab einer bestimmten Länge des Arbeitsweges: Pauschale in Euro		70
Rentner: Pauschale in Euro		49
Studierende: Pauschale in Euro		58

End of Block: Mobilitätsbudget

Start of Block: Intro_WTP

Nehmen Sie an, dass Ihr monatliches Mobilitätsbudget nach 15 Tagen aufgebraucht ist. Ein automatisches, kostenloses „Auffüllen“ des Budgets erfolgt erst im nächsten Monat. Für die verursachten negativen Auswirkungen (z.B. Emissionen, Flächenverbrauch) jeder weiteren Fahrt müssen Sie also ab sofort für den Rest des Monats selbst aufkommen.

Nehmen Sie an, dass Ihr monatliches Mobilitätsbudget nach 20 Tagen aufgebraucht ist. Ein automatisches, kostenloses „Auffüllen" des Budgets erfolgt erst im nächsten Monat. Für die verursachten negativen Auswirkungen (z.B. Emissionen, Flächenverbrauch) jeder weiteren Fahrt müssen Sie also ab sofort für den Rest des Monats selbst aufkommen.

Nehmen Sie an, dass Ihr monatliches Mobilitätsbudget nach 25 Tagen aufgebraucht ist. Ein automatisches, kostenloses „Auffüllen" des Budgets erfolgt erst im nächsten Monat. Für die verursachten negativen Auswirkungen (z.B. Emissionen, Flächenverbrauch) jeder weiteren Fahrt müssen Sie also ab sofort für den Rest des Monats selbst aufkommen.

End of Block: Intro_WTP

Start of Block: Intro_WTP2

Sind Sie bereit, um die weiteren Fahrten mit dem Auto tätigen zu können, extra Coins zu kaufen?

- ○ ja
- ○ nein
- ○ keine Angabe

Display This Question:

If Sind Sie bereit, um die weiteren Fahrten mit dem Auto tätigen zu können, extra Coins zu kaufen? = nein

Sie sind nicht bereit, extra Coins für weitere Autofahrten bis zum Ende des Monats hinzuzukaufen. Was machen Sie dann?

- ☐ Die Autofahrten generell vermeiden (zuhause bleiben)
- ☐ Auf kostengünstigere Verkehrsmittel umsteigen (ÖPNV, Fahrrad, zu Fuß)
- ☐ ⊗ Ich weiß nicht

End of Block: Intro_WTP2

Start of Block: WTP

Nehmen Sie an, dass Sie für die negativen Auswirkungen jeder weiteren Fahrt mit öffentlichen Verkehrsmitteln nun zusätzlich zum Ticket 0.25 Euro pro Kilometer zahlen müssten. Fahrten mit dem Fahrrad wären kostenlos. Wieviel wären Sie im Vergleich hierzu bereit für jede weitere Autofahrt zusätzlich **pro Kilometer** zu zahlen, um weiterhin mit dem Auto mobil zu sein?

Euro pro Kilometer

	0	1	1	2	2	3
Arbeits-/Ausbildungsweg						
Einkaufsweg						
Freizeitweg						

Nehmen Sie an, dass Sie für die negativen Auswirkungen jeder weiteren Fahrt mit öffentlichen Verkehrsmitteln nun zusätzlich zum Ticket 0.5 Euro pro Kilometer zahlen müssten. Fahrten mit dem Fahrrad wären kostenlos. Wieviel wären Sie im Vergleich hierzu bereit für jede weitere Autofahrt zusätzlich **pro Kilometer** zu zahlen, um weiterhin mit dem Auto mobil zu sein?

Euro pro Kilometer

	0	1	1	2	2	3	3	4	4	5
Arbeits-/Ausbildungsweg										
Einkaufsweg										
Freizeitweg										

Nehmen Sie an, dass Sie für die negativen Auswirkungen jeder weiteren Fahrt mit öffentlichen Verkehrsmitteln nun zusätzlich zum Ticket 0.75 Euro pro Kilometer zahlen müssten. Fahrten mit dem Fahrrad wären kostenlos. Wieviel wären Sie bereit für jede weitere Autofahrt zusätzlich **pro Kilometer** zu zahlen, um weiterhin mobil zu sein?

Euro pro Kilometer

	0	1	1	2	2	3	3	4	4	5
Arbeits-/Ausbildungsweg										
Einkaufsweg										
Freizeitweg										

End of Block: WTP

Start of Block: WTS

Da Sie viel Fahrrad fahren, haben Sie nach 15 Tagen noch die Hälfte Ihres Mobilitätsbudgets übrig (im Wert von 50€). Sie können auf dem Markt einen Teil Ihrer Coins gegen Geld verkaufen. Wieviel der 50€ würden Sie zu diesem Zeitpunkt auf dem Markt verkaufen?

	0	5	10	15	20	25	30	35	40	45	50
Euro											

Da Sie viel Fahrrad fahren, haben Sie nach 25 Tagen noch die Hälfte Ihres Mobilitätsbudgets übrig (im Wert von 50€). Sie können auf dem Markt einen Teil Ihrer Coins gegen Geld verkaufen. Wieviel der 50€ würden Sie zu diesem Zeitpunkt auf dem Markt verkaufen?

	0	5	10	15	20	25	30	35	40	45	50
Euro											

Da Sie viel Fahrrad fahren, haben Sie nach 15 Tagen noch dreiviertel Ihres Mobilitätsbudgets übrig (im Wert von 75€). Sie können auf dem Markt einen Teil Ihrer Coins gegen Geld verkaufen. Wieviel der 75€ würden Sie zu diesem Zeitpunkt auf dem Markt verkaufen?

	0	8	15	23	30	38	45	53	60	68	75
Euro											

Da Sie viel Fahrrad fahren, haben Sie nach 25 Tagen noch dreiviertel Ihres Mobilitätsbudgets übrig (im Wert von 75€). Sie können auf dem Markt einen Teil Ihrer Coins gegen Geld verkaufen. Wieviel der 75€ würden Sie zu diesem Zeitpunkt auf dem Markt verkaufen?

	0	8	15	23	30	38	45	53	60	68	75
Euro											

End of Block: WTS

Start of Block: DCEmoco

In den folgenden Fragen werden Ihnen erneut 6 verschiedene Szenarien präsentiert. Nehmen Sie an, dass das **"MobilityCoin"** System eingeführt wurde. Sie müssen also zusätzlich zu den üblichen Fahrtkosten für die negativen Auswirkungen (CO2-Emissionen, Stau, Lärm usw.), die Sie verursachen, mit MobilityCoins aus Ihrem monatlichen Budget bezahlen.

Nehmen Sie bitte **für alle Szenarien** an, dass Sie sich für Zweck **${e://Field/purpose_DE}** fortbewegen wollen und **für alle angezeigten Wege** durchschnittlich zwischen **${e://Field/dc_show_DE}** zurücklegen.
Ihnen werden verschiedene **Wetterverhältnisse** (sonnig, regnerisch) angezeigt.
Hier sehen Sie ein Beispiel eines Szenarios mit verschiedenen Verkehrsmitteln und damit verbundenen Eigenschaften:

Es ist Tag **${e://Field/days_into_month}** im Monat und Sie haben ein Restbudget von **${e://Field/mocosi_cs5_cbudget_DE}** übrig.

Tag im Monat: Wie weit der Monat schon vorangeschritten ist.
Restbudget: Wie viel von Ihrem monatlichen Mobilitätsbudget übrig ist.
Fahrtzeit: Die Zeit für die Nutzung eines Verkehrsmittels/ die Zeit die man zum Laufen benötigt.
Zu- & Abgangszeit: Die Zeit zu Fuß zur Starthaltestelle des öffentlichen Verkehrsmittels plus die Zeit von der Endhaltestelle zum Ziel.
Takt: Der Zeitabstand zwischen zwei verfügbaren ÖPNV-Verbindungen.
Umsteigen: Die Anzahl der Umstiege für die ÖPNV-Verbindung.
Fahrtkosten: Die Reisekosten für einen Weg im jeweiligen Verkehrsmittel.
MobilityCoin Ausgaben: Ausgaben aufgrund der negativen Auswirkungen für Wege im Auto oder ÖPNV.
MobilityCoin Einnahmen: Einnahmen (Belohnung) für den Weg mit dem Fahrrad, weil es keine negativen Auswirkungen hat.
Qualität Radweg: Eine allgemeine Einschätzung der Qualität des Radwegs (z.B. Sicherheit, vom Autoverkehr getrennter Weg usw.)

Bitte wählen Sie auf Basis aller gegeben Informationen aus, für welches Verkehrsmittel Sie sich bevorzugt entscheiden würden.

Szenario 2	Option 1: Auto	Option 2: ÖPNV	Option 3: Fahrrad	Option 4: Zu Fuß
Fahrtzeit	11 min	5 min	14 min	53 min
Zu- & Abgangszeit		15 min		
Takt		alle 5 min		
Umsteigen		0 x		
Fahrtkosten	2,8 €	2,9 €		
MobilityCoin Ausgaben	3,2 €	1,05 €		
MobilityCoin Einnahmen			0,1 €	
Qualität Radweg			schlecht	

End of Block: DCEmoco

Start of Block: Verständnis

Was ist Ihrer Meinung nach der wesentliche Unterschied der MobilityCoins zu einer Straßenmaut?

- ○ Es gibt keinen Unterschied.
- ○ Nachhaltige Verkehrsmittel können finanziell belohnt werden.
- ○ Der motorisierte Individualverkehr wird finanziell belohnt.

Display This Question:

If Q_URL != https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G

And Q_URL != https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G?Q_CHL=qr

Sie haben die Umfrage vollständig ausgefüllt, dafür bedanken wir uns sehr herzlich! Bitte entscheiden Sie nun, wie sie die Vergütung von 15€ nutzen möchten.

- ○ Wunschgutschein (Partner sind z.B. Amazon, Zalando, H&M, MediaMarkt etc.)
- ○ Spende Nothilfe Ukraine an "Bündnis Entwicklung Hilft" und "Aktion Deutschland Hilft"
- ○ Spende an Umweltstiftung WWF Deutschland - Einsatz gegen Waldbrände

Display This Question:

If Q_URL != https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G

And Q_URL != https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G?Q_CHL=qr

Bitte geben Sie nun Ihre E-Mail an, damit wir Ihnen den Gutschein/die Informationen zur Spende zusenden können. Wir nutzen Ihre E-Mail **nur** für diesen Zweck. Sie erhalten den Gutschein/die Spendeninformation innerhalb von einer Woche.

____

Display This Question:

If Q_URL != https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G?Q_CHL=qr

And Q_URL != https://tummgmt.eu.qualtrics.com/jfe/form/SV_9RHvikM90SEsF4G

Bitte validieren Sie Ihre E-Mail, die Sie uns eben angegeben haben:

${incentive_email/ChoiceTextEntryValue}

Ist diese korrekt?

- Ja
- Nein

Display This Question:

If Bitte validieren Sie Ihre E-Mail, die Sie uns eben angegeben haben:... = Nein

*

Bitte geben Sie Ihre E-Mail erneut ein. Besten Dank.

____

Dieses letzte Feld bietet Ihnen nun die Möglichkeit, Anregungen, Kritik, Lob und Kommentare zu unserer Umfrage zu äußern.

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End of Block: Verständnis

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CURRICULUM VITAE

PERSONAL DATA

Name	Thomas Schatzmann
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EDUCATION

2018 – 2023	Swiss Federal Institute of Technology (ETH) Zurich Institute of Transport Planning and Systems
2014 – 2017	University of Zurich (UZH) *Master of Arts* in Economics
2016 – 2016	Free University of Amsterdam (VU) Exchange semester in Spatial, Transport and Environmental Economics
2007 – 2013	University of Zurich (UZH) *Bachelor of Arts* in Banking and Finance

PROFESSIONAL EXPERIENCE

2018 – 2023	Research assistant *Swiss Federal Institute of Technology (ETH) Zurich* Zurich, Switzerland
2014 – 2016	Part-time employee (40%) *Credit Suisse* Zurich, Switzerland Swiss Economy, Real Estate and Industry Research
2008 – 2014	Part-time employee (30%) *Finanz und Wirtschaft, Tamedia Group* Zurich, Switzerland Assistant to Head Financial Data

PUBLICATIONS

ARTICLES IN PEER-REVIEWED JOURNALS

Hintermann, B., B. Schoeman, J. Molloy, **T. Schatzmann**, C. Tchervenkov and K.W. Axhausen (2023) The impact of COVID-19 on mobility choices in Switzerland, *Transportation Research Part A: Policy and Practice*, **169** 103582.

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PEER-REVIEWED CONFERENCE CONTRIBUTIONS

Schatzmann, T., G. Sarlas and K.W. Axhausen (2019) Spatial modelling of origin-destination commuting flows in Switzerland, paper presented at the *98th Annual Meeting of the Transport Research Board (TRB 2019)*, Washington, D.C.

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OTHER CONFERENCE CONTRIBUTIONS

Schatzmann, T., B. Schoeman, B. Hintermann and K.W. Axhausen (2022) Modeling mobility tool ownership and usage in Switzerland, paper presented at the *22nd Swiss Transport Research Conference*, Ascona, Switzerland.

WORKING PAPERS

Molloy, J., C. Tchervenkov, **T. Schatzmann**, B. Schoeman, B. Hintermann and K.W. Axhausen (2020) MOBIS-COVID19/01: Results as of 06/04/2020, *Working Paper*, **1489**, IVT, ETH Zurich, Zurich.

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