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CONNECTING TIME-USE, TRAVEL AND SHOPPING BEHAVIOR: RESULTS OF A MULTI-STAGE HOUSEHOLD SURVEY

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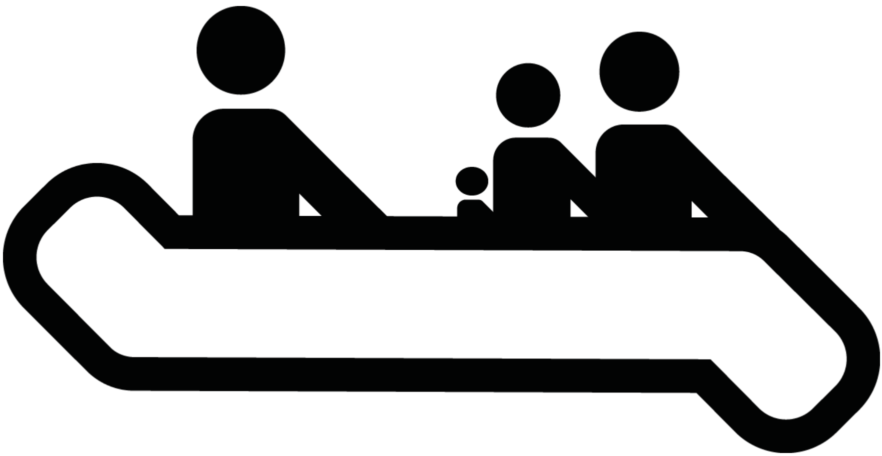
To my grandmother Emma



ABSTRACT

The main research question addressed by this thesis is how individual preferences for time-use, expenditure allocation and different level-of-service related attributes – including mode-specific travel times of traditional and emerging modes, shopping channel characteristics and travel/shopping costs – are related, and how respondents trade-off these aspects in their choice and scheduling behavior using sophisticated econometric modeling approaches. We demonstrate how different research fields and data collection methods are united to come up with a deeper understanding of human behavior in general and travel behavior in particular.

Data were collected as part of the *Post-Car World* study, an interdisciplinary project trying to investigate possible transitions and scenarios of a world where the ownership and usage of private cars is reduced to a minimum, but assuming an increased public support of innovative mode sharing systems such as carsharing (CS) and carpooling (CP). The empirical basis is a multi-day travel, non-physical/online and expenditure diary that is required to obtain the personalized reference values for the subsequent behavioral experiments, but also to provide a solid empirical basis to analyze and understand behavior in the presence.

The value of leisure (VoL) is estimated based on respondents' time-use and expenditure allocation, and used to decompose the value of travel time savings (VTTS) for traditional and emerging modes, obtained from a pooled RP/SP choice model. The VTTS summarizes the value of liberated time (opportunity cost of travel; VoL), while the remaining (mode-specific) value of time assigned to travel (VTAT) represents the gain/loss when travel time is reduced – which is why it relates to the conditions of travel. We find that the VoL of about 23 CHF/h and the VTTS for walk (24.9 CHF/h), bike (16.9 CHF/h), private car and motorbike (MIV; 28.9 CHF/h), public transportation (PT; 13.8 CHF/h), CS (27.3 CHF/h) and CP (31.3 CHF/h) imply a negative VTAT for the (private and public) car modes and a positive VTAT for PT and bike. Our findings indicate that CS and CP have a hard time when competing with the traditional modes: Market shares may be difficult to expand – even in the complete absence of private cars: On average, individuals do not seem to enjoy traveling with these modes and rather choose PT or bike.

Results of the shopping channel choice model reveal a further potential for online shopping services, given the relatively high VTTS for shopping trips of about 50 CHF/h for groceries (G; typical experience goods) and 30 CHF/h for standard electronic appliances (E; typical search goods) compared to the value of delivery time (VDTS) ranging between 9 CHF/day for G and 1 CHF/day for E. From a travel behavior perspective, avoiding a shopping trip thus produces more benefits than waiting for the delivery of the products, especially when purchasing search goods such as E. Also, in the case of grocery shopping, shopping costs are perceived as less unpleasant relative to delivery costs. Online retailers should take note of that when designing an effective pricing strategy: From a behavioral perspective, incorporating delivery in shopping costs would increase customers' utilities and therefore the market shares of online shopping.

To what degree individuals would be changing car usage when mobility costs are reaching unprecedented proportions is analyzed using two stated adaptation experiments: In the daily scheduling experiment, variable travel costs are changed systematically for one selected day by asking respondents how they would change and adapt their daily plan. In the mobility tool ownership experiment, households were asked about their yearly mobility plans, including possible adaptations in vehicle ownership and motorization. The median MIV cost elasticities of travel demand differ substantially between these two experiments, ranging between –0.37% in case of the former and –0.13% in case of the latter. We argue that in the short/medium-run, people adapt more strongly, since substitution effects towards more energy efficient vehicles are unlikely. In the long-run, however, the elasticity does reflect those substitution patterns, so that ultimately the overall distance traveled by MIV may not be decreasing that much. This finding is important for elaborating future congestion policies: In case of increasing fuel prices, for example, results indicate that in the long-run, this would only lead to a relatively small effect on the overall traffic volume.

ZUSAMMENFASSUNG

Diese Dissertation befasst sich mit dem Thema, wie die individuellen Präferenzen für Zeitnutzung, Konsumausgaben und verschiedene Angebotsvariablen – einschliesslich Fahrzeiten traditioneller und aufkommender Verkehrsmittel, Einkaufskanaleigenschaften und Reise-/Einkaufskosten – zusammenhängen und wie die Befragten diese Aspekte in ihrem Entscheidungs- und Planungsverhalten gegenüberstellen. Mit Hilfe von ausgefeilten ökonometrischen Modellierungsansätzen zeigen wir, wie verschiedene Forschungsbereiche und Datenerfassungsmethoden zusammengeführt werden, um ein tieferes Verständnis des menschlichen Verhaltens, insbesondere des Reiseverhaltens, zu erzielen.

Die Daten wurden im Rahmen der *Post-Car World* Studie erhoben, einem interdisziplinären Projekt, das versucht, mögliche Übergänge und Szenarien einer Welt zu untersuchen, in welcher der Besitz und die Nutzung von Privatfahrzeugen auf ein Minimum reduziert werden, ausgehend unter der Annahme einer verstärkten öffentlichen Unterstützung von innovativen Verkehrsmittelsystemen wie Carsharing (CS) und Carpooling (CP). Die empirische Grundlage ist ein mehrtägiges Reise-, Online- und Ausgaben-Tagebuch, das erforderlich ist, um die personalisierten Referenzwerte für die nachfolgenden Verhaltensexperimente zu ermitteln, aber auch um eine solide empirische Grundlage für die Analyse und das Verständnis des Verhaltens in der Gegenwart bereitzustellen.

Der Wert der Freizeit (VoL) wird auf der Grundlage des Zeit- und Ausgabenverhaltens der Befragten geschätzt und verwendet, um den Wert der Reisezeitersparnis (VTTS) für traditionelle und aufkommende Verkehrsmittel zu zerlegen, welcher anhand eines gepoolten RP/SP-Entscheidungsmodells ermittelt wird. Der VTTS umfasst zum einen den Wert der frei gewordenen Zeit (Opportunitätskosten des Reisens; VoL), während der verbleibende (verkehrsmittel-spezifische) Zeitwert (VTAT) den Nutzengewinn/Verlust bei Verkürzung der Reisezeit darstellt. Wir zeigen, dass der VoL von ca. 23 CHF/h und der VTTS für zu Fuss (24.9 CHF/h), Velo (16.9 CHF/h), privates Auto und Motorrad (MIV; 28.9 CHF/h), öffentliche Verkehrsmittel (ÖV; 13.8 CHF/h), CS (27.3 CHF/h) und CP (31.3 CHF/h) einen negativen VTAT für die (privaten und öffentlichen) Fahrzeugmodi und einen positive VTAT für den ÖV und das Velo bedeuten. Unsere Ergebnisse zeigen, dass CS und CP es schwer haben, mit den traditionellen

Verkehrsmitteln zu konkurrieren: Marktanteile lassen sich möglicherweise nur schwer ausbauen – und dies auch im Falle ohne jegliche Verfügbarkeit von Privatfahrzeugen: Die Befragten reisen in diesen Verkehrsmitteln nicht sehr gerne und wählen in vielen Fällen eher den ÖV oder das Velo.

Die Ergebnisse des Modells zur Wahl des Einkaufskanals zeigen ein weiteres Potenzial für Online-Einkaufsdienste, da der VTTS für die Beschaffung von Lebensmitteln (G; typische Erfahrungsgüter) mit rund 50 CHF/h und Standard-Elektrogeräten (E; typische Suchgüter) mit 30 CHF/h im Vergleich zum Wert der Lieferzeit (VDTS) zwischen 9 CHF/Tag für G und 1 CHF/Tag für E deutlich höher liegt. Aus Sicht des Reiseverhaltens bringt das Vermeiden einer Einkaufsreise daher mehr Vorteile als das Warten auf die Lieferung der Produkte, insbesondere beim Kauf von Suchgütern. Weiter werden beim Einkauf von Lebensmitteln die Einkaufskosten im Vergleich zu den Versandkosten als weniger unangenehm empfunden. Online-Händler sollten dies bei der Entwicklung einer effektiven Preisstrategie berücksichtigen: Aus verhaltenstechnischer Sicht würde die Einbeziehung der Lieferkosten in die Einkaufskosten die Nutzen der Kunden und damit die Marktanteile des Online-Einkaufs erhöhen.

Inwieweit Personen ihr Reiseverhalten mit dem Auto ändern würden, wenn die Mobilitätskosten ein beispielloses Ausmass erreichen, wird anhand von zwei Anpassungsexperimenten analysiert: Im täglichen Planungsexperiment werden variable Reisekosten für einen ausgewählten Tag systematisch verändert, wobei die Teilnehmer gefragt wurden, wie sie ihren Tagesplan ändern und anpassen würden. Im Mobilitätswerkzeugwahl-Experiment wurden die Haushalte nach ihrem jährlichen Mobilitätsverhalten befragt, einschliesslich möglicher Anpassungen im Fahrzeugbesitz und in der Motorisierung. Die Kostenelastizitäten der MIV Verkehrsnachfrage unterscheiden sich zwischen diesen beiden Experimenten erheblich und liegen zwischen –0.37% im ersteren und –0.13% im letzteren Fall. Wir argumentieren, dass sich die Personen kurz- und mittelfristig stärker anpassen, da Substitutionseffekte für energieeffizientere Fahrzeuge unwahrscheinlich sind. Langfristig jedoch spiegelt die Elastizität diese Substitutionseffekte wider, so dass letztendlich die von MIV zurückgelegte Gesamtdistanz nicht so stark abnimmt. Diese Erkenntnis ist für die Ausarbeitung künftiger Stau- und Verkehrsüberlastungsszenarien wichtig: Bei steigenden Benzinpreisen deuten beispielsweise die Ergebnisse darauf hin, dass dies auf lange Sicht nur zu einer relativ geringen Auswirkung auf das gesamte Verkehrsaufkommen führen würde.

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DECLARATION OF PERSONAL CONTRIBUTION

Chapter 2 is a revised, reformatted and extended version of the paper Schmid et al. (2019b). Basil Schmid developed the survey design in collaboration with Kay Axhausen, conducted the fieldwork and collected the data, on which all chapters in this thesis are based. Basil Schmid wrote the manuscript and did the data analysis. Milos Balac programmed the two stated adaptation survey tools. Kay Axhausen helped in editing the manuscript.

Chapter 3 builds on Hössinger et al. (2019) and is adapted to the current dataset. Basil Schmid's contribution to this paper was to develop the survey design of the choice experiments and to provide the results of the discrete choice models to calculate all value of (travel) time components for Austria. Basil Schmid also helped with the research design and the editing of the manuscript. Sergio Jara-Diaz developed the theoretical model, Reinhard Hössinger wrote the manuscript, did the data collection and model estimation with the help of Simona Jokubauskaite and Florian Aschauer. Stefanie Peer and Regine Gerike helped with the research design and the editing of the manuscript.

Section 3.1 and Section 3.2 are heavily based on Hössinger et al. (2019) and extended to the current application for the data collected in Zurich. Section 3.3 is based on the modeling framework described in Hössinger et al. (2019) and extended to the current application. Basil Schmid's methodological contribution includes a refined modeling framework using interaction terms and random effects for estimating the baseline utility coefficients. From Section 3.4 onward, the new results are presented, and innovative calculation and decomposition techniques for the value of leisure are introduced.

Chapter 4 is based on Schmid et al. (2019a) and extended to the current application, using a similar methodology to estimate the value of travel time savings (VTTS) for Austria. In this paper, Basil Schmid developed the modeling framework, did the coding and estimation of the discrete choice models, the interpretation of results and the writing of the manuscript. The co-authors helped with the research approach and the editing of the manuscript.

Section 4.1, Section 4.2, Section 4.3 and Section 4.4 are heavily based on Schmid et al. (2019a) and extended to the current application for the data collected in Zurich. From Section 4.5 onward, the new results are presented. Furthermore, Basil Schmid had the idea to investigate the correlations between the VTTS and the value of leisure (obtained in Chapter 3) – both measures were obtained at the individual-level and for the same set of respondents – which is presented in a comprehensive synthesis in Section 4.5.3.

Chapter 5 is a revised, reformatted and extended version of the paper Schmid and Axhausen (2019b). Basil Schmid developed the modeling framework, did the coding and estimation of the hybrid choice models, the interpretation of results and the writing of the manuscript. Kay Axhausen helped with the editing of the manuscript.

Chapter 6 contains new material. Basil Schmid developed the modeling framework, did the coding and estimation of the models, the interpretation of results and the writing.

CONTENTS

NOTATION

GLOSSARY

AICc:	For small sample size corrected Akaike Information Criterion
CP:	Carpooling
CS:	Carsharing
df:	Degrees of freedom
G:	Groceries
E:	Standard electronic appliances
EVE:	Swiss household budget survey
HCM:	Hybrid choice model
HH:	Household
ICLV:	Integrated choice and latent variable
ID:	Individual
IID:	Independent and identically distributed
ICT:	Information and communication technology
IQR:	Interquartile range
IVT:	Institute for Transport Planning and Systems
LL:	Log-likelihood
LOS:	Level-of-service
LR:	Likelihood-ratio
LV:	Latent variable
MAED:	Mobility-Activity-Expenditure diary
MIMIC:	Multiple indicators multiple causes
MIXL:	Mixed Logit
MIV:	Motorized individual vehicle (private car and motorbike)
MLHS:	Modified Latin hypercube sampling
MNL:	Multinomial Logit
MPE:	Marginal probability effect
MPV:	Motorized public vehicle (carsharing, carpooling and taxi)

MZMV: Swiss Microcensus for Mobility and Travel Behavior
N: Number of respondents/households
OL: Ordered Logit
PCW: Post-Car World (project name)
PT: Public transportation
RP: Revealed preference
SD: Standard deviation
SEM: Structural equations model
SP: Stated preference
VDTS: Value of delivery time savings
VoL: Value of leisure
VTAT: Value of time assigned to travel
VTAW: Value of time assigned to work
VTTS: Value of travel time savings
WTP: Willingness to pay

FREQUENTLY USED UNITS

CHF Swiss Francs (1 CHF $\approx$ 1 US$)
h Hour(s)
km Kilometer(s)
min Minute(s)
l Liter(s)

FREQUENTLY USED INDICES

i Choice alternative
j Choice alternative $\neq i$
n Individual/household
t Observation/trip
r Random draw

1

INTRODUCTION

Money may not buy happiness, but I'd rather cry in a Jaguar than on a bus.

— Françoise Sagan

1.1 POST-CAR WORLD IN THE CONTEXT OF SHARED MOBILITY

Policy decisions in many developed countries, especially for urban areas, tend to favor car reducing and pedestrian/bicycle-friendly environments to reduce traffic congestion and improve the overall transportation network efficiency. In fact, a technological and behavioral transformation is already under way towards a world with a reduced role of privately owned and operated cars, which are substituted by various forms of shared mobility. For policy implementations aiming to enhance a quasi car-less transport system, it is important to know the expected market shares and behavioral preferences depending on the mode, trip and population characteristics.

Data were collected as part of the *Post-Car World*[1] study, an interdisciplinary project of Swiss architects, philosophers, engineers and transportation planners investigating possible scenarios in a situation where the ownership and usage of private cars is reduced to a minimum. While the name of the project might suggest the investigation of a purely hypothetical, strictly car-less scenario, we would like to stress that one focus of this thesis is about understanding possible transition mechanisms *towards* such a state (i.e. a ***Pre***-*Post-Car World*). This is done by first obtaining a better understanding on how individuals' preferences affect activity behavior in general – and car travel in particular – in the presence and which factors play a role in the choice and adaptation behavior of traditional as well as emerging modes in different contexts.

In a recent study investigating the choice and ownership of mobility tools (i.e. the possession and/or availability of motorized vehicles such as cars and motorbikes, bikes, and public transportation national/regional season tickets and discount cards; following the definition in Scott and Axhausen, 2006), we investigated possible substitution patterns between the

1 Project website: postcarworld.epfl.ch

membership in Switzerland's biggest station-based carsharing (CS) provider *Mobility* and traditional modes using data from the Swiss Microcensus for Mobility and Travel Behavior (MZMV) (Becker et al., 2017). We found that CS is a strong supplement to a public transportation (PT) oriented lifestyle, revealing a user-profile of mainly younger and highly educated respondents living in smaller households, urban areas and the German speaking part of Switzerland.

More flexible, free-floating CS systems are already under way, operating without fixed CS stations, advance reservations or return-trip requirements. Becker et al. (2018) found that in Basel, Switzerland, free-floating CS users exhibit a substantially and significantly reduced level of car ownership, and similar as in the case of station-based CS, the availability of free-floating CS enforces a modal shift towards PT.

Apart from free-floating CS, another form of shared mobility that is investigated as part of this thesis is carpooling (CP), which is defined as a ridesharing alternative that can be organized via the Internet and ordered to a desired, accessible place (Ciari and Axhausen, 2012). Ciari and Axhausen (2013) argue that in Switzerland, especially well educated and high income respondents would be willing to use CP as a potential mode alternative. However, in order to exploit the full potential (which has been shown to be large, especially in the metropolitan area of Zurich; Dubernet et al., 2012), a framework is necessary to address some of the typical issues related to CP, mainly regarding safety and practical concerns if CP is arranged on a one-way basis.

Only a few studies have conducted behavioral experiments explicitly including emerging modes like CS and CP. As discussed in Schmid et al. (2016) and reproduced below, Ciari and Axhausen (2012) conducted a survey on private car use, CS and CP in Switzerland, finding that the choice of innovative modes is not only of economic nature, but other motivations – social and environmental – also play an important role. Le Vine et al. (2014a) used a stated adaptation approach, showing that frequent grocery shoppers exhibit a higher propensity to use a free-floating CS system in London. In another related study, Le Vine et al. (2014b) pointed out that the market share of CS in London would increase substantially by introducing a more flexible free-floating instead of a round-trip CS system. Catalano et al. (2008) analyzed the role of CS and CP in Palermo under a hypothetical scenario favoring an ecologically friendly transport system, supporting the findings of Litman (2000) and Loose et al. (2006) for Germany that there is a large market potential for these modes. Correia and Viegas (2011) found that in Lisbon, CP is seen a realistic alternative to private cars especially for lower income and younger people not having their own vehicle. Abraham (1999) showed that for the case of Calgary, socioeconomic characteristics contribute more to the choice of joining a CS organization than the attributes describing it. De Luca and Di Pace (2015) also found that besides access time to the transport mode, the most important predictors for choosing CS and CP in Salerno were socioeconomic characteristics rather than actual service attributes.

Findings indicate that urban and transport planning can benefit from better understanding the behavioral mechanisms of choosing innovative modes for optimizing the supply and organization of CS and CP systems. Therefore, one goal of this thesis is to integrate those shared mobility services as potential mode alternatives in multifaceted behavioral experiments, and to investigate their relative performance in terms of choice behavior and the valuation of related service attributes.

1.2 OUTLINE, OBJECTIVES AND MAIN CONTRIBUTIONS

Chapter 2: Survey methods and response behavior

Substantial data collection efforts were undertaken that are not comparable to previous studies conducted at the Institute for Transport Planning and Systems (IVT)[2]: A three-stage household survey was carried out in the Canton of Zurich, Switzerland, using innovative data collection methods and tools that try to capture choice behavior in multiple dimensions for the same set of respondents. All behavioral experiments in the second and third stage of the survey were personalized based on revealed preference (RP) data from the first stage of the survey.

Apart from a broad range of socioeconomic characteristics, respondents were asked to give information on their daily travel, non-physical/online activity and expenditure behavior for a one week reporting period (stage I), followed by multiple stated preference (SP) experiments and attitudes towards traditional and emerging transportation modes, shopping related aspects and personality traits (stage II). The absence of private cars in the SP experiments was justified to the respondents by car-reducing policy developments, suggested by an increased public support of CP and CS systems, leaving PT as the only traditional reference mode for longer distances. The stated adaptation (SA) experiments (stage III) were designed

2 Institute website: www.ivt.ethz.ch

to investigate the effects of increasing car travel costs on activity, scheduling and travel behavior on a daily and yearly basis. The two experiments were constructed based on respondents' reported travel behavior for one selected day as well as households' current mobility tool ownership.

Detailed analyses of the response behavior are conducted and possible drawbacks are discussed when conducting such burdensome and long-duration studies. A meta-analysis based on previous studies at the IVT shows how response rates vary with the burden, participation choice models are estimated to investigate the effect of incentive payments on survey participation and drop-out, and fatigue effects are investigated for the travel and non-physical/online activity diaries. The presented methods help to plan the budget and fieldwork of a study, providing econometric tools to investigate potential sampling problems and to detect decreasing commitment over the reporting period.

Chapter 3 and Chapter 4: The value of (travel) time

The detailed collection of travel behavior data implicitly reveals information on respondents' time-use patterns for different activities (work, leisure, shopping, etc.), which, in combination with individuals' short- and long-term expenditures for committed and uncommitted goods (see also e.g. Aschauer et al., 2018; Hössinger et al., 2019), allows to estimate a microeconomic time-use and expenditure allocation choice model (e.g. Jara-Diaz and Guevara, 2003; Jara-Diaz et al., 2008) to obtain the value of leisure (VoL; also referred to as the value of time as a resource). The inclusion of a non-physical/online activity questionnaire allows to infer leisure activity duration at home (e.g. watching TV or playing computer games), which is treated conceptually different in the VoL model estimation than out-of-home leisure activities. This is the main subject of Chapter 3, where the VoL is estimated using a sophisticated extension of the original Jara-Diaz et al. (2008) model formulation.

A shift of focus from the value of travel time savings (VTTS) to its two components – the VoL and the value of time assigned to travel (VTAT) – helps assessing the options under a budget constraint, i.e. investing in average speed or improving the conditions of in-vehicle travel (Jara-Diaz and Astroza, 2013; Hössinger et al., 2019). To obtain the VTTS, we combine the SP data on respondents' mode and route choice preferences for current (PT, bike and walk) and emerging modes (CS and CP; see also Schmid et al.

(2016)) with the RP trip data from the travel diary (e.g. Train, 2009; Schmid et al., 2019a), estimating pooled RP/SP models as presented in Chapter 4.

One main contribution is the merge of individual VoL and VTTS estimates obtained from the same set of respondents, which – for the first time – allows to investigate the correlations between those two key measures in transportation research. Time-use research has established the general consensus that the VoL and VTTS are positively related (or even identical, as postulated by the work of Johnson (1966)). Chapter 4 concludes with a critical investigation of this hypothesis and synthesizes the results.

Chapter 5: In-store or online shopping?

Internet and communication technologies (ICT) have experienced a persistent increase in usage over the last decades, allowing for a more flexible spatial and temporal accomplishment of all kinds of activities (Mokhtarian et al., 2006), as e.g. in the case of shopping (e.g. Mokhtarian, 2004; Farag et al., 2006). By investigating potential interrelations between travel behavior and ICT usage, Chapter 5 focuses on shopping behavior for two types of goods, for which we conducted a SP experiment on the choice between in-store and online shopping (Schmid and Axhausen, 2019b).

Chapter 5 presents the first alternative-specific hybrid choice model (Ben-Akiva et al., 2002; Vij and Walker, 2016) using SP data in the field of shopping behavior research, exploring the trade-offs individuals face when choosing between those two shopping channels. One key output is the comparison between the VTTS for shopping trips and the value of delivery time savings (VDTS), investigating the potentials for online shopping services from a travel behavior perspective.

By applying an integrated choice and latent variable (ICLV) approach, we included respondents' attitudes towards shopping and ICT related aspects. The LV structural model reveals information of individual attitudes conditional on observable socioeconomic characteristics, which in turn affect the choice of the shopping channel: Given a specific target consumer segment, one can predict alternative-specific market shares and/or the heterogeneity in attribute sensitivities such as shopping costs and based on that, develop an effective retailing strategy. We show that the ICLV modeling approach, despite its complexity, exhibits some clear advantages over a reduced form model without attitudes, such that it allows to structure respondent heterogeneity more efficiently and in a more intuitive way.

Chapter 6: Adaptations in car usage

The main research question addressed by Chapter 6 is to what degree individuals would be changing travel modes, time allocation and activity patterns (e.g. Weis, 2012; Schmid and Axhausen, 2017) and how they would react regarding their longer-term ownership in mobility tools (e.g. Arentze et al., 2004; Erath and Axhausen, 2010), assessing radical pricing effects from an activity-based perspective. The focus is to better understand and quantify the transition towards a car-reducing society where privately owned vehicles may be substituted by PT season ticket ownership (see also e.g. Scott and Axhausen, 2006) and/or shared mobility services such as CS and CP, where pricing mechanisms are considered as the driving force to achieve substantial changes in behavior.

The data obtained from the two SA experiments – adaptations in daily scheduling and mobility tool ownership – are analyzed by using a similar modeling framework that allows a direct comparison of results: Aggregated response functions are estimated to obtain cost elasticities of travel demand for a daily and yearly time horizon, where all the relevant choice dimensions are not modeled explicitly (given the relatively small sample size), but are considered by the respondents in their decision processes. We thus assume a cost-minimizing behavior conditional on respondents' underlying preferences regarding their activity and mobility plans in the short- and long-run. A comparison between the cost elasticities of travel demand for these two conceptually different survey approaches helps to shed light on the speed of adaptation in such a car-reducing society from a mobility pricing perspective. A key issue that is critically discussed is the artificial nature of the experiments, which may impose a hypothetical bias on the estimated parameters.

Chapter 7: Discussion and conclusions

The final chapter summarizes the results, critically discusses the main findings and limitations, presents the implications for policy makers and practitioners and gives an outlook on future research. Last but not least, it also provides additional inputs and possible directions for future researchers working with the current *Post-Car World* dataset. The amount of data collected as part of this project exceeds by far the scope and resources to adequately analyze each aspect as part of this thesis.

2 SURVEY METHODS AND RESPONSE BEHAVIOR

If you put good apples into a bad situation, you'll get bad apples.

— Philip G. Zimbardo

This chapter is based on Schmid et al. (2019b) published in *Transportation*.

2.1 INTRODUCTION

The survey forms and behavioral experiments described in this chapter – all part of the multi-stage *Post-Car World* study – set the foundation for all subsequent chapters.[1] The main attempt of the data collection efforts was to combine multiple established survey methods to investigate and compare different aspects of travel behavior for the same set of respondents and for a whole work-leisure cycle. It includes a seven-day reporting period of individual travel, expenditure and activity behavior (e.g. Golob and Meurs, 1986; Kitamura and Bovy, 1987; Axhausen et al., 2002; Löchl et al., 2005; Aschauer et al., 2018), attitudinal and psychometric scales (e.g. Kitamura et al., 1997; Axhausen et al., 2002; Handy et al., 2005; Rieser-Schüssler and Axhausen, 2012; Becker et al., 2017) as well as stated preference (SP) (e.g. Weis et al., 2012; Fröhlich et al., 2012; Axhausen et al., 2014; Weis et al., 2017) and stated adaptation (SA) experiments (e.g. Arentze et al., 2004; Hanson and Hildebrand, 2011; Le Vine et al., 2011; Weis, 2012). The detailed collection of revealed preference (RP) travel, expenditure and non-physical/online activity data was a key measure to provide personalized choice sets for the behavioral experiments, which has been shown to help respondents to better identify with the choice tasks (e.g. Rose et al., 2008; Hess and Rose, 2009b). Data were collected from households living in the Canton of Zurich (see Figure 2.1), Switzerland, that cover a broad range of household types in terms of socioeconomic characteristics and mobility tool ownership (i.e. the possession and/or availability of motorized

1 The data collected as part of this project is exceeding by far the scope and resources to analyze all of it as part of this thesis. Thus, this chapter should give a general overview of what kind of data has been collected (which can be consulted as a guideline for further research with this comprehensive dataset), while each subsequent chapter is focusing on one specific aspect.

vehicles such as cars and motorbikes, bikes, and public transportation national/regional season tickets and discount cards; following the definition in Scott and Axhausen, 2006).

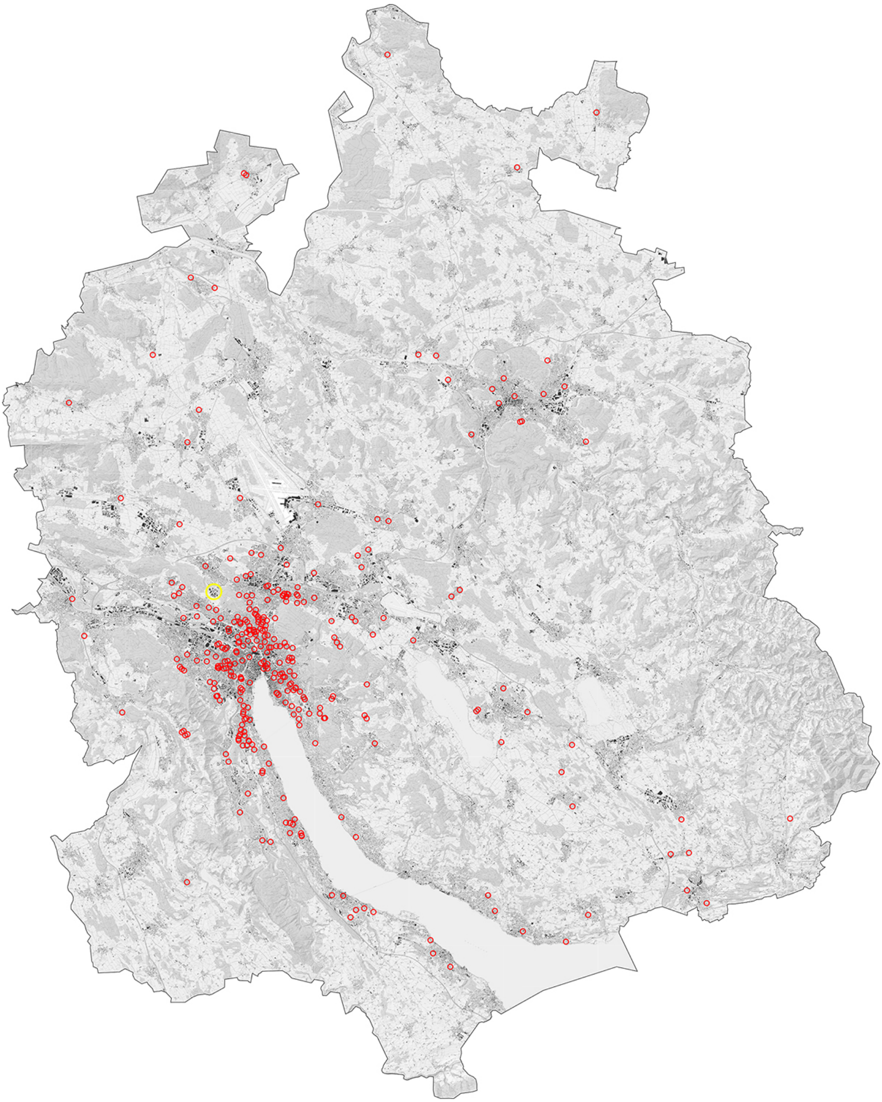
Considering the longer reporting period, high response burden and complexity of the survey, the investigation of the data quality, sampling structure and response behavior requires special attention (e.g. Golob and Meurs, 1986; Groves et al., 2000; Axhausen et al., 2002, 2007, 2015). Results in this chapter cover these issues and analyses of the recruitment and screening process, sampling structure, response and participation likelihood, fatigue and drop-out incidence are conducted. Understanding the respondents' motivation and self-selection to participate in the study play a key role when later analyzing the data and interpreting the results.

The structure of this chapter is as follows: Section 2.2 first gives a detailed overview of the recruitment and survey process, describes the methods used in each stage of the survey, discusses potential problems observed when conducting the fieldwork and provides an overview of the experimental designs and assumptions made when conducting the behavioral experiments. Section 2.3 provides detailed analyses of response behavior, starting with a meta analysis to investigate the relationship between response burden and response rates based on previous studies conducted at the IVT. Participation choice models are estimated to investigate the effect of different incentive levels and socioeconomic characteristics on participation and drop-out incidence. Descriptive figures of the recruited samples' characteristics are compared with data from the Swiss Microcensus for Mobility and Travel Behavior (MZMV), revealing potential sampling biases. Data are tested for the presence of reporting fatigue to evaluate if respondents show a decreasing commitment over the survey period, and if incentive levels affect the number of reported trips and activities. Finally, Section 2.4 provides a discussion of the results and gives an outlook for future research.

2.2 SURVEY METHODS

No previous studies are known to serve as an example for this survey as a whole. Apart from a multi-day reporting period to capture respondents' travel, expenditure and non-physical/online activity behavior including questionnaires asking for socioeconomic characteristics and attitudes, SP experiments and interactive SA interviews for daily activity scheduling and mobility tool ownership, were conducted.

FIGURE 2.1: Residential location of respondent households who completed the survey (small red circles) within the study area (Canton of Zurich, Switzerland). Yellow circle: Location of the Institute for Transport Planning and Systems (IVT).



The general structures were adopted from Axhausen et al. (2002), Weis (2012), Fröhlich et al. (2012) and Erath and Axhausen (2010), and the survey has been designed using many suggestions from the literature (e.g. Dillman, 2000; Porter, 2004; Axhausen et al., 2007; Galesic and Bosnjak, 2009), trying to account for potential response rate problems that arise when dealing with long-duration and burdensome studies:

- Medium: Paper-and-pencil surveys have led to higher response rates in studies conducted at the IVT (Axhausen et al., 2015), and Internet-based methods were avoided also because of the complexity of the survey. The exclusive use of telephone interviews was not feasible due to the duration of the weekly travel diary, and because it is assumed that the subjective feeling of confidentiality would be lower compared to a paper-based survey, where a large effort was put into the design and structure of the questionnaires. For the even more complex and interactive last part of the survey, computer-aided face-to-face interviews were conducted.

- Confidentiality and rights: The survey was approved by the ETH ethics committee (ethics approval number: EK 2014-N-53). Due to the high data sensitivity, respondents were reminded about the strict confidentiality of their responses and that participation happens on a voluntary basis.

- Organization and communication: Apart from a sophisticated recruitment process (well-formulated invitation letters with the ETH university logo offering on-going assistance, followed by the telephonic recruitment), motivation and help calls have been conducted. A personal relationship between the respondents and the project manager (Mr. Basil Schmid) has been built up during the survey process.

- Incentives: Respondents faced an exceptional effort to complete the whole survey. Therefore, a monetary incentive for successful completion was promised during recruitment. Four different incentive levels were tested in the pre-test in order to analyze the effect on the response rate: 50 CHF, 70 CHF, 80 CHF and 100 CHF (1 CHF $\approx$ 1 US$). Based on the findings in the pre-test (Schmid and Axhausen, 2015), the incentive level was fixed at the lowest level of 50 CHF for the main survey waves, which is still higher than just symbolic but substantially lower than a market-based time compensation rate (Doherty and Miller, 2000). This is the main focus in Section 2.3.3.

- Response burden and fatigue effects: The response burden was substantial and not comparable to most previous studies conducted at the IVT, which is further discussed in Section 2.3.1. A problem that might occur with such long-duration studies is that the number of reported items (trips, activities, etc.) or response quality as a whole might decrease over time as respondents get tired of answering, which is investigated in Section 2.3.4.

- Leverage-saliency theory (Groves et al., 2000): The motivation to participate in and complete a survey might be influenced by the respondents' interest in the topic. Especially in long-duration surveys, saliency effects might become more substantial regarding initial participation choice, drop-out and fatigue. This chapter presents evidence of a participation bias for distinct socioeconomic clusters as discussed in Section 2.3.2, Section 2.3.3 and Section 2.3.4, which can be partly explained by the field of research and the topic of the study.

The survey protocol is depicted in Table 2.1 and organized in three stages, of which each of them is presented in the following subsections. Data collection took place between January 2015 and April 2016, and each reporting period was covering one season. The regular communication and correspondence was conducted in the following steps and order:

- Draw of household addresses and phone numbers from a commercially available address database: In order to limit travel times and expenses for the personal interviews in the last stage of the survey, only households resident in the Canton of Zurich were selected.

- Invitation letters with general information and announcement of a recruitment call: The participants were informed about the procedure of the survey, estimated effort to complete the survey, the monetary incentive and the confidentiality and support precautions.

- Up to three recruitment call attempts per household were conducted, including a short screening interview asking both – participants and non-participants – for some basic socioeconomic characteristics.

- Stage I questionnaires (empirical basis and travel diary; see Section 2.2.1) were sent to the participants.

- Coding of the responses of stage I questionnaires.

- Stage II questionnaires (SP and attitudinal questionnaires; see Section 2.2.2) were sent to the participants.
- Coding of the responses of stage II questionnaires.
- Scheduling of stage III (face-to-face SA interviews; see Section 2.2.3).
- Face-to-face SA interviews, debriefing and payment of incentives.

TABLE 2.1: Survey protocol and household participation, by survey wave.

	Pre-Test	Wave 1	Wave 2	Wave 3
Stage I survey period:	Jan. 2015	Jul. 2015	Oct. 2015	Apr. 2016
Number of households invited:	800	1600	3500	1600
Invalid addresses:	92	187	449	177
Total response burden scores:	4250	2450	2450	2050
Contacted by phone:	270	676	1110	546
Rejected participation:	203	543	919	428
without screening interview	97	278	619	217
with screening interview	106	265	300	127
Accepted participation:	67	133	191	118
Response burden scores of stage I:	3500	1700	1700	1700
Completion of stage I:	35	73	124	79
Response rate stage I:	52.2%	54.8%	64.9%	66.9%
Response burden scores of stage II:	530	350	350	350
Completion of stage II:	35	73	118	75
Response rate stage II:	52.2%	54.8%	61.7 %	63.6%
Response burden scores of stage III:	270	500	500	–
Completion of stage III:	35	72	115	–
Estimated total response time	360 min.	215 min.	215 min.	170 min.
Final response rate:	52.2%	54.1%	60.2%	63.6%

Note: The response burden score calculation is described in Axhausen et al. (2015).
12 response burden points ≈ 1 min. response time.

2.2.1 *Stage I: Empirical basis*

The empirical basis is an enriched one-week travel diary that is required to explore the individual patterns in daily travel behavior, the planning style and to obtain the reference values for the later SP (stage II) and SA (stage III) tasks. Note that in the pre-test, we asked for a two-week reporting period, which, given the very large administrative effort and response burden (see also Table 2.1), was reduced to a one-week reporting period in the main survey waves.

The design of the travel diary is based on the well-tested *Mobidrive* protocol (Axhausen et al., 2002; Löchl et al., 2005): For each trip conducted, respondents were asked to state the day of the week, starting and arrival times, exact destination addresses, chosen modes, trip purpose, accompanying persons, presence of dogs and out-of-pocket travel costs. The diary is organized in a longitudinal structure, where each new trip follows its predecessor. It implicitly reveals information about activity durations for nine different activity types (derived from the trip purposes): (1) Home activity, (2) accompanying trip, (3) work or education, (4) short- (grocery shopping) and (5) long-run (durable goods) purchase, (6) errands, (7) business trip, (8) leisure and (9) other activity.

The amount and usage of ICT interactions are captured in a separate questionnaire, asking for daily E-shopping, entertainment, banking, communication and social network activities, including daily duration and expenditures for each of those categories. In addition, there are detailed household and personal questionnaires, mobility tool ownership as well as short- and long-term expenditure questionnaires providing a rich variety of socioeconomic, mobility- and consumption-related information. Examples of stage I questionnaires are included in the Appendix, Figure A.1-Figure A.16. Stage I questionnaires were completed by 476 respondents (311 households; see also Table 2.1).

2.2.2 *Stage II: Stated choice and attitudinal questionnaires*

To construct the SP tasks, a substantial effort was spent on the creation of the experimental designs, including the selection of attributes that may be relevant to the decision makers (mainly based on the work of Fröhlich et al. (2012) for the mode and route choice experiments, and Hsiao (2009) for the shopping channel choice experiment) and the coding of the personalized choice sets based on revealed preference (RP) data from stage I of the survey. In this section, the travel time, cost and other level-of-service (LOS) attributes are presented for the three different SP tasks, highlighting the pivot design approach to help respondents to better identify themselves with the individually tailored and more familiar choice situations.

This was crucial, given that the experiments already involved rather hypothetical situations and assumptions: Especially car owners might face unfamiliar choice situations which increases the vulnerability of the choices to hypothetical bias (see e.g. Fifer et al., 2014). Furthermore, respondents were asked to choose only based on the attribute values presented and to unlink their behavior from experienced fixed costs regarding actual mobility tool ownership, as respondents might replace missing attributes with implicit values from the real world (McFadden, 2001).

A broad range of attitudinal traits were assessed together with the SP experiments.[2] The attitudinal questionnaires are based on the *MOBIDrive* protocol (Axhausen et al., 2002), a set of psychometric scales developed by Rieser-Schüssler and Axhausen (2012) and for shopping related aspects, some selected, modified items from Mokhtarian et al. (2009). The main goal is to reveal respondents' attitudes towards existing and hypothetical transportation modes, environmental awareness as well as personality traits (i.e. risk aversion, variety seeking, extroversion) for assessing heterogeneity with respect to their travel, choice and activity behavior (e.g. Hess and Beharry-Borg, 2012; Paulssen et al., 2014; Schmid and Axhausen, 2019b). Examples of stage II questionnaires are included in the Appendix, Figure A.17-Figure A.30. Stage II questionnaires were completed by 466 respondents (301 households; see also Table 2.1).

2.2.2.1 *Mode choice experiment*

Respondents were introduced to the mode choice experiment by outlining a future scenario that restricts car availability to a minimum but supports innovative mode sharing systems such as carsharing (CS) and carpooling (CP), also including traditional modes such as public transportation (PT), taxi, walk and bike (see Appendix, Figure A.17 and Figure A.18 for some example choice situations). In the experimental framing, similar to a mobility project in Basel, Switzerland (Becker et al., 2015, 2018), CS is defined as a flexible free-floating service, giving access to a fleet of cars which can be picked up and dropped of at any public parking space within the service area. CP is introduced as a ridesharing alternative that can be organized via Internet and ordered to a desired place, but assuming two-person carpools only (Dubernet et al., 2012). These assumptions are justified by superior levels of overall accessibility and a highly developed transport infrastructure as well as a large potential for CS and CP organizations in Zurich

2 The pre-test included a much more detailed attitudinal questionnaire, which was radically shortened based on the feedback of respondents that some questions were too personal.

(Becker et al., 2015; Dubernet et al., 2012; Ciari and Axhausen, 2012). For the CS option, decision makers were always assumed to be vehicle drivers, while CP was described as a mode offered to passengers only, assuming that the driver is unknown to the decision maker.[3] This explicit framing of scenarios helped to place respondents in homogeneous choice situations and kept the number of different modal alternatives manageable.

Reference trips were routed with the agent-based transport simulation software *MATSim* (Horni et al., 2016) to calculate the shortest path travel times in the congested network (*SPTT*), related (in-vehicle) distances (*IVD*) and other attributes for both the chosen and unchosen alternatives (i.e. walk, bike, car and PT).[4] Most attribute levels are calculated as percentage changes relative to the individual reference values (Rose et al., 2008). Trip purposes – outlined as part of the scenario description – for the mode choice experiment focus on work, shopping and leisure trips, where respondents were randomly assigned to one of these categories, given that they conducted at least one trip for a given category. Mode-specific RP travel costs R_{tc} are calculated based on current Swiss market prices.

The following alternatives, attributes and reference values are included and summarized in Table 2.2:

Alternative 1: Walk or bike (W/B)

– **Travel time** walk and bike: Travel time for walk and bike is calculated based on Dobler (2013), using reference speeds for walk (4.8 km/h) and bike (16.2 km/h) and accounting for individuals' gender, age and steepness of the links.

Alternative 2: Taxi (TA)

– **Travel cost**: The RP cost structure for taxi is based on the *UberPop* service for Zurich (www.uber.com/cities/zurich), charging about half of the price of current taxis fares:

$$R_{tc,taxi} = 3\ [\text{CHF}] + IVD \cdot 1.35\ [\text{CHF/km}] + SPTT \cdot 0.3\ [\text{CHF/min}]$$

– **Travel time**: *SPTT* for the car route

– **Waiting time**: Percentage of *SPTT*

3 If the CP driver would be using his/her personal or a free-floating CS car was left open.
4 The same procedure was also applied to all the other trips reported in the travel diary to construct the RP mode choice dataset, as further discussed in Section 4.2.

TABLE 2.2: Experimental design for mode choice experiment.

Attributes	W/B	TA	CP	CS	PT	Levels
Travel cost [CHF]		$\surd$	$\surd$	$\surd$	$\surd$	$-20\%, +10\%, +40\%$
Travel time W/B [min]	$\surd$					Fix
Travel time MPV [min]		$\surd$	$\surd$	$\surd$		$-15\%, +5\%, +20\%$
Travel time PT [min]					$\surd$	$-20\%, -5\%, +10\%$
Access + egress time MPV [min]			$\surd$	$\surd$		$15\%, 20\%, 25\%^1$
Access + egress time PT [min]					$\surd$	$-30\%, -10\%, +10\%$
Waiting time [min]		$\surd$				$10\%, 15\%, 20\%^1$
Risk of missing driver [%]			$\surd$			$5\%, 10\%, 20\%$
Number of transfers [#]					$\surd$	$-1, 0, +1^2$
Headway [min]					$\surd$	$-30\%, -10\%, +10\%^3$

W/B = Walk and bike, TA = taxi, CP = carpooling, CS = carsharing, PT = public transportation.
MPV = Motorized public vehicle (TA, CS and CP). ^{1} : Percentage of in-vehicle travel time.
^{2} : Bounded between 0 and 4. ^{3} : ≥ 3 min. $\surd$: Attribute included.

Alternative 3: Carpooling passenger (CP)

- **Travel cost**: The RP cost structure for carpooling is based on a cost calculator found on www.mitfahrgelegenheit.ch, assuming a mark-up of 20%, two passengers per car and a minimum cost of 2 CHF per trip (i.e. the minimum amount for which a car driver is willing to catch up a passenger for a small distance trip). In addition, the driver should be considered as unknown to the respondent and the fuel consumption factor and price per liter of fuel are set according to the following equation:

$$R_{tc,CP} = \max\left(1.5 \cdot IVD \cdot 8\ [\text{l/km}] \cdot 2\ [\text{CHF/l}] \cdot \frac{1}{2}, 2\ [\text{CHF}]\right)$$

- **Travel time**: Travel time for carpooling is calculated based on the assumption that the driver has imperfect geographical knowledge about the respondent's start and destination locations: A detour factor of 20% is added to *SPTT* for the car route.

- **Access and egress time**: Percentage of *SPTT*

- **Risk to miss the driver**: Probability of missing the ride

Alternative 4: Free-floating carsharing driver (CS)

– **Travel cost**: The RP cost structure for carsharing is based on the cost calculator on www.catch-a-car.ch, a pilot study of free-floating carsharing in the region of Basel, Switzerland, assuming an average reservation time (i.e. access time to the next available car) of 7 minutes. With a reservation fare of 0.27 CHF/min., this leads to a fixed cost component of about 2 CHF ≈ 7 [min.] $\cdot$ 0.27 [CHF/min.] per trip:

$$R_{tc,CS} = 2\ [\text{CHF}] + SPTT \cdot 0.37\ [\text{CHF/min}]$$

– **Travel time**: Travel time for carsharing is calculated based on the assumption that the driver spends some time to find a parking space: A detour factor of 10% is added to *SPTT* for the car route

– **Access and egress time**: Percentage of *SPTT*

Alternative 5: Public transportation (PT)

– **Travel cost**: The RP cost structure for PT is based on the routed distances and estimated average km-prices (Allgemeiner Personentarif, Direkter Verkehr Schweiz, 2014): Respondents that reported any kind of regional or national season ticket were assigned to the PT cost category "With season ticket", containing the cost structure for people owning a half fare card (see also Table 2.3).

TABLE 2.3: Travel cost structure for PT alternative.

In-vehicle trip distance	Without season ticket	With season ticket
< 5 km	0.75 CHF/km	0.38 CHF/km
5-14 km	0.45 CHF/km	0.23 CHF/km
15-48 km	0.38 CHF/km	0.19 CHF/km
49-150 km	0.30 CHF/km	0.15 CHF/km
> 150 km	0.28 CHF/km	0.14 CHF/km
Minimum cost per trip	3.00 CHF	2.20 CHF

– **Travel time**: Travel time for PT is based on the routed door-to-door travel time excluding waiting, transfer, access and egress time

– **Access and egress time**: Sum of access and egress time

– **Number of transfers**: According to the route with the lowest generalized costs

– **Headway**: The headway is calculated based on the following four steps:
(1) Finding connection closest to the departure time
(2) Searching for alternative connections within $+/-$ 2 hours
(3) Eliminating alternatives which are more than 30 % slower than (1), or which are "much less direct", i.e. require at least 2 more transfers
(4) Counting remaining connections $n-1$ and computing the headway by dividing the time difference between the first and last connection by $n-1$

Table 2.2 highlights the pivot design approach to create the individual choice situations: Most attribute levels are varied relative to some reference values explained above. *D*-efficient designs (e.g. Rose and Bliemer, 2009) with 24 choice situations blocked in three parts were generated using *Ngene* (ChoiceMetrics, 2014), including weak parameter priors and assigning eight choice situations to each respondent. Choice sets with strongly superior travel time relative to travel cost alternatives (and vice versa) were excluded and travel time differences between taxi, CS and CP were held realistic. Based on the pre-test results and to further improve the efficiency, the design for the main survey was updated by modifying the parameter priors and attribute levels.[5]

Depending on the distance traveled in the reference trip, driving license ownership and chosen modes in the travel diary, respondents were assigned to one out of six mode choice experiments including the choice alternatives PT, taxi, CS, CP and, for short distances, walk or bike. While respondents without a driving license did not receive CS as a choice alternative, trip distances greater than five and 15 km excluded the walk and bike alternative, respectively (see Appendix, Table A.1).

2.2.2.2 *Choice between in-store and online shopping*

The in-store vs. online shopping choice experiment requested respondents to trade-off different attributes related to their ICT (online shopping/ordering) and out-of-home (personal procurement) shopping activities for two different shopping purposes, investigating how sensitive individuals react to changes in attributes for a given shopping purpose:

5 Note that the taxi alternative was excluded in the main survey, as it was only chosen by one respondent in one choice situation.

– Groceries: Daily/weekly shopping (food, drinks, cosmetics, detergent, etc.)

– Standard electronic appliances: Multimedia, HiFi and electronic (household) appliances[6]

Reference values of shopping time, shopping cost, travel time and travel cost attributes were calculated based on reported shopping trips and average grocery shopping expenditures.[7] A *D*-efficient design with 24 choice situations blocked in three parts was generated using *Ngene* (ChoiceMetrics, 2014), including weak parameter priors and assigning eight choice situations to each respondent.

The experiments were introduced to frame the choice environment for the respondents and place them in a coherent choice situation (see Appendix, Figure A.22 for some example choice situations). Shopping trips are often chained with other activities (e.g. Adler and Ben-Akiva, 1979), which was ruled out by outlining that respondents should imagine a home-based round trip for the in-store alternative. To eliminate social motives and shopping trips as pure leisure activities (Hsiao, 2009), respondents were told that buying the specific goods is the one and only purpose of doing this shopping task. To account for this issue, purchases were explicitly defined as either groceries or standard electronic appliances and were outlined as part of the the scenario description. Depending on reported shopping trips, respondents were assigned to one of these two experiments. The attributes presented below and summarized in Table 2.4 are included in the SP experiment:

Alternative 1: Online shopping

– **Shopping cost**: If assigned to the grocery shopping experiment, respondents were assigned to one out of three reference expenditure categories based on average shopping expenditures for groceries: 40

6 This category also exhibits the highest E-shopping market share in Switzerland (Rudolph et al., 2015).

7 Durable goods expenditures, including standard electronic appliances, were part of a separate questionnaire on an aggregated yearly basis (see Appendix, Figure A.19) and not used for reference value calculation. If a respondent did not report any shopping trip during the multi-day reporting period, a potential shopping location was chosen offering a high variety of goods and high level of accessibility, assigning this respondent to the standard electronic appliances experiment as from a behavioral aspect it might be more problematic to postulate a travel distance to a grocery store. In addition, reference travel time and travel cost to the store were calculated for either CS, CP or PT. To avoid anchoring effects with respect to transportation modes, a specific mode for the in-store alternative was never explicitly mentioned.

CHF, 80 CHF and 120 CHF. If assigned to the standard electronic appliances shopping experiment, respondents were randomly assigned to one out of three reference expenditure categories: 150 CHF, 300 CHF and 600 CHF.

- **Time spent for shopping**: Based on average shopping duration for either groceries or durable goods, respondents were assigned to one out of three reference shopping duration categories (groceries: 15 min, 30 min and 50 min; electronic appliances: 25 min, 40 min and 60 min).

- **Delivery cost** including duty: 0 CHF / 5 CHF / 10 CHF / 15 CHF

- **Delivery time** groceries: Within one day / 1-2 days / more than 2 days; standard electronic appliances: 2-4 days / 4-7 days / more than 1 week

Alternative 2: In-store shopping

- **Shopping cost**: Same as for the online alternative

- **Time spent for shopping**: Same as for the online alternative

- **Travel cost** is calculated based on current Swiss market prices for CS, CP and PT (see also Section 2.2.2.1). They depend on the reported mode in the travel diary and the distance to the store for the reference shopping trip. If the reported mode was ...
  (1) car or motorbike: Average of CP and CS travel costs
  (2) PT: Personalized PT travel costs

- **Travel time** depends on the reported mode in the travel diary and the distance to the store for the reference shopping trip. If the reported mode was ...
  (1) car or motorbike: Car travel time, including an additional detour factor of 10% assuming that the driver spends some time to find a parking space
  (2) PT: PT door-to-door travel time

In addition, an attribute reflecting the **size/weight of the goods basket** is included in the choice experiments (the same for both alternatives), indicating how convenient it is to do a specific shopping task.

TABLE 2.4: Attribute levels of online vs. in-store shopping choice experiment.

Attributes	O	S	Levels
Shopping cost [CHF]	$\surd$		$-10\%, -5\%, 0\%$
Shopping cost [CHF]		$\surd$	$-5\%, 0\%, +5\%$
Time for shop. [min]	$\surd$		$-20\%, -10\%, +5\%$
Time for shop. [min]		$\surd$	$-10\%, 0\%, +10\%$
Del. cost incl. duty [CHF]	$\surd$		0, 5, 10, 15 CHF
Travel cost [CHF]		$\surd$	$-20\%, +10\%, +40\%$
Del. time groceries [d]	$\surd$		$<$ 1 day, 1-2 days, $>$ 2 days
Del. time electronics [d]	$\surd$		2-3 days, 4-7 days, $>$ 1 week
Travel time [min]		$\surd$	$-30\%, 0\%, +30\%$
Size/weight of the good basket [-]	$\surd$	$\surd$	Low, medium, high (same for both alternatives)

O = online, S = in-store. $\surd$: Attribute included.

2.2.2.3 *Route choice experiment*

To investigate how different travel related attributes such as travel time and cost are perceived by the respondents for a given mode and trip purpose (outlined as part of the the scenario description), simple route choice experiments were conducted.[8] By abstracting from (often unobserved) mode-specific preferences, respondents' choices can be more directly related to the offered trade-offs in choice attributes (see Appendix, Figure A.21 and Figure A.22 for some example choice situations).

Depending on driving license ownership, either the CS or the PT route choice experiment was assigned to a respondent, using the same reference trip as for the mode choice experiment (see also Section 2.2.2.1): If a respondent has a driving license and did not report any PT trips, the CS route choice experiment was assigned. If a respondent has no driving license, the PT route choice experiment was assigned. If both a driving license and PT trips were reported by a respondent, either the CS or PT experiment was randomly assigned.

For both route choice experiments, *D*-efficient designs with twelve choice situations blocked in three parts were generated using *Ngene* (ChoiceMetrics, 2014), including three choice alternatives, weak parameter priors and assigning four choice situations to each respondent. Choice sets with dom-

8 Note that the route choice experiments were only included in the main survey waves.

inant alternatives were excluded (see e.g. Bliemer et al., 2017), as they do not add any trade-off information in an unlabeled choice experiment.

TABLE 2.5: Attribute levels of carsharing and public transportation route choice experiments.

Attributes	Levels CS	Levels PT
Travel cost [CHF]	$-20\%, +10\%, +40\%$	$-20\%, +10\%, +40\%$
In-vehicle travel time [min]	$-15\%, +5\%, +20\%^3$	$-15\%, +5\%, +20\%^3$
Congestion time [min]	$5\%, 10\%, 20\%^{1,4}$	–
Access + egress time [min]	$7.5\%, 15\%, 22.5\%^{1,3}$	$-30\%, 0\%, +30\%$
Number of transfers [#]	–	$-1, 0, +1^2$
Headway [min]	–	$-30\%, -10\%, +10\%$

^{1} : Percentage of in-vehicle travel time. ^{2} : Bounded between 0 and 4.

^{3} : $\geq$ 3 min. ^{4} : $\geq$ 1 min. – : Attribute not included.

2.2.3 *Stage III: Stated adaptation interviews*

In stage III of the survey we investigate to what degree individuals would change time allocation, mode choice and activity patterns in the short-run (tool I) after experiencing large changes in travel costs, and how they would react regarding their longer-term ownership in mobility tools (tool II), assessing radical pricing effects from an activity-based perspective.

The underlying reasoning for these hypothetical future scenarios were outlined to the respondents. The basic assumptions are that future policies, such as road tolls and congestion taxes for motorized individual vehicles (MIV) are introduced and that fuel prices increase up to a possible pain threshold, while motorized public vehicles (MPV; including CS, CP and taxi) and PT are subsidized by the government, but prices are still increasing relative to current levels.

Due to the interactivity of the experiments, they were implemented as computer-assisted personal interviews (CAPI), consisting of two Java-based stated adaptation (SA) tools (see e.g. Lee-Gosselin, 1996; Arentze et al., 2004; Jäggi et al., 2013). Both experiments start with the preparation and verification of the base scenario, and the experimental setup is explained by the interviewer. Then, the respondent was asked to indicate his/her reaction (tool I) or the reaction of the complete household (tool II) for progressively increasing travel costs in four adaptation scenarios. Both experiments are described in Section 2.2.3.1 and Section 2.2.3.2.

Personal interviews took around 40 minutes in the main survey, including possible adjustments/corrections of stage I and II responses followed by a debriefing and the payment of the incentive. The interviews were completed by 222 households[9] (see also Table 2.1).

2.2.3.1 *Tool I: Adaptations in daily scheduling*

The first SA experiment (see Appendix, Figure A.31, for one example choice situation) is based on respondents' busiest day reported in the travel diary in which a car was preferably chosen at least once. For this day, after the explanation and verification of the selected base scenario schedule, the interviewers introduced changes in mode-specific RP travel costs R_{tc} by predefined factors in four adaptation scenarios. For MPV modes we used the same reference cost calculation as discussed in Section 2.2.2.1, while for MIV (car and motorbike) we calculated the travel costs based on average car and/or motorbike fuel consumption FC in a household, assuming a mark-up factor of 1.5 with a current fuel price of 1.5 CHF/l:

$$R_{tc,MIV} = 1.5 \cdot IVD \cdot 1.5 \text{ [CHF/l]} \cdot FC \text{ [l/km]}$$

MIV alternatives experience the highest increase in travel costs, adding a fixed cost amount to each trip and increasing marginal trip costs by factors of 1.5 up to 8, while the increases in PT travel costs range between factors of 1.1 and 1.5 of current prices. MPV modes are integrated as well, with travel costs increasing by the factors defined in Table 2.6 relative to current prices. Note that in contrast to the work of Weis (2012), travel times were not changed systematically.

The sum of the daily travel costs is automatically calculated and shown at the bottom of the tool. The choice set now contains the whole daily schedule (Lee-Gosselin, 1996; Weis, 2012): Respondents can skip/delete, add or change the order of activities, change the modes, departure times and activity durations. When changing activity locations (e.g. to a closer shop or leisure activity), distances, travel times and costs are automatically

9 This number is referring to the conducted interviews (households that were eligible for the payment of the incentive). Note that because of technical problems with the first SA tool, some households had to be excluded from the final dataset. The number of valid respondent/household observations are presented for each tool separately in Section 2.2.3.1 and Section 2.2.3.2. Also note that tool II (adaptations in mobility tool ownership) was not yet available in the pre-test and that in wave III, no interviews were conducted anymore as the survey budget was exhausted.

TABLE 2.6: Experimental design (tool I): Adaptations in daily scheduling.

Mode	Sc. 1 [in CHF]	Sc. 2 [in CHF]	Sc. 3 [in CHF]	Sc. 4 [in CHF]
Car	$R_{tc} \cdot 1.5 + 0.4$	$R_{tc} \cdot 2 + 0.8$	$R_{tc} \cdot 4 + 1.4$	$R_{tc} \cdot 8 + 2$
Motorbike	$R_{tc} \cdot 1.5 + 0.2$	$R_{tc} \cdot 2 + 0.4$	$R_{tc} \cdot 4 + 0.7$	$R_{tc} \cdot 8 + 1$
PT	$R_{tc} \cdot 1.1$	$R_{tc} \cdot 1.2$	$R_{tc} \cdot 1.3$	$R_{tc} \cdot 1.5$
CS	$R_{tc} \cdot 1.1$	$R_{tc} \cdot 1.2$	$R_{tc} \cdot 1.3$	$R_{tc} \cdot 1.5$
CP	$R_{tc} \cdot 1.5$	$R_{tc} \cdot 2$	$R_{tc} \cdot 4$	$R_{tc} \cdot 8$

CP = carpooling, CS = carsharing, PT = public transportation, Sc. = scenario number.

recalculated by using a *google-maps* interface. The interviewers made sure that the respondents are aware of all their possibilities to reorganize their day, and if necessary pointed out behavioral inconsistencies. After the exclusion of seven erroneous interviews, valid observations were obtained from 237 respondents (215 households).

2.2.3.2 *Tool II: Adaptations in mobility tool ownership*

The second SA experiment is based on households' revealed mobility tool ownership and their yearly distances traveled with MIV, MPV and PT, asking them to adapt to increasing mobility costs within a longer-term (yearly) horizon. First, the respondent (a household representative) was asked about the mobile persons in the household (see Appendix, Figure A.32), the current motorized vehicles in the household (see Appendix, Figure A.33) and their estimated yearly distances traveled with MIV, MPV and/or PT for weekly, monthly and yearly trips, and the average percentage of PT trips that are within the covered region of the regional season ticket (if available). This information is entered in the SA tool and results in a comprehensive base scenario including mobility tool ownership, mode-specific distance traveled among all household members and the resulting total yearly fixed and variable costs (for up to three vehicles and two season tickets per household member; see Appendix, Figure A.34).

Car cost structures are based on the *TCS*[10] mobility cost calculator for nine different car categories (see Table 2.7): Small cars (micro, subcompact), medium cars (minivan, lower mid-range, mid-range) and large cars (van, limousine, SUV, sports car). For company cars, fixed and variable costs are always set to zero. Fixed costs for motorbikes are always set to 1'500 CHF. The cost structures were implemented in the tool for a real-time calculation

10 Touring Club Schweiz: www.tcs.ch, Switzerland's largest car drivers association.

of yearly fixed and variable mobility costs. Different cost scaling factors were implemented depending on the car type (see Table 2.7), fuel type (see Table 2.8), fuel consumption (see Table 2.8), engine type (see Table 2.9) and actual price paid for the current vehicle(s).

More specifically, the fixed reference costs for different car types depend on the standardized catalog prices presented in Table 2.7. To better reflect individual preferences in the price class of current vehicle(s) owned by household n, the standardized catalog price (CAP_j) of vehicle $j \in J_n$ is scaled according to the actual price paid by the household ($P_{0,j}$) and adjusted by the fuel type ($VPF_{0,j}$) and engine type ($EPF_{0,j}$) of the current vehicle(s) (denoted by subscript 0 referring to the base scenario; see Equation (2.1)). This scaled catalog price then determines the reference price from which the price dependent yearly fixed costs are calculated (see Equation (2.2)).[11] This includes depreciation (D_j; new car: 12%; used car: 7%), interest rates (R; 0.05%), impairment (I; 2%) and own damage insurance (O; 1.4%), which – together with the maintenance fixed costs (MC_j; including yearly transportation taxes, insurance, garage storage, repair works, services and other expenditures) – add up to the total yearly fixed costs ($c_{fixed,j}$). To better reflect the long-term dimension of this experiment, respondents were told that changing the car, fuel or engine type (which, in reality, of course would imply purchasing a new vehicle) only changes – apart from the variable costs – the yearly fixed costs.

$$f_{fixed} = \frac{1}{J_n} \sum_{j=1}^{J_n} \frac{P_{0,j}}{CAP_{0,j} \cdot VPF_{0,j} \cdot EPF_{0,j}} \tag{2.1}$$

$$c_{fixed,j} = f_{fixed} \cdot CAP_j \cdot VPF_j \cdot EPF_j \cdot (D_j + R + I + O) + MC_j \tag{2.2}$$

Similarly, the variable reference costs are calculated by first obtaining a household-specific cost factor based on actual (observed) fuel consumption $F_{0,j}$ relative to catalog fuel consumption $FC_{0,j}$ for a given car type j, which is then used to calculate the yearly variable travel costs $R_{tc,j}$ for each household n, using a current fuel price of 1.5 CHF/l:

$$f_{variable} = \frac{1}{J_n} \sum_{j=1}^{J_n} \frac{F_{0,j}}{FC_{0,j} \cdot FCF_{0,j} \cdot EPF_{0,j}} \tag{2.3}$$

$$R_{tc,j} = (1.5\ [\mathrm{CHF/l}] \cdot f_{variable} \cdot FC_j \cdot FCF_j \cdot EPF_j + TI_j) \cdot distance_j \tag{2.4}$$

11 The standardization of yearly fixed costs was important to keep the experiment manageable in cases where respondents changed the car, fuel or engine type in the adaptation scenarios.

TABLE 2.7: Reference values for different car types based on the *Touring Club Schweiz* (www.tcs.ch) mobility cost calculator.

Car type	Catalog price [CHF] *CAP*	Mainten. costs [CHF/year] *MC*	Fuel cons. [l/100km] *FC*	Tires [CHF/km] *TI*
Micro	14'000	3'157	4.5	0.01
Subcompact	25'000	3'157	5.5	0.03
Lower mid-range	30'000	3'327	6	0.04
Minivan	35'000	3'377	7.5	0.05
Mid-range	45'000	3'627	7.5	0.06
Van	50'000	3'627	9	0.07
Limousine	70'000	4'012	9	0.08
SUV/luxury car	90'000	4'162	11.5	0.11
Sports car	80'000	4'162	12.5	0.11
Motorbike	–	1'500	4	0.01

TABLE 2.8: Fuel consumption and vehicle price factors for different fuel types.

Fuel type	Fuel consumption factor [-] *FCF*	Vehicle price factor [-] *VPF*
Gasoline	1	1
Diesel	0.75	1.25
Gas	0.9	1.15
Hybrid	0.65	1.35
Electric	0.5	1.6

TABLE 2.9: Fixed and variable price factors for different engine types.

Engine type	Engine price factor [-] *EPF*
Economical	0.8
Normal	1
Powerful	1.2

TABLE 2.10: Yearly reference fixed costs and related variable cost factor for different PT season tickets (2015) based on information from the *Schweizerische Bundesbahnen* (SBB; www.sbb.ch) and the *Zürcher Verkehrsverbund* (ZVV; www.zvv.ch).

Type of season ticket	2nd class [CHF]	1st class [CHF]	Var. cost factor[1]
Half fare card	175	175	0.5
National season ticket (GA)	3'655	5'970	0
GA student	2'600	4'430	0
GA junior (16 - 25 years)	2'600	4'430	0
GA partner	2'560	4'115	0
GA senior	2'760	4'635	0
GA disabled	2'370	3'870	0
GA dog	780	780	0
Local season ticket (ZVV)	450	747	0
ZVV 1-2 zones	756	1251	0
ZVV 3 zones	1'116	1'845	0
ZVV 4 zones	1'476	2'439	0
ZVV 5 zones	1'809	2'988	0
ZVV All zones	2'160	3'564	0

[1] : Relative to full ticket prices. ZVV: Only in cases where a respondent travels within the zone.

For CS, the fixed costs are set to 290 CHF/year (i.e. the annual fee of Switzerland's biggest carsharing provider) and variable costs to 0.7 CHF/km, while for CP we used an average variable cost of 0.16 CHF/km. For PT, prices for different types of regional and national annual season tickets were collected (see Table 2.10), while the same variable cost structure was used as for the reference values in the SP experiments.

The fixed and variable household mobility costs were verified by the respondents in the base scenario, after which the hypothetical SA scenarios were introduced with differentiated increases in mobility costs similar to the first SA experiment (see Table 2.11). Note that MIV and CS fixed costs c_{fixed} were not changed systematically between scenarios, only introducing changes in mode-specific variable RP travel costs R_{tc}. Then, all possible adaptation options together with the potential impacts on activity patterns and travel behavior were outlined to the respondents.

Apart from changing the total distance traveled by each mode, respondents could also change vehicle ownership (affecting both fixed and vari-

Table 2.11: Experimental design (tool II): Adaptations in mobility tool ownership.

Mode	Sc. 1 [in CHF]	Sc. 2 [in CHF]	Sc. 3 [in CHF]	Sc. 4 [in CHF]
Car	$R_{tc} \cdot 1.5 + c_{fixed}$	$R_{tc} \cdot 2 + c_{fixed}$	$R_{tc} \cdot 4 + c_{fixed}$	$R_{tc} \cdot 8 + c_{fixed}$
M.bike	$R_{tc} \cdot 1.5 + 1500$	$R_{tc} \cdot 2 + 1500$	$R_{tc} \cdot 4 + 1500$	$R_{tc} \cdot 8 + 1500$
PT	$(R_{tc} + c_{fixed}) \cdot 1.1$	$(R_{tc} + c_{fixed}) \cdot 1.2$	$(R_{tc} + c_{fixed}) \cdot 1.3$	$(R_{tc} + c_{fixed}) \cdot 1.5$
CS	$R_{tc} \cdot 1.1 + 290$	$R_{tc} \cdot 1.2 + 290$	$R_{tc} \cdot 1.3 + 290$	$R_{tc} \cdot 1.5 + 290$
CP	$R_{tc} \cdot 1.5$	$R_{tc} \cdot 2$	$R_{tc} \cdot 4$	$R_{tc} \cdot 8$

CP = carpooling, CS = carsharing, PT = public transportation, Sc. = scenario number.

able MIV costs), engine and fuel type, or change PT season ticket ownership. For example, a more expensive regional season ticket typically leads to a decrease in variable PT travel costs, while a smaller car leads to decreasing fixed and variable MIV travel cost. The interviewers made sure that the adaptations of the respondents were made in a behaviorally consistent manner. Valid observations were obtained from 187 households.

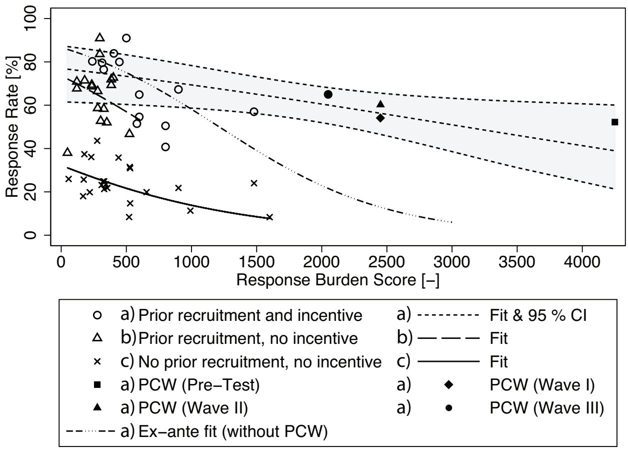
2.3 RESPONSE BEHAVIOR

2.3.1 *Relationship between response burden and response rates*

An initial idea of the response rate and required address sample size usually helps to plan the budget and fieldwork of a study. While response behavior, survey quality and response burden have been treated in the literature (see e.g. Dillman (2000), for a broad discussion about different survey techniques, response burden and response rates), an ex-ante assessment of response rates predicted by the burden has not been a widely discussed topic so far. In this section, a meta-analysis based on the assessment of response burden scores – using a predefined scheme for different types of questions and tasks (Axhausen et al., 2015; Schmid and Axhausen, 2019a) – and response rates (according to the The American Association for Public Opinion Research (2015) definitions) is conducted for past IVT studies. As all observations belong to the same field of research, saliency effects (Groves et al., 2000) across studies are assumed to be minimal.

Figure 2.2 shows the response burden and response rates of previous IVT studies for three different categories: a) "prior recruitment and incentive", b) "prior recruitment, no incentive" and c) "no recruitment, no

FIGURE 2.2: Response burden and response rates: Meta-analysis based on previous IVT studies (Axhausen et al., 2015). Fitted, back-transformed values are based on the category-specific models in Table 2.12.



incentive". Clearly, no incentives and no prior recruitment of the respondents (category c) exhibits the worst performance in terms of response rates and personal interaction (category b) combined with incentives (category a; also including the current *Post-Car World* study) yields much higher response rates. In all categories, a higher response burden leads to lower response rates, flattening out to the right.

To statistically quantify these relationships[12], the following logistic regression model is estimated for the three categories (denoted by subscript c) including sampling weights to capture the number of potential respondents (i.e. who received the questionnaires) each study/survey wave n represents.[13] The Logit transformation is applied to the dependent variable (response rate; in %) mainly to solve the boundedness problem of the original dependent variable (i.e. the probability of participation in a survey), and the response burden is scaled down to maintain readability of the coefficients:

$$\log\left(\frac{y_{c,n}}{100 - y_{c,n}}\right) = \alpha_c + \beta_c \frac{x_{c,n}}{1000} + \epsilon_{c,n} \tag{2.5}$$

12 The range of incentive levels across the studies/survey waves is not large enough to estimate a per dollar impact, or a per dollar/response burden impact.

13 Models were estimated in *Stata 15.1* using the *nl* command.

The marginal effect of a unit increase in response burden is given by (e.g. Winkelmann and Boes, 2006)

$$ME_c = \left(\exp\left(\frac{\beta_c}{1000}\right) - 1\right) \cdot 100\ \% \tag{2.6}$$

and reflects the expected percentage change in the odds of participating in a survey.

Table 2.12 presents the estimated relationship between response burden and response rates for the three different categories (all slope coefficients significant at $p < 0.1$; fitted values are visualized in Figure 2.2) as well as for a pooled model (same slope coefficient β, but different intercepts). Importantly, the decay is strongest for the two "no incentive" categories and becomes much flatter when the study team has put effort in recruiting and paying an incentive to the respondents.

The pooled model shows a slightly lower AICc (for small sample size corrected Akaike Information Criterion; Wagenmakers and Farrell (2004)), which is defined as

$$AICc = -2\mathcal{LL} + 2df\frac{N}{N - df - 1} \tag{2.7}$$

where $\mathcal{LL}$ is the log-likelihood at convergence, df the degrees of freedom of the model and N the number of observations.[14] This indicates that the pooled model is considered to be more appropriate, but the difference is small. Also, it does not allow to distinguish between category-specific decays, estimating an average slope coefficient ($p < 0.01$) that lies in between the ones for the separate categories: For an increase in the response burden by 100 points, the expected decrease in the response rate is 6%.

The current *Post-Car World* survey exhibits response rates[15] much above the predicted ex-ante trend line (before adding the new data points; see Figure 2.2), hence speaks in favor of the large recruitment effort and the payment of an incentive. However, the prediction accuracy for such a high response burden is not reliable and out of range and more observations

14 Note that this measure is used throughout this thesis for relative comparisons of nested models, where a smaller value means a better fit.

15 See also Table 2.1: Given average survey response duration between three (wave III) and six hours (pre-test), the response rate was always above 52.2%. Note that in the pre-test, many respondents reported a general discontent regarding the high response burden, especially for stage I of the survey. To reduce the response burden in the main survey, a natural consequence was to skip and simplify some of the questionnaires to achieve a higher data quality of the remaining tasks and to reduce drop-out incidence.

TABLE 2.12: Estimation results: Effect of response burden on response rates (including PCW). Observations are weighted by the total number of potential respondents that each study/survey wave targeted (= respondents + drop-outs + non-respondents).

	Pooled model	Category a)	Category b)	Category c)
Incentive		$\surd$	–	–
Recruitment		$\surd$	$\surd$	–
Variable	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
Constant	–	1.206^{***}	1.021^{***}	-0.743^{***}
		(0.29)	(0.21)	(0.24)
Constant category a)	1.395^{***}	–	–	–
	(0.27)			
Constant category b)	0.750^{***}	–	–	–
	(0.12)			
Constant category c)	-0.957^{***}	–	–	–
	(0.13)			
Response burden	-0.599^{***}	-0.389^{**}	-1.480^{*}	-1.087^{***}
	(0.17)	(0.13)	(0.81)	(0.24)
N	57	17	17	23
R^2	0.74	0.20	0.09	0.35
AICc	93.8		94.1	

Robust standard errors: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$. $-$: Not included.

are needed to improve the validity of the survey length versus response trade-off.

2.3.2 *Descriptive analysis of the sample*

Descriptive figures of respondents' characteristics (PCW sample: 301 households, 466 respondents; after completion of stage II) are presented in Table 2.13 and compared with data from the MZMV 2015 (Swiss Federal Statistical Office ARE, 2015), a weighted, representative sample of the Swiss[16] population. While the residential area, the number of vehicles as well as gender of the household members are well represented by the PCW sam-

16 To compare with the PCW sample, only a subsample of the MZMV 2015 is considered, limited to the Canton of Zurich.

ple, older and larger households with kids, high income and education levels[17] as well as season ticket owners are overrepresented. Although the PCW sample size is small, it indicates the usual sample selection problems with many studies conducted at the IVT (e.g. Rieser-Schüssler and Axhausen, 2012; Weis et al., 2012): An overrepresented share of higher-income, well-educated, PT affine and middle-aged respondents[18]. We account for these differences by testing/including the most relevant socioeconomic characteristics as explanatory variables in subsequent models.

TABLE 2.13: Descriptive statistics: MZMV 2015 and PCW sample.

Variable	Value	MZMV [%]	PCW [%]
Household size	1	31.6	17.9
	2	37.4	29.5
	3	12.4	20.2
	≥ 4	18.6	32.5
Household income	Not reported	24.1	5.3
	$<$ 4'000 CHF	14.9	3.6
	4'000-6'000 CHF	17.5	5.0
	8'000-10'000 CHF	14.5	12.9
	10'000-12'000 CHF	10.6	12.9
	$>$ 12'000 CHF	18.4	60.3
Personal income	$\leq$ 6'000 CHF	–	49.4
	$>$ 6'000 CHF	–	50.6
Household type	Single-person household	31.6	17.9
	Couple without kids	33.0	23.8
	Couple with kids	26.6	49.7
	Single-parent household	5.8	5.0
	Living community	3.1	3.6

Continued on next page

17 Low education: No education, obligatory school, lower commercial school or apprenticeship. Medium education: Grammar school, higher education entrance qualification, proficient diploma or professional school. High educ.: Higher technical academy, college or university.

18 A major problem involved the recruitment of all eligible (older than 18 years) household members, simultaneously affecting the age distribution in the PCW sample: Although larger households are overrepresented, mostly fractions (e.g. parents or the addressed household heads) of all eligible household members actually participated in the survey.

Table 2.13 – *Continued from previous page*

Variable	Value	MZMV [%]	PCW [%]
Residential location area	City centre	38.9	41.4
	Agglomeration	54.8	42.1
	Rural	6.3	16.6
Number of cars in HH	0	24.5	24.5
	1	49.1	52.3
	2	21.7	18.9
	≥ 3	4.6	4.3
Number of bikes in HH	0	30.1	10.6
	1	21.3	15.6
	2	22.2	17.9
	≥ 3	26.4	56.0
Sex	Female	54.3	51.0
	Male	45.7	49.0
Age	18-35 years	20.7	12.9
	36-50 years	29.4	38.6
	51-65 years	27.4	44.6
	66-80 years	22.5	3.9
Education	Low	21.0	18.0
	Medium	54.9	24.4
	High	24.1	57.6
Season tickets	Half-fare card	51.8	39.4
	National or regional season ticket	17.4	47.8
	None of above	30.8	15.6
Car availability	Always	74.6	60.6
	Sometimes	18.0	24.2
	Never	7.3	15.2
Married	Yes	46.4	58.7
	No	53.6	41.3
Store accessibility	Next shop $\leq$ 10 min. of walk	–	90.1
	Next shop $>$ 10 min. of walk	–	9.9
Working hours	Non-working	–	14.9

Continued on next page

Table 2.13 – *Continued from previous page*

Variable	Value	MZMV [%]	PCW [%]
	Weekly working hours 1-19 h	–	9.5
	Weekly working hours 20-35 h	–	26.2
	Weekly working hours 36-44 h	–	28.8
	Weekly working hours > 44 h	–	20.6

– : Not available.

2.3.3 *Incentive levels and participation choice*

Research has no conclusive suggestions regarding the implementation of incentives (e.g. Dillman, 2000; Porter, 2004). A high incentive payment is generally assumed to positively influence both participation rate and response quality, but the effects are not always that clear. E.g. Groves et al. (2000) show that higher incentive payments lead to lower response rates for respondents with high community involvement. Hence, for the main survey, it was of special interest for the budgeting and ex-ante assessment of response behavior how the "optimal" incentive should look like. Therefore, the incentive levels in the pre-test were varied randomly between four different levels: 50, 70, 80 and 100 CHF.[19] *Each* respondent within a household would receive the same and prior (in the invitation letter) specified amount of money when completing the survey.

Data are analyzed based on the screening interviews with non-recruited (N = 624) and recruited (N = 457) households, of whom 284 households completed the survey[20], to measure the effects of the different incentive levels on the willingness to (1) participate in the survey and (2) complete the survey. Table 2.14 shows that 57.9% of households who were offered 50 CHF rejected participation, while in the case of 100 CHF, only 44.1% did so. However, it indicates that offering a high incentive payment is also associated with a higher drop-out incidence conditional on participation (52.6% in case of 100 CHF vs. 37.5% in case of 50 CHF) and that the net-

19 In Table 2.14 and for model estimation, given the relatively small sample size where the incentive level was varied, the medium incentive categories (70 CHF and 80 CHF) were pooled together, as their effects on response behavior were not substantially different from each other.

20 Note that these numbers are slightly smaller than the ones reported in Table 2.1, as the data analyzed in this section only includes households who completed the screening interview.

TABLE 2.14: Households' response behavior for different incentive levels.

		N	Reject [%]	Participate [%]	Drop-out [%]	Complete [%]	Total [%]
Incentive	50 CHF	989	57.9	42.1	37.5	63.5	26.7
	70/80 CHF	58	62.1	37.9	50.0	50.0	19.0
	100 CHF	34	44.1	55.9	52.6	47.4	26.5
Sample	N	1081	624	457	156	284	284

effect on completion is essentially the same (26.5% in case of 100 CHF vs. 26.7% in case of 50 CHF).

Participation and completion choice of household n is modeled using a Heckman (1976) type sample selection Probit model (Van de Ven and Van Praag, 1981), where the same factors X_n (incentive level, survey wave and socioeconomic characteristics of the household) are affecting the selection (i.e. participation) and outcome (i.e. completion) equation.[21] The selection equation is given by

$$y^*_{1,n} = \zeta + X_n\gamma + \epsilon_{1,n} \text{ , } \epsilon_{1,n} \sim N(0,1) \tag{2.8}$$

and the outcome equation by

$$y^*_{2,n} = \alpha + X_n\beta + \epsilon_{2,n} \text{ , } \epsilon_{2,n} \sim N(0,1) \tag{2.9}$$

We actually observe the binary choices $y_{1,n} = \mathbf{1}(y^*_{1,n} > 0)$ and $y_{2,n} = \mathbf{1}(y^*_{2,n} > 0|y^*_{1,n} > 0)$, with the latter being only observed if household n participates. Furthermore, the correlation between error terms is given by

$$\text{corr}(\epsilon_{1,n}, \epsilon_{2,n}) = \kappa \tag{2.10}$$

For a unit increase in explanatory variable z, the marginal probability effect is given by (e.g. Winkelmann and Boes, 2006)

$$MPE_z = \Phi\left(\alpha + \overline{X}_{n,t}\beta + \Delta x_z\beta_z\right) - \Phi\left(\alpha + \overline{X}_{n,t}\beta\right) \tag{2.11}$$

21 Arguing that the traditional Heckman estimator in such a case is problematic, Sartori (2003) derives an estimator under the assumption that the error terms in both equations are identical, which, in the Heckman approach, is not the case (i.e. the correlation between error terms, κ, is estimated from the data). In the current application, however, both approaches yield exactly the same results, and we stick to the traditional Heckman approach.

and depends on the particular values of $X_{n,t}$, for which we take the mean $\overline{X}_{n,t}$ when reporting the results in Table 2.15[22], and Φ is the cumulative standard normal probability density function.

A likelihood-ratio (LR) test indicates that the two equations are not independent ($p < 0.05$) with an estimate of κ close to 1. This is expected, given that the same sets of explanatory variables are included in both equations and processes that model "similar" choices (i.e. participation and completion of a survey) are likely to exhibit similar error terms (Sartori, 2003). Importantly, not accounting for the error term correlation would lead to a sample selection bias in the outcome equation (e.g. Van de Ven and Van Praag, 1981).

The differences in respondent characteristics of the PCW compared to the MZMV sample discussed in Section 2.3.2 mostly coincide with the marginal probability effects on participation (column 1) and completion (column 3): Better education, a higher share of season tickets (= number of season tickets per household member) and higher income show significant and positive effects ($p < 0.05$) on the probability of both participation and completion of the survey.

The substantial effect of season ticket ownership is most probably because frequent users of PT are more interested in the topic of future urban transportation systems and this effect might be even reinforced by the higher education level. This finding is supported by the leverage-saliency theory (Groves et al., 2000): The motivation to participate in a survey is influenced by the respondents' interest in the topic. Especially in long-duration surveys, saliency effects might become much more substantial regarding initial participation choice, drop-out and fatigue.

Results also indicate that wave III exhibits an increased completion rate of about 18 percentage points (p < 0.05; relative to the pre-test), which can be attributed to the lower response burden without personal interviews. Older households living in rural areas exhibit a lower probability to participate ($p < 0.1$), but the net effect on completion is not significantly different from zero.

The incentive level, only varied in the pre-test, shows an ambiguous effect: While offering 100 CHF per household member increases the expected initial participation probability by 28.1 percentage points ($p < 0.05$; relative to the base category 50 CHF), it facilitates a later drop-out as shown by the negative effect on completion conditional on participation (column 2; -33.2 percentage points; p $\approx$ 0.2). One explanation is that when realizing

22 Models were estimated in *Stata 15.1* using the *heckprob* command.

TABLE 2.15: Participation choice: Sample selection Probit model of (1) initial participation and (2) completion of the survey.

Variable	(1) dy/dx/(SE)	(2) | (1) dy/dx/(SE)	(2) dy/dx/(SE)
50 CHF	*Base*	*Base*	*Base*
70 CHF or 80 CHF	0.067	−0.176	−0.030
	(0.11)	(0.18)	(0.10)
100 CHF	0.281**	−0.332	0.045
	(0.12)	(0.21)	(0.11)
Pre-test	*Base*	*Base*	*Base*
Wave 1	0.026	−0.154	−0.048
	(0.09)	(0.14)	(0.09)
Wave 2	0.012	−0.100	−0.034
	(0.09)	(0.14)	(0.09)
Wave 3	0.236**	0.063	0.180**
	(0.09)	(0.15)	(0.09)
Medium education	0.091*	0.147*	0.121**
	(0.05)	(0.09)	(0.05)
High education	0.118***	0.042	0.095**
	(0.04)	(0.07)	(0.04)
Age/100	−0.486***	0.378	−0.159
	(0.16)	(0.31)	(0.15)
City center	0.079*	0.032	0.065
	(0.04)	(0.07)	(0.04)
Share of season tickets	0.151***	0.056	0.122***
	(0.03)	(0.05)	(0.03)
Share of motorized vehicles	0.048	−0.052	0.010
	(0.03)	(0.06)	(0.03)
Share of workers	−0.088	0.235**	0.041
	(0.05)	(0.10)	(0.05)
Income 6'000 - 9'000 CHF	0.117**	0.025	0.087*
	(0.05)	(0.08)	(0.05)
Income 9'000 - 12'000 CHF	0.131***	0.040	0.102**
	(0.05)	(0.08)	(0.05)
Income > 12'000 CHF	0.182***	0.068	0.147***
	(0.05)	(0.08)	(0.05)
N (# censored/# uncensored)		1081 (624/457)	
ρ^2		0.36	
Prob. > χ^2: Indep. equations (H_0)		0.05	
Prob. > χ^2: Model		0.00	

Robust standard errors: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

the high response burden, the survey was perceived as work effort rather than a social contribution and the inhibition threshold to drop-out was lower for such high incentives.[23] The net effect is not significantly different from zero and there is little point of paying an incentive higher than 50 CHF to keep respondents on board. Therefore, for the three main survey waves, the incentive was fixed at 50 CHF (Schmid and Axhausen, 2015).

2.3.4 *Reported travel behavior and fatigue*

A key feature of testing the validity of the longitudinal data structure is to investigate travel and activity behavior over time, checking for possible inconsistencies, decreasing number of trips or other exogenous influences (e.g. Axhausen et al., 2002, 2007). A first investigation of the *Post-Car World* data therefore focuses on descriptive analyses for investigating the representativeness of travel behavior and the number of trips and online activities over the reporting period, detecting a possible prevalence of reporting fatigue. The analyzed sample comprises 466 respondents who completed stage II of the survey.[24]

Key mobility figures are found to be comparable to the MZMV 2015 (see Table 2.16), and regarding the average number of trips (mobile days and all days) no substantial decreasing commitment has been detected for the second reporting week (pre-test only). There is a higher share of mobile person days in the PCW sample, which is even slightly increasing in the second week (pre-test only). The average number of trips per day are very similar as in the MZMV 2015 and findings indicate no manifestations of reporting fatigue.

Although the length of the seven days reporting period in the main survey and 14 days in the pre-test is moderate compared to the six weeks in *MobiDrive* (Axhausen et al., 2002; Löchl et al., 2005), it is still exceeding most of the Swiss transportation studies. There is, for example, a higher share of walking trips in the MZMV 2015, which may be due to the fact that it asks for respondents' one day travel behavior, eventually leading to a higher trip resolution by detecting more short-distance trips. Regarding the chosen main modes in the MZMV 2015 and PCW sample, as expected there is a clear tendency of choosing PT instead of MIV, while for the other

23 A slightly different interpretation is that high incentives might convince people who are actually not interested in the survey topic to participate, but when realizing the enormous response burden, they decide to drop-out.

24 Note that four respondents are excluded for analyzing the number of online activities. They were classified as complete, but did not fill in the online diary.

TABLE 2.16: MZMV 2015 and PCW key mobility figures, chosen main mode and trip purpose distributions.

		MZMV [%]	PCW[1] [%]	PCW 2nd week[2] [%]
Mobility figures	Share of mobile person days	88.5	93.6	95.1
	Avg. # trips (all person days)	3.3	3.4	3.3
	Avg. # trips (mobile days)	3.8	3.8	3.5
Main mode	Walk	31.1	18.4	20.4
	Bike	5.9	14.0	5.9
	Car or motorbike (MIV)	43.3	38.0	39.4
	Public transportation (PT)	18.7	28.4	34.0
	Other	1.0	1.4	0.3
Trip purpose	Return home	36.7	37.2	38.9
	Accompanying trips	3.4	4.3	3.3
	Work / eductation	15.7	19.8	15.5
	Shopping	12.2	9.5	10.7
	Errands	4.1	4.4	4.3
	Business	1.9	3.0	2.5
	Leisure	24.9	21.3	17.8
	Other purpose	1.0	0.5	7.1

[1] : All waves (incl. pre-test). [2] : Week 2 only available in the pre-test.

modes, the PCW sample is comparable. Also, the observed trip purpose distribution in the PCW sample is very similar to the MZMV 2015.

Figure 2.3 presents the average (only mobile days) number of trips and the average number of *different* online activities in the pre-test and main survey waves. For the number of trips, a clear daily pattern is observable, exhibiting significantly fewer trips on Sundays (day 7 and 14), which is similar to the number of different online activities, though much more pronounced. At first glance, fatigue effects are not present and seem to be dominated by learning effects, whereby the number of reported trips even slightly increased in the second week (pre-test only). Also, on a daily basis, the 95% confidence bands in Figure 2.3 indicate that behavior is not significantly different between the four survey waves.[25] However, the number of reported online activities exhibit a negative trend which is consistent between all waves, but then jumps up again in the second week.

To empirically investigate the relationship between reporting behavior, respondent characteristics and incentive levels, random-effects Poisson regressions (Hausman et al., 1984; Baltagi, 2008) of the form

$$f(y_{n,t}|X_{n,t}, \epsilon_n) = \frac{\exp(-\lambda_{n,t}) \cdot \lambda_{n,t}^{y_{n,t}}}{y_{n,t}!} \tag{2.12}$$

$$\lambda_{n,t} = \epsilon_n \cdot \exp\left(\alpha + X_{n,t}\beta\right) \tag{2.13}$$

are conducted to account for the panel structure, the discreteness and non-negativity of the dependent variables.[26] $\epsilon_n \sim \Gamma(1, \theta)$ is a random intercept following a Gamma distribution, capturing unobserved heterogeneity by shifting the constant of each individual n by the respective amount relative to the overall intercept, α.

For a unit increase in explanatory variable z, the marginal effect (the change in the expected value of the dependent variable $y_{n,t}$, assuming a random effect of zero) is given by (e.g. Winkelmann and Boes, 2006)

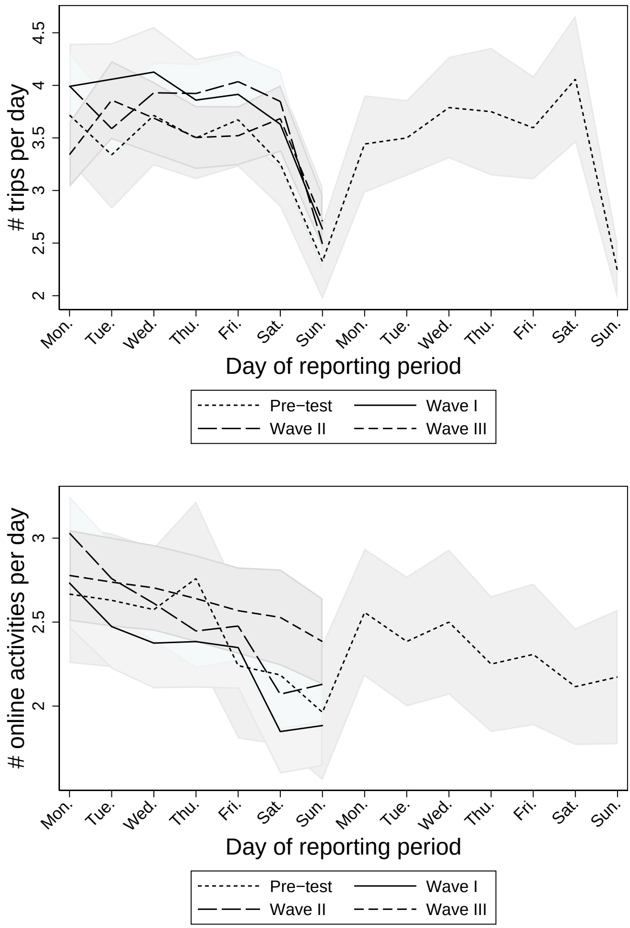
$$ME_z = \exp\left(\alpha + \overline{X}_{n,t}\beta + \Delta x_z\beta_z\right) - \exp\left(\alpha + \overline{X}_{n,t}\beta\right) \tag{2.14}$$

and depends on the particular values of $X_{n,t}$, for which we take the mean $\overline{X}_{n,t}$ when reporting the predicted changes in the counts.

25 While the general weather conditions varied strongly between the four survey waves, all four seasons are represented in the sample, and we made sure that the stage I reporting periods did not overlap with any special events or school holidays.

26 Models were estimated in *Stata 15.1* using the *xtpoisson* command.

FIGURE 2.3: Average number of reported trips and different non-physical/online activities per day.



The main goal is to investigate if there is a significant deviation from a steady number of reported trips and online activities per day, additionally controlling/testing for the survey wave, weekend effects, incentive levels, sex, age, car availability, education, income and season ticket ownership. In addition, interaction terms of the day of reporting period with these characteristics are tested, investigating if e.g. higher incentives prevents respondents from fatigue. Results are reported in Table 2.17, excluding all variables with a $|\text{t-value}| < 1$.

Regarding the number of trips per day, there is no clear global trend observable over the reporting period. Results are comparable to Axhausen et al. (2007), where positive learning rather than negative fatigue effects are present, and the number of trips in the second week (pre-test only) even slightly increased. There are some significant level effects for the survey waves, indicating that in the pre-test, respondents reported less trips on average, which can be attributed to the season (i.e. on average about 0.5 trips per day less in Winter).

Incentive levels, only varied in the pre-test, and its interactions with the day of reporting period are non-significant, showing that higher incentives have no effect either on the absolute number of reported trips nor on fatigue, except for the medium incentive level (70 or 80 CHF) which exhibits a positive level effect ($p < 0.05$; on average about 0.5 trips per day).[27]

Interestingly, the number of trips per day for respondents having a car always available are on a higher level (0.3 trips; $p < 0.01$), but response behavior of this group slightly decreases over the reporting period ($p < 0.1$; about 0.4 trips per day less after seven days), while for season ticket owners, no significant effects have been detected. Also, while education exhibits no significant level effect, the interaction with the day of reporting period indicates that highly educated respondents report slightly more trips over time ($p < 0.1$; about 0.4 trips more after seven days).

For the number of online activities, a significant and negative global trend has been detected ($p < 0.01$; about 0.6 activities less after seven days), and in addition, this number decreased in the second week by about 0.1 activities ($p < 0.1$; pre-test only), indicating some sort of decreasing commitment over time. While younger and male respondents perform significantly more online activities ($p < 0.01$), incentive levels show no significant level effect and the differences between the survey waves are also not significant.

27 Due to the relatively low number of (independent) observations for which the incentive levels were varied (56 respondents), results have to be treated with caution.

TABLE 2.17: Random-effects Poisson regressions: Number of reported trips and different online activities per day.

	# trips per day		# online activities	
Variable	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
Constant	1.104***	1.101***	1.479***	1.469***
	(0.05)	(0.06)	(0.15)	(0.16)
Day/100	0.440	0.519	−3.558***	−3.284**
	(0.58)	(0.98)	(0.58)	(1.61)
Saturday	−0.027	−0.028	−0.078***	−0.078***
	(0.03)	(0.03)	(0.03)	(0.03)
Sunday	−0.418***	−0.418***	−0.054*	−0.055*
	(0.04)	(0.04)	(0.03)	(0.03)
Wave I	0.184***	0.183***	0.065	0.065
	(0.05)	(0.05)	(0.14)	(0.14)
Wave II	0.167***	0.166***	0.122	0.122
	(0.05)	(0.05)	(0.14)	(0.14)
Wave III	0.111**	0.111**	0.119	0.119
	(0.05)	(0.05)	(0.14)	(0.14)
Week 2 (pre-test only)	0.027	0.028	−0.059*	−0.059*
	(0.03)	(0.03)	(0.03)	(0.03)
Incentive: 50 CHF	*Base*	*Base*	*Base*	*Base*
70 or 80 CHF	0.146**	0.133*	0.150	0.195
	(0.06)	(0.08)	(0.15)	(0.14)
100 CHF	0.028	0.064	0.202	0.024
	(0.08)	(0.09)	(0.18)	(0.19)
Car always avail.	0.066**	0.130***	–	–
	(0.03)	(0.05)		
High education	0.042	−0.025	–	–
	(0.03)	(0.05)		
Male	–	–	0.170***	0.170***
			(0.04)	(0.05)
Age/100	–	–	−1.311***	−1.281***
			(0.19)	(0.21)

Continued on next page

Table 2.17 – *Continued from previous page*

	# trips per day		# online activities	
Variable	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
70 or 80 CHF × day/100	–	0.339	–	−1.203
		(1.63)		(1.50)
100 CHF × day/100	–	−0.977	–	4.563***
		(1.08)		(1.77)
Car × day/100	–	−1.682*	–	–
		(0.92)		
Educ. × day/100	–	1.773*	–	–
		(0.92)		
Male × day/100	–	–	–	−0.004
				(0.87)
Age/100 × day/100	–	–	–	−0.802
				(3.32)
N (# respondents)	3391 (466)		3593 (462)	
Pseudo R^2	0.06	0.06	0.12	0.12
AICc	12989	12992	11753	11758
Prob. > χ^2: Model	0.00	0.00	0.00	0.00
Pr. > χ^2: RE vs. pooled	0.00	0.00	0.00	0.00

Robust standard errors (clustered by ID): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

− : Not included. RE: Random effects.

Given the pattern in Figure 2.3 that is consistent between all waves and the erratic increase in the beginning of the second week (pre-test only), it may also be plausible to argue that respondents actually conduct less different online activities during the course of a week which is unrelated to fatigue. However, results indicate that offering the highest incentive level leads to an increasing number of reported activities ($p < 0.01$; about 0.8 activities more after seven days), offsetting the negative global trend. Note that (i) due to the relatively low number of observations for which the incentive levels were varied (56 respondents), results have to be treated with caution and (ii) for both, trips and activities, the model fit does not significantly increase (AICc increases) when including interactions terms with the day of reporting period.

2.4 CONCLUSIONS

Long-duration, multi-stage and/or just very burdensome studies face different problems when recruiting and motivating respondents, but they may add a substantial value to the empirical basis for transportation related planning and policy decisions. Combined with respondents' SP choices and attitudes, this dataset might help to get a better understanding of individuals' daily scheduling, mobility tool ownership and travel behavior in different socioeconomic and travel-related contexts.

Based on the findings in the pre-test (Schmid and Axhausen, 2015), several adaptations were proposed to improve the work flow, efficiency and response behavior, and the "optimal" incentive level was fixed at 50 CHF given the results obtained from the participation choice models. Apart from changes in the survey and recruitment process, questionnaires were radically shortened, improved and/or skipped to reduce the response burden, and respondents were better instructed and accompanied during the initial recruitment interviews and reporting period. These measures helped to reduce the drop-out incidence and improved the response quality in the main survey. We also present a quantitative model to predict response rates based on previous studies conducted at the IVT, where we show that decreasing the response burden by 100 points ($\approx$ 8-9 minutes response time) increases the expected response rate by about 6%.

An initial idea of the respondents' motivation for participating in the survey was found to play an important role when improving the survey process. Importantly, a high incentive level leads to a significantly higher initial participation rate, but the net-effect on completion is zero. One explanation might be that when realizing the high response burden, high incentives might convince people who are actually not interested in the survey topic to participate, but when realizing the enormous response burden, they may decide to drop-out.

Findings indicate a general sampling problem observed in many transportation studies. Certain socioeconomic characteristics are consistently overrepresented: Better educated and higher income households seem to be more interested in the topic and tend to participate more frequently, but they also exhibit a higher probability to complete the survey. Similarly, the share of PT season tickets in the households strongly affects both participation and completion of the survey. Minimizing saliency effects, e.g. by better addressing and involving the group assumed to be less interested in the topic (e.g. in the current case, the actual car users), should therefore receive highest priority.

Response behavior seems to be influenced by respondents' interest in the survey, supporting the leverage-saliency theory with regard to the current project investigating travel behavior in a world with restricted car ownership and usage. This is further confirmed when investigating fatigue effects, whereby the number of reported trips over the reporting period are positively affected by education and negatively affected by car availability. Importantly, while higher incentive levels did not affect completion of the survey, results indicate an increased response quality in terms of more reported trips and a stabler reporting behavior of online activities. However, more data, especially in the longitudinal dimension, would be necessary to confirm these findings. Also, it is not fully clear if the above mentioned respondent characteristics indeed are related to response quality, or if these groups just behave in different ways with respect to their weekly activity patterns.

3

THE VALUE OF LEISURE

Time flies like an arrow; fruit flies like a banana.
— Anthony G. Oettinger

This chapter is based on Hössinger et al. (2019) published in *Transportation*, using a similar modeling framework developed to estimate the value of leisure for Austrian workers.

3.1 INTRODUCTION

An individual who makes a travel decision not only maximizes his/her utility in this particular choice, but also in the surrounding time-expenditure space. In order to combine both components, Jara-Diaz and Guevara (2003) developed a microeconomic time-use modeling framework that can be applied to estimate the values for different aspects of time-use. A key output is the value of leisure (VoL), which represents the monetary value of a marginal increase in the available time assigned to all activities that exceed the necessary minimum.

Following DeSerpa (1971), Jara-Diaz and Guevara (2003) show that estimating the VoL permits a deeper examination of the value of travel time savings (VTTS) obtained from travel choice models, arguing that the VTTS equals the VoL minus the value of time assigned to travel (VTAT). The intuition behind this is that the VTTS summarizes the value of the liberated time (opportunity cost of travel; VoL), while the VTAT represents the gain/loss when travel time is reduced – which is why it relates to the conditions/quality of travel. Therefore, the VoL is a key piece of information for the integration of travel decisions into the framework of individuals' home production. Furthermore, the VTAT is also important because it represents the direct (dis-)utility derived from the time spent on traveling. The VoL is always positive and depends on the time assigned by the individual to all activities including travel and on their trade-offs. The VTAT depends on the conditions of travel and can be positive or negative; if negative, it contributes to increase the VTTS above the VoL. The VTAT may differ between modes and according to mode-specific characteristics such as comfort, or the possibility to use the in-vehicle time productively.

The VTTS is usually obtained from conditional indirect utility functions estimated using discrete choice models; for a given level of utility, it represents the marginal willingness-to-pay (WTP) for a reduction in travel time in the context of travel choices – this is the main topic of Chapter 4.

Obtaining the VTAT is more difficult: To be computed it requires the VoL and the VTTS (see also Section 4.5.2). Estimating the VoL, in turn, requires a large amount of information from each individual, most importantly time assignment patterns including travel, and the allocation of expenditures to various commodities over a period of sufficient length to be considered as the long-term equilibrium of the individual (Jara-Diaz and Rosales-Salas, 2015, 2017). Furthermore, estimating the VoL requires more advanced econometric skills than estimating a simple choice model (see Section 3.3; not least because no built-in software package exists so far to estimate this type of models), and the data preparation tends to be a critical, time consuming and demanding procedure that requires many momentous a-priori assumptions (see Section 3.2). As a main consequence, only a few attempts have been made so far to estimate the VoL with the aforementioned modeling framework.

Table 3.1 lists the results obtained with the original model formulation presented by Jara-Diaz and Guevara (2003) and later refined by Jara-Diaz et al. (2008). They reveal a huge variability of VoL estimates ranging from 0.12 Euro/h to 123 Euro/h, and the VoL/w-ratio ranges between 0.04 and 6.83. Note, however, that the results from Jara-Diaz and Guevara (2003) were obtained with a limited preliminary version of the model, where the optimal assignment of time to activities other than work and consumption of goods were not explicitly taken into account. Also, the results from the Netherlands reported by Jara-Diaz et al. (2016) are rather implausible, using retrospective data which may lead to biased mean values (Browning and Gørtz, 2012). If these studies are not considered, the VoL/w-ratio only moves from 0.57 to 2.48. Nonetheless, only a small part of this range can be explained by socioeconomic characteristics or structural factors such as the survey year or the economic development of the country. Most VoL estimates follow the order of each country's well-being index from the World Values Survey (Frey and Stutzer, 2010), but the differences are too large to result from this factor alone. The main part of variability remains unexplained; this raises the question how to estimate the VoL to reflect the time and cost preferences in a reliable manner.

Table 3.1: Mean values of leisure (VoL; Euro/h) estimated from microeconomic time-use models, wage rates (w; Euro/h), and ratios between them reported in the literature. Sources: 1) Jara-Diaz and Guevara (2003); 2) Munizaga et al. (2008); 3) Jara-Diaz et al. (2008); 4) Jara-Diaz and Astroza (2013); 5) Jara-Diaz et al. (2013); 6) Konduri et al. (2011); 7) Jara-Diaz et al. (2016); 8) Hössinger et al. (2019).

Source	Country	Year	Segment	VoL [E./h]	w [E./h]	VoL/w
1)	Chile	1991	Medium income	0.12	3.12	0.04
1)	Chile	1991	High income	0.31	6.90	0.05
2)	Chile	2001	Full sample	3.07	4.97	0.62
3)	Chile	1991	Full sample	2.31	3.50	0.66
3)	Germany	1999	Full sample	11.92	9.95	1.20
3)	Switzerl.	2003	Full sample	23.66	26.94	0.88
4)	Chile	2001	Women	2.25	2.44	0.92
4)	Chile	2001	Men	1.78	3.11	0.57
5)	Chile	2001	Men, SCL-East	6.82	9.61	0.71
5)	Chile	2001	Men, SCL-S.East	2.24	2.68	0.83
5)	Chile	2001	Men, SCL-West	1.56	2.12	0.74
5)	Chile	2001	Men, SCL-North	1.68	1.90	0.88
5)	Chile	2001	Men, SCL-South	1.45	1.90	0.76
5)	Chile	2001	Women, SCL-East	6.48	5.92	1.09
5)	Chile	2001	Women, SCL-S.East	2.57	2.12	1.21
5)	Chile	2001	Women, SCL-West	2.12	1.79	1.19
5)	Chile	2001	Women, SCL-North	2.24	1.68	1.33
5)	Chile	2001	Women, SCL-South	2.12	1.68	1.27
6)	USA	2008	Low income	12.70	10.50	1.21
6)	USA	2008	Medium income	14.31	17.42	0.82
6)	USA	2008	High income	76.75	30.97	2.48
6)	USA	2008	Women	24.56	21.52	1.14
6)	USA	2008	Men	39.94	18.17	2.20
7)	Netherl.	2012	Full sample	122.80	17.99	6.83
8)	Austria	2016	Full sample	8.17	12.14	0.68

Continued on next page

Table 3.1 – *Continued from previous page*

Source	Country	Year	Segment	VoL [E./h]	w [E./h]	VoL/w
8)	Austria	2016	Low income	6.19	9.46	0.71
8)	Austria	2016	High income	10.20	14.89	0.66
8)	Austria	2016	Urban	8.46	12.53	0.68
8)	Austria	2016	Agglo./rural	8.08	12.01	0.67
8)	Austria	2016	Men	8.89	12.76	0.70
8)	Austria	2016	Women	7.45	11.51	0.65
8)	Austria	2016	Age $<$ 46 y.	7.56	11.42	0.66
8)	Austria	2016	Age $\geq$ 46 y.	8.74	12.82	0.68
8)	Austria	2016	Low educ.	6.99	10.35	0.68
8)	Austria	2016	High educ.	8.93	13.29	0.67
8)	Austria	2016	No kids	6.92	11.80	0.59
8)	Austria	2016	With kids	8.60	12.72	0.68
8)	Austria	2016	Single worker hh.	8.39	12.05	0.70
8)	Austria	2016	Multi worker hh.	8.11	12.16	0.67

Results in nominal prices and converted to Euro/h. Exchange rates for conversion were gained from three sources: 1991-1994: fred.stlouisfed.org; 1995-1998: data.oecd.org since 1999: data.worldbank.org

A possible source of unsystematic fluctuations are deficits and gaps in the data. One of the Chilean samples includes a specific population segment (long-distance commuters to downtown Santiago) who completed a three-day activity diary – expenditures, however, were not reported (Jara-Diaz et al., 2004; Munizaga et al., 2008). Other Chilean datasets were constructed from origin-destination surveys (Jara-Diaz and Guevara, 2003; Jara-Diaz et al., 2013). The German and Swiss data used in Jara-Diaz et al. (2008) are based on a six-week travel diary – again, expenditures were not reported and non-travel activities were inferred from the trip purposes (Axhausen et al., 2002; Löchl et al., 2005). The Dutch results (Jara-Diaz et al., 2016) are based on the LISS panel (Longitudinal Internet Studies for the Social Sciences), which is a retrospective survey of average activity duration and expenditures; trip details such as the chosen travel modes were not reported. Finally, the U.S. results are based on a synthetic dataset obtained from a probabilistic merge of participants of a time-use and a consumer expenditure survey (Konduri et al., 2011). The dataset has been used to estimate various time-use and expenditure allocation models including the multiple discrete-continuous extreme value model (MDCEV; see Castro et al. (2012)). Both time-use and expenditure information is of high quality, but the probabilistic merge remains a questionable source of uncertainty, given that the aim of such models is to estimate the trade-offs between time-use and expenditures at the individual-level.

So far, only one dataset exists that includes information on travel behavior, time-use and expenditures (Mobility-Activity-Expenditure Diary; MAED) for Austrian workers, where we collected data for all components from the same individuals at the same time (Aschauer et al., 2018). Methodologically, the current dataset (PCW) clearly goes in this direction: Although we also infer non-travel activities from the trip purposes similar as in Jara-Diaz et al. (2008) for the Swiss and German datasets, expenditures and home entertainment/online leisure activities were asked in supplementary questionnaires for the same individuals. Note that the PCW and MAED datasets are conceptually comparable and were also developed in strong collaboration. However, while the MAED dataset is clearly superior in revealing refined activity patterns (in fact, the survey was perfectly tailored to estimate the VoL), the PCW study was primarily designed to investigate behavioral reactions in the SP/SA experiments presented in Chapter 2, why we had to forgo to ask for the same degree of details as in the Austrian study. In any case, one has to stress that estimating the VoL relies on many (sometimes debatable) assumptions especially related to the data preparation, where the most important ones are discussed and critically scrutinized in this chapter.

As a key contribution to the literature, apart from the unique dataset used to estimate the VoL, this chapter presents a sophisticated time-use modeling approach including interaction terms with socioeconomic characteristics and random taste parameters. One main goal is to estimate the VoL for each respondent conditional on observed and unobserved heterogeneity, which then is decomposed into its three basic elements: A *preference*, an *available money* and an *available time* component (the latter two could be summarized into a *data-driven* component). For the first time, this allows to investigate the correlations between the VoL and the VTTS derived in Chapter 4, and to investigate which part(s) of the VoL are actually (if at all) associated with changes in the VTTS.

The structure of this chapter is as follows: Section 3.2 discusses the methodology used to aggregate and prepare the time-use and expenditure data, and describes the variables that enter the model formulation presented in Section 3.3. It also presents the main interaction/segmentation variables used to reveal observed heterogeneity in the VoL. For the sake of consistency, we include exactly the same variables as in Chapter 4 to investigate mode- and user-type effects in the VTTS. Section 3.4 presents the results of the time-use models and investigates the sources of heterogeneity in the VoL for the different respondent characteristics defined in Section 3.2. The results of a comprehensive sensitivity analysis are discussed, where we examine the implications on the VoL in different scenarios. Finally, Section 3.5 summarizes and discusses the main findings and limitations and gives an outlook on future work.

3.2 DATA PREPARATION AND DESCRIPTION

The estimation of time-use models (following the specification first presented in Jara-Diaz et al. (2008); see Section 3.3) requires to classify the reported activity and expenditure[1] categories into model variables, which are described in the following two subsections. The main subject is the sophisticated prior data preparation that is needed to estimate time-use models based on a dataset in which activities (mainly inferred from trip purposes) and expenditures are obtained in a diary-based survey. While the underlying dataset is broadly depicted in Section 2.2, the focus here is related to the necessary data adjustments[2] to reduce the incidental variation in the diary data and to better reflect the long-term equilibrium of the individuals, which is a key assumption of the model.

Note that the PCW data do not provide a one-to-one mapping between activities and expenditures, and accounting for these relations would require assumptions which are not needed in the Jara-Diaz et al. (2008) model. The model explicitly recognizes that activities have a cost through the market goods bought, but we do not attempt to find the proportions by which expenditures are allocated to individual activities.[3]

1 While the original model is formulated for goods consumption (Jara-Diaz et al., 2008), replacing consumption by expenditures does not change the basic model structure.

2 All models used for adjustment, smoothing or imputation were estimated in *Stata 15.1*.

3 There is only one attempt in the literature which introduces technical relationships between goods and time (Jara-Diaz et al., 2016); this model yields rather implausible results, underlining the experimental character of this branch of research. Also, the PCW data do not include expenditures for external service providers, which prevents the use of another recent experimental extension: The introduction of domestic activities as a decision of households to hire external providers (Rosales-Salas and Jara-Diaz, 2017).

3.2.1 *Duration of activities*

A key problem with respect to the duration of activities is the working time reported in the diary. It can deviate from the usual amount due to incidental events during the reporting week, such as workload peaks, holidays, sickness, training courses, etc. The result is an unsystematic variation of the reported working time $T_{w_{obs.}}$, which would cause unrealistic balances of income and expenditures, because the working time (along with the wage rate and fixed income from other sources but paid work) determines the implied income in the time-use model (see also Equation (3.2)). We addressed this problem by asking for the regular weekly hours worked T_w (i.e. the *effective working time* according to the contract; including the usual hours of overtime) in the personal questionnaire, which was also used to calculate the wage rate w based on reported personal labor income.

For model estimation, we replaced the reported working time in the diary with the effective working time, which mainly implies a reduction of the working time variance (i.e. by 10.4%). The duration of the non-work activities were adjusted accordingly to satisfy the time constraint. We assume an asymmetric adjustment pattern in the sense that an incidental increase of working time (beyond the usual level) causes different re-arrangement patterns than an incidental reduction (below the usual level). For this purpose, we estimated two separate OLS regression models which were used for the adjustment of activity duration of the two different groups (see Appendix, Table A.2; the coefficients indicate how less/more working time is replaced by additional/less time spent on other activities):

– Persons who worked less than usual in the reporting week ($T_{w_{obs.}} < T_w$; 9 parameters; $R^2 = 0.11$): Increase of the working time to the usual effective working time and reduction of non-work activities to meet the time constraint.

– Persons who worked more than usual in the reporting week ($T_{w_{obs.}} > T_w$; 9 parameters; $R^2 = 0.23$): Reduction of working time to the usual effective working time and increase of non-work activities to meet the time constraint.

The resulting correlation between the effective and reported working time is +0.58, and the average correlation between reported and adjusted non-work activities is +0.95.

Table 3.2 presents the average hours per week of the main time-use categories in the PCW data (after adjustments), the MAED data (after adjust-

TABLE 3.2: Descriptive statistics for time-use [average hours per week]: PCW vs. MAED vs. ATUS 2008/09. Last column: Model variable.

Category	PCW [h]	MAED [h]	ATUS [h]	Variable
Working	36.2	37.8	36.9	T_w
Leisure	–	28.9	32.3	$Tf1$
Out-of-home leisure	16.4	–	–	$Tf1$
In-home leisure	9.6	–	–	$Tf2$
Eating	–	9.3	8.6	$Tf2$
Shopping	–	2.1	2.0	$Tf2$
Committed time	–	80.6	80.1	Tc
Travel	10.6	9.3	8.1	Tc
Shopping	1.9	–	–	Tc
Other	0.8	–	–	Tc
At home	92.5	–	–	Tc
Total (time constraint)	168.0	168.0	168.0	τ

Note: MAED: exchange rate: 1 Euro = 1.2 CHF.

ments) and the Austrian time-use survey (ATUS 2008/09) and shows how the activity categories were assigned to the time-use model variables. This allocation is critical because it is arbitrary, but clearly affects the results. Basically, there are four main model variables: Paid working time (T_w), freely chosen time in leisure activity i ($Tf1$ and $Tf2$) and committed activity time (Tc) where respondents try to stick to the technical minimum (this is discussed in more detail in Section 3.3). Sample distributions (N = 369) of T_w, $Tf1$, $Tf2$ and Tc in the PCW dataset are presented in the Appendix, Figure A.35, and of the wage rate w (median = 49.5 CHF/h) in Figure 3.1a.

Our definition of Tc mainly follows the one in Jara-Diaz et al. (2013), but using stronger assumptions given the much less fine grained distinction of activity types. For example, from the travel diary we know how much time a person spent at home, but we do not have any further information on home activities such as cooking, cleaning or personal care, etc. However, we know how much time a person spent for online/entertainment activities, such as watching TV, playing computes games, etc. This amount, aggregated to in-home leisure ($Tf2$), was subtracted from the time spent at home to get an estimate of Tc, while out-of-home leisure time ($Tf1$) was directly inferred from the travel diary.

According to our definition, sleeping is also classified as a committed activity – most probably one of the biggest components in *Tc*. Similar to travel, sleep is special in the sense that one cannot pay other persons to perform it without loosing its intrinsic value (unlike e.g. domestic work); at the same time, sleep exhibits a minimum time requirement for humans to survive in the long-run. However, classifying sleeping as a committed activity is not straightforward – it could be and also has been classified as leisure as well (for a comprehensive discussion on the importance of sleep in time-use modeling, see also Jara-Diaz and Rosales-Salas, 2017).

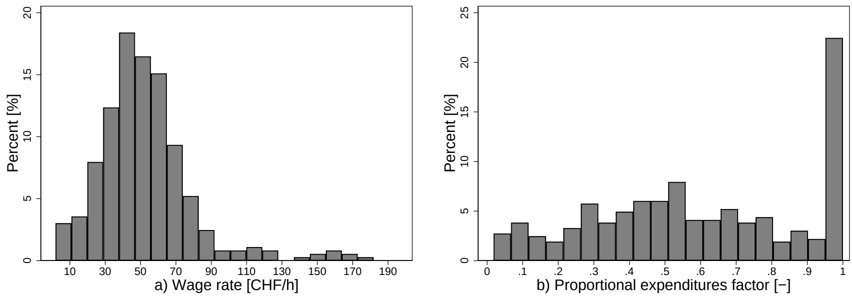
Table 3.2 indicates that the duration of weekly activities are quite comparable to the Austrian case.[4] However, there are some noticeable differences observable, also regarding the classification of activities: While we define $Tf1$ and $Tf2$ to be out-of-home and in-home leisure, respectively (thus, the duration of both activities is entirely freely chosen), in Hössinger et al. (2019) $Tf1$ corresponds to leisure, while eating and shopping together define $Tf2$, arguing that respondents have exceeded the technical minimum necessary to perform these activities (clearly, a similar argument that could be made for sleeping). After all, we expect that in the PCW sample, *Tc* tends to be overestimated, while a finer grained resolution of the time at home (now the main part of *Tc*) might reduce this amount. This, however, would still not answer the question if respondents stick to the technical minimum when performing a committed activity. Possible implications on results are discussed in Section 3.4.2.

3.2.2 *Expenditures*

Linked to the reporting of expenditures is the large variability of purchase rhythms of goods and services. In line with conventional expenditure surveys, expenditure information was collected in two separate sections of the questionnaire: Frequently purchased items were reported in the expenditure diary at the individual-level, whereas long-term expenditures were reported at the household-level. For those expenditure categories where double-counting was inevitable (e.g. in case of vacation in the long-term questionnaire, and hotel/accommodation in the expenditure dairy), we included the maximum value resulting from either source after bringing all expenditures to a common (weekly) time unit, as we observed a systematic under-reporting of expenditures in both types of questionnaires – one main drawback of the very high response burden in this survey. For es-

4 Note that there is no official Swiss time-use survey.

FIGURE 3.1: Sample distributions of the wage rate and proportional income/expenditures factor (N = 369).



sential expenditure categories such as insurance and food, or categories that are not plausible to exhibit zero expenditures in the long-term equilibrium such as clothes, zero spending and missing values were replaced by imputation (see e.g. Aschauer et al., 2019; Hössinger et al., 2019).

The collection of expenditure data at two levels (personal and household) induces the need of some rules to allocate the expenditures to those individuals who generate income (i.e. workers), which is done based on the assumption of "proportional expenditures" according to the labor income of all participating respondents P_h in household h (see Figure 3.1b):[5]

$$\text{Proportional expenditures factor}_n = \frac{income_n}{\sum_{n=1}^{P_h} income_n} \tag{3.1}$$

This yields a clear balance between labor income and long-term expenditures at the individual-level and allows a comparison with existing studies reported in Table 3.1, which have used one-worker households (Jara-Diaz et al., 2016) or one-person-one-worker households (Konduri et al., 2011). Possible implications of this assumption are discussed in Section 3.4.2.

Another important issue associated with the expenditures is the large variation of short-term expenditures in the diary. A randomly selected week can deviate from the long-term equilibrium for two reasons: Excep-

5 One main drawback of the PCW sample is that in many cases, only a fraction of all eligible household members participated in the survey (see also Section 2.3.2). Thus, we applied additional quality checks, such that if the reported household income was substantially higher than the sum of personal incomes of the participating household members P_h (i.e. household income $- \sum income_n > 2'000$ CHF/month; note that household income was asked much less fine grained than personal income), the expenditures assigned to those individuals were diminished proportionally according to this difference.

tionally large purchases and implausible zero spendings on essential goods such as food or clothes. Reported zeros may be reduced by a longer observation period and face-to-face support of participants, as is usually done in conventional expenditure surveys. However, this was clearly outside the scope of the current study. Furthermore, erroneous entries resulting from both types of questionnaires (i.e. short- and long-term) may lead to influential outliers. Therefore, we employed a model-based smoothing of expenditures with the intention to reduce the large incidental variation caused by the aforementioned problems, but to retain the individual variability as much as possible. The applied procedure is a simplified version of the one presented in Hössinger et al. (2019) and consists of two main steps:

– Predict the individual monthly savings [in CHF] using an auxiliary OLS model with a wide range of personal and household characteristics as explanatory variables (36 parameters; $R^2 = 0.37$; see Appendix, Table A.3).

– For each expenditure category and respondent, calculate the share of this category to the total expenditures. Multiply this share with the predicted savings (which can be positive or negative), and add this to the actual/observed expenditures in this category.

This procedure ensures that the reported expenditures are carefully adjusted only to the necessary extent in order to fix the balance between income, savings and expenditures (average correlation between adjusted and reported total expenditures = +0.97). This still allows for some over-/ underspending as long as $w \cdot T_w + Y - Ec \geq 0$ holds: Committed expenditures should not exceed total (= labor + fixed) income, which would imply a negative VoL in Equation (3.14) and can cause negative square roots in Equation (3.11).[6] Importantly, this smoothing approach is less restrictive compared to the case where adjustments are made until total expenditures equal income (average correlation between adjusted and reported total expenditures = +0.84).

The classification of committed expenditures (Ec) mainly follows Aschauer et al. (2019) and Mokhtarian and Chen (2004): Expenditures on goods associated with physical needs or maintenance were classified as "committed". People need to eat (food), pay taxes and need a dwelling (housing) with equipment (furniture). Further committed expenditures are

6 For 34 respondents violating this condition, $Ec - Y$ was imputed based on an auxiliary OLS model shown in the Appendix, Table A.4 (N = 335; R^2 = 92%).

health, education, insurance, services not related to leisure activities, communication and mobility. Freely chosen expenditures include out-of-home accommodation (visiting restaurants and hotels), holidays, leisure and recreational goods ($Ef1$), as well as electronics and communication devices, which are mainly used for entertainment ($Ef2$). Clothing was also classified as "non-committed", although it is at least partially essential ($Ef2$). The reason is that clothing expenditures add up to a fairly high amount in our sample, indicating that the "technical minimum" is well exceeded. Therefore, a clear distinction between $Ef1$ and $Ef2$ was made, such that $Ef1$ is related to purely freely chosen goods consumption, while $Ef2$ covers at least some essential needs. However, similar as in the case of the duration of activities, there is no clear line to be drawn between committed and freely chosen expenditures. For example, mobility expenditures clearly are ambivalent: Maintaining a sports car is still treated as a committed expenditure, while a cheaper and efficient Japanese car would do it as well. A similar argument could be made for housing, food, furniture, etc. Possible implications of our current classification are discussed in Section 3.4.2.

Table 3.3 presents the share of expenditures in the PCW data (after adjustments; sample distributions of $Ef1$, $Ef2$, Ec and $Ec - Y$ are presented in the Appendix, Figure A.36), the Austrian MAED data (after adjustments) and the Swiss household budget survey (EVE 2005). While time-use was found to be quite similar across the two neighboring countries Switzerland and Austria, this is not the case for expenditures: Clearly, income in Switzerland is substantially higher and the tax system and housing market are conceptually different. Furthermore, while fixed income from other sources but paid work (Y) only plays a minor role in Austria (6.1% of personal labor income), Table 3.3 shows that in Switzerland, its average share relative to household labor income in the EVE dataset is about 14.5% (i.e. for households, where at least one member is working). Neglecting this extra amount of money would lead to an underestimation of total income and thus of the VoL (this is further discussed in Section 3.4.2). As Y was not available in the PCW data, we estimated an auxiliary exponential[7] regression model (see Appendix, Table A.5) to impute Y based on information from the EVE dataset for Eastern Switzerland and the greater region of Zurich (N = 689; $R^2 = 0.35$), including all influential and commonly avail-

7 This ensures that the predictions of Y are well defined and strictly positive (Wooldridge, 1992), and also accounts for the right-skewed distribution observed in the EVE dataset.

able socioeconomic characteristics.[8] Thus, on average, 9.2% of personal labor income is added to the PCW respondents' available money (note that this relatively low amount is mainly reflected by the very high labor income of PCW respondents, as in the EVE dataset household labor income exhibits a strong and negative effect on fixed income; see Table A.5).

TABLE 3.3: Descriptive statistics for expenditures [%]: PCW vs. MAED vs. EVE 2005 (for Eastern Switzerland and the greater region of Zurich; only including households where at least one household member is working). Last column: Model variable.

Category	PCW [%]	MAED [%]	EVE [%]	Variable
Hotel, restaurants and holidays	11.4	6.2	7.5	$Ef1$
Leisure	2.9	7.8	3.9	$Ef1$
Clothes and accessories	5.3	5.6	3.1	$Ef2$
Electronics	2.2	3.6	2.0	$Ef2$
Taxes	23.1	–	10.8	Ec
Housing	18.6	23.2	18.7	Ec
Food	10.2	17.3	9.1	Ec
Health (incl. insurance)	7.0	2.4	9.8	Ec
Mobility	5.0	12.7	6.8	Ec
Communication	1.6	–	2.2	Ec
Furniture	1.6	2.4	1.3	Ec
Education	1.3	2.0	1.6	Ec
Services	1.8	3.1	2.0	Ec
Insurances[1]	3.0	8.2	17.6	Ec
Other expenditures	4.9	4.7	3.5	Ec
Avg. weekly expenditures [CHF]	1931.0	560.1	2309.7	$\sum Ef_j + Ec$
Avg. weekly labor income [CHF]	1995.6	550.7	2296.8	$w \cdot T_w$
Avg. weekly fixed inc.[2] [CHF]	182.9	33.7	334.1	Y

Note: MAED: Exchange rate 1 Euro = 1.2 CHF. EVE: Expenditures/income at the household-level.

[1] : PCW: Mobility insurance included in *Mobility*. MAED: Including mobility and health insurance.

[1] : EVE: Including social security contributions.

[2] : PCW: Imputed based on the EVE 2005 dataset (see Appendix, Table A.5).

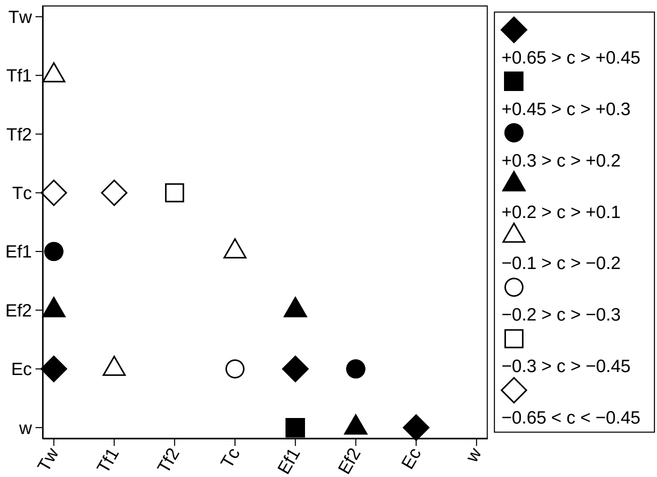
The EVE and the PCW dataset exhibit comparable expenditure shares in more or less all categories. The main difference is related to the absolute

8 Note that the EVE is a household survey. Individual characteristics such as age, working hours and gender were included in the model by using the average values within households.

levels: In the EVE dataset, the average weekly expenditures correspond to the whole household, exhibiting a similar value as for a an average working respondent in the PCW dataset. This is also reflected in the substantially higher share of expenditures spent on taxes, given the larger labor income of PCW respondents. Compared to our Austrian neighbors (apart from structural differences), in relative terms the MAED respondents spend more money on food, housing, mobility and leisure, while the PCW respondents exhibit higher values for holidays and health. Interestingly, expenditure shares show substantial differences in leisure between the three datasets (very small in PCW), but when added with hotel, restaurant and holidays, their sum becomes pretty similar.

Figure 3.2 shows the correlation patterns of the main model variables. As expected, T_w is positively related with Ec and negatively with Tc: For example, men typically tend to work and earn more than women, but exhibit less committed time related to home activities such as childcare, cooking and cleaning. Another aspect to be noted is the opposite pattern of time-use and expenditure variables: While time-use variables tend to be negatively correlated due to the common time constraint, the expenditure variables are positively correlated among each other and also with T_w. This follows from the equalizing effect of labor income: It increases with T_w, thus increasing the available budget for all types of goods.

FIGURE 3.2: Correlation patterns of main model variables (N = 369).



3.2.3 *Interaction variables*

Heterogeneity in the value of time is an important issue, given the large differences in VoL estimates of different population segments in previous studies, as shown in Table 3.1. These studies have consistently used a-priori segmentation (i.e. segments were treated as independent samples and separate models were estimated for each segment; for a comparison of different approaches, see also Hössinger et al. (2019)).

The interaction approach applied here is conceptually different for the following two reasons: (1) Our sample is relatively small and estimation would be inefficient, if it is divided a-priori into subsamples to estimate the VoL segment-specific and (2) one main goal of this (and the subsequent) chapter is – apart from obtaining the individual VTAT – to investigate the correlations between the VoL and VTTS. This requires that both measures are calculated once (for the full sample) and for each individual, conditional on his/her socioeconomic characteristics (for the VoL, see Section 3.4.1; for the VTTS, see Section 4.5.1).

The variables presented below (for summary statistics, see also Table 2.13) and shown in Figure 3.3 were selected based on prior investigations of the set of possible characteristics that are typically assumed to affect respondent heterogeneity in time-use and travel choice models (e.g. Hössinger et al., 2019; Schmid et al., 2019a):

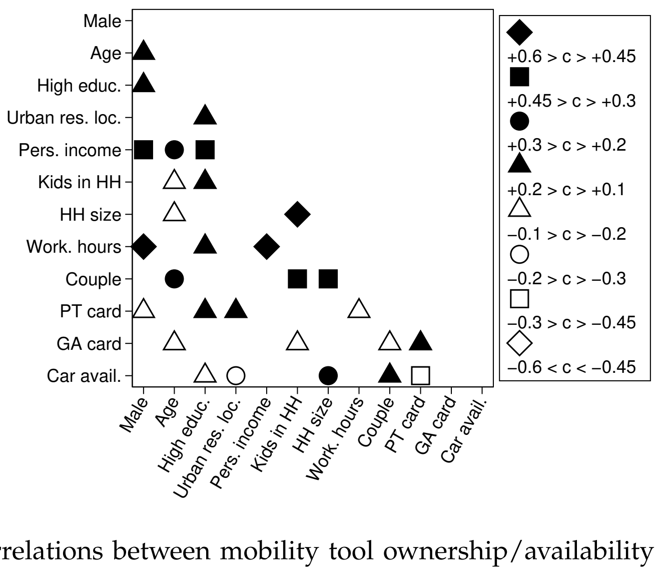
- **Male**: Male (dummy)
- **Age**: Mean-normalized and zero-centered (continuous)
- **High education**: Higher technical academy degree or higher (dummy)
- **Urban**: Urban residential location area (dummy)
- Personal **income**: Mean-normalized and zero-centered (continuous)
- **Kids** in HH: Children ($<$ 18 years) living in the household (dummy)
- **Household size**: Number of household members; mean-normalized and zero-centered (continuous)
- **Working hours**: Weekly working hours $>$ 40 h (dummy)
- **Couple**: Respondent lives in a relationship (dummy)
- **PT card**: Any kind of PT season ticket in possession (dummy)

– **GA card**: Swiss national season ticket in possession (dummy)

– **Car availability**: Car always available (dummy)

Figure 3.3 gives an overview on how socioeconomic characteristics are linked to each other and also provides some intuition about potential collinearity issues. Important for model estimation – especially when including interaction terms between all main effects and socioeconomic characteristics at once – and the interpretation of results, however, it indicates that all correlations of respondent characteristics are small to moderate and never exceed $+/-0.6$. Nonetheless, due to the relatively high correlation of household size with the occurrence of kids in households, as well as working hours with gender and personal income, household size and working hours are not included in subsequent analyses.

Figure 3.3: Correlation patterns of socioeconomic characteristics of working respondents (N = 369).



The correlations between mobility tool ownership/availability (car and season ticket) and urban residential location indicate, that people in urban areas are more likely to own a PT season ticket, but have a lower level of car accessibility, which is typical for European cities (e.g. Becker et al., 2017). Also, given their endogenous nature with respect to choice set generation as discussed in Section 2.2.2.1 and Section 4.2 for the travel choice model, mobility tool ownership variables are not included in subsequent analyses.

All the remaining covariates are tested/included in subsequent analyses, including: Male, age, high education, urban, income, kids and couple.

3.3 MODELING FRAMEWORK

The utility function presented in Equation (3.2) is a log-linear version of a Cobb-Douglas production function (Zellner et al., 1966) including three terms which relate to the utility gained from the time assigned to work (T_w), the time assigned to activity i (T_i) and the expenditures assigned to good j (E_j).[9] The logarithms enforce diminishing marginal utility (i.e. satiation) as the consumption level of a particular input increases. This assumption yields a multiple discreteness model – that is, the choice of multiple alternatives can occur simultaneously (see e.g. Bhat, 2005, 2008). The constrained maximization problem (omitting subscript n) is given by

$$\begin{aligned} \max \;\; U = \;& \theta_w \log(T_w) + \sum_{i=1}^{I} \theta_i \log(T_i) + \sum_{j=1}^{J} \psi_j \log(E_j) \\ \text{s.t.} \;\; & \tau - T_w - \sum_{i=1}^{I} T_i = 0 \quad (\mu) \qquad T_i - T_i^{min} \geq 0, \, \forall i \in A^c \quad (\kappa_i) \\ & w \cdot T_w + Y - \sum_{j=1}^{J} E_j \geq 0 \quad (\lambda) \qquad E_j - E_j^{min} \geq 0, \, \forall j \in G^c \quad (\eta_j) \end{aligned} \tag{3.2}$$

where θ_w is the baseline utility parameter[10] of working time T_w, θ_i is the baseline utility parameter of activity i, ψ_j is the baseline utility parameter of expenditures assigned to good j, τ is the total time constraint (i.e. 168 hours $\forall$ n), w is the wage rate, Y is the fixed income from other sources but paid work, μ and λ are the Lagrange multipliers representing the marginal utility of increasing available time and available money, κ_i is the Lagrange multiplier representing the marginal utility of reducing the minimum time constraint of committed activity $i \in A^c$ and η_j is the Lagrange multiplier representing the marginal utility of reducing the minimum expenditure constraint of committed good $j \in G^c$.

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9 Note that for numerical reasons, we use ten-minute-units for time and CHF for money, which ensures that the estimation procedure treats time and money error terms in more or less equal-value units.

10 A baseline utility (input elasticity) parameter corresponds to the marginal utility (the slope of the utility function, given by the first derivative of U with respect to the input variable x) when the first unit is consumed (for a schematic illustration, see also Appendix, Figure A.37).

As discussed in Section 3.2, committed activities and goods are those which are necessary for personal and household maintenance such as sleeping, eating, cleaning, traveling, etc. They are limited at the bottom by technical constraints (i.e. people would like to assign less time and money, but cannot because of the technical constraints). The amount of time and expenditures assigned to those activities and goods is given exogenously: It is inferred from the data and included in the equations as $Tc = \sum_{i \in A^c} T_i^{min}$ and $\widetilde{Ec} = \sum_{j \in G^c} E_j^{min} - Y = Ec - Y$, limiting the freely chosen amounts (Jara-Diaz et al., 2008).

Furthermore, we assume that each individual assigns non-zero amounts of time and money to each unconstrained activity and consumed good, as the logarithms in Equation (3.2) do not allow zeros. This is reasonable, as we are dealing with an aggregated view of activities and expenditures assigned to a whole work-leisure cycle (i.e. one week), which prevents the presence of zero assignments.

Following Jara-Diaz et al. (2008), we obtain the first order conditions to find the optimal allocation of activity duration and expenditures. They yield a solution for T_w, T_i and E_j, which can be used to calculate μ and λ, and consequently the VoL for each individual.

The first order conditions are

$$\frac{\theta_w}{T_w} + \lambda w - \mu = 0 \tag{3.3}$$

$$\frac{\theta_i}{T_i} - \mu = 0 \ \forall i \in A^f \tag{3.4}$$

$$\frac{\psi_j}{E_j} - \lambda = 0 \ \forall j \in G^f \tag{3.5}$$

where A^f and G^f denote the set of freely chosen activities and freely consumed goods, respectively. From this follows that μ (the marginal utility of increasing available time for freely chosen activities; subject to satiation) and λ (the marginal utility of increasing available money for freely consumed goods; subject to satiation) are defined as

$$\mu = \frac{\partial U}{\partial T_i} = \frac{\Theta}{\tau - T_w - Tc} \tag{3.6}$$

$$\lambda = \frac{\partial U}{\partial E_j} = \frac{\Psi}{w \cdot T_w - \widetilde{Ec}} \tag{3.7}$$

The parameters Θ and Ψ correspond to the sum of individual time coefficients θ_i and expenditure coefficients ψ_j. Note that the first order conditions include five baseline utility parameters (i.e. θ_w, θ_{Tf1}, θ_{Tf2}, ψ_{Ef1} and ψ_{Ef2}). For identification purposes, Θ is set to 1 (by dividing the equations by Θ; from this follows that $\theta_{Tf2} = 1 - \theta_{Tf1}$; see also Hössinger et al. (2019)), which enables us to estimate the original Jara-Diaz et al. (2008) model parameters directly from the non-linear equation system as shown below. Therefore, Ψ – the baseline utility parameter of freely chosen expenditures *relative to time* – is estimated directly (from this follows that $\psi_{Ef2} = \Psi - \psi_{Ef1}$), and we end up with four baseline utility parameters to be estimated: $\Lambda_{x,n} \in \{\theta_w, \theta_{Tf1}, \psi_{Ef1}, \Psi\}$

In the most exhaustive model specification with socioeconomic characteristics and random components (TUMIX), we apply a random effects approach with interaction terms to account for observed and unobserved heterogeneity in those four baseline utility parameters such that

$$\Lambda_{x,n} = \pm \exp(\zeta_x + Z_n \beta_x + \rho_{x,n}) \tag{3.8}$$

where ζ_x is the fixed main effect of baseline utility parameter $\Lambda_{x,n}$, Z_n is a (1 × L) vector of socioeconomic characteristics and β_x is a (L_x × 1) baseline-utility-specific parameter vector. $\rho_{x,n} \sim N(0, \sigma_x^2)$ is an individual- and baseline-utility-specific random component capturing unobserved heterogeneity. The log-normal distribution ensures that no sign violations occur[11] with respect to θ_{Tf1} (> 0), ψ_{Ef1} (> 0) and Ψ (> 0). θ_w could be either positive, zero or negative, although previous investigations have shown that (i) only negative values of conditional estimates of θ_w occurred in our sample and (ii) a negative log-normal distribution exhibited a slightly better model fit.

Rewrite Equation (3.3) into Equation (3.9), and insert Equation (3.6) and Equation (3.7) into Equation (3.9) to obtain Equation (3.10), such that

$$T_w(\lambda w - \mu) + \theta_w = 0 \tag{3.9}$$

$$T_w \left(\frac{\Psi}{w \cdot T_w - \widetilde{Ec}} \cdot w - \frac{\Theta}{\tau - T_w - Tc} \right) + \theta_w = 0 \tag{3.10}$$

11 As both μ and λ are positive, the first order conditions indicate that the baseline utility parameters of time and money assigned to freely chosen activities and goods must be positive as well. However, this is not the case for working time, as there is a monetary compensation (see Equation (3.3)), indicating that θ_w could be either positive, zero or negative.

and solve the quadratic equation

$$T_w^* = \frac{(\Psi + \theta_w)(\tau - Tc) + \frac{\widetilde{Ec}}{w}(\Theta + \theta_w)}{2(\Theta + \Psi + \theta_w)} + \frac{\sqrt{\left(\frac{\widetilde{Ec}}{w}(\Theta + \theta_w) + (\Psi + \theta_w)(\tau - Tc)\right)^2 - 4\frac{\widetilde{Ec}}{w}(\tau - Tc)\theta_w(\Theta + \Psi + \theta_w)}}{2(\Theta + \Psi + \theta_w)} \tag{3.11}$$

to obtain the optimal working time T_w^*. Insert Equation (3.6) in Equation (3.4) with T_w^* to obtain T_i^*

$$T_i^* = \frac{\theta_i}{\Theta}(\tau - T_w^* - Tc) \tag{3.12}$$

and insert Equation (3.7) in Equation (3.5) with T_w^* to obtain E_j^*

$$E_j^* = \frac{\psi_j}{\Psi}(w \cdot T_w^* - \widetilde{Ec}) \tag{3.13}$$

Then, the VoL and the value of time assigned to work (VTAW; see e.g. Jara-Diaz (2007)) are given by

$$VoL = \frac{\partial U / \partial T_i}{\partial U / \partial E_j} = \frac{\mu}{\lambda} = \frac{w \cdot T_w^* + Y - Ec}{\Psi(\tau - T_w^* - Tc)} \tag{3.14}$$

$$VTAW = \frac{\partial U / \partial T_w}{\partial U / \partial E_j} = \frac{\mu}{\lambda} - w = VoL - w \tag{3.15}$$

Under the normality assumption of the error terms, the parameters in the non-linear equations system (i.e. for the three equations Equation (3.11), Equation (3.12) and Equation (3.13)) are estimated using maximum simulated likelihood. The likelihood for individual n is given by the four-dimensional integral

$$L_n(\cdot) = \int f(\epsilon_n | X_n, Z_n, \Omega, \rho_{x,n})\, h(\rho_{x,n} | \Sigma)\, d\rho_{x,n} \tag{3.16}$$

where Ω is the set of fixed parameter vectors, and $h(\rho_{x,n}|\Sigma)$ is the multivariate distribution of the independent random components with the corresponding vector of standard deviations Σ. The joint density can be expressed as[12]

$$f(\epsilon_n|X_n, Z_n, \Omega, \rho_{x,n}) = \exp(-f(\epsilon_1)^2)\exp(-f(\epsilon_2|\epsilon_1)^2)\exp(-f(\epsilon_3|\epsilon_1, \epsilon_2)^2)$$

where

$$\epsilon_e = Y_e - \underbrace{g_e(X_n, Z_n, \Omega, \rho_{x,n})}_{Y_e^*} \quad e \in \{1, 2, 3\} \tag{3.17}$$

Y_e is the dependent variable (i.e. T_w, $Tf1$ or $Ef1$), g_e denotes a function of input variables X_n and respondent characteristics Z_n, Ω and random components $\rho_{x,n}$ to obtain Y_e^*, and $\epsilon_e \sim N(\mu_e, \sigma_e)$ are the error terms we want to minimize, explicitly accounting for correlations between the equations.

The integral in Equation (3.16) is approximated by using a smooth simulator that is consistent and asymptotically normal (e.g. Train, 2009). This is done by drawing values from the $h(\rho_{x,n}|\Sigma)$ distributions, with superscript r referring to draw $r \in \{1, ..., R\}$: $\widetilde{L_n}(\cdot)$ shown in Equation (3.19) is the simulated likelihood for individual n, and the maximum simulated likelihood estimator contains the values in $\widehat{\Omega}$ and $\widehat{\Sigma}$ that maximize $\widetilde{LL}(\Omega, \Sigma)$.

$$\max \widetilde{LL}(\Omega, \Sigma) = \sum_{n=1}^{N} \log\left(\widetilde{L_n}(\cdot)\right) \tag{3.18}$$

$$\widetilde{L_n}(\cdot) = \frac{1}{R} \sum_{r=1}^{R} f(\epsilon_n|X_n, Z_n, \Omega, \rho^r_{x,n}) \tag{3.19}$$

Models were estimated in *R 3.2.2* (CMC, 2017). Quasi-random draws were generated using Modified Latin Hypercube Sampling (MLHS) as proposed by Hess et al. (2006). The main criteria regarding identifiability and simulation bias as discussed in Vij and Walker (2014) were investigated: With 2'000 draws, estimates were carefully considered to be robust and stable. Robust standard errors were calculated using the Eicker-Huber-White sandwich estimator (e.g. Zeileis, 2006).

12 For maximizing the joint density, the exponents of the negative of the squared error terms are taken to ensure that the log-likelihood function is well-behaved.

3.4 RESULTS

Four models with increasing complexity are presented in Table 3.4, which were found to represent behavior in our sample appropriately.[13] The base model (BASE)[14] is a simple time-use model estimating the four main effects θ_w, θ_{Tf1}, ψ_{Ef1} and Ψ, the second model (EXP) is nothing else than the base model but using exponents to restrict the signs of the baseline utilities as discussed in Section 3.3, the third model (INTER) includes the interaction terms of socioeconomic characteristics with all four main effects and the fourth model (TUMIX) adds the random components. Those parameters with a $|\text{t-value}| < 1$ are removed for the final model specification.[15]

The estimated baseline utilities in the BASE model indicate that, ceteris paribus, increasing T_w decreases the utility of respondents ($\widehat{\theta}_w = -0.97$), while increasing freely chosen activity time ($Tf1$ and $Tf2$) and freely consumed goods ($Ef1$ and $Ef2$; note that $Ef2$ implicitly also includes savings, since the money budget constraint is not binding) increase utility. As expected, $\widehat{\theta}_{Tf1} = 0.65$ indicates that on average, consuming the first unit of out-of-home leisure time exhibits a substantially larger increase in utility than consuming the first unit of in-home leisure time (i.e. $\widehat{\theta}_{Tf2} = 1 - \widehat{\theta}_{Tf1} = 0.32$): Ceteris paribus, our average Zurich respondent still appreciates the time outside more than online/tele entertainment. On the other hand, $\widehat{\psi}_{Ef1} = 0.33$ indicates that spending the first unit of expenditures on pure leisure activities (such as going to the cinema, holidays and restaurant visits) exhibits a substantially lower increase in utility than

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13 From the original sample with N = 369 respondents, six were excluded based on the analysis of residuals (i.e. one respondent with large T_w and five with large $Ef1$ residuals) and one based on a still negative money balance (after imputation of $Ec - Y$), leading to a final estimation sample with N = 362 respondents. The distribution of residuals in the TUMIX model are presented for the final estimation sample in the Appendix, Figure A.38. It indicates visually that the normality assumption of the error terms holds approximately, although Shapiro-Francia normality tests (Shapiro and Francia, 1972) reject the null that they are normally distributed ($p < 0.01$) except for the T_w residuals ($p = 0.09$). Furthermore, the residuals vs. fitted values of the T_w^*, $Tf1^*$ and $Ef1^*$ equations indicate that (i) heteroscedasticity in the error terms is present (most pronounced in the $Tf1^*$ and $Ef1^*$ equation) and (ii) that the residuals are more positive for larger values of $Tf1^*$, indicating that there is some pattern in the data that the model has not captured well with respect to the freely chosen activities. Nevertheless, one should note that the model diagnostics have improved substantially in the TUMIX compared to the BASE model by adding the interaction terms and random components (see also Table 3.4 at the bottom for the improvement in equation-specific R^2's).

14 This model is just reported for facilitating the interpretation of coefficients of the subsequent models. Note that the BASE and EXP model exhibit exactly the same results and model fit.

15 This includes the following interaction terms in the INTER model: Urban × θ_w, couple × θ_w, urban × Ψ, couple × Ψ, income × Ψ, kids × θ_{Tf1}, urban × ψ_{Ef1} and couple × ψ_{Ef1}.

spending the first unit of expenditures on clothes, electronics and savings (i.e. $\widehat{\psi}_{Ef2} = \widehat{\Psi} - \widehat{\theta}_{Ef1} = 0.56$), which can be explained by the more essential (to some extent committed) nature of the latter.

Adding the interaction terms between baseline utilities and respondent characteristics (INTER) exhibits a significant increase in overall model fit (AICc decreases by 64 units). For all discrete interaction terms we used weighted effects coding for unbalanced data (e.g. Daly et al., 2016; Te Grotenhuis et al., 2017), leaving the main effect estimates of the sample mean unaffected. Important for the VoL, results show that the main effect Ψ increases relative to the EXP model, indicating that the baseline utility of freely consumed goods relative to time increases when controlling for socioeconomic characteristics. At the same time, the baseline utility of time assigned to work, θ_w, decreases: Equation (3.3) indicates that a smaller value of θ_w is associated with a larger Ψ to satisfy the condition in Equation (3.15) that the marginal utility of work plus labor income equals the marginal utility of leisure.

Older and male respondents with high education/income and no kids exhibit a more negative θ_w (partly explained by their higher working time) and, at the same time, exhibit a higher Ψ and ψ_{Ef1}, and consequently a lower *preference-driven* component of the VoL (this is further discussed in Section 3.4.1, where the VoL is decomposed into a preference-driven and data-driven component). All these characteristics – more or less associated with higher income (see also Figure 3.3) – show that the preference-driven effect on the VoL tends to be negative (i.e. higher baseline utility of freely consumed goods relative to time), while the data-driven components clearly exhibit a positive effect (ceteris paribus, less available time and more disposable money for freely chosen activities and expenditures, respectively). These findings illustrate an important mechanism of the model which is related to satiation: Consuming more uncommitted time or goods is associated with a higher corresponding baseline utility.

Distinct effects are found for θ_{Tf1}, where older and female urban residents with high education exhibit an increased baseline utility of out-of-home leisure. Remembering that $\theta_{Tf2} = 1 - \theta_{Tf1}$, especially the strong effect of age is somewhat expected: It indicates that, ceteris paribus, younger respondents obtain a substantially higher utility from online/tele entertainment activities than older respondents.

TABLE 3.4: Estimation results: Time-use and expenditure allocation models.

	BASE Coef./(SE)	EXP Coef./(SE)	INTER Coef./(SE)	TUMIX Coef./(SE)
Working time ($\widehat{\theta}_w$)	-0.97^{**}	-0.04	0.31	0.33
	(0.39)	(0.40)	(0.33)	(0.22)
Freely cons. goods ($\widehat{\Psi}$)	0.89^{***}	-0.12	0.11	0.12
	(0.16)	(0.18)	(0.17)	(0.12)
Out-of-home leisure ($\widehat{\theta}_{Tf1}$)	0.68^{***}	-0.39^{***}	-0.40^{***}	-0.41^{***}
	(0.02)	(0.03)	(0.03)	(0.03)
Leisure goods ($\widehat{\psi}_{Ef1}$)	0.33^{***}	-1.12^{***}	-0.92^{***}	-0.94^{***}
	(0.07)	(0.20)	(0.17)	(0.12)
Male × θ_w ($\widehat{\beta}_{\theta_w,male}$)	–	–	0.39^{*}	0.40^{***}
			(0.21)	(0.15)
Age × θ_w ($\widehat{\beta}_{\theta_w,age}$)	–	–	2.63^{**}	2.61^{***}
			(1.11)	(0.64)
Kids × θ_w ($\widehat{\beta}_{\theta_w,kids}$)	–	–	-0.49^{*}	-0.46^{***}
			(0.26)	(0.17)
Educ. × θ_w ($\widehat{\beta}_{\theta_w,educ.}$)	–	–	0.23^{*}	0.21^{**}
			(0.13)	(0.10)
Inc. × θ_w ($\widehat{\beta}_{\theta_w,income}$)	–	–	0.28	0.29^{***}
			(0.17)	(0.09)
Male × Ψ ($\widehat{\beta}_{\Psi,male}$)	–	–	0.22	0.22^{**}
			(0.14)	(0.10)
Age × Ψ ($\widehat{\beta}_{\Psi,age}$)	–	–	1.85^{***}	1.86^{***}
			(0.52)	(0.33)
Kids × Ψ ($\widehat{\beta}_{\Psi,kids}$)	–	–	-0.29^{**}	-0.27^{***}
			(0.14)	(0.10)
Educ. × Ψ ($\widehat{\beta}_{\Psi,educ.}$)	–	–	0.09	0.08
			(0.09)	(0.07)
Male × θ_{Tf1} ($\widehat{\beta}_{\theta_{Tf1},male}$)	–	–	-0.04	-0.04^{*}
			(0.03)	(0.02)
Age × θ_{Tf1} ($\widehat{\beta}_{\theta_{Tf1},age}$)	–	–	0.49^{***}	0.45^{***}
			(0.13)	(0.09)

Continued on next page

Table 3.4 – *Continued from previous page*

	BASE Coef./(SE)	EXP Coef./(SE)	INTER Coef./(SE)	TUMIX Coef./(SE)
Couple × θ_{Tf1} ($\widehat{\beta}_{\theta_{Tf1},couple}$)	–	–	−0.03	−0.02
			(0.02)	(0.02)
Urban × θ_{Tf1} ($\widehat{\beta}_{\theta_{Tf1},urban}$)	–	–	0.05*	0.04**
			(0.03)	(0.02)
Educ. × θ_{Tf1} ($\widehat{\beta}_{\theta_{Tf1},educ.}$)	–	–	0.03	0.03*
			(0.02)	(0.02)
Inc. × θ_{Tf1} ($\widehat{\beta}_{\theta_{Tf1},income}$)	–	–	−0.05	−0.04
			(0.05)	(0.03)
Male × ψ_{Ef1} ($\widehat{\beta}_{\psi_{Ef1},male}$)	–	–	0.29*	0.30***
			(0.15)	(0.11)
Age × ψ_{Ef1} ($\widehat{\beta}_{\psi_{Ef1},age}$)	–	–	2.01**	1.93***
			(0.79)	(0.46)
Kids × ψ_{Ef1} ($\widehat{\beta}_{\psi_{Ef1},kids}$)	–	–	−0.29*	−0.28***
			(0.15)	(0.11)
Educ. × ψ_{Ef1} ($\widehat{\beta}_{\psi_{Ef1},educ.}$)	–	–	0.16	0.15*
			(0.10)	(0.08)
Inc. × ψ_{Ef1} ($\widehat{\beta}_{\psi_{Ef1},income}$)	–	–	0.17	0.18**
			(0.15)	(0.08)
SD work. time ($\widehat{\sigma}_{\theta_w}$)	–	–	–	*n.r.*
SD free. cons. goods ($\widehat{\sigma}_{\Psi}$)	–	–	–	0.12**
				(0.05)
SD out-of-home leis. ($\widehat{\sigma}_{\theta_{Tf1}}$)	–	–	–	0.11***
				(0.02)
SD leisure goods ($\widehat{\sigma}_{\psi_{Ef1}}$)	–	–	–	0.19***
				(0.04)
# estimated parameters	4	4	24	28
# respondents	362	362	362	362
# draws	–	–	–	2000
R^2: T_w^* equation	0.73	0.73	0.73	0.77
R^2: $Tf1^*$ equation	0.64	0.64	0.67	0.75

Continued on next page

Table 3.4 – *Continued from previous page*

	BASE Coef./(SE)	EXP Coef./(SE)	INTER Coef./(SE)	TUMIX Coef./(SE)
R^2: $Ef1^*$ equation	0.30	0.30	0.41	0.57
$\mathcal{LL}_{null}$	–	−6304.15	−6304.15	−6304.15
$\mathcal{LL}_{final}$	−5592.85	−5592.85	−5528.83	−5510.05
AICc	11193.81	11193.81	11109.22	11080.97

– : Not included in the model. *n.r.* : Not reported in the table because |t-value| < 1.

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

Finally, the estimated standard deviations of the random components are significant for Ψ, θ_{Tf1} and ψ_{Ef1} and substantial relative to the main effect estimates: Unobserved heterogeneity is most pronounced for the baseline utility of freely chosen leisure expenditures ($Ef1$), followed by out-of-home leisure time ($Tf1$) and overall freely chosen expenditures relative to time. In all cases, the INTER and TUMIX coefficients are not significantly different, but slightly increase (in absolute values) in the latter model. At the same time, estimation efficiency increases remarkably (i.e. throughout smaller standard errors in the TUMIX model).

Of note, the overall model fit only increases marginally relative to the INTER model (AICc decreases by 18 units): Obviously, by using aggregated observations for each respondent, accounting for unobserved heterogeneity is not affecting results that strongly as in the case with panel data. However, the explained variance (R^2) for each equation reported in Table 3.4 at the bottom indicates that the fit substantially increases when including the random components, especially in case of the $Ef1^*$ equation (increase in R^2 by 27%-points relative to the BASE model) followed by the $Tf1^*$ equation (increase in R^2 by 11%-points). This shows that adding this additional layer of complexity helps to achieve a closer fit with respect to the three main equations used to estimate the VoL.

3.4.1 *VoL heterogeneity in respondent characteristics*

To predict the sample distribution of the VoL in the TUMIX model, first the conditional baseline utility estimates are calculated as the most likely mean values for each respondent (using R = 2'000 draws), conditional on observed behavior and fitted baseline utility distributions, by applying Bayes' rule (Equation (3.20); see e.g. Revelt and Train, 2000; Hess et al., 2005; Train, 2009; Schmid and Axhausen, 2019b; Schmid et al., 2019a):

$$\widehat{\Lambda}_{x,n} = \frac{\sum_{r=1}^{R}\left[f(\epsilon_n|X_n, Z_n, \widehat{\Omega}, \widehat{\Sigma}, \rho^r_{x,n})\Lambda^r_{x,n}\right]}{\sum_{r=1}^{R} f(\epsilon_n|X_n, Z_n, \widehat{\Omega}, \widehat{\Sigma}, \rho^r_{x,n})} \tag{3.20}$$

where $\Lambda^r_{x,n}$ corresponds to a baseline utility coefficient according to Equation (3.8) for a given individual and draw. Then, the resulting conditional baseline utility coefficients $\widehat{\Psi}_n$ and $\widehat{\theta}_{w_n}$ are inserted into Equation (3.11) to obtain the optimal time assigned to work, $\widehat{T_w}^*$. Finally, $\widehat{\Psi}_n$ and $\widehat{T_w}^*$ are inserted into Equation (3.14), and the VoL is calculated according to

$$\widehat{VoL}_n = \frac{w \cdot \widehat{T_w}^* + Y - Ec}{\widehat{\Psi}_n(\tau - \widehat{T_w}^* - Tc)} \tag{3.21}$$

representing the marginal rate of substitution between available time and money for freely chosen activities and expenditures (subject to satiation).

Table 3.5 presents the results of the VoL from the three different models presented above: The BASE[16] model exhibits a median VoL of about 28.8 CHF/h, which is about 60% of the median wage rate of 49.5 CHF/h in the sample (i.e. the VoL/w-ratio lies in the lower range compared to previous studies shown in Table 3.1). This value is again decreasing when accounting for respondent heterogeneity (by the inclusion of interaction effects and random components) to about 52% (median VoL $\approx$ 23 CHF/h; see also Figure 3.4).[17] Note that a similar result has been obtained by Mas and Pallais (2019) for the U.S., using experimental data of job applicants on randomized wage rate vs. working hour bundles, coming up with VoL/w-ratio of 58%. Although the obtained VoL is close to the one reported in Jara-Diaz et al. (2008) for Thurgau, Switzerland (26.7 CHF/h), the average wage rate was also substantially lower (30.4 CHF/h), exhibiting a much higher VoL/w-ratio of 88%. As shown by Jara-Diaz (2007) and others, our relatively low VoL/w-ratio implies that the value of time assigned to work (VTAW) is substantial and negative in all models (median = -22.4 CHF/h in the TUMIX), meaning that the typical respondent only works for the money and dislikes work as an activity.

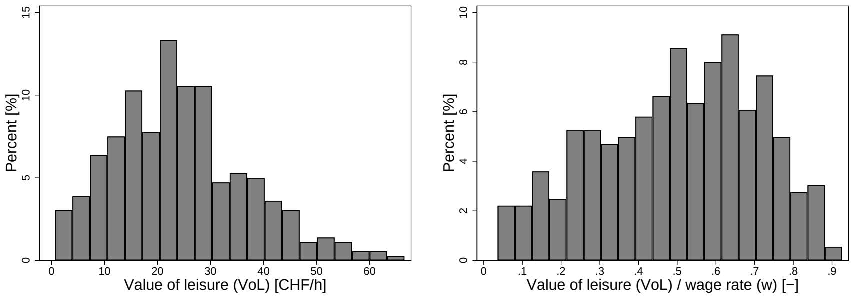
Results in Table 3.5 indicate that there is a substantial amount of heterogeneity in the VoL with respect to the different population segments de-

16 Again, note that the EXP model would yield exactly the same results.
17 The correlation between the VoL resulting from the BASE and TUMIX model is +0.64.

TABLE 3.5: Median VoL and VTAW [CHF/h] and interquartile range (IQR) for each model and segment. Last column: Standard deviation (SD) of working time [h/week] in the full sample and each segment.

	BASE	INTER	TUMIX	N	SD(T_w)
Median VoL	28.8	23.4	22.9	362	12.8
Mean VoL	32.3	25.3	24.8		
IQR	(22.8)	(16.4)	(16.9)		
Median(VoL / wage)	0.60	0.52	0.52		
Mean(VoL / wage)	0.57	0.51	0.50		
IQR	(0.21)	(0.32)	(0.32)		
Median VTAW	−19.3	−22.0	−22.4		
Mean VTAW	−23.0	−30.1	−30.5		
IQR	(12.0)	(23.9)	(24.2)		
VoL_{female}	22.3	23.1	23.0	181	12.7
VoL_{male}	36.0	23.9	22.9	181	9.3
$VoL_{rural/agglo.}$	28.4	23.3	22.9	214	13.0
VoL_{urban}	29.3	23.7	22.9	148	12.5
$VoL_{age_{<median}}$	27.9	26.4	26.1	176	12.2
$VoL_{age_{\geq median}}$	29.1	20.3	20.5	186	13.5
$VoL_{no\ kids}$	28.6	18.0	18.1	188	12.7
$VoL_{with\ kids}$	28.9	29.5	28.9	174	12.9
$VoL_{low\ educ.}$	20.3	20.6	20.5	142	13.6
$VoL_{high\ educ.}$	33.8	25.5	25.5	220	11.1
$VoL_{income_{<median}}$	19.1	20.1	19.8	178	12.5
$VoL_{income_{\geq median}}$	39.9	27.4	27.0	184	9.5
VoL_{single}	28.4	20.9	20.7	139	10.4
VoL_{couple}	29.1	26.1	25.5	223	14.1

FIGURE 3.4: Value of leisure (VoL) distribution [CHF/h], and in relation to the individual wage rate (TUMIX; N = 362).



fined in Section 3.2.3. For all models we used ex-post segmentation of the values calculated according to Equation (3.21). There are some notable differences between the BASE model and the interaction models (INTER and TUMIX), with the latter approach showing more heterogeneous values between the segments except for gender, education and income. Importantly, while in Hössinger et al. (2019) we argue that the full interaction model is less appropriate, as the large number of degrees of freedom makes the estimation process sensitive to the variance of working time within each segment (i.e. increasing VoL for a decreasing variance in T_w), this is not the case here. In fact, especially in the segments men, high income and high education, where the standard deviation of T_w tends to be substantially lower (see last column in Table 3.5), the interaction models show more moderate fluctuations around the median than the BASE model. One explanation for this improved robustness of the segment-specific VoL could be the inclusion of fixed income (with exhibits a substantially larger share in Switzerland than Austria), partially smoothing the increased income differences that result from distinct labor conditions in those segments.

Focusing on the TUMIX model, the presence of children in the household exhibits the strongest VoL heterogeneity: As discussed in Jara-Diaz et al. (2013), children require a lot of time, which translates into more time pressure and/or stronger preferences for leisure activities compared to childless households, increasing the VoL to 28.9 CHF/h. The second strongest effect is found for income, as expected increasing the VoL to 27.0 CHF/h, although to a much lower extent than in the BASE model. Similarly, while gender exhibits a very strong VoL heterogeneity in the BASE model, the differences almost vanish in the TUMIX model: Although men and high income respondents tend to work more and have more available money, their baseline utility of freely chosen expenditures relative to time is also significantly higher, leading to a median VoL more similar to the one of women and low income respondents than in the BASE model.

Where does the heterogeneity in the VoL exactly come from? According to Equation (3.21), it is useful to look at the VoL as the multiplication of two terms: A taste coefficient or *preference-driven* component (i.e. resulting from the estimated baseline utility parameter of freely chosen expenditures relative to time, $\widehat{\Psi}_n$) and an expenditure rate or *data-driven* component (i.e. the purchasing power for freely chosen goods per unit of freely assigned time available to spend it; Jara-Diaz and Ortúzar (1989)). The data-driven component directly results from the observed wage rate w, time assigned to work T_w^*[18], fixed income Y, committed time Tc and expenditures Ec.

Taking the logarithm of Equation (3.21) allows to empirically disentangle the VoL in an elegant way, which, according to Equation (3.22), now is the sum of the two terms explained above. Intuitively, the signs in Equation (3.22) indicate that having (i) a **lower** preference for goods relative to time and (ii) a **higher** purchasing power per unit of time available to spend it are associated with a higher VoL. The latter term (i.e., the expenditure rate) can be further split up into (i) available money for freely chosen goods and (ii) available time for freely assigned activities, where the signs indicate that having **more** *available money* and **less** *available time* are associated with a higher VoL. Importantly, this decomposition not only helps to better understand the sources of heterogeneity in the VoL, but also to analyze its sensitivity with respect to the data quality and structure.

$$\begin{aligned}\log(\widehat{VoL_n}) &= -\log\underbrace{\left(\widehat{\Psi}_n\right)}_{\text{pref.}} + \log\underbrace{\left(\frac{w\cdot\widehat{T_w}^* + Y - Ec}{\tau - \widehat{T_w}^* - Tc}\right)}_{\text{expenditure rate}} \\ &= -\log\underbrace{\left(\widehat{\Psi}_n\right)}_{\text{pref.}} + \log\underbrace{\left(w\cdot\widehat{T_w}^* + Y - Ec\right)}_{\text{avail. money}} - \log\underbrace{\left(\tau - \widehat{T_w}^* - Tc\right)}_{\text{avail. time}}\end{aligned} \tag{3.22}$$

18 Strictly speaking, $\widehat{T_w}^*$ is – to some extent – also preference-driven, given the inclusion of both $\widehat{\Psi}_n$ and $\widehat{\theta}_{w_n}$ to calculate $\widehat{T_w}^*$. However, given the very high correlation of observed T_w and $\widehat{T_w}^*$ of +0.88, we use the term *data-driven*.

TABLE 3.6: Correlations between the VoL and its components (TUMIX).

	log(VoL)	log(pref.)	log(money)	log(time)
log(pref.)	-0.31^{***}	1		
log(money)	$+0.44^{***}$	$+0.44^{***}$	1	
log(time)	-0.46^{***}	-0.07	$+0.23^{***}$	1
log(exprate)	$+0.71^{***}$	$+0.44^{***}$	$+0.74^{***}$	-0.49^{***}

pref. = preference component; money = available money component; time = avail. time component; exprate = expenditure rate (data-driven component)

Significance levels: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

The correlation analysis in Table 3.6 of the log(VoL) and its three components shows that all of them contribute more or less equally to the VoL heterogeneity, with the *available time* component exhibiting the strongest correlation (–0.46), followed by the *available money* (+0.44) and the *preference* (–0.31) component. It also shows that freely disposable money is positively correlated (+0.44) with the preference for freely chosen expenditures relative to time, while more freely available time is positively associated with disposable money (+0.23). Furthermore, the expenditure rate exhibits a very strong and positive correlation with the VoL (+0.71), indicating that the data-driven component clearly dominates the preference component. This highlights the basic structure of the VoL, where a high data quality plays a twofold crucial role in getting proper VoL estimates – not only regarding the estimation of unbiased baseline utility parameters, but also when finally calculating the VoL according to Equation (3.21).

With regard to the modeling structure, this decomposition nicely illustrates that if the interaction effects would be neglected in the model, Equation (3.22) shows that heterogeneity in the VoL could only result from the *data-driven* component; the *preference* component would stay constant across respondents, which clearly seems to be a too simplified assumption.

Table 3.7 completes the analysis by investigating which respondent characteristics actually affect the data-driven components of the VoL, showing that (i) older and male respondents with high income and education have significantly more available money for freely chosen goods and (ii) older respondents with kids have significantly less available time for freely chosen activities. While both (i) and (ii) are directly associated with a higher VoL (via a higher expenditure rate), results shows that the preference-driven component is higher for older and male respondents with high income

Table 3.7: Correlations between respondent characteristics, the VoL and its components (TUMIX).

	log(money)	log(time)	log(exprate)	log(pref.)	log(VoL)
Age [years]	$+0.34^{***}$	-0.12^{**}	$+0.39^{***}$	$+0.78^{***}$	-0.19^{***}
Male	$+0.33^{***}$	-0.09	$+0.36^{***}$	$+0.49^{***}$	$+0.00$
High educ.	$+0.27^{***}$	-0.07	$+0.29^{***}$	$+0.19^{***}$	$+0.16^{***}$
Urban res. loc.	$+0.04$	$+0.05$	$+0.00$	-0.00	$+0.01$
Couple	$+0.03$	-0.09^{*}	$+0.09$	-0.02	$+0.10^{*}$
Kids	-0.10^{*}	-0.12^{**}	$+0.00$	-0.55^{***}	$+0.43^{***}$
Inc. [CHF]	$+0.62^{***}$	-0.10^{*}	$+0.63^{***}$	$+0.38^{***}$	$+0.37^{***}$

Money = available money component; time = available time component; exprate = expenditure rate; pref. = preference component

Significance levels: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

and education, such that the total effects on the VoL tend to cancel out (thus dampening the segment-specific deviations in Table 3.5 compared to the BASE model, with income still exhibiting the second strongest effect; correlation = +0.37), or are even reversed as in the case of age. In contrast, it shows that the positive effect of kids in the household on the VoL mainly results from a significantly lower baseline utility of freely chosen goods relative to time, after all exhibiting the strongest total effect on the VoL (correlation = +0.43). The correlation between the VoL and expenditure rate is essentially zero: Although respondents with kids have less available time, they also exhibit less available money, such that these effects tend to cancel out.

3.4.2 *Sensitivity analyses*

Data preparation is a crucial issue in time-use modeling: Several assumptions were imposed regarding the time assignment and expenditure allocation among household members, the classification of committed and freely chosen activities and expenditures, as well as the inclusion of fixed income, which was imputed from another dataset (and thus deserves a more complete investigation). All of them are more or less debatable (see also the discussions in Section 3.2) and involve an additional layer of uncertainty that is more of conceptual nature. Therefore, the subsequent sensitivity analyses give an idea to what extent and in which direction the VoL is influenced by changing those assumptions.

Eight insightful scenarios were elaborated, and for each of them a simple time-use model (without interaction terms and random components) is estimated and compared with the results of the BASE model[19], where the obtained median VoL was 28.8 CHF/h. Results are presented in Table 3.8 and Table 3.9.

Scenario 1: No fixed income

Given that income from other sources but paid work was imputed based on an external dataset, we tested the sensitivity of results in the case where income is only generated from labor (i.e. $Y = 0$). Results indicate that the median VoL would be 19.9 CHF/h (31% lower compared to the BASE model) and neglecting this source of income would lead to a severe underestimation of the VoL. The difference arises from less available money and a higher estimate of Ψ (baseline utility of freely chosen goods relative to time), as $Ef1$ and $Ef2$ remain constant but increase relative to income, such that marginal utility of income also increases. The effect of θ_w becomes much stronger and the expenditures have more statistical influence on the working time than in the BASE model (see also the increased R^2 of the T_w^* equation of 0.82 compared to 0.73 in the BASE model), with labor income now being the only income-generating source in the model.

Scenario 2: Equal distribution of fixed income among household members

We investigated the implications of a cooperative version of the model with respect to Y, where fixed income is distributed equally among household members (instead of a proportional distribution according to labor income). Results indicate that the median VoL would be 31.0 CHF/h (8% higher compared to the BASE model). The difference arises from a lower estimate of Ψ: The implicit transfer of income between household members implies that the expenditures have less statistical influence on the working

19 This is done mainly for practical concerns: The full models make things much more complicated when analyzing and discussing the results. This sensitivity analysis should mainly serve as a qualitative check on what happens if the basic structure of the main input variables changes, which – we assume – is mostly unaffected by the inclusion of additional socioeconomic variables and random effects. Also, one only needs to investigate the behavior of four parameters, which may allow clearer statements about the effects of a change in the input variables. Furthermore, the BASE model comes closest to the state of the art in the literature, so it allows a better comparison with other studies.

TABLE 3.8: Time-use model sensitivity analyses I. S1: No fixed income. S2: Equal distribution of fixed income among household members. S3: Increase in fixed income by 20%. S4: Decrease in fixed income by 20%.

	S1 Coef./(SE)	S2 Coef./(SE)	S3 Coef./(SE)	S4 Coef./(SE)
Working time ($\widehat{\theta}_w$)	-2.02^{**}	-0.77^{***}	-0.68^{***}	-1.16
	(0.81)	(0.27)	(0.19)	(1.07)
Freely cons. goods ($\widehat{\Psi}$)	1.01^{***}	0.76^{***}	0.80^{***}	0.91^{**}
	(0.24)	(0.11)	(0.09)	(0.41)
Out-of-home leisure ($\widehat{\theta}_{Tf1}$)	0.68^{***}	0.68^{***}	0.67^{***}	0.68^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Leisure goods ($\widehat{\psi}_{Ef1}$)	0.50^{***}	0.29^{***}	0.28^{***}	0.36^{**}
	(0.13)	(0.05)	(0.04)	(0.18)
# parameters	4	4	4	4
# respondents	363	362	361	362
R^2: T_w^* eq.	0.82	0.76	0.70	0.74
R^2: $Tf1^*$ eq.	0.67	0.65	0.63	0.65
R^2: $Ef1^*$ eq.	0.35	0.28	0.27	0.31
$\mathcal{LL}_{final}$	-5530.38	-5577.55	-5593.36	-5582.53
med. VoL [CHF/h]	19.9	31.0	32.5	26.6
Deviation [%][1]	-31	$+8$	$+13$	-8
med. (VoL / wage)	0.42	0.65	0.68	0.56

[1] : %-deviations are calculated relative to the BASE model (median VoL = 28.8 CHF/h).

Robust standard errors: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

time (which still remains the same across household members; similar, but reversed mechanism as in scenario 1), and that on average (within households), the marginal utility of income decreases.

Scenario 3: Increase in fixed income by 20%

Given that Y was imputed with uncertainty, we investigated the implications of an increase in fixed income by 20%. Results indicate that the median VoL would increase to 32.5 CHF/h (13% higher compared to the BASE model). The difference arises from a lower estimate of Ψ and more available money for freely chosen goods (similar, but reversed mechanism as in scenario 1).

Scenario 4: Decrease in fixed income by 20%

Results indicate that the median VoL would decrease to 26.6 CHF/h (8% lower compared to the BASE model). The difference arises from a higher estimate of Ψ and less available money for freely chosen goods (similar mechanism as in scenario 1).

Scenarios 3 and 4 indicate that a change in fixed income is associated with a smaller change in the VoL, exhibiting an inelastic although still substantial response. Given all these findings, explicitly asking for fixed income resulting from shares, rents and other transfer payments should receive a high priority in future time-use studies, eliminating the need for imputation based on an external dataset (which always remains subject to uncertainty).

Scenario 5: Equal expenditures on freely chosen goods

We investigated the implications of a cooperative version of the model with respect to Ef_j, where household expenditures on freely chosen goods are equally distributed among household members (instead of a proportional distribution according to labor income). Results indicate that the median VoL would be 32.1 CHF/h (11% higher compared to the BASE model). The difference arises from a lower estimate of Ψ: The implicit transfer of income between household members implies that the expenditures have less statistical influence on the working time (similar, but reversed mechanism as in the scenario without fixed income), because freely chosen expenditures are equalized, but T_w still differs between members of the same household. This results in a lower sensitivity of T_w with respect to changes in expenditures, and consequently a higher VoL.

Scenario 6: Classification of committed expenditures

The variables created to estimate the VoL are based on several assumptions regarding the committed nature of expenditures. We believe that Ec tends to be overestimated (and expenditures on freely chosen goods underestimated), as respondents do not necessarily stick to the technical minimum in those categories: Some respondents drive luxury cars, live in fancy apartments and eat high quality food – things that are classified as committed, but clearly may exceed the basic needs. We therefore investigated a scenario where *Ec* is decreased by 20% and at the same time $Ef1$ and $Ef2$ were increased proportionally (such that the total expenditures remain constant). Results indicate that the median VoL would be 17.5 CHF/h (39% lower compared to the BASE model). While available money for freely chosen goods increases (ceteris paribus, increasing the VoL), the baseline utility of freely chosen expenditures relative to time increases to an even stronger extent ($\widehat{\Psi}$ more than doubles compared to the BASE model). Remember that the satiation effect implies a decreasing marginal utility for an increasing input. Given that $Ef1$ and $Ef2$ are uniformly higher now, the corresponding baseline utility (i.e. the marginal utility of the first unit consumed) must also be higher.[20]

Scenario 7: Classification of committed time

The variables created to estimate the VoL are based on several assumptions regarding the committed nature of activities. Similar to the previous scenario, we believe that *Tc* tends to be overestimated (and time assigned to freely chosen activities underestimated), as respondents do not necessarily stick to the technical minimum in those categories: Some respondents enjoy to sleep longer, like to clean their apartment and spend more time on shopping at the local Zurich mart than needed – things that are classified as committed, but clearly may exceed the basic needs. We therefore investigated a scenario where *Tc* is decreased by 20% and at the same time $Tf2$ is increased proportionally (assuming that out-of-home leisure $Tf1$ was measured much more precisely, and that mainly in-home leisure $Tf2$ is underestimated) such that the total time budget remains constant. Results indicate that the median VoL would be 34.7 CHF/h (20% higher compared to the BASE model): Similar to the previous scenario, while the available time for freely chosen activities increases (ceteris paribus, decreasing the VoL), the baseline utility of goods consumption relative to time decreases to an even higher extent.

20 We run an additional model (results not reported) to investigate the case, where $Ef1$ and $Ef2$ only correspond to expenditures that can be considered as entirely freely chosen (i.e. holidays, accommodation and leisure; those were part of $Ef1$) without satisfying any basic needs (i.e. clothes, accessories and electronics; those were part of $Ef2$). Thus, $Ef1$ now corresponds to holidays and accommodation and $Ef2$ to leisure, while clothes, accessories and electronics are now included in *Ec*. As expected, the median VoL increases (30.0 CHF/h; +4%), but results are very similar to the BASE model.

Scenario 8: Single worker households

By only considering single worker households, there would be not need for a proportional expenditures factor to equally assign household expenditures to the different income-generating household members, which clearly can be seen as a debatable assumption. Results indicate that the median VoL of the household head in single worker households would be 33.7 CHF/h (17% higher compared to the BASE model), mainly resulting from a lower estimate of Ψ. Also, workers in such households exhibit a substantially higher income and working time than their counterparts, which both tend to increase the VoL.

TABLE 3.9: Time-use model sensitivity analyses II. S5: Equal distribution of freely chosen expenditures among household members. S6: Decrease in committed expenditures Ec by 20%, proportional increase in $Ef1$ and $Ef2$; S7: Decrease in committed time Tc by 20%, proportional increase in $Tf2$; S8: Model only including single worker households.

	S5 Coef./(SE)	S6 Coef./(SE)	S7 Coef./(SE)	S8 Coef./(SE)
Working time ($\widehat{\theta}_w$)	-0.70^{***}	-2.49^{*}	-0.31^{***}	-0.84
	(0.19)	(1.33)	(0.10)	(0.54)
Freely cons. goods ($\widehat{\Psi}$)	0.76^{***}	1.99^{***}	0.41^{***}	0.78^{***}
	(0.09)	(0.69)	(0.04)	(0.22)
Out-of-home leisure ($\widehat{\theta}_{Tf1}$)	0.67^{***}	0.68^{***}	0.39^{***}	0.65^{***}
	(0.02)	(0.02)	(0.01)	(0.03)
Leisure goods ($\widehat{\psi}_{Ef1}$)	0.26^{***}	0.80^{***}	0.14^{***}	0.31^{***}
	(0.03)	(0.29)	(0.02)	(0.10)
# parameters	4	4	4	4
# respondents	362	361	362	77
R^2: T_w^* eq.	0.74	0.70	0.74	0.68
R^2: $Tf1^*$ eq.	0.65	0.63	0.61	0.70
R^2: $Ef1^*$ eq.	0.24	0.51	0.25	0.20
$\mathcal{LL}_{final}$	−5572.64	−5638.28	−5693.59	−1180.48
med. VoL [CHF/h]	32.1	17.5	34.7	33.7
Deviation [%][1]	+11	−39	+20	+17
med. (VoL / wage)	0.67	0.37	0.73	0.65

[1] : %-deviations are calculated relative to the BASE model (median VoL = 28.8 CHF/h).

Robust standard errors: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

3.5 CONCLUSIONS

The value of leisure (VoL) is estimated for a dataset, where most information required for modeling has been collected from the same individuals at the same time in a diary-based format: While the duration of non-travel activities, including out-of-home leisure, was inferred from the trip purposes in the travel diary, the duration of in-home leisure activities (approximated by online/tele entertainment) as well as expenditures on a daily (at the individual-level) and yearly (at the household level) basis were asked in additional questionnaires. Enormous efforts were undertaken to clean and prepare the data (including the imputation of fixed income from the Swiss household budget survey) and to come up with effective assumptions to aggregate the different time-use and expenditure categories.

The sample median of 23 CHF/h (when controlling for observed and unobserved heterogeneity) indicates that the VoL is about half of the wage rate (52%), and that for our typical Zurich respondent, the consumption of freely chosen goods exhibits a relatively high importance relative to time. The obtained VoL/w-ratio is at the lower bound compared to previous studies and broadly reflects the relatively low leisure relative to goods consumption preferences of Swiss individuals. Clearly supporting this finding, the national referendum in 2012, where the majority of Swiss citizens (66.5%) voted against the obligatory warranty of six weeks holidays per year, also attracted international media attention.[21] Comprehensive sensitivity analyses have shown that the VoL/w-ratio – although fluctuating substantially – is always well below one, indicating that this general statement seems quite robust and that the value of time assigned to work (VTAW) is negative, meaning that the typical respondent mainly works for the money and dislikes work as an activity.

The obtained VoL serves as a basis to decompose the value of travel time savings (VTTS) obtained in the subsequent chapter, allowing to calculate all components of the complete Jara-Diaz and Guevara (2003) model formulation for the first time at the individual-level. As a result, the value of time assigned to travel (VTAT) can be calculated, which represents the direct (dis-)utility derived from the time spent on traveling – which is why it also relates to conditions of travel. The VoL represents the value of the liberated time when travel time is reduced: This holds under the crucial assumption that travel is a committed activity, where individuals try to stick to a necessary minimum.

21 See e.g. www.bbc.com from March 2012 (last access: July 27, 2019).

The VoL can be decomposed into two main elements: The preference-driven part corresponds to the baseline utility of freely chosen goods relative to time and expresses the trade-off between time and money when the first unit is consumed. The data-driven part expresses the amount of available money relative to time for freely chosen goods and activities, which then is scaled with the preference component to obtain the VoL, reflecting the marginal rate of substitution between time and money subject to satiation. This decomposition helps to better understand the sources of heterogeneity in the VoL: It shows that all components (i.e. preference for freely chosen goods relative to time, available money and available time) contribute more or less equally to the VoL. Importantly, it also reveals the origin of the differences in the VoL for different respondent characteristics. For example, the strongest heterogeneity in the VoL is found in the presence of kids in the household, showing that respondents with children exhibit a substantially higher VoL of about 28.9 CHF/h: They have a significantly weaker preference for goods relative to time and also exhibit less available time, such that the the total effect on the VoL is even amplified. High income respondents, although exhibiting more available money and less available time, also have a higher preference for goods relative to time, such that the total effect on the VoL is dampened (but still positive and substantial). Similarly, older respondents have more available money and less available time, but such a strong preference for goods relative to time, that the total effect on the VoL is even reversed. These findings are linked to an important mechanism of the model which is related to satiation: Consuming more freely chosen goods (as e.g. done by older and high income respondents) is also associated with a higher baseline utility of goods consumption. Results stand in contrast to the basic time-use model, where no interaction terms with the baseline utilities are included and the preference-driven part remains constant across respondents.

Going ahead towards the practical usability of the values of time obtained from time-use models not only requires advanced econometric skills, but (possibly even more so) data of high quality, where the Austrian MAED dataset serves as a perfect example. Also, the decomposition of the VoL has shown that a high data quality plays a twofold crucial role: For the estimation of unbiased baseline utility parameters (i.e. the preference component) and the final calculation of the VoL (i.e. the data-driven component). Importantly, sensitivity analyses have shown that a proper specification of time-use and expenditure categories is crucial and that a mis-classification could lead to a substantial bias.

As one main limitation of the current analysis, the PCW dataset is only partially suitable to estimate the VoL, as no refined information was obtained on time-use for home activities (e.g. sleeping) and secondary activities (e.g. checking *facebook* while being at work). Also, the reporting quality of expenditures leaves room for improvement, which was a main drawback of the very high response burden of the study. Last but not least, even with the best data quality at hand, there will be always room for debate whether respondents actually *perceive* certain activities and expenditures as committed or freely chosen, for example by assigning more than the minimum necessary amount of time to certain activities; this would be an interesting and fruitful topic for further research.

4

THE VALUE OF TRAVEL TIME SAVINGS

Nothing happens until something moves.
— Albert Einstein

This chapter is based on Schmid et al. (2019a) published in *Transportation Research Part A: Policy and Practice*, using a similar modeling framework developed to investigate mode and user-type effects in the value of travel time savings for Austrian workers.

4.1 INTRODUCTION

Discrete choice models have been used extensively to evaluate policy implications and level-of-service (LOS) changes, providing a powerful transportation planning tool for developing effective travel demand forecasts (e.g. Ben-Akiva and Lerman, 1985; Bhat, 1998; Jara-Diaz, 2007; Ortúzar and Willumsen, 2011). As a key valuation indicator, the value of travel time savings (VTTS)[1] has always been subject to extensive debate in both academia and practice, because savings in travel time account for the biggest share of user benefits in most cost-benefit analyses (e.g. Jara-Diaz, 1990; Wardman and Lyons, 2016; Hensher et al., 2016).

Recent research has shown a trend towards a potentially more insightful way to decomposing the VTTS – typically derived from mode, route and/or destination choice models – into two separate elements:

$$VTTS_{i,n} = VoL_n - VTAT_{i,n} \tag{4.1}$$

Following Jara-Diaz and Guevara (2003), Jara-Diaz et al. (2008) and others[2], the VTTS in Equation (4.1) for mode i and individual n represents the willingness to pay to reduce travel time by one unit and is the sum of two components: (i) the value of leisure (VoL; also referred to as the value of time as a resource; see Chapter 3) representing the monetary equiva-

1 We use the old terminology "value of travel time savings" (instead of "value of travel time"; see e.g. Daly and Hess (2019)), which is in line with the more traditional literature on the microeconomic foundations of the value of time (e.g. Jara-Diaz, 2007).

2 See also the work of DeSerpa (1971), Truong and Hensher (1985), Bates (1987) and, for a good theoretical overview, Gonzalez (1997) and Jara-Diaz (2007).

lent to the willingness to substitute a restricted/committed activity (in this case, travel) in favor of other activities that generate more utility, and (ii) the monetary value of the reduction in direct (dis-)utility derived from the time assigned to travel (VTAT). The VoL is always positive and depends on the time assigned by the individual to all activities including travel and on their trade-offs. The VTAT depends on the conditions/comfort of travel and can be positive or negative; if negative, it contributes to increase the VTTS above the VoL[3]. If positive, the VTTS is lower than the VoL.

Importantly, what matters for cost-benefit analyses and related project evaluations is the VTTS. Hence, the question becomes, how the enormous efforts of obtaining the VoL are justified from a policy perspective? A shift of focus from the VTTS to its two components, i.e. the VoL and the VTAT, would help assessing options under a budget constraint.[4] For example, from a public transportation (PT) operator's point of view, it would allow a comparative evaluation of investments in (i) faster connections (captured by the VoL) or (ii) the conditions/quality of in-vehicle travel (captured by the VTAT), as schematically illustrated in Table 4.1:

Table 4.1: Hypothetical examples of policy recommendations when considering the VoL in addition to the VTTS under the assumption of decreasing marginal impacts of additional investments on user benefits.

VTTS [CHF/h]	VoL [CHF/h]	VTAT [CHF/h]	Invest in ...	Implication
20	5	−15	Conditions	VTTS ↓
20	20	0	Cond./speed	VTTS/travel time ↓
20	35	15	Speed	Travel time ↓

Assuming a *constant VTTS* and *decreasing marginal impacts of additional investments on user benefits*, a high VoL is reflected in a high VTAT, and investing in speed might be more beneficial (by eventually decreasing the travel time), since the opportunity costs of travel are relatively high, and the conditions of travel are already at a high level (thus leaving less room for improvement). On the other hand, a low VoL is reflected in a low VTAT,

3 This shows that for the VTTS to be negative (i.e. individuals are willing to pay to increase their travel time) the VTAT has to be larger than the VoL. For example, if the conditions of travel permits to read while traveling and the individual chooses to read in the vehicle, the value of reading while traveling should be larger than the value of reading at home for VTTS to be negative. We acknowledge Sergio Jara-Diaz who has clarified this issue at one of our project meetings in Vienna.

4 We acknowledge Sergio Jara-Diaz who has proposed this implication at one of our project meetings in Vienna.

and investing in the conditions of travel might be desired (by eventually decreasing the VTTS), since the opportunity costs of travel are relatively low, and the conditions of travel are at a low level (thus leaving more room for improvement). After all, one should note that the final policy recommendation crucially depends on the available budget, the investment costs of a specific action and the feasibility of the investment from an engineering perspective. Furthermore, the VTAT may receive increasing attention in the context of autonomous cars, since a release from the driving task enables secondary activities during travel similar as in PT (Jokubauskaite et al., 2019). Consequently, car travel time may be perceived as more useful, resulting in a higher VTAT and eventually a lower VTTS.

It is a common finding that the VTTS is lower for bus, tram and underground compared to car and rail, while car and rail tend to be valued similarly. This finding has not only been confirmed in large-scale meta-analyses (e.g. Wardman, 2004; Shires and de Jong, 2009), but also in recent national valuation studies, as reported in Table 4.2 for Sweden and the Netherlands.

Table 4.2: VTTS [Euro/h] for other European countries. Sweden: Börjesson and Eliasson (2014); Netherlands: Kouwenhoven et al. (2014); Germany: Axhausen et al. (2014); Switzerland 2010: Fröhlich et al. (2012); Switzerland 2015: Weis et al. (2017); Austria: Schmid et al. (2019a)

Country	Sweden	Netherl.	Germany	Switzerl.	Switzerl.	Austria[2]
Date of study	2008	2010	2012	2010	2015	2016
Car	12.6	9.8	4.8	12.0	11.0	12.3
Bus[1]	4.1	7.3	5.0	8.8	10.2	8.1
Train[1]	7.9	10.1	5.0	8.8	10.2	8.1

Inflation-adjusted values in 2015 prices. Source: ec.europa.eu/eurostat

[1] : In the German, Swiss and Austrian studies, bus and train are just one category "public transportation". [2] : The Autrian study only includes working respondents.

In the Austrian study, we find a substantial gap between the VTTS for car and PT, following a similar pattern as in Sweden and Switzerland for 2010. The valuation pattern is thus reversed to what one would expect based on the comfort typically associated with each of these modes. It implies that car travelers are willing to pay more to reduce travel time than PT users, and hence, that an equal increase in travel time in all modes would increase the mode share of bus, tram and underground. To a large extent, this (maybe counter-intuitive) finding can be attributed to two confounding effects: On the one hand, the mode effect[5] describes differences in the VTTS across modes that are due to differences in the direct utility derived from in-vehicle travel time. This utility is in turn driven by (latent) mode-specific characteristics that affect comfort and how well in-vehicle time can be used for secondary activities. On the other hand, differences in user-types may be due to observables such as socioeconomic characteristics (e.g. people with higher income may exhibit a lower travel cost sensitivity, leading to a higher VTTS), or may also be attributed to self-selection in terms of VTTS heterogeneity (e.g. Mabit and Fosgerau, 2009; Fosgerau et al., 2010): Travelers with a high opportunity value of time (reflected in the VoL) are likely to choose (and have access to) faster modes such as car, train or plane.[6]

Table 4.3 gives an overview of the indicators that are used to investigate mode and user-type[7] effects after controlling for a wide range of trip characteristics. Apart from the traditional modes typically investigated in valuation studies (i.e. MIV, PT, walk and bike), we also obtain VTTS estimates for emerging modes such as CS and CP, which is one of the main contributions of this chapter. While the MIV alternative is only available in the RP dataset, the CS and CP options were only included in the SP tasks. Only the PT, walk and bike options are available in both (RP/SP) datasets.

While the RP dataset – based on the one-week travel diary – allows to investigate travel behavior for multiple trips and different modes chosen by the same individual, the SP dataset allows a better analysis of trade-off behavior, e.g. between travel time and cost, which is often problematic in "pure" RP data due to the high correlations between attributes (e.g. Train, 2009). Furthermore, it also allows to investigate taste preferences for emerging modes, for which the market shares are still very low. For example, in Becker et al. (2017) we have shown that the share of subscribed CS members in Switzerland are barely exceeding 3% of the Swiss population, while the share of CP users is not even reported in the Swiss Microcensus for Mobility and Travel Behavior (MZMV) dataset. Therefore, applying a joint RP/SP modeling approach ensures robustness and efficiency in parameter estimation and also overcomes the limitations of pure RP or SP models (i.e. the former typically providing limited trade-off information

5 Other terms present in the literature are "comfort effect" (Fosgerau et al., 2010), "pleasantness effect" (Mackie et al., 2001) and "mode valued effect" (Wardman, 2004). We mainly follow the terminology used by Flügel (2014).

6 For instance, Börjesson and Eliasson (2014) find that some differences in the VTTS across modes can be attributed to differences in socioeconomic characteristics between user groups. However, a large part of the variation is due to idiosyncratic variation across trips.

7 See also the discussion on the inclusion of different user characteristics in Section 3.2.3.

TABLE 4.3: Mode, user and trip characteristics, and random components included in subsequent analyses.

Mode	User	Trip	Random
MIV	Sex	Distance	Error components
PT	Age	Purpose (work/education,	Scale
CS	Kids in HH	shopping, leisure, other)	VTTS
CP	Couple	Weekend vs. weekday	
Bike	Residential location area	Daily weather	
Walk	Education	Inertia (tour-based)	
	Personal income		

MIV: Motorized individual vehicle (car driver and motorbike.)

PT: Public transportation; CS: Carsharing; CP: Carpooling

only obtained for well-established modes, and the latter suffering from a hypothetical bias, anchoring effects and strategic behavior).

Mode effects can best be identified if, for the same group of users, the VTTS is measured for different modes, whereas user-type[8] effects can best be identified if the VTTS is observed for different user groups for the same mode. This, however, requires not only a large cross-sectional set of different respondents, but also multiple observations for one and the same individual over a longer time period and/or for different SP tasks, choosing differently among a set of travel modes for different kinds of trips. We use the term user-type such that it allows us to distinguish between different socioeconomic characteristics for respondents who have used (i.e. chosen) a specific mode at least once. Thanks to our comprehensive dataset at hand, this allows for a fair comparison between users who are "familiar" with specific modes when calculating the mode and user-type effects, accounting for a form of self-selection at the individual-level.

If the user-type effect is accounted for (i.e. by controlling for user characteristics in the model), the remaining mode-specific VTTS may indicate that, for example, the time spent in a car is valued less than in PT, hence, reversing the ordering that tends to emerge if the mode and user-type effects are confounded. However, recent technological innovations (smartphones etc.) enable PT passengers to use in-vehicle time more productively, which may in turn lead to a lower value attached to travel time savings in PT (e.g. Mokhtarian and Salomon, 2001; Litman, 2008; Hensher et al., 2016; Ward-

8 Note that in subsequent analyses, user-types correspond to a manifestation of a specific univariate segment with two levels, e.g. male/female or urban/non-urban residents.

man and Lyons, 2016; Weis et al., 2017). In particular, train travel time – especially for longer distances – can be used for engaging in all kinds of activities (Lyons et al., 2013). Additional explanations for the VTTS being lower for PT than for car are brought forward by Guevara (2017), suggesting that the higher VTTS for car may result from the marginal consumption being dependent on car travel time (including expenses for fuel, oil, maintenance, etc.) but not for PT trips, and that car use may induce more complex schedules for which time as a resource is valued higher.

Regarding the emerging modes, we expect the VTTS of MIV and CS to be similar (hence, a small mode effect), given their similarities in both comfort and handling. However, in Schmid et al. (2016) we argue that the VTTS of CP is expected to be higher, given the assumptions made in the SP experiments that the driver is unknown to the decision maker, probably resulting from the negatively perceived social interaction with the non-acquainted driver and thus showing a higher disutility of travel time.

Differences in the VTTS across modes have important implications for policy appraisals: The outcome of costs-benefit analyses and evaluation of shared mobility services may strongly depend on whether user-type and/or mode effects are removed from the VTTS (Flügel, 2014). It has been suggested that mode effects should not be removed as otherwise resources may be allocated inefficiently, while – for equity reasons – the removal of user-type effects seems advisable. In any case, a good understanding of the sources of differences in the VTTS across modes is crucial (see e.g. Mackie et al. (2001) and Börjesson and Eliasson (2014) for further discussions).

Finally, the VTTS estimates obtained in this chapter are used to calculate all components of the complete Jara-Diaz and Guevara (2003) model formulation according to Equation (4.1). Therefore, our results are combined with the corresponding VoL estimates from the time-use and expenditure allocation model presented in Chapter 3 for the same respondents. Having obtained both indicators at the individual-level by calculating the conditional parameter estimates, this allows us, for the first time, to test the following two hypotheses empirically:

- The VoL and VTTS are positively related: Ceteris paribus, individuals with a high opportunity value of time exhibit a higher willingness to pay to reduce travel time, since the liberated travel time could be used for other activities that generate more utility (i.e. leisure or work).

- The VTAT and VTTS are negatively related: For a constant VoL and for a given mode, it follows directly from Equation (4.1) that a improved travel conditions diminish the willingness to pay to reduce travel time.

The structure of this chapter is as follows: Section 4.2 explains the different data sources and attributes used to model choice behavior, while Section 4.3 discusses the issue of inertia typically observed when analyzing mode choice panel data. Section 4.4 presents the pooled RP/SP Mixed Logit modeling and estimation approach. Section 4.5 shows the estimation results of four models, serving as a basis to calculate the conditional mode-specific VTTS estimates. A formal definition of mode and user-type effects is presented in Section 4.5.1 and the mode-specific VTTS are investigated for different user-types. Section 4.5.2 presents a synthesis of results with the continuous time-use and expenditure allocation choice model, for the first time calculating the VTAT at the individual-level. Finally, an empirical investigation on the relationship between the VTTS, VoL and VTAT is presented in Section 4.5.2. Section 4.6 summarizes and discusses the main findings and limitations and gives an outlook on future work.

4.2 THE POOLED RP/SP MODE AND ROUTE CHOICE DATASET

The data used in subsequent analyses is based on a combination of all data/experiment types into one pooled data set, which is depicted in Table 4.4. The RP dataset comprises 8'692 choice observations of 356 working respondents (i.e. the same respondents used to estimate the VoL in Chapter 3), where not all alternatives are always available (availability conditions are similar to those used by Fröhlich et al. (2012), Weis et al. (2017) and Schmid et al. (2019a)):

- **MIV**: Available if a respondent has a driving license and stated that he/she always, often or sometimes has access to a car/motorbike. Note that car passenger choice observations were excluded in the final model specifications.[9]
- **PT**: Available if a PT route was identified in the network LOS files
- **Walk**: Always available if a route was identified
- **Bike**: Available if household owns ≥ 1 bikes

9 Besides the difficulties of defining the availability conditions for car passengers, the appropriate calculation of travel costs and how/if they were shared with the driver is also problematic. For a comprehensive discussion on this topic, see also Schmid et al. (2019a).

The SP dataset comprises 3'902 choice observations, with the biggest share resulting from the SP mode choice experiment (2'710 observations). Availability conditions (i.e. choice set assignment) in the SP experiments are discussed in Section 2.2. Detailed summary statistics for each data/experiment type are presented in the Appendix, Table A.6-Table A.9.[10]

The total number of choice observations per respondent ranges between nine and 90, thus having an unbalanced panel with an average of 38.2 observations per respondent, as illustrated in Figure 4.1a. For each data/experiment type q, availability conditions are pre-multiplied with the respective contribution to the Logit choice probability. This data structure allows for the estimation of scale parameters for each different data/experiment type to control for differences in error variance (Train, 2009).

Figure 4.1b presents the choice frequency by alternative in each data/experiment type. It shows that in the RP dataset, which includes about 65% of all observations, the market shares of MIV and PT are very similar (34% and 33%, respectively). Although this is not unexpected for the Canton of Zurich, given its very reliable, fast and comfortable PT services, the share of PT trips is clearly over-represented in the PCW sample, as already discussed in Chapter 2 (see also Table 2.16). Also, the market share of bike is considerably high (15%) and over-represented (see also Table 2.16), which is another typical pattern for Zurich in general and our sample in particular. This pattern is also reflected in the SP mode choice dataset. It shows that even in the complete absence of private cars, respondents considerably more often choose PT (mode share = 54%) rather than CS (16%) or CP (15%), while the mode share of bike is still relatively high (15%).[11]

The following attributes are included in the RP data and SP choice experiments, as listed below:

- **Travel cost**: Out-of-pocket (variable) travel cost (MIV, PT, CS and CP; attribute included in all data/experiment types)
- **Travel time**: In-vehicle travel time (all modes; attribute included in all data/experiment types)

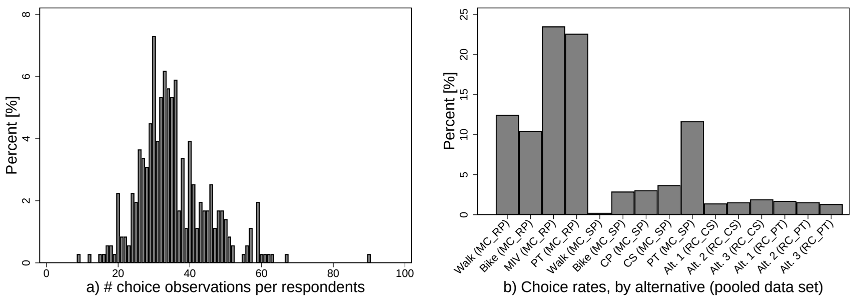
10 Experimental designs, the routing of mode alternatives, and the calculation of RP travel costs (MIV: See Section 2.2.3.1; PT: See Section 2.2.2.1; for respondents owning a national season ticket, we assumed a cost factor of 0.10 CHF/km; for respondents owning a regional season ticket, we assumed a cost factor of 0.10 CHF/km within the zone, and for larger distances the cost factors as shown in Table 2.3) and other LOS attributes are presented in Section 2.2.2.

11 Please note that market shares obtained from SP data are not very informative, since they depend on the experimental design and the attribute levels. The mode-specific constants are discussed in Section 4.5, but eventually come to the same conclusion: In the SP mode choice experiment, respondents strongly prefer PT and bike over CS and CP.

TABLE 4.4: Pooled data set: Overview.

Data/experiment type q	# choices	# indiv.	Available alternatives	Sum. stats.
RP mode choice (MC_RP)	8'692	356	Walk, bike, MIV, PT	Table A.6
SP mode choice (MC_SP)	2'710	339	Walk, bike, CP, CS, PT	Table A.7
SP route choice CS (RC_CS)	612	153	Unlabeled; 3 alts.	Table A.8
SP route choice PT (RC_PT)	580	145	Unlabeled; 3 alts.	Table A.9

FIGURE 4.1: Observations per individual and choice rates by experiment type.



– **Access and egress time**: Walking time to and from the pick-up/drop-off place/PT stop to the destination (CS, CP and PT; attribute included in all data/experiment types)

– **Number of transfers** (PT only; attribute included in MC_RP, MC_SP and RC_PT)

– **Headway**: PT service interval (PT only; attribute included in MC_RP, MC_SP and RC_PT)

– **Congestion time**: Time spent in a congested road network (CS only; attribute included in RC_CS)

– **Risk of missing the driver**: Probability of missing the ride (CP only; attribute included in MC_SP)[12]

In addition, the following trip and daily weather characteristics were considered to be important variables to explain choice behavior:

12 Note that we did not include this attribute for PT: If one misses a train/bus in Switzerland, it is typically the person's own fault. In the case of CP, however, the driver may have problems to locate the passenger (or other reasons for skipping the service), which was considered as a relevant attribute.

- **Distance**: Crowfly distance (continuous)
- **Trip purpose**: Dummy coded with levels "work/education", "shopping", "leisure" and "other" (= reference)[13]
- **Day of week**: Dummy coded with levels "weekend" and "weekday" (= reference; RP data only)
- **Air temperature**: Dummy coded with levels $< 8°C$, 8-15°C (= reference) and $> 15°C$ (RP data only)
- **Sunshine duration**: Dummy coded with levels $\leq 3.5h$ (= reference) and $> 3.5h$ per day (RP data only)
- **Rain**: Dummy coded with levels $\leq 2mm$ (= reference) and $> 2mm$ per day (RP data only)

4.3 HABITUAL MODE CHOICE AND NON-TRADING BEHAVIOR

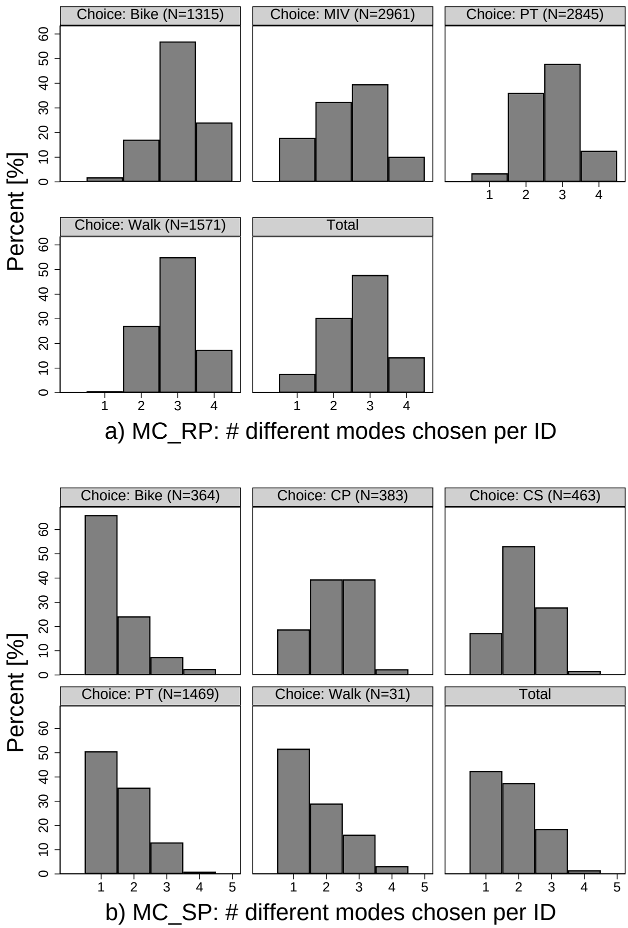
Inertia effects and the influence of habits in the context of mode choice have been extensively debated in the literature, referring to the tendency that previous choices may affect the present choice (e.g. Cantillo et al., 2007; Cherchi and Manca, 2011). Especially when dealing with diary-based RP data, the tendency of respondents sticking to the same mode has been shown to be substantial (e.g. Cherchi and Cirillo, 2014; Schmid et al., 2019a).

In cases where an analyst knows with certainty if respondents were indeed captive and had no choice, they should be excluded from the estimation sample (e.g. Ortúzar and Willumsen, 2011). Swait and Ben-Akiva (1987) argue that – apart from biased ASCs – slope effects might become weakened in the presence of captivity. However, if the circumstances are not that clear (as it is the case in the current dataset), Hess et al. (2010) argue that if non-trading is a result of utility maximizing behavior with extreme preferences, such respondents should not be excluded, and in absence of further information on respondents' consideration set, the best one can do is a dedicated treatment of such preferences. Furthermore, our mode choice non-traders may still have completed the route choice SP tasks, revealing trade-off information to estimate the VTTS for their "assigned" mode, so they are not excluded from the sample.

Figure 4.2a shows that in the MC_RP dataset, the share of respondents always choosing the same mode is almost 10% (10%-points lower compared

13 Note that trip purpose "other" is only included in the RP dataset.

FIGURE 4.2: Trading behavior of respondents in the mode choice RP (MC_RP) and SP (MC_SP) data sets.



to our similar dataset for Austria; Schmid et al. (2019a)), which is most pronounced for MIV (i.e. 20% of respondents choosing MIV at least once, chose it always). To account for inertia, we decided to follow a similar approach as described in Börjesson et al. (2013): The tendency to stick to the same mode is captured by lagged variables that relate the current choice with the previous tour(s) (a new tour starts when leaving home and ends when arriving at home) made with the same mode and for the same tour purpose, which, for simplicity, is the purpose for the first trip starting from home (Börjesson et al., 2013; Schmid et al., 2019a). Thus, for each RP mode alternative, a lagged variable is included in the model that has a value of one if the mode chosen by individual n for RP trip t at the beginning of a given tour is the same as that chosen in the previous tour made with the same purpose and zero otherwise.[14]

In the MC_SP experiment shown in Figure 4.2b – remembering that MIV is not part of the choice set anymore – the share of respondents always choosing the same mode is now highest for bike (i.e. about 65% of respondents choosing bike at least once, chose it always; note, however, that this corresponds to a rather small group of respondents), followed by PT. Not only in our hypothetical SP experiment, but Zurich in general, and the central urban area in particular, can be seen as a bike-friendly environment utilized persistently by an inveterated group of locals. Also, the total share of respondents always choosing the same mode is considerably higher than in the RP case (about 40%), which is often observed in mode choice experiments (e.g. Hess et al., 2010; Schmid et al., 2019a).

Clearly, inertia in SP choices is conceptually different from the RP ones and is mainly treated here by the inclusion of random error components (e.g. Yáñez et al., 2011; Cherchi and Manca, 2011; Schmid et al., 2019a), allowing for correlations in individual preferences for each mode (see Section 4.4). E.g. Cherchi and Manca (2011) show that when including error components, the size and significance of fixed inertia effects decrease substantially, strengthening our confidence of a sufficient treatment of potential inertia patterns in the RP as well as the SP mode choice data.

14 Please note that longer time lags have not been considered so far.

4.4 MODELING FRAMEWORK

The utility equations for individual $n \in \{1, 2, ..., N\}$ in choice scenario $t \in \{1, 2, ..., T_n\}$ are, for the labeled alternatives in the most exhaustive model with random parameters (MIXL), given by

$$\begin{aligned} U^{RP}_{walk,n,t} = \alpha_{walk} - \widetilde{\psi}_{n,t} \cdot tt^{RP}_{walk,n,t} \cdot \widetilde{VTTS}_{walk,n,t} + P^{RP}_{n,t}\gamma^{RP}_{walk} + \\ Z_n\lambda_{walk} + I^{RP}_{walk,n,t}\omega^{RP}_{walk} + \eta_{walk,n} + \epsilon^{RP}_{walk,n,t} \end{aligned} \tag{4.2}$$

$$\begin{aligned} U^{RP}_{bike,n,t} = \alpha_{bike} - \widetilde{\psi}_{n,t} \cdot tt^{RP}_{bike,n,t} \cdot \widetilde{VTTS}_{bike,n,t} + P^{RP}_{n,t}\gamma^{RP}_{bike} + \\ Z_n\lambda_{bike} + I^{RP}_{bike,n,t}\omega^{RP}_{bike} + \eta_{bike,n} + \epsilon^{RP}_{bike,n,t} \end{aligned} \tag{4.3}$$

$$\begin{aligned} U^{RP}_{MIV,n,t} = \alpha_{MIV} - \widetilde{\psi}_{n,t} \cdot (tt^{RP}_{MIV,n,t} \cdot \widetilde{VTTS}_{MIV,n,t} + tc^{RP}_{MIV,n,t}) + \\ P^{RP}_{n,t}\gamma^{RP}_{MIV} + Z_n\lambda_{MIV} + I^{RP}_{MIV,n,t}\omega^{RP}_{MIV} + \eta_{MIV,n} + \epsilon^{RP}_{MIV,n,t} \end{aligned} \tag{4.4}$$

$$\begin{aligned} U^{RP}_{PT,n,t} = \; - \widetilde{\psi}_{n,t} \cdot (tt^{RP}_{PT,n,t} \cdot \widetilde{VTTS}_{PT,n,t} + tc^{RP}_{PT,n,t} + X^{RP}_{PT,n,t}WTP^{RP}_{LOS}) + \\ I^{RP}_{PT,n,t}\omega^{RP}_{PT} + \eta_{PT,n} + \epsilon^{RP}_{PT,n,t} \end{aligned} \tag{4.5}$$

where Equation (4.2)-Equation (4.5) correspond to the mode choice RP data (MC_RP; reference for estimating the three scale parameters σ_q for each data/experiment type q), and

$$\begin{aligned} U^{SP}_{walk,n,t} = \sigma_{\text{MC\_SP}} \cdot (\alpha_{walk} - \widetilde{\psi}_{n,t} \cdot tt^{SP}_{walk,n,t} \cdot \widetilde{VTTS}_{walk,n,t} + \\ P^{SP}_{n,t}\gamma^{SP}_{walk} + Z_n\lambda_{walk} + \eta_{walk,n}) + \epsilon^{SP}_{walk,n,t} \end{aligned} \tag{4.6}$$

$$\begin{aligned} U^{SP}_{bike,n,t} = \sigma_{\text{MC\_SP}} \cdot (\alpha_{bike} - \widetilde{\psi}_{n,t} \cdot tt^{SP}_{bike,n,t} \cdot \widetilde{VTTS}_{bike,n,t} + P^{SP}_{n,t}\gamma^{SP}_{bike} + \\ Z_n\lambda_{bike} + \eta_{bike,n}) + \epsilon^{SP}_{bike,n,t} \end{aligned} \tag{4.7}$$

$$\begin{aligned} U^{SP}_{CS,n,t} = \sigma_{\text{MC\_SP}} \cdot (\alpha_{CS} - \widetilde{\psi}_{n,t} \cdot (tt^{SP}_{CS,n,t} \cdot \widetilde{VTTS}_{CS,n,t} + tc^{SP}_{CS,n,t} + \\ X^{SP}_{CS,n,t}WTP^{SP}_{LOS}) + P^{SP}_{n,t}\gamma^{SP}_{CS} + Z_n\lambda_{CS} + \eta_{CS,n}) + \epsilon^{SP}_{CS,n,t} \end{aligned} \tag{4.8}$$

$$\begin{aligned} U^{SP}_{CP,n,t} = \sigma_{\text{MC\_SP}} \cdot (\alpha_{CP} - \widetilde{\psi}_{n,t} \cdot (tt^{SP}_{CP,n,t} \cdot \widetilde{VTTS}_{CP,n,t} + tc^{SP}_{CP,n,t} + \\ X^{SP}_{CP,n,t}WTP^{SP}_{LOS}) + P^{SP}_{n,t}\gamma^{SP}_{CP} + Z_n\lambda_{CP} + \eta_{CP,n}) + \epsilon^{SP}_{CP,n,t} \end{aligned} \tag{4.9}$$

$$\begin{aligned} U^{SP}_{PT,n,t} = \sigma_{\text{MC\_SP}} \cdot (-\widetilde{\psi}_{n,t} \cdot (tt^{SP}_{PT,n,t} \cdot \widetilde{VTTS}_{PT,n,t} + tc^{SP}_{PT,n,t} + \\ X^{SP}_{PT,n,t}WTP^{SP}_{LOS}) + \eta_{PT,n}) + \epsilon^{SP}_{PT,n,t} \end{aligned} \tag{4.10}$$

where Equation (4.6)-Equation (4.10) correspond to the mode choice SP experiment (MC_SP). For the unlabeled alternatives $i \in \{1, 2, 3\}$ in case of the CS route choice SP experiment (RC_CS), we define the following generic utility functions:

$$U^{CS}_{\{1,2,3\},n,t} = \sigma_{\text{RC\_CS}} \cdot (-\widetilde{\psi}_{n,t} \cdot (tt_{i,n,t} \cdot \widetilde{VTTS}_{CS,n,t} + tc_{i,n,t} + X_{i,n,t} WTP_{LOS})) + \epsilon_{\{1,2,3\},n,t} \quad (4.11)$$

and for the unlabeled alternatives $i \in \{1, 2, 3\}$ in case of the PT route choice SP experiment (RC_PT), we define the following generic utility functions:

$$U^{PT}_{\{1,2,3\},n,t} = \sigma_{\text{RC\_PT}} \cdot (-\widetilde{\psi}_{n,t} \cdot (tt_{i,n,t} \cdot \widetilde{VTTS}_{PT,n,t} + tc_{i,n,t} + X_{i,n,t} WTP_{LOS})) + \epsilon_{\{1,2,3\},n,t} \quad (4.12)$$

$X_{i,n,t}$ is a (1 × J) vector of LOS attributes related to alternative i, and WTP_{LOS} is a (J × 1) coefficient vector (i.e. mode-specific for PT headway [CHF/h], PT transfers [CHF/#], PT access time [CHF/h], CS congestion time [CHF/h], CP risk of missing the driver [CHF/%] and CS and CP access time [CHF/h]). $P_{n,t}$ is a (1 × Q) vector of weather conditions and trip characteristics (that are mode-invariant), including trip purpose and day of the week, and γ is a (Q × 1) alternative-specific parameter vector, shifting the intercepts relative to the reference alternative PT in the mode choice domains. Similarly, Z_n is a (1 × L) vector of socioeconomic characteristics and residuals of the time-use model[15] and λ is a (L × 1) alternative-specific parameter vector. $I_{i,n,t}$ is a mode-specific lagged inertia variable for RP mode choice and ω^{RP} is the corresponding parameter (see Section 4.3).

Models are parameterized in the willingness-to-pay (WTP) space by normalizing the parameter of travel cost $tc_{i,n,t}$ to -1 (e.g. Sillano and Ortúzar, 2005; Train and Weeks, 2005; Train, 2009), mainly to estimate the distribution of WTP values for each corresponding attribute directly[16] and to avoid the ex-post division by a distributed cost coefficient (Hess and Train, 2017), often leading to more unreasonable WTP distributions (Daly et al., 2012c).

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15 Travel, activity time and expenditure allocation are choices that may belong to the same superordinate framework of utility maximization (Munizaga et al., 2008). In contrast to the authors accounting for bidirectional correlations between time-use, expenditure allocation and mode choice using a complex analytical framework, we use a control-function approach including the residuals of the time-use in the choice model affecting the constants of the mode choice utilities (e.g. Petrin and Train, 2010; Guevara, 2015). Thus, we intuitively assume that if endogeneity is present, the path passes from the longer-term to the shorter-term decisions.

16 Using travel cost as the numeraire and the fact that Equation (4.13) incorporates scale leads to a facilitated interpretation of results, as the scale-free terms can be directly interpreted as WTPs (Train and Weeks, 2005).

The scale coefficient is defined as the following strictly positive function with several parameters

$$\widetilde{\psi}_{n,t} = \exp\left(\beta_{scale} + Z_n\kappa_{scale} + \eta_{scale,n}\right)\left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\theta_{scale}} > 0 \;\forall\; n,t \qquad (4.13)$$

and accounts for scale heterogeneity in all LOS-related attributes (see Equation (4.2)-Equation (4.12)). Importantly, in WTP space the heterogeneity in travel cost sensitivity and scale are perfectly confounded (see also e.g. Train and Weeks (2005), Scarpa et al. (2008) and Hess and Rose (2012)).

From the traditional microeconomic framework of consumer behavior (see e.g. Jara-Diaz, 2007) follows that $\widetilde{\psi}_{n,t}$ is the marginal utility of income. Because income enters the conditional indirect utility function as $income_n - tc_{i,n,t}$, increasing travel cost is like diminishing income, and the derivative with respect to income is equal to minus the derivative with respect to cost (we use the term *travel cost sensitivity*).

$\widetilde{\psi}_{n,t}$ follows a log-normal mixture distribution according to a fixed parameter β_{scale}, a $(1 \times F)$ vector of socioeconomic characteristics Z_n with a $(F \times 1)$ vector of parameters κ_{scale} as well as a random component $\eta_{scale,n}$. The non-linear interaction term with trip distance $dist_{n,t}$ ($\overline{dist}$ represents the sample mean; see also e.g. Mackie et al. (2003)) additionally allows for heterogeneity with respect to the trip length: If the distance elasticity of travel cost, θ_{scale}, is negative, $\widetilde{\psi}_{n,t}$ decreases for increasing distance, implying a (i) lower travel cost sensitivity and (ii) higher error variance for longer trips[17]. For an estimate of $\theta_{scale} = 0$ or the mean trip distance, the interaction disappears. Importantly – in contrast to the traditional microeconomic theory – we thus allow that the marginal utility of income is not only individual-, but also context-dependent (see also e.g. Tversky and Kahneman, 1986; Hensher and Rose, 2009; Schmid et al., 2019a).

Obtaining a special treatment in subsequent analyses, the coefficients of mode-, individual- and trip-specific travel time $tt_{i,n,t}$ are denoted by

17 This has been observed in other valuation studies (see e.g. Fröhlich et al., 2012; Axhausen et al., 2014; Weis et al., 2017): While these authors estimated the models in preference space, the same non-linear interaction terms of trip distance with travel cost and time revealed a significant decrease in both parameters (with the former often dominating the latter, ceteris paribus, leading to increasing VTTS for larger distances), indirectly implying higher error variances in relative attribute sensitivities such as VTTS. One explanation might be that for larger distances, potentially relevant but unobservable factors may gain in relative importance, which are not included in the utility function.

$\widetilde{VTTS}_{i,n,t}$ [CHF/h], and travel costs are included as the numeraire for all LOS related attributes. The VTTS values are parameterized as

$$\widetilde{VTTS}_{i,n,t} = (VTTS_i + P_{n,t}\rho_{VTTS,i} + Z_n\kappa_{VTTS,i} + \eta_{VTTS,i,n}) \left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\theta_{VTTS,i}} \tag{4.14}$$

which are distributed with sample mean $VTTS_i$, according to a vector of trip characteristics $P_{n,t}$ with parameters $\rho_{VTTS,i}$, socioeconomic characteristics Z_n with parameters $\kappa_{VTTS,i}$, trip distance $dist_{n,t}$ (same functional form as for the travel cost parameter) with parameters $\theta_{VTTS,i}$ and random components $\eta_{VTTS,i,n}$. For all discrete interaction terms we used weighted effects coding for unbalanced data (e.g. Daly et al., 2016; Te Grotenhuis et al., 2017), leaving the VTTS sample mean unaffected. This specification was useful in the case where attributes are only available in the RP mode choice data (i.e. day of the week and trip purpose "other"), while in the SP experiments no such data were collected, thus only contributing to the VTTS sample mean.

To account for correlations across choices and unobserved heterogeneity, and to reduce the risk of omitted variable bias (e.g. Hensher, 2001; Sillano and Ortúzar, 2005; Greene et al., 2006), additional components were added to the utility function that vary across individuals but are constant over choice situations. $\eta_{ASC,i,n} \sim N(0, \sigma^2_{ASC,i})$ is an individual- and mode-specific random error component with mean zero and standard deviation $\sigma_{ASC,i}$, accounting for alternative-specific error variances and agent effects (e.g. Bhat, 1995; Greene and Hensher, 2007; Walker et al., 2007). $\eta_{VTTS,i,n} \sim N(0, \sigma^2_{VTTS,i})$ is an individual- and mode-specific random component capturing unobserved VTTS heterogeneity. Similarly, $\eta_{cost,n} \sim N(0, \sigma^2_{cost})$ is an individual-specific random component capturing unobserved scale heterogeneity (see e.g. Greene and Hensher, 2010).

The choice of alternative i is modeled by maximizing the utility $U_{i,n,t}$ for each individual n and choice scenario t:

$$c_{i,n,t} = \begin{cases} 1 \text{ if } U_{i,n,t} > U_{j,n,t} \\ 0 \text{ if } U_{i,n,t} \leq U_{j,n,t} \end{cases} \tag{4.15}$$

Assuming that the random components $\eta_{i,n}$ are mutually independent and $\epsilon_{i,n,t}$ is IID extreme value type I, the unconditional joint probability $L_n(\cdot)$ – the expected value over all possible values of $\eta_{i,n}$ that individual n

chooses alternative i among a sequence of choices T_n – is defined by the 13-dimensional integral of the product of conditional choice probabilities over the distributions of $\eta_{i,n}$ (e.g. Walker and Ben-Akiva, 2002; Train, 2009):[18]

$$L_n(\cdot) = \int \prod_{i=1}^{I_n} \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, P_{n,t}, Z_n, I_{i,n,t}, \Omega, \eta_{i,n})^{c_{i,n,t}} \times h(\eta_{i,n}|\Sigma)\ d\eta_{i,n} \tag{4.16}$$

where Ω is the set of fixed parameter vectors, $h(\eta_{i,n}|\Sigma)$ is the multivariate distribution of the independent random components with the corresponding vector of standard deviations Σ, and

$$P(c_{i,n,t} = 1 | X_{i,n,t}, P_{n,t}, Z_n, I_{i,n,t}, \Omega, \eta_{i,n}) = \frac{\exp(U_{i,n,t})}{\exp(U_{i,n,t}) + \sum_j a_j \exp(U_{j,n,t})} \tag{4.17}$$

is the conditional choice probability, where a_j is a dummy variable defining the availability of alternative j in each choice situation.

Using maximum simulated likelihood methods, Equation (4.16) is approximated by calculating the probability for any given value of the random components using a smooth simulator that is consistent and asymptotically normal (e.g. Train, 2009). This is done by drawing values from the $h(\eta_{i,n}|\Sigma)$ distributions, with superscript r referring to draw $r \in \{1, ..., R\}$: $\widetilde{L_n}(\cdot)$ shown in Equation (4.19) is the simulated likelihood for individual n, and the maximum simulated likelihood estimator contains the values in $\widehat{\Omega}$ and $\widehat{\Sigma}$ that maximize $\widetilde{LL}(\Omega, \Sigma)$:

$$\max\ \widetilde{LL}(\Omega, \Sigma) = \sum_{n=1}^{N} \log\left(\widetilde{L_n}(\cdot)\right) \tag{4.18}$$

$$\widetilde{L_n}(\cdot) = \frac{1}{R} \sum_{r=1}^{R} \prod_{i=1}^{I_n} \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, P_{n,t}, Z_n, I_{i,n,t}, \Omega, \eta_{i,n}^{r})^{c_{i,n,t}} \tag{4.19}$$

Models were estimated in *R 3.4.1*. The *R*-code builds on the *maxLik* package using the BFGS algorithm (Molloy et al., 2019). The main criteria regarding identifiability and simulation bias were investigated: With R = 1'000 Sobol draws, the estimates were considered to be robust and stable, but

18 To simplify notation, please note that $tc_{i,n,t}$, $tt_{i,n,t}$ and $dist_{n,t}$ now are part of $X_{i,n,t}$, and that $\eta_{scale,n}$ is not alternative-specific.

the model reported in Table 4.5 is estimated using 5'000 draws.[19] Cluster-robust (at the individual-level) standard errors were calculated using the Eicker-Huber-White sandwich estimator (Zeileis, 2006).

4.5 RESULTS

Four models with increasing complexity are presented in Table 4.5, which were found to represent choice behavior in our sample appropriately. The base model (RMNL) is a simple MNL model that includes all alternative-specific attributes presented in Section 4.2 and the residuals from the time-use model (TUMIX) presented in Chapter 3, and accounts for scale heterogeneity with respect to trip distance and the different data/experiment types. The second model (TMNL) adds all the trip characteristics, the third model adds all the user characteristics (UMNL) and the fourth model adds the random components (MIXL). After each increase in complexity, parameters with a $|\text{t-value}| < 1$ are removed for the final model specifications.

The alternative-specific constants (ASCs) indicate that – for given LOS attributes – MIV, CP and especially CS exhibit a significantly lower choice probability relative to the reference alternative PT (all $p < 0.05$). The ASC of bike is significant and negative as well, but this mainly results from the imposed availability conditions of bike in the RP dataset. Additional investigations (not reported) have shown that when only analyzing the mode choice SP dataset, the ASC of bike is positive (but not significant), while the ASCs for CS and CP remain highly significant and negative. This indicates that on average, also in the complete absence of private cars, respondents would rather prefer PT and bike.

A likelihood-ratio test indicates that endogeneity in mode choice with respect to time-use is present (8 degrees of freedom compared to a basic MNL model; increase in LL by 34.8 units; AICc decreases by 50.9 units) and significant at all common levels. However, the relative increase in LL is not substantial, and even more important, the model coefficients are only marginally affected when correcting for endogeneity.

In all model specifications, coefficients of choice attributes show the expected signs, are statistically significant at the 1% level, are consistent (same signs) between the different models and are not significantly different (the 95% confidence intervals $\approx \pm 2$ SE are not overlapping): The

19 Just because we can (at this point, we again acknowledge the work of Joe Molloy for developing the very efficient estimation code), we use 5'000 draws, like a military parade shooting rockets in the sky for celebration purposes only. Estimation of the MIXL took 16.7 hours using 24 cores on the ETH *Euler* supercluster.

WTPs for a reduction in PT access time range between 14.6 CHF/h and 17.3 CHF/h, exhibiting substantially higher values for CS and CP (between 26.7 CHF/h and 29.5 CHF/h). This difference could be explained by an increasing amount of uncertainty/unfamiliarity in case of CS and CP access time, which respondents tend to perceive more negatively than for PT. The WTPs for congestion time range between 31.7 CHF/h and 35.8 CHF/h, as expected exhibiting substantially higher values than for in-vehicle time of essentially all modes. The WTPs for PT transfers range between 2.0 CHF/-transfer and 2.30 CHF/transfer and for PT headway between 9.2 CHF/h and 10.4 CHF/h. Results are in line with the expectations and, in relative magnitude, comparable to the Swiss, German and Austrian valuation studies (see also Fröhlich et al., 2012; Axhausen et al., 2014; Weis et al., 2017; Schmid et al., 2019a). A higher probability of missing the CP ride exhibits a value of about 0.4 CHF/%, which – for a 20% increase – corresponds to a monetary value of about 8 CHF.

Adding the trip characteristics (TMNL) and random components (MIXL) substantially increase the model fit, while the user characteristics (UMNL) do not add substantial explanatory power. Including the full set of 84 additional parameters in the UMNL compared to the TMNL (35 effects for the ASCs, 7 effects for the cost/scale parameter and 42 effects for mode-specific VTTS), only 15 exhibited a $|\text{t-value}| > 1$; an AICc comparison did not reject the full (AICc = 17'483) in favor of the more parsimonious model (AICc = 17'397; see Table 4.5 at the bottom).

Interesting patterns were found for trip related variables such as purpose, daily weather and weekend. While rain and air temperature did not show any substantial effects, only sunshine duration exhibited a persistent (significant across all models) and positive effect on the choice of bike (relative to PT). Focusing on the strongest ($p < 0.05$) and most persistent effects of trip characteristics, work/education trips exhibit a lower choice probability of MIV and CS, while for shopping trips the opposite was found. In Switzerland, many of the longer distance commuting (i.e. work/education) trips are conducted by PT, while especially for shopping, MIV can be seen as more convenient. While leisure trips exhibit a higher VTTS for MIV and PT of about 3 CHF/h (relative to the mode-specific VTTS sample means), weekend trips show the opposite for MIV and walk of about 4 CHF/h (also, the choice of walk is more pronounced at the weekends). These findings can be explained by more relaxed time constraints for weekend trips, making the choice less dependent on travel time, while leisure trips (conducted during *and* at the end of a week) are not associated with a lower travel time resistance.

Similar to other valuation studies, the VTTS tends to increase for larger distances, in the current case mainly for bike and PT, as indicated by the positive distance elasticities. The distance elasticity of the VTTS for bike more than doubles in the MIXL, indicating a very strong increase for larger distances. This is partly offsetting the very large point estimate of 33.9 CHF/h, which is related to the sample mean of 7.4 km for all trips. For an average bike distance of 2.2 km (see also Appendix, Table A.6), the VTTS for bike adjusts to about 23.8 CHF/h ($\approx 33.9 \cdot (2.2/7.4)^{0.29}$).

Inertia effects in the RP data show the expected habitual patterns, exhibiting very strong and substantial effects on choice behavior (all $p < 0.01$). Keeping in mind our definition of inertia, results indicate that in the MIXL the strongest habitual choice behavior on a tour-purpose level occurs for MIV, followed by PT, walk and bike.

Regarding the user characteristics, the typical candidates such as income (see e.g. Gunn, 2001; Jiang and Morikawa, 2004) do not affect preference heterogeneity at all, which may be explained by the rather homogeneous sample with respect to income and education. While we expect this tendency to hold more and more for developed countries – given by the rather low share of travel expenditures (i.e. 5% in the PCW sample; see also Table 3.3) – for poorer countries, of course, this might not be the case (Zamparini and Reggiani, 2007). Important for subsequent analyses, it already implies that for one of the main factors of the VoL, namely income, we do not find a noticeable effect on the mode-specific VTTS.

Focusing on the MIXL, the strongest effects occur for urban residential location and kids in the household: The former is associated with a lower choice probability of MIV and a lower VTTS of about 7 CHF/h for MIV, while the latter is associated with a lower choice probability of walk and MIV, and a higher VTTS of about 2.5 CHF/h for PT (all $p < 0.01$). While men exhibit a higher choice probability of CS (remembering that MIV is not available in the SPs anymore), they also have a substantially lower VTTS for MIV of about 5.5 CHF/h, indicating that, ceteris paribus, driving a motorized vehicle is less of a displeasure for men than for women. The persistent and negative effect of age on the VTTS for MIV, CS and CP (all $p < 0.05$) is also noticeable, which may be explained by more relaxed time constraints and/or a higher perceived comfort of older respondents when choosing a car mode.

TABLE 4.5: Estimation results: MNL and MIXL models.

Base category: PT	RMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
ASC walk ($\widehat{\alpha}_{walk}$)	0.02	1.11***	1.21***	1.50***
	(0.33)	(0.31)	(0.29)	(0.34)
ASC bike ($\widehat{\alpha}_{bike}$)	−2.56***	−2.40***	−2.36***	−4.65***
	(0.31)	(0.35)	(0.33)	(0.45)
ASC MIV ($\widehat{\alpha}_{MIV}$)	−1.51***	−1.08***	−1.08***	−1.96***
	(0.31)	(0.31)	(0.30)	(0.35)
ASC CP ($\widehat{\alpha}_{CP}$)	−1.36**	−1.22**	−1.06*	−1.91**
	(0.58)	(0.56)	(0.56)	(0.84)
ASC CS ($\widehat{\alpha}_{CS}$)	−1.09**	−1.09**	−1.07**	−2.70***
	(0.47)	(0.44)	(0.44)	(0.76)
Fixed scale effect ($\widehat{\beta}_{scale}$)	−1.17***	−1.30***	−1.30***	−0.82***
	(0.08)	(0.08)	(0.08)	(0.10)
VTTS walk	18.36***	21.27***	22.18***	25.04***
	(1.92)	(1.97)	(2.06)	(3.05)
VTTS bike	19.12***	18.84***	19.16***	33.87***
	(2.07)	(2.01)	(2.03)	(3.93)
VTTS MIV	25.17***	27.77***	27.99***	30.51***
	(2.40)	(2.59)	(2.56)	(2.96)
VTTS PT	14.43***	13.77***	13.43***	13.85***
	(1.59)	(1.58)	(1.49)	(1.43)
VTTS CS	19.82***	23.91***	24.35***	27.20***
	(1.92)	(1.90)	(1.83)	(2.28)
VTTS CP	26.56***	26.72***	27.85***	35.82***
	(3.83)	(4.62)	(4.83)	(5.43)
WTP access time (PT)	14.63***	15.22***	15.62***	17.33***
	(1.58)	(1.51)	(1.57)	(1.93)
WTP acc. time (CS and CP)	26.86***	26.59***	26.91***	29.47***
	(2.80)	(2.77)	(2.81)	(3.27)
WTP congestion time (CS)	31.71***	32.52***	33.15***	35.78***
	(3.79)	(3.89)	(3.88)	(5.10)

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Table 4.5 – *Continued from previous page*

Base category: PT	RMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
WTP risk miss. driver (CP)	0.41***	0.40***	0.43***	0.44***
	(0.08)	(0.08)	(0.08)	(0.08)
WTP transfers (PT)	1.96***	2.04***	2.04***	2.27***
	(0.24)	(0.24)	(0.25)	(0.27)
WTP headway (PT)	9.24***	7.83***	8.00***	10.44***
	(1.77)	(1.78)	(1.82)	(1.43)
Scale parameter MC_SP	0.63***	0.72***	0.72***	0.83***
	(0.06)	(0.07)	(0.06)	(0.08)
Scale parameter RC_CS	1.75***	1.97***	1.98***	1.16
	(0.18)	(0.20)	(0.19)	(0.13)
Scale parameter RC_PT	1.84***	2.04***	2.04***	1.22
	(0.21)	(0.24)	(0.24)	(0.15)
Residuals T_w (walk)	3.44*	2.07*	2.58**	2.39
	(1.91)	(1.13)	(1.15)	(1.67)
Residuals $Tf1$ (walk)	−2.35	–	–	–
	(2.35)			
Residuals $Ef1$ (walk)	1.35	–	–	–
	(0.94)			
Residuals T_w (bike)	1.90	1.82	2.17	−8.67**
	(1.61)	(1.57)	(1.61)	(4.31)
Residuals $Ef1$ (MIV)	1.37	–	–	–
	(1.01)			
Residuals $Ef1$ (CS)	2.83**	2.18*	1.78	4.35*
	(1.35)	(1.21)	(1.18)	(2.28)
Residuals T_w (CP)	−4.36	−4.23*	−5.50**	−13.41***
	(2.72)	(2.40)	(2.64)	(3.50)
Residuals $Tf1$ (CP)	5.08	5.04	6.39*	*n.r.*
	(3.75)	(3.32)	(3.45)	
Distance × scale ($\widehat{\theta}_{scale}$)	−0.41***	−0.43***	−0.40***	−0.25***
	(0.03)	(0.03)	(0.03)	(0.04)
Dist. × VTTS bike ($\widehat{\theta}_{VTTS,bike}$)	–	0.11*	0.13*	0.29***
		(0.06)	(0.06)	(0.09)

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Table 4.5 – *Continued from previous page*

Base category: PT	RMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
Dist. × VTTS PT ($\widehat{\theta}_{VTTS,PT}$)	–	0.17***	0.17***	0.11**
		(0.03)	(0.03)	(0.04)
Dist. × VTTS CP ($\widehat{\theta}_{VTTS,CP}$)	–	0.11*	0.11*	*n.r.*
		(0.06)	(0.07)	
Inertia RP (walk)	–	2.60***	2.60***	2.16***
		(0.23)	(0.24)	(0.31)
Inertia RP (bike)	–	3.49***	3.46***	2.11***
		(0.26)	(0.26)	(0.32)
Inertia RP (MIV)	–	3.97***	3.78***	3.07***
		(0.18)	(0.18)	(0.24)
Inertia RP (PT)	–	2.60***	2.59***	2.25***
		(0.18)	(0.19)	(0.19)
Air temp. $<$ 8°C (bike)	–	−0.19	−0.17	*n.r.*
		(0.18)	(0.17)	
Sun. dur. $>$ 3.5h (bike)	–	0.13*	0.14**	0.35***
		(0.07)	(0.07)	(0.11)
Sun. dur. $>$ 3.5h (MIV)	–	0.16***	0.18***	0.13
		(0.06)	(0.06)	(0.09)
Work/educ. (walk)	–	0.54***	0.51**	0.37*
		(0.20)	(0.20)	(0.21)
Leisure (walk)	–	−0.44	−0.45	*n.r.*
		(0.30)	(0.29)	
Work/educ. (MIV)	–	−0.57***	−0.39***	−0.54***
		(0.20)	(0.13)	(0.12)
Shopping (MIV)	–	1.23***	0.79***	1.42***
		(0.38)	(0.13)	(0.18)
Work/educ. (CS)	–	0.63*	0.63*	1.50**
		(0.33)	(0.34)	(0.76)
Weekend (walk)	–	0.59***	0.57***	0.74***
		(0.12)	(0.12)	(0.16)
Work/educ. × VTTS walk	–	2.60**	2.64**	1.80
		(1.19)	(1.26)	(1.17)

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Table 4.5 – *Continued from previous page*

Base category: PT	RMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
Shopping × VTTS walk	–	2.45***	2.73***	1.45
		(0.80)	(0.85)	(1.04)
Leisure × VTTS walk	–	−4.87***	−5.10***	−3.72**
		(1.46)	(1.54)	(1.68)
Work/educ. × VTTS MIV	–	−3.33*	−1.20	*n.r.*
		(1.98)	(1.31)	
Shopping × VTTS MIV	–	5.40	–	–
		(4.25)		
Leisure × VTTS MIV	–	2.92***	3.10***	2.81***
		(0.95)	(1.00)	(1.05)
Leisure × VTTS PT	–	1.83**	2.24***	2.82***
		(0.71)	(0.73)	(0.83)
Shopping × VTTS CS	–	−11.97***	−12.22***	−7.24
		(3.40)	(3.44)	(5.20)
Weekend × VTTS MIV	–	−3.03***	−3.03***	−4.07***
		(1.09)	(1.14)	(1.36)
Kids (walk)	–	–	−0.23**	−0.30**
			(0.09)	(0.12)
Income (bike)	–	–	−0.26*	*n.r.*
			(0.14)	
Age (bike)	–	–	0.81*	*n.r.*
			(0.46)	
Urban (MIV)	–	–	−0.72***	−1.48***
			(0.19)	(0.27)
Kids (MIV)	–	–	−0.17*	−0.60***
			(0.09)	(0.21)
Male (CS)	–	–	0.49**	1.16**
			(0.25)	(0.45)
Male × VTTS bike	–	–	−1.78**	−2.24***
			(0.88)	(0.72)
Male × VTTS MIV	–	–	−2.35***	−5.49***
			(0.82)	(1.17)
Age × VTTS MIV	–	–	−20.33***	−20.85***

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Table 4.5 – *Continued from previous page*

Base category: PT	RMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
			(4.65)	(5.66)
High educ. × VTTS MIV	–	–	1.31**	*n.r.*
			(0.67)	
Urban × VTTS MIV	–	–	−6.02***	−6.83***
			(2.09)	(2.01)
Kids × VTTS PT	–	–	1.62***	2.38***
			(0.58)	(0.78)
Male × VTTS CS	–	–	2.80*	3.65*
			(1.50)	(1.88)
Age × VTTS CS	–	–	−18.62***	−19.02**
			(5.01)	(7.41)
Age × VTTS CP	–	–	−20.72***	−18.64**
			(7.09)	(7.62)
$\widehat{\sigma}_{ASC,walk}$	–	–	–	1.15***
				(0.19)
$\widehat{\sigma}_{ASC,bike}$	–	–	–	2.82***
				(0.29)
$\widehat{\sigma}_{ASC,MIV}$	–	–	–	2.08***
				(0.20)
$\widehat{\sigma}_{ASC,PT}$	–	–	–	3.46***
				(0.57)
$\widehat{\sigma}_{ASC,CS}$	–	–	–	3.58***
				(0.53)
$\widehat{\sigma}_{ASC,CP}$	–	–	–	2.57***
				(0.57)
$\widehat{\sigma}_{scale}$	–	–	–	0.38***
				(0.04)
$\widehat{\sigma}_{VTTS,walk}$	–	–	–	4.97***
				(0.93)
$\widehat{\sigma}_{VTTS,bike}$	–	–	–	18.07***
				(2.34)
$\widehat{\sigma}_{VTTS,MIV}$	–	–	–	13.03***
				(1.74)

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Table 4.5 – *Continued from previous page*

Base category: PT	RMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
$\widehat{\sigma}_{VTTS,PT}$	–	–	–	5.94^{***}
				(1.02)
$\widehat{\sigma}_{VTTS,CS}$	–	–	–	*n.r.*
$\widehat{\sigma}_{VTTS,CP}$	–	–	–	11.82^{***}
				(1.91)
# est. parameters	30	52	66	79
# respondents	356	356	356	356
# choice observations	12594	12594	12594	12594
# draws	–	–	–	5000
$\mathcal{LL}_{null}$	−21249.01	−21249.01	−21249.01	−21249.01
$\mathcal{LL}_{final}$	−10875.39	−8791.19	−8617.38	−6548.87
AICc	21816.51	17704.58	17397.37	13301.54

Note: Time-use residuals, age and income are mean-normalized and zero-centered.

– : Not included in the model. *n.r.* : Not reported in the table because |t-value| < 1.

Robust standard errors (clustered by ID): $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

In all models the scale parameter defined in Equation (4.13) decreases for increasing trip distance ($p < 0.01$), implying a decreasing relative cost sensitivity and precision in estimating relative attribute sensitivities such as the VTTS. This underpins our argumentation from above that cost sensitivity is not context-independent. One explanation might be that for larger distances, potentially relevant but unobservable factors may become more important, which are not included in the utility function.

Finally, the estimated standard deviations of the random components are all significant ($p < 0.01$; except VTTS for CS) and substantial: Unobserved preference heterogeneity is largest for CS, while VTTS heterogeneity is most pronounced for bike. Importantly, including them does not contradict previous results regarding signs of other coefficients: In most cases, the UMNL and MIXL coefficients are not significantly different, except for the ASC of bike, the fixed scale and distance elasticity of scale coefficient, the VTTS for bike, and the scale parameters for both route choice experiments. However, our results indicate a consistent (i.e. for all modes) increase in VTTS point estimates when adding the trip, user and the random components, implying that when omitting them, VTTS tend to be underestimated (see also e.g. Hensher, 2001).

4.5.1 *VTTS heterogeneity in modes and user-types*

Results indicate that a substantial amount of VTTS heterogeneity is present, following distributions according to trip (distance, purpose and day of the week), observed (residential location area, gender, age and kids in the household) and unobserved (random) user characteristics. Especially the latter are important from an econometric point of view, reducing the risk of omitted variable bias when investigating mode and user-type effects: Potentially important variables *directly related* to comfort in a given mode, for example seat occupancy rates or WiFi availability in PT, were not available in the data, not to mention *truly latent* characteristics such as the ability for productive time-use or "comfort" in a broader sense (see also e.g. the discussion in Bhat, 1995).

To correctly predict mode and user-type specific VTTS distributions, the calculation of conditional VTTS estimates is seen as the most coherent method of valuation inference (Sillano and Ortúzar, 2005). This is done by calculating the most likely mean VTTS values for each respondent (using R = 5'000 draws), conditional on the observed sequence of choices and fitted VTTS distributions, by applying Bayes' rule (Equation (4.20); see e.g. Revelt and Train, 2000; Hess et al., 2005; Train, 2009; Schmid et al., 2019a):

$$\widehat{VTTS}_{i,n} = \frac{\sum_{r=1}^{R}\left[\prod_{i=1}^{I_n}\prod_{t=1}^{T_n} P(c_{i,n,t}=1|X_{i,n,t},...,\widehat{\Omega},\widehat{\Sigma},\eta_{i,n}^{r})^{c_{i,n,t}}\widetilde{VTTS}_{i,n}^{r}\right]}{\sum_{r=1}^{R}\prod_{i=1}^{I_n}\prod_{t=1}^{T_n} P(c_{i,n,t}=1|X_{i,n,t},...,\widehat{\Omega},\widehat{\Sigma},\eta_{i,n}^{r})^{c_{i,n,t}}} \tag{4.20}$$

where $\widetilde{VTTS}_{i,n}^{r}$ denotes the VTTS for a given mode, individual and draw (using the individual-specific mean values of variables that vary *within* respondents; i.e. trip purpose, distance and day of the week). Furthermore, a restriction is included, which is important from a behavioral perspective: Although the conditional VTTS estimates are defined even if the alternative is never chosen, for subsequent analyses, mode-specific VTTS values are only considered for those respondents who have chosen the corresponding mode at least once. Inferring a VTTS for an individual who has *never* used a certain mode during the observation period (and for whom we do not know, if he/she has even considered it) remains questionable. Although this restriction does, in most cases, not affect results substantially, it still has some noticeable effects.

Descriptive statistics of $\widehat{VTTS}_{i,n}$ are presented for each model[20] and mode in Table 4.6. For a better comparability between models, VTTS are adjusted by the RP mean distances of the corresponding modes (see also Appendix, Table A.6) according to the non-linear interaction effects, affecting reported VTTS for bike, PT and CP. The mode-specific sample VTTS distributions for the MIXL are illustrated in Figure 4.3.

The median VTTS for MIV ranges between 28.3 CHF/h (TMNL) and 28.9 CHF/h (MIXL), for CS between 24.2 CHF/h (UMNL) and 27.3 CHF/h (MIXL), for CP between 27.2 CHF/h (UMNL) and 31.3 CHF/h (MIXL) and for PT between 13.7 CHF/h (UMNL) and 14.1 CHF/h (TMNL). The median VTTS for bike ranges between 15.1 CHF/h (UMNL) and 16.9 CHF/h (MIXL), while for walk it ranges between 21.6 CHF/h (TMNL) and 24.9 CHF/h (MIXL). The mode-specific ranking in the VTTS of traditional modes was similarly observed in other recent valuation studies in Switzerland and Germany (Fröhlich et al., 2012; Axhausen et al., 2014; Weis et al., 2017), but is much more pronounced here for the difference between MIV and PT, a similar result that we obtained for Austria (Schmid et al., 2019a). Interestingly, the VTTS for all motorized car modes (i.e. MIV, CS and CP) lie in a similar range (around 30 CHF/h in the MIXL), of which CP exhibits the highest value, confirming our hypothesis that the negatively perceived social interaction with the non-acquainted driver exhibits a higher disutility of travel time.

Table 4.6 indicates that the VTTS differences between the different models are small. Importantly, it also shows that on average, the VTTS differences between the different modes are not much affected by the inclusion of trip, user and random components. In other words, removing the user-type effects (i.e. by controlling for user characteristics in the model) does not affect the total mode-effects. The question remains, whether the mode effects can be explained by characteristics of the users, or if the mode-specific VTTS remain persistent across respondents. For subsequent analyses, we focus our attention on the mode effects between MIV (as a reference mode) and the three public modes (i.e. PT, CS and CP).

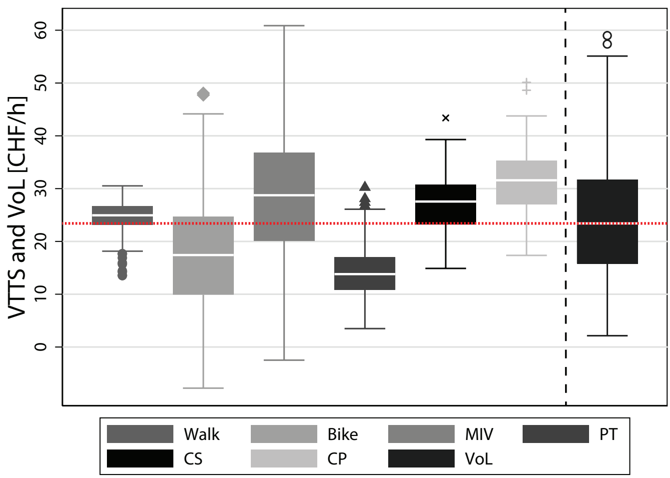
Our definitions of mode and user-type effects are as follows: *For a given user-type* (i.e. the manifestation of a specific univariate segment with two

20 Note that in the model without random coefficients (TMNL and UMNL), $\widehat{VTTS}_{i,n}$ corresponds to the predicted mean VTTS of respondent n for mode i.

TABLE 4.6: Median VTTS [CHF/h] and interquartile range (IQR) for each model and mode. Values are calculated based on the conditional mode-specific VTTS estimates, only including respondents who have chosen the corresponding mode at least once (last column).

	TMNL Value/(IQR)	UMNL Value/(IQR)	MIXL Value/(IQR)	N
VTTS walk	21.6	22.4	24.9	256
	(2.5)	(2.6)	(3.6)	
VTTS bike	15.7	15.1	16.9	166
	(2.2)	(2.5)	(14.7)	
VTTS MIV	28.3	28.8	28.9	253
	(2.4)	(9.2)	(17.7)	
VTTS PT	14.1	13.7	13.8	331
	(2.9)	(3.8)	(6.1)	
VTTS CS	24.5	24.2	27.3	219
	(1.2)	(5.8)	(7.3)	
VTTS CP	27.4	27.2	31.3	120
	(2.4)	(5.6)	(8.2)	

FIGURE 4.3: Sample distributions of conditional mode-specific VTTS estimates (MIXL) and the VoL (TUMIX).



levels a and b, e.g. male and female), the mode-specific part of utility is driven by characteristics specific to each mode that may affect the quality of travel and how productively in-vehicle time can be used for other utility-generating activities (**mode effect**; i.e. the VTTS difference between mode i and j; subsequently referred to as $\Delta VTTS_{i-j}$), while *for a given mode*, VTTS differences in user-types (**user-type effect**; i.e. the VTTS difference between two user groups a and b; subsequently referred to as $\Delta VTTS_{a-b}$) can be attributed to socioeconomic characteristics.

Following the definition by Flügel (2014), the **total mode effect** (subsequently referred to as Total $\Delta VTTS_{i-j}$) can be decomposed into the weighted average of two separate mode effects, one for each user-type a and b, where N_a and N_b correspond to the number of respondents in each segment:

$$\begin{aligned}\text{Total } \Delta VTTS_{i-j} &= \frac{N_a(VTTS_{i,a} - VTTS_{j,a}) + N_b(VTTS_{i,b} - VTTS_{j,b})}{N_a + N_b} \\ &= \frac{N_a \Delta VTTS_{i-j,a} + N_b \Delta VTTS_{i-j,b}}{N_a + N_b}\end{aligned} \tag{4.21}$$

Our definition of the **total user-type effect** (subsequently referred to as Total $\Delta VTTS_{i-j,a-b}$) corresponds to the difference in the two user-type effects for mode i and j, which is approximately[21] the difference in the two mode effects for user-types a and b. Thus, a higher (in absolute value) total user-type effect implies a larger heterogeneity in the related mode effects:

$$\begin{aligned}\text{Total } \Delta VTTS_{i-j,a-b} &= (VTTS_{i,a} - VTTS_{i,b}) - (VTTS_{j,a} - VTTS_{j,b}) \\ &= \Delta VTTS_{a-b,i} - \Delta VTTS_{a-b,j} \\ &\approx \Delta VTTS_{i-j,a} - \Delta VTTS_{i-j,b}\end{aligned} \tag{4.22}$$

To properly disentangle the total mode effects, only those respondents are considered who have chosen the corresponding modes at least once, allowing for a fair comparison between users who are familiar with both modes under evaluation. This accounts for some sort of self-selection at the individual level, as our main advantage is that individuals were observed choosing differently among a set of travel modes for different kinds of

21 Deviations may occur between the numbers reported in Table 4.7 and Table 4.8, as not all user groups choosing either mode i or j (Table 4.8) also choose mode i *and* j (Table 4.7).

TABLE 4.7: Mode effects: Median VTTS difference [CHF/h] between MIV and PT, CS and CP by user characteristic ($\Delta VTTS_{i-j}$) for a given user-type. Values are calculated based on the conditional mode-specific VTTS estimates (MIXL), only including those N respondents who have chosen both modes at least once.

	MIV–PT	MIV–CS	MIV–CP
Total $\Delta VTTS_{i-j}$	15.8	–0.1	–2.1
Interquartile range (IQR)	(19.0)	(20.1)	(17.3)
N_{total}	233	173	98
Female $\Delta VTTS_{i-j}$	21.2	10.9	2.2
N_a	117	82	49
Male $\Delta VTTS_{i-j}$	8.7	–7.9	–5.7
N_b	116	91	49
Agglo./rural $\Delta VTTS_{i-j}$	19.3	5.1	1.2
N_a	147	111	70
Urban $\Delta VTTS_{i-j}$	5.9	–6.5	–10.8
N_b	86	62	28
Age < median $\Delta VTTS_{i-j}$	17.8	0.9	–2.1
N_a	112	82	39
Age $\geq$ median $\Delta VTTS_{i-j}$	13.9	-1.4	–2.1
N_b	121	91	59
No kids $\Delta VTTS_{i-j}$	17.9	2.5	–3.2
N_a	114	79	47
With kids $\Delta VTTS_{i-j}$	12.8	–0.2	–1.2
N_b	119	94	51

trips. The sample distributions of $\Delta VTTS_{i-j}$ for the MIXL are illustrated in the Appendix, Figure A.39. In each of the three cases, there is a substantial amount of heterogeneity present between MIV and the mode in comparison.

Results of Total $\Delta VTTS_{i-j}$ and for the different user groups are presented in Table 4.7 (only reporting those categories with a |t-value| > 1 in Table 4.5; note that in the MIXL, couple, income and education did not exhibit any substantial effects on the VTTS).[22] The median VTTS difference

22 While certainly interesting, we do not further investigate VTTS heterogeneity in trip characteristics as they vary *within* individuals. Remember that the main goal of this chapter is to

between MIV and PT users is largest (15.8 CHF/h), while the total mode effects are small and similar for CS (−2.1 CHF/h) and CP (−0.1 CHF/h), all of them exhibiting comparable sample distributions with interquartile ranges of about 20 CHF/h (see also Figure A.39).

In the case of $\Delta VTTS_{MIV-PT}$, urban residents exhibit the lowest mode effect of about 5.9 CHF/h (which is almost 10 CHF/h below the total mode effect of 15.8 CHF/h). For urban residents, the more similar magnitude between these two modes can be explained by the higher flexibility in this user-groups' choices (i.e. higher PT accessibility and lower demand for MIV). While rural residents use PT less frequently, regardless of its service quality, this does not directly affect the VTTS for PT, but indirectly for MIV, which in rural regions is, in most cases, also the fastest mode. This argumentation is consistent with the results in Table 4.5, showing that urban residents exhibit a substantially lower VTTS for MIV of 6.8 CHF/h compared to the sample average.[23] $\Delta VTTS_{MIV-CS}$ and $\Delta VTTS_{MIV-CP}$ are, in turn, similarly affected by that, exhibiting substantial and negative mode effects for urban residents, which is strongest for CP.

Men have a lower $\Delta VTTS_{MIV-PT}$ of about 8.7 CHF/h, resulting from their significantly lower VTTS for MIV. While men tend to have a substantially higher income, and income has no effect on the VTTS for any mode, this result is not unexpected, given that men tend to enjoy driving a vehicle more than women. In the case of $\Delta VTTS_{MIV-CS}$ and $\Delta VTTS_{MIV-CP}$, while the total mode effects are close to zero, there is also a clear gender gap, such that men exhibit a lower median VTTS for MIV than for CS and CP. Especially in the case of CS, women might see this mode as a convenient alternative in terms of travel comfort and flexibility, exhibiting a lower disutility of travel time relative to MIV. Finally, for all three mode comparisons, the heterogeneity in mode effects for age and kids is not that pronounced.

Regarding the user-type effects, again, one should note that the differences in user-type effects between mode *i* and *j* (i.e. the total user-type effects) coincide with the differences in mode effects between two user-types. Results are confirmed when looking at Table 4.8: The heterogeneity in total user-type effects is largest for gender and residential location area. Women (strongest effect for MIV–CS; 19.5 CHF/h) and rural residents (strongest

provide VTTS estimates that vary *between* different users for calculating the VTAT based on the VoL, which by definition does not vary *within* individuals.

23 Qualitatively, we got the same result for Austria, where the smallest mode effect was found for urban residents ($\Delta VTTS_{MIV-PT} = 3$ Euro/h in the MIXL, relative to the total mode effect of 4.9 Euro/h; Schmid et al. (2019a)).

TABLE 4.8: User-type effects: Median VTTS difference [CHF/h] between user-type a and b ($\Delta VTTS_{a-b}$) for a given mode. Values are calculated based on the conditional mode-specific VTTS estimates (MIXL), only including respondents who have chosen a specific mode at least once.

Mode	MIV: i	PT: j	CS: j	CP: j
$\Delta VTTS_{female-male}$	12.5	−0.9	−7.0	1.2
Total $\Delta VTTS_{i-j,female-male}$	–	13.4	19.5	11.3
$\Delta VTTS_{rural-urban}$	13.4	−0.2	−1.1	−2.3
Total $\Delta VTTS_{i-j,rural-urban}$	–	13.6	14.4	15.7
$\Delta VTTS_{age_{<median}-age_{\geq median}}$	5.8	1.5	5.5	6.3
Total $\Delta VTTS_{i-j,age_{<median}-age_{\geq median}}$	–	4.3	0.3	−0.5
$\Delta VTTS_{no\ kids-with\ kids}$	1.6	−4.6	−1.2	−1.0
Total $\Delta VTTS_{i-j,no\ kids-with\ kids}$	–	6.2	2.8	2.6

effect for MIV–CP; 15.7 CHF/h) exhibit substantially higher VTTS for MIV compared to all other modes. Importantly, our results indicate that in case of PT, the total mode effect always dominates the user-type effects and the mode effects remain more or less persistent for all investigated user-types, while in the case of CS and CP, the heterogeneity in user-types is much more pronounced compare to the total mode effect.

More distinct mode and user-type effects could be obtained when user characteristics would have been combined to form more specific user groups. While one could be tempted to make inferences based on combined user characteristics, the validity of such a procedure is empirically questionable given the often very low actual number of corresponding respondents in our sample.

4.5.2 *The value of time assigned to travel (VTAT)*

The value of time assigned to travel (VTAT) for mode i and individual n is calculated according to

$$VTAT_{i,n} = \widehat{VoL}_n - \widehat{VTTS}_{i,n} \tag{4.23}$$

using the individual VoL (Equation (3.21); resulting from the TUMIX) and conditional VTTS estimates (Equation (4.20); resulting from the MIXL). Equation (4.23) shows that unless one has an estimate of the VoL, the VTAT simply cannot be calculated just based on the VTTS. However, as we show in Appendix A, the VoL is not needed to investigate mode and total user-type effects in the VTAT, as it cancels out (Jokubauskaite et al., 2019). For example, $\Delta VTTS_{MIV-PT}$ corresponds to $-\Delta VTAT_{MIV-PT} = \Delta VTAT_{PT-MIV}$, saying that for the median respondent the value of time assigned to travel is 15.8 CHF/h higher in PT than MIV (see discussion below). Thus, one of the main insights resulting from this VTTS decomposition is related to (i) the comparison between the VTAT levels for the different modes and user groups and (ii) the resulting implications on investment recommendations as discussed in Section 4.1.

Importantly, the VoL is not only estimated for the same set of individuals used to estimate the VTTS[24]; the VTAT is calculated for each user based on his/her individual VoL *and* VTTS, thus allowing more powerful statements by analyzing the mode-specific VTAT distributions.

The VTAT represents the direct benefit that results from the time assigned to travel and depends on the travel conditions such as comfort, crowding, safety, the possibility to use the travel time productively, and potentially other (unobserved) characteristics not only of the chosen mode per se, but also of the individual itself. The VTAT can be positive or negative; if negative, it contributes to increase the VTTS above the VoL (i.e. the willingness to pay to reduce travel time is larger than the opportunity value of time); if positive, the VTTS is lower than the VoL.

The median VTAT are presented in Table 4.9 for each model and mode (the VTAT sample distribution is illustrated in Figure 4.4 for the MIXL), following the reversed ranking in mode-specific VTTS as shown in Figure 4.3. Results are consistent between the different models (except for the VTAT for walk, which is close to zero anyway): Focusing on the MIXL, the lowest VTAT is found for CP (−8.9 CHF/h), followed by MIV (−4.8 CHF/h), CS (−2.7 CHF/h) and walk (−0.7 CHF/h), while the values for bike (6.9 CHF/h) and PT (10.3 CHF/h) are positive.

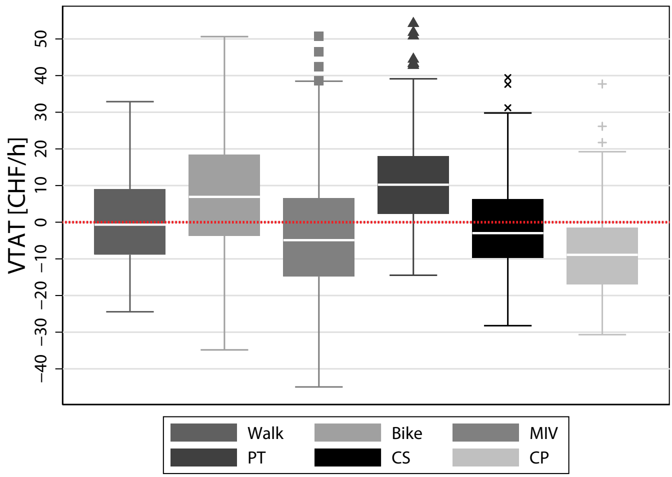
The main implication is that on average, the travel conditions of bike and, especially, PT are perceived as more pleasant than those in MIV, CS and CP, which seems to capture well the outstanding service quality of PT in Zurich. There are other reasons why PT users might perceive the time assigned to travel more pleasant than in a car (and therefore, are less

24 This is, by itself, already an important contribution to the literature, so far only done in Hössinger et al. (2019) and Jokubauskaite et al. (2019). However, the main limitation in these studies is that the VTTS is included as a sample average/median to calculate the VTAT.

TABLE 4.9: Median VTAT [CHF/h] and interquartile range (IQR) for each model and mode. Values are calculated based on the VoL and conditional mode-specific VTTS estimates, only including respondents who have chosen the corresponding mode at least once (last column).

	TMNL Value/(IQR)	UMNL Value/(IQR)	MIXL Value/(IQR)	N
VTAT walk	3.2	2.2	−0.7	256
	(16.5)	(16.8)	(17.8)	
VTAT bike	8.4	8.7	6.9	166
	(13.6)	(14.6)	(22.1)	
VTAT MIV	−3.8	−4.2	−4.8	253
	(15.5)	(16.5)	(21.0)	
VTAT PT	9.2	9.4	10.3	331
	(16.9)	(15.7)	(15.9)	
VTAT CS	−0.8	−0.5	−2.7	219
	(18.4)	(16.5)	(16.4)	
VTAT CP	−4.5	−5.9	−8.9	120
	(14.8)	(14.7)	(15.5)	

FIGURE 4.4: Sample distributions of mode-specific VTAT (MIXL and TUMIX).



time sensitive)[25]: They are released from the driving task and can engage in any kind of secondary activities, making the time in PT more comfortable, entertaining and useful. In case of bike, apart from the good bike infrastructure in Zurich, riding a bike seems to be an enjoyable activity; an effect that may be even enforced by the nice scenery in Zurich, as well as the health and fitness benefits when using this active mode. On the other hand, results clearly indicate that especially the time assigned to travel in CP is valued highly negative, again underlining our argumentation in Section 4.5.1 that the negatively perceived social interaction with the non-acquainted driver exhibits a high discomfort of travel. Finally, from a PT operator's point of view, our results indicate that investing in speed may exhibit a higher marginal impact on user benefits, since the VTAT is already at a very high level, while for a CS or CP operator, investing in the quality of travel may be suggested.

Table 4.10 shows the VTTS and VTAT for all different user groups, now also presenting the results for those variables that are not included in the choice model, but were fairly affecting the VoL. Results indicate that the VTAT for MIV is substantially higher for urban residents (0.2 CHF/h), younger (−3.0 CHF/h) and male (−0.5 CHF/h) respondents with high income (−0.5 CHF/h) and kids (1.6 CHF/h). In the case of PT, there is no single user group that exhibits a negative VTAT, with the highest values found for high income (14.7 CHF/h) and younger (12.1 CHF/h) respondents with kids (13.4 CHF/h). Clearly, while the VTTS is not affected by income, but high income respondents exhibit a higher VoL (27.0 CHF/h compared to the sample median of 22.9 CHF/h; see also Table 3.5), this automatically affects the VTAT.[26] The VTAT for CS are all negative (except for women and respondents with kids), with the lowest values occurring for childless (−7.8 CHF/h) and male (−7.3 CHF/h) respondents, which could partly be explained by an increased reluctance of male bachelors (owning a more luxury and powerful car) towards driving an unknown and potentially less appealing vehicle one is not used to. Finally, the VTAT for CP are below the ones for CS, with the lowest values found for childless (−14.3 CHF/h), low income (−12.6 CHF/h) and urban (−11.5 CHF/h)[27] respondents.

25 Flügel (2014) provides a summary of why PT users may be less time-sensitive than car travelers.

26 Similarly for respondents with kids: While this variable is not affecting VTTS heterogeneity substantially (except in the case of PT), it has a big impact on the VoL (i.e. respondents with kids exhibit a median VoL of 28.9 CHF/h; see also Table 3.5).

27 This could be explained by a higher anonymity in urban areas, possibly causing higher displeasure for these respondents when sharing a ride with complete strangers.

TABLE 4.10: Median VTTS [CHF/h] and VTAT [CHF/h] for different modes and all user groups (MIXL).

	MIV	PT	CS	CP
$VTTS_{female}$	35.5	13.4	23.2	32.0
$VTTS_{male}$	23.0	14.3	30.2	30.8
$VTAT_{female}$	−10.3	10.1	0.6	−9.9
$VTAT_{male}$	−0.5	10.7	−7.3	−8.6
$VTTS_{rural/agglo.}$	33.9	13.7	26.7	30.8
$VTTS_{urban}$	20.5	13.8	27.8	33.1
$VTAT_{rural/agglo.}$	−10.4	10.3	−3.4	−7.9
$VTAT_{urban}$	0.2	10.3	−1.4	−11.5
$VTTS_{age_{<median}}$	32.3	14.6	30.3	34.8
$VTTS_{age_{\geq median}}$	26.4	13.1	24.7	28.5
$VTAT_{age_{<median}}$	−3.0	12.1	−1.0	−8.2
$VTAT_{age_{\geq median}}$	−7.1	7.7	−4.4	−10.1
$VTTS_{no\ kids}$	29.6	11.2	26.9	30.8
$VTTS_{with\ kids}$	27.9	15.8	28.1	31.8
$VTAT_{no\ kids}$	−10.8	6.4	−7.8	−14.3
$VTAT_{with\ kids}$	1.6	13.4	2.3	−4.3
$VTTS_{low\ educ.}$	30.5	13.0	25.4	30.0
$VTTS_{high\ educ.}$	28.6	14.4	28.2	32.9
$VTAT_{low\ educ.}$	−7.4	7.5	−5.0	−12.6
$VTAT_{high\ educ.}$	−3.3	11.4	−1.2	−7.8
$VTTS_{income_{<median}}$	32.0	13.6	25.5	31.9
$VTTS_{income_{\geq median}}$	26.2	13.9	28.8	30.2
$VTAT_{income_{<median}}$	−10.1	7.0	−5.4	−12.6
$VTAT_{income_{\geq median}}$	−0.5	14.7	0.7	−5.4
$VTTS_{single}$	29.9	12.4	27.6	32.0
$VTTS_{couple}$	28.7	14.7	27.0	31.2
$VTAT_{single}$	−8.8	9.11	−4.9	−11.3
$VTAT_{couple}$	−2.2	10.9	−1.2	−7.9

4.5.3 *Correlations between the VTTS, VoL and VTAT*

The last section of this chapter is dedicated to the question: Is the VTTS related to the VoL? This issue is deeply ingrained in the history of time-use and consumer behavior research, where the underlying consensus prevails that the opportunity cost of time is one main component of the value of travel time savings (see e.g. Train and McFadden, 1978; Ramjerdi et al., 1997; Mackie et al., 2001; Jiang and Morikawa, 2004). For example, Jara-Diaz et al. (2008) mention that ...

> *... this value [VoL] is not only indicative of the pure perception of time, but also is part of the willingness to pay to reduce exogenously constrained activities [VTTS], which is at the heart of the appraisal of projects in sectors as transport.*

In his pioneering work, Johnson (1966) showed that the inclusion of work time in the utility function implies a value of time equal to the wage rate plus a subjective value of time assigned to work. He then claimed that this essentially *is* the VTTS. Theoretically, this makes sense, as a reduction in travel time could be assigned to either work and/or leisure, thus increasing the traveler's utility one-by-one (Jara-Diaz, 2007).

DeSerpa (1971) then introduced and Jara-Diaz and Guevara (2003) refined the technical relations between goods and time, such that the consumption of a specific good requires a minimum amount of time and vice versa. This ended up in showing that the value of saving time in an activity (VTTS) equals the value of doing something else that generates more utility (VoL) minus the value of time assigned to that activity (VTAT). While this well-formulated theory builds the microeconomic foundation of the value of travel time savings (see e.g. Mackie et al., 2001), nobody so far has tested it empirically. In other words: To what extent is the value of liberated travel time related to the value of doing something else?

Let us consider an individual with a high VoL. According to Johnson (1966), this individual would also exhibit a high VTTS, as the time spent for traveling could be used more productively – either for more leisure, or work to generate more income. Remember that income is one key component of the VoL, resulting from the definition of the VoL in Equation (3.21) (directly via more available money and indirectly via less available time), and the trade-off between working time, leisure and goods consumption in the utility function, affecting the preferences of freely consumed goods. Clearly, for given preferences, higher income directly increases the opportunity value of time (see also e.g. Jiang and Morikawa, 2004). Given that

TABLE 4.11: Correlations between mode-specific VTTS (MIXL), the VoL (TUMIX) and VTAT.

	corr[VoL,VTTS]	corr[log(VoL),VTTS]	corr[VTAT,VTTS]	N
Walk	+0.07	+0.09	-0.19^{***}	256
Bike	+0.04	+0.05	-0.64^{***}	166
MIV	+0.05	$+0.12^{*}$	-0.57^{***}	253
PT	$+0.17^{***}$	$+0.20^{***}$	-0.14^{**}	331
CS	+0.09	$+0.13^{*}$	-0.22^{***}	219
CP	+0.03	+0.07	-0.48^{***}	120

Significance levels: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

income does not exhibit any noticeable effect on the VTTS, the question remains to which degree the VoL is actually related to the VTTS.

Table 4.11 shows that the correlations between the VTTS and log(VoL)[28] are always positive, but only small in size (see also Figure 4.5), indicating that the mode-specific VTTS and the VoL are mostly unrelated. One explanation is that income and the presence of kids in the household both exhibit a strong and positive effect on the VoL (for the former by showing a strong and positive effect on available money for freely consumed goods, and a negative effect on available time for freely chosen activities; for the latter by showing a strong and negative effect on the preference of freely consumed goods). On the other hand, the VTTS is mostly affected by gender (men have a lower VTTS for MIV and bike, and a higher VTTS for CS) and urban residential location (lower VTTS for MIV). The main connecting element is the presence of kids, also exhibiting a significant and positive effect on the VTTS for PT, which in turn leads to the strongest positive correlation between the VoL and the VTTS of about +0.20 ($p < 0.01$). In fact, even in the case of PT, however, the VoL would only explain a very small fraction of the VTTS variance ($R^2 = 0.04$). Furthermore, the weak positive correlations between the VoL and the VTTS for MIV (+0.12; $p < 0.1$) and CS (+0.13; $p < 0.1$) are mainly related to the negative effect of age on both the VTTS and the VoL.

Using the decomposed VoL elements (i.e. *preference* for freely consumed goods relative to time, *available money* and *available time* for freely chosen expenditures and activities, respectively) may better explain the sources of heterogeneity in the VTTS that are associated with the VoL. The re-

28 As shown in Table 4.11, taking the logarithm slightly strengthens the relationship, hence we focus on the logarithmic transformation from here on.

FIGURE 4.5: Correlations between mode-specific VTTS (MIXL) and the VoL (TU-MIX).

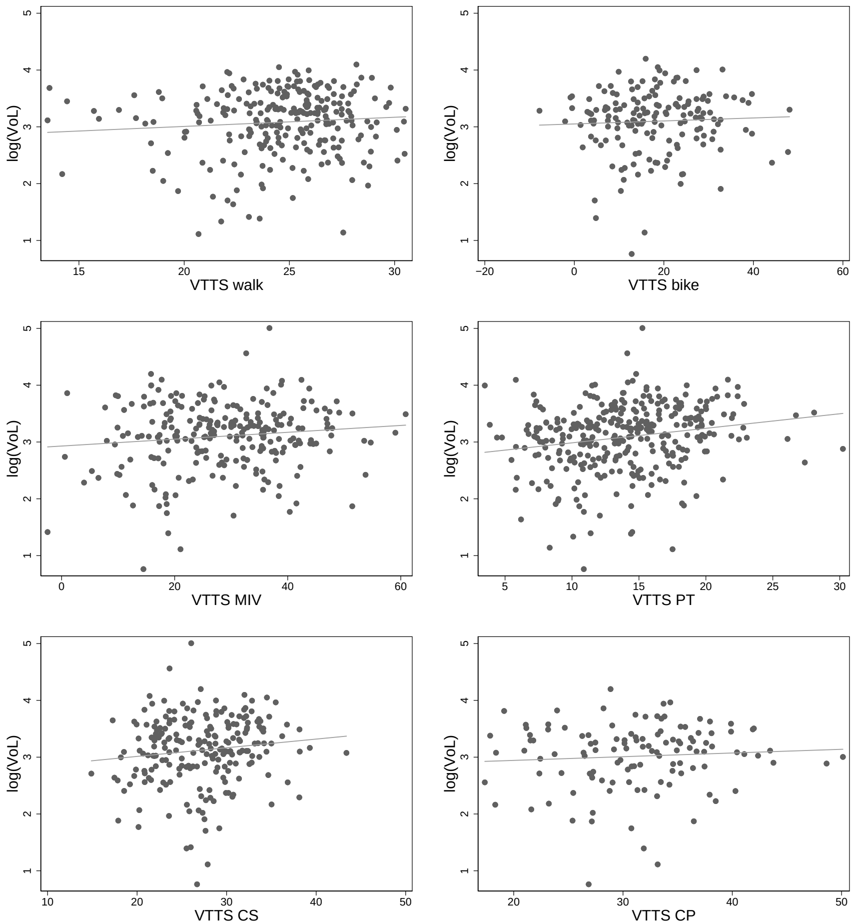


TABLE 4.12: Correlations between mode-specific VTTS (MIXL) and VoL components (TUMIX).

	VTTS walk	VTTS bike	VTTS MIV
log(preference)	-0.04	-0.11	-0.41^{***}
log(avail. money)	-0.10	0.01	-0.21^{***}
log(avail. time)	-0.18^{***}	0.07	0.09
N	256	166	253

	VTTS PT	VTTS CS	VTTS CP
log(preference)	-0.23^{***}	-0.16^{**}	-0.36^{***}
log(avail. money)	0.00	0.05	-0.18^{**}
log(avail. time)	0.01	0.08	0.10
N	331	219	120

Significance levels: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

fined correlation analysis in Table 4.12 shows that in the case of walk, intuitively more available time exhibits a negative correlation with the VTTS ($p < 0.01$), while the other two components do not show a substantial effect. However, the negative correlation with more available money is counter-intuitive and dampens the effect of the available time component, leading to a correlation between the VoL and VTTS that is close to zero. While no correlations are found for bike, intuitively a stronger preference for freely consumed goods relative to time exhibits a substantial and negative correlation with the VTTS for MIV. In contrast, more available money exhibits a strong and negative association with the VTTS, canceling out with the negative correlation of freely consumed goods relative to time and the VTTS, such that the correlation between the VoL and VTTS is very small (a similar, though less pronounced mechanism is at play in the case of CP). In the case of PT, while the correlation between the preference component is again negative and strong, the effects of the time and money components are essentially zero, such that the correlation between the VoL and VTTS remains positive and significant as shown above (a similar, though less pronounced mechanism is at play in the case of CS).

What does this mean for the VTAT? Clearly, for a constant VoL, the correlations between mode-specific VTTS and VTAT would be -1. However, as the VoL varies strongly across respondents, this is not the case, and the question becomes how of much of the heterogeneity in the VTTS is actually reflected in the VTAT. Table 4.11 shows that for the MIXL, as expected the correlations between VTTS and VTAT are always negative and substantial, especially for bike (–0.64), MIV (–0.57) and CP (–0.48; all $p < 0.01$). Also, the lowest correlation is found for PT (–0.14), whose VTTS exhibited a positive correlation with the VoL (+0.20): In the case of PT, a higher willingness to pay to reduce travel time is not much associated with a lower perceived travel comfort, but rather with a higher opportunity value of time.

What does this mean for transportation policy appraisals? The main purpose of this analysis is to get a deeper understanding on what lies behind the VTTS, and to answer the question to what extent the value of liberated travel time is actually related to the value of doing something else. We show that the VoL and VTTS are positively related for PT, MIV and CS, such that a higher opportunity value of time is associated with a higher willingness to pay to reduce travel time: Ceteris paribus, investing in speed (for example, by building separated CS lanes, expanded highways for MIV or train tunnels for faster PT connections) would particularly reward individuals with a high VoL, while no such connection is found for walk, bike and CP. However, the correlations are small: The VTTS and VoL are only weakly related to each other, with the former primarily depending on individual travel preferences that are mostly uncoupled with the opportunity value of time.

4.6 CONCLUSIONS

As part of the *Post-Car World* project, the value of travel time savings (VTTS) presented in this chapter are not only estimated for traditional modes, but also for shared mobility services such as carsharing (CS) and carpooling (CP). Using a state-of-the-art pooled RP/SP modeling approach by making use of the benefits of both data types, discrete choice models reveal median VTTS estimates for walk (24.9 CHF/h), bike (16.9 CHF/h), MIV (28.9 CHF/h), PT (13.8 CHF/h), CS (27.3 CHF/h) and CP (31.3 CHF/h). Given that a large variation in the VTTS is attributed to the characteristics of the trip and individual, VTTS are adjusted by controlling for trip purpose, distance, weekend trips, weather and habitual choice behavior as well as (observed and unobserved) taste heterogeneity.

The sample consists of 356 Zurich workers, for which we also collected data on time-use and expenditure allocation to estimate the value of leisure (VoL) to calculate all components of the complete Jara-Diaz and Guevara (2003) model formulation: The value of time assigned to travel (VTAT) is calculated (to our best knowledge, for the first time mode- and individual-specific) as a residual between the VoL and VTTS, representing the direct benefit that results from the time assigned to travel, which depends on the conditions of travel such as comfort and the possibility to use travel time productively. The user characteristics investigated in this chapter were previously defined to be in line with the corresponding time-use and expenditure allocation model being analyzed in Chapter 3.

An important implication is that the VTAT has inverse signs for different modes, following the reverse ranking in mode-specific VTTS: The VTAT is negative for CP (−8.9 CHF/h), MIV (−4.8 CHF/h), CS (−2.7 CHF/h) and walk (−0.7 CHF/h), and positive for bike (6.9 CHF/h) and PT (10.3 CHF/h). Clearly, together with MIV, the two emerging modes CS and CP exhibit the worst performance in terms of VTAT, which indicates that the value of time assigned to travel in car modes is substantially lower than in PT. This seems to capture well the outstanding service quality of PT in Switzerland in general and Zurich in particular. It also may indicate that PT benefits from the possibility to use in-vehicle time more productively for secondary activities such as work, communication, or entertainment, which is positively affecting the perceived comfort. From a transportation planning perspective, the results support those who claim that the quality of travel matters greatly (e.g. Litman, 2008; Lyons et al., 2013; Flügel, 2014) and investments in travel conditions are as important as in higher speed. Finally, from a PT operator's point of view, our results indicate that investing in speed may exhibit a higher marginal impact on user benefits, since the VTAT is already at a very high level.

From a modeling perspective, the mode-specific characteristics (e.g. the possibility to use travel time productively) are latent and cannot be observed directly; they were therefore not included as explanatory variables but are reflected in the estimated VTTS parameters and error variances, which is a standard way of how these latent characteristics are taken into account. Apart from all observable mode-specific and trip related characteristics available to us, our modeling structure minimizes the risk of omitted variable bias by including random error components and taste parameters. Furthermore, besides the fact that we do not observe e.g. WiFi availability or seat occupancy rates in PT, we also think that they do not reflect the possibility to use travel time productively in an appropriate way. Similar arguments can be made for other, even more latent characteristics such as "comfort".

Our findings indicate that CS and CP have a hard time when competing with the traditional modes. Market shares may be difficult to expand by just providing a higher accessibility (which was one main emphasis when framing the respondents in the SP experiments), even in the complete absence of private cars: On average, individuals do not seem to enjoy traveling in these modes, and they rather choose PT or bike. From a CS or CP operator's point of view, it seems advisable that – given the very low VTAT – investing in the quality of travel should receive a high priority. Also, simplified membership models reducing the up-front costs (e.g. yearly mileage packages) and satisfying high ecological standards still could further stimulate the use of these modes: As discussed in Schmid et al. (2016), for traditional car users this may be achieved by *facilitating* the usage as a direct policy intervention for acquiring the technologically less capable and conservative population; for PT-affine people this may be achieved by *decreasing* the costs to increase demand, at the same time providing more Eco-friendly and sustainable vehicles to satisfy the preferences of environmentally sensitive people.

The investigation of mode and user-type effects is important for identifying and separating the idiosyncratic differences in VTTS across modes that (i) are due to differences in the direct utility derived from in-vehicle travel time (mode effect) and (ii) can be attributed to the characteristics of the users (user-type effect). For example, the substantial and persistent difference between the VTTS for MIV and PT is striking. This stands in contrast to other European studies, in which the average mode effects were much smaller, and/or were typically dominated by the user-type effects. Our results indicate that the main user characteristics being able to explain this large difference between MIV and PT of about 15.8 CHF/h are, in decreasing order, urban residential location, gender, kids and age. While for neither of these groups, the mode effect vanishes, the substantially reduced mode effect of about 5.9 CHF/h for urban residents can be explained by a higher flexibility in this user-group's choices.

Data were collected in a broader way (i.e. apart from travel, to obtain individuals' time-use and expenditure allocation data), which has the main disadvantage that we do not know much about the context of a specific travel choice. It can always be argued that self-selection in terms of VTTS heterogeneity might not only occur at the individual, but also at the trip level (e.g. if one is in a hurry and/or has tighter scheduling constraints, more relative emphasis will be put on travel time attributes). Even though we control for different trip characteristics, especially this latter type of self-selection cannot be tackled sufficiently given our available data, which has to be seen as a main limitation of this work. Either way, to perfectly disentangle mode and user-type effects, one would also need a "perfect" instrument provided by the data, which was not available (see also e.g. the discussions in Mabit and Fosgerau (2009) on self-selection and instrument validity in the context of estimating VTTS, which – in practice – are very challenging issues).

Finally, having obtained the VTTS and VoL for each individual, we show that both measures exhibit relatively low correlations. For example, it shows that income – one key factor of the VoL – does not exhibit any substantial effect on the VTTS, a similar result that has been obtained for Austria (Schmid et al., 2019a). This is striking, given that travel behavior research in general, and valuation studies in particular, often have (explicitly or implicitly) assumed that the VTTS and VoL have a close relationship. At least in our sample, mode-specific VTTS are only partly associated with a higher VoL, primarily depending on individual travel preferences that are uncoupled with the opportunity value of time. The only significant correlation between the VoL and VTTS could be found for PT, where the main connecting element is the significant and positive effect of kids in the household. Findings have to be verified for other user segments, regions or countries (e.g. with a larger heterogeneity in income, and/or with travel exhibiting a substantially larger share of total expenditures; see also e.g. Zamparini and Reggiani (2007)), and it would be interesting to see in future studies, if our findings are just a peculiarity for the Canton of Zurich and the specific sample of respondents with high income and education, or if this is more the rule than the exception.

5

IN-STORE OR ONLINE SHOPPING?

The quickest way to know a woman is to go shopping with her.

— Marcelene Cox

This chapter is based on Schmid and Axhausen (2019b) published in the *Journal of Choice Modelling*.

5.1 INTRODUCTION

Information and communication technologies (ICT) have experienced a persistent increase in usage over the last decades, which, in the context of online shopping, allow for a more flexible spatial and temporal accomplishment of shopping activities (Mokhtarian, 2004). A shift from the traditional store towards online shopping has been ongoing for some time and has become more and more important in terms of market shares and individual behavior, as discussed in Rudolph et al. (2015) for the case of Switzerland. Regarding the interdependencies with travel behavior, Mokhtarian et al. (2006) argue that apart from expanding individuals' choice sets, the potential effects of ICT are ambiguous and require further empirical investigations (see also e.g. Salomon (1986), Farag et al. (2007) and Cao (2009), for extended literature reviews on the topic). But what are the key attributes in individual decision making for either visiting a store or shopping online? How do people value travel, delivery and shopping/ordering time when directly facing the trade-offs between these two alternative shopping channels? Is there a difference between product categories, and how do socioeconomic characteristics and soft factors, such as attitudes towards shopping and ICT related aspects, affect these trade-offs?

As discussed in Chapter 1, one main objective of the *Post-Car World* project is to investigate how today's people behave in a possible future situation where private cars would no longer be part of their daily travel (Schmid et al., 2016). In the context of shopping, the main motivation is to explore how under such conditions, the choice behavior between in-store and online shopping and the heterogeneity in taste parameters can be explained by socioeconomic characteristics, attitudes and perceptions.

However, although important for the overall project guidelines, the reader has to be alerted that presented results only hold under the current hypothetical situation and cannot be generalized to real world applications.

More than 30 years after the first study investigating the demand for teleshopping using discrete choice analysis (Manski and Salomon, 1987), we present an innovative survey design and a sophisticated modeling approach by investigating the relative importance of attributes related to the choice between in-store and online shopping for two product categories: Groceries, typical experience goods, and standard electronic appliances, typical search goods. The key characteristics of search goods can more easily be evaluated from externally provided information, while experience goods need to be physically inspected or tried (e.g. Peterson et al., 1997). Results provide new insights on purchasing channel preferences by allowing attribute sensitivities to differ by product type: In Switzerland, electronic appliances are often purchased online, while the main product characteristics of groceries are mainly obtained in-store (Rudolph et al., 2015). Importantly, multi-channel shopping, i.e. explicitly distinguishing between pre-purchase and purchase channels (Mokhtarian and Tang, 2013; Zhai et al., 2017), and multi-purpose shopping trips (Leszczyc et al., 2004) were ruled out to break down the experimental design to a manageable level of complexity.

As one of the first coherent studies, Salomon and Koppelman (1988) discuss the underlying factors affecting the choice between in-store and teleshopping. They define shopping as a process of collecting information on product attributes until the final purchase decision. Alternative-specific attributes (service, delivery, travel time, etc.) and personal characteristics (socioeconomic background) are hypothesized to affect the perceptions of shopping alternatives (being among people, pleasure, time-use, etc.), while attitudes towards shopping alternatives (shopping/store enjoyment, variety seeking, perceptions, risk, service quality, etc.; see e.g. Childers et al. (2001); Rohm and Swaminathan (2004); Soopramanien and Robertson (2007); Clemes et al. (2014); Scarpi et al. (2014) and others) are mainly determined by personal characteristics. The ultimate factors affecting shopping behavior are the perceptions of alternatives and the attitudes. Dijst et al. (2008) present a model for online and in-store shopping of media products, in which attitudes play a major role in explaining shopping channel preferences. Farag et al. (2005) show that positive attitudes towards online shopping increase the frequency of online shopping, with more positive attitudes among young and single males with high education and income living in urban residential locations, a similar user profile of online shoppers that has been revealed in many other related studies (Farag et al., 2006; Cao, 2009; Chocarro et al., 2013) and in the case of Switzerland (Rudolph et al., 2004). Bellman et al. (1999) also mention the potential importance of a lower time budget – measured by the amount of household working hours – on the propensity to shop online. Regarding the pleasure of shopping, e.g. Scarpi et al. (2014) found that shopping for fun is stronger associated with in-store than online shopping, although the general consensus in the literature is not clear (see also e.g. Perea y Monsuwé et al. (2004), for an extended literature review on what drives consumers to shop online).

Several studies have shown substantial product-specific heterogeneity in factors affecting the choice between in-store and online shopping (e.g. Chiang and Dholakia, 2003; Girard et al., 2003; Liu et al., 2013; Zhen et al., 2016). E.g. Peterson et al. (1997), Chiang and Dholakia (2003), Rotem-Mindali and Salomon (2007), Chocarro et al. (2013) and Zhai et al. (2017) argue that the intention to shop online is much higher for search (e.g. electronic appliances, books or other media products) than experience goods (e.g. fresh food, perfume or cars), as online shopping reduces search costs substantially while the dominant product attributes of experience goods cannot be obtained online. Another main criterion to shop online often referred to is the (lower) price in combination with facilitated price comparisons (e.g. Farag et al., 2007), one of the main driving forces when considering online shopping in Switzerland (Rudolph et al., 2015). Also, the general product risk which is typically higher for expensive and experience goods, may lead to a decreasing propensity for online shopping. However, especially expensive electronics, soft- and hardware may partially compensate these risks by offering a high level of shopping convenience. Chocarro et al. (2013) argue that high involvement goods – expensive goods with low purchase frequency – increase the risks for consumers, and conditional on the distance to the store, exhibit a higher probability of in-store shopping. For search goods, the authors show that a higher travel time has a positive effect on online shopping.

While all of the aforementioned studies used revealed preference (RP) data, there has been only little research on how individuals explicitly trade-off attributes specific to each shopping channel. Our approach is therefore comparable to Hsiao (2009): The author conducted a simple stated preference (SP) experiment on book purchasing behavior in Taiwan by assessing channel-specific effects including the product price, travel time, travel cost and delivery time. He concludes that avoiding a shopping trip produces more benefits in terms of monetary values than waiting for the delivery of an online purchased book, highlighting the potentials of ICT services in the context of a typical search good. One key contribution of this chapter to existing literature is to incorporate those different key facets to better explain shopping channel preferences – product and channel-specific, including socioeconomic and psychological factors – in a dedicated way.

Two latent variables (LVs) that are hypothesized to affect the choice of the shopping channel were tested, capturing the acceptance level of online shopping and the pleasure of shopping: We applied an integrated choice and latent variable (ICLV) modeling approach that enables the simultaneous estimation of attitudes defined by various socioeconomic characteristics (Ben-Akiva et al., 2002), allowing for a dedicated representation of the decision process which may help to structure respondent heterogeneity efficiently and more intuitively compared to a reduced form Mixed Logit model (Vij and Walker, 2016). Further considerations with ICLV models arise when dealing with panel data, which, even in advanced literature, was often not taken into account (see e.g. Kim et al. (2014), for an overview of hybrid choice models applied in travel behavior research). One main contribution of this chapter is the application of advanced econometric methods to better understand individual decision making in the context of shopping channel choice, which, to our best knowledge, is the first alternative-specific hybrid choice model using stated preference data in the field of shopping behavior research.

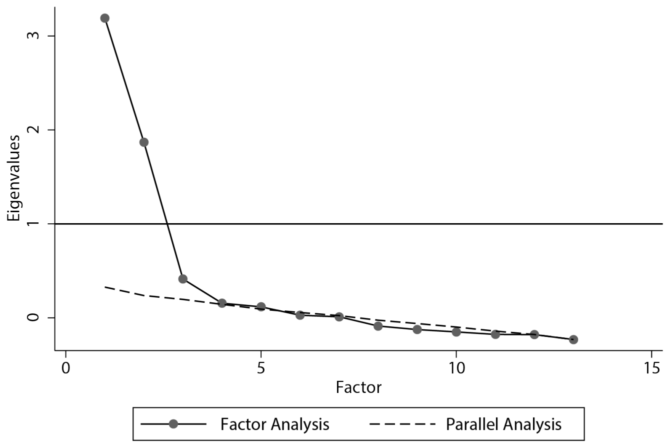
The structure of this chapter is as follows: Section 5.2 explains how the attitudes towards online shopping and the pleasure of shopping were assessed. Section 5.3 provides an overview on the modeling framework. Section 5.4 presents the results and discusses the implications on behavior and valuation indicators. Finally, Section 5.5 provides a discussion, some concluding remarks and the main limitations of the study.

5.2 ATTITUDES AND SOCIOECONOMIC CHARACTERISTICS

A broad range of attitudinal traits were assessed together with the SP experiments (see Section 2.2.2). To focus on attitudes that are related to online and in-store shopping, 13 four-point-Likert scale items (strongly agree to strongly disagree) were considered in subsequent analyses.[1]

1 We also tested four other latent constructs that were available in the data and may have affected the choice between in-store and online shopping, including the love of variety, risk

Figure 5.1: Scree-plot for exploratory factor analysis, suggesting a two-factor-solution (factor 1: Pro-online shopping; factor 2: Pleasure of shopping).



According to our hypotheses and the factor structure of a previously conducted exploratory factor analysis, two latent constructs that explain the most important dimensions of variability were defined. The validity of the two latent constructs is confirmed by the Scree-plot and Eigenvalue criterion as shown in Figure 5.1, clearly speaking in favor of two LVs to be retained (Hayton et al., 2004). Cronbach's α (= 0.78; measures the reliability of the latent constructs) and the Kaiser-Meyer-Olkin criterion (= 0.82; measures the degree of sampling adequacy) further confirm the validity of the constructs (in both cases, a value of 0.8 is considered acceptable).

The first set of items (factor 1) measures the attitudes regarding the general risks and perceptions of online shopping, and whether respondents make use and are aware of this technology (**pro-online shopping LV; onl1-onl10**), while the second set (factor 2) mainly covers the pleasure/enjoyment of in-store shopping (**pleasure of shopping LV; ple1-ple3**; signs of factor loadings in brackets):

- **onl1:** I often order products on the internet (+)
- **onl2:** Online shopping is associated with risks (−)

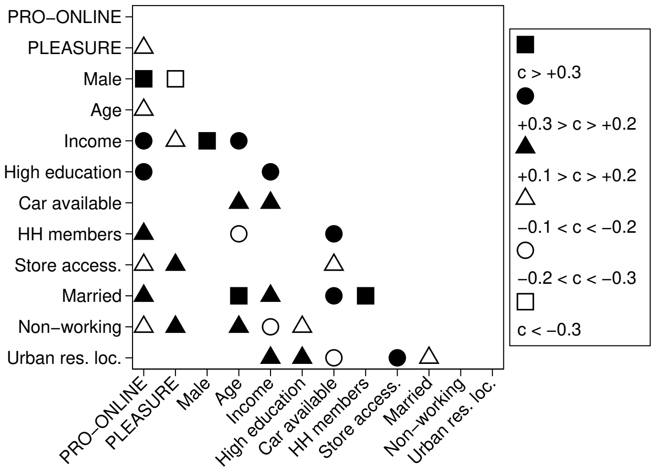
attitudes and environmental awareness, but none of them showed a significant or substantial effect.

- **onl3:** Credit card fraud is one of the reasons why I don't like online shopping (−)
- **onl4:** The internet has more cons than pros (−)
- **onl5:** A disadvantage of online shopping is that I cannot physically examine the products (−)
- **onl6:** Online shopping facilitates the comparison of prices and products (+)
- **onl7:** The risk of receiving a wrong product is one of the main reasons why I don't like online shopping (−)
- **onl8:** I like to follow the new developments in the tech industry (+)
- **onl9:** All I need, I find in the shops (−)
- **onl10:** Number of different IT gadgets in possession (+)
- **ple1**: I like to visit shops, even if I don't want to buy something, just for looking around (+)
- **ple2:** Shopping is exhausting and does not make fun (−)
- **ple3**: Shopping usually is an annoying duty (−)

Each LV is defined by a set of socioeconomic characteristics (see also Table 2.13, for some basic summary statistics). The key variables which were found to describe the two LVs best and are included in subsequent analyses are:

- **Male** (dummy)
- **Age** (continuous; scaled down by factor 100)
- Personal monthly **income** (continuous; scaled down by factor 10'000)
- **High education** (dummy for high-school degree or higher)
- **Car** always **available** (dummy)
- **Store accessibility** (dummy; next store accessible within 10 minutes walk from home location)
- **Married** (dummy)

FIGURE 5.2: Correlation patterns of socioeconomic characteristics and attitudes.



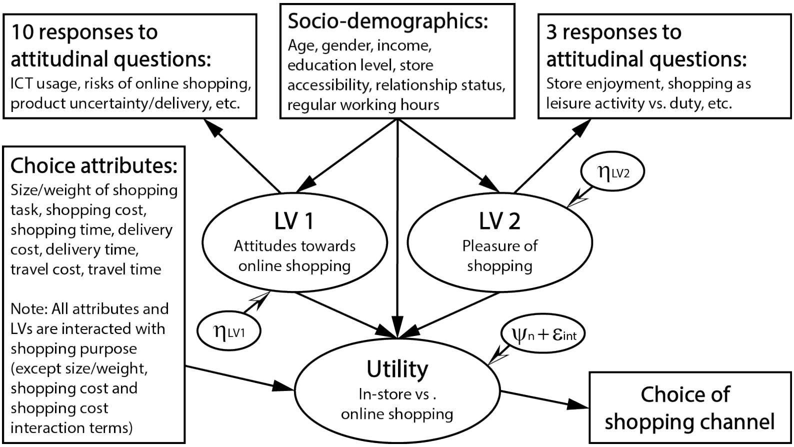
– **Non-working** (dummy; weekly regular payed job working hours ≤ 5 hours)

Regarding the two soft factors, besides a moderate negative correlation between each other, Figure 5.2 indicates that pro-online shopping attitudes are more pronounced in men with higher education and income, while the pleasure of shopping is higher for non-working women living near a supermarket.

5.3 MODELING FRAMEWORK

The hybrid choice modeling (HCM) approach described in Ben-Akiva et al. (2002) – illustrated in Figure 5.3 for the current application – is an integration of the random utility-maximization (RUM) framework and functionalities such as error heterogeneity, random parameters and latent variables (Walker and Ben-Akiva, 2002). The integration of latent variables (LVs) into RUM models is an example of the general HCM framework which addresses the problem of attitudes and perceptions of individuals, which are at the same time relevant to the choice process and hard to observe directly. The LVs are defined in the structural models by measurable socioeconomic characteristics, whereby the measurement model links the LVs with indi-

Figure 5.3: Hybrid choice modeling framework.



cators that are assumed to be affected by the latent constructs. The attitudinal part of this integrated choice and latent variable (ICLV) model with the measured "indicator variables – LV" relationships is therefore often represented by a multiple-indicator multiple-cause (MIMIC) model (Jöreskog and Goldberger, 1975).

To summarize our hypotheses regarding the effects of LVs according to Figure 5.3, we test if 1) pro-online attitudes increase the choice probability of online-shopping, 2) this increase is lower for standard electronic appliances (E) than for groceries (G), as it may take less overcoming to purchase typical search goods than typical experience goods online, 3) pro-online shopping attitudes are positively related to cost sensitivity, given the expanded alternative set such respondents may consider, 4) higher pleasure of shopping attitudes decrease the choice probability of online shopping, 5) this decrease is lower for E, as in-store shopping of groceries may entail more pleasure, 6) higher pleasure of shopping attitudes decrease in-store shopping time sensitivity, 7) this decrease is smaller when buying E, given the nature of search (E) compared to experience goods (G).

5.3.1 *Structural model*

The utility equations for shopping channel $i \in \{O, S\}$ and individual $n \in \{1, 2, ..., N\}$ in choice scenario $t \in \{1, 2, ..., T_n\}$ with choice attributes $X_{i,n,t}$

and the latent variables $LV_{z,n}$ with $z \in$ {online shopping attitudes, pleasure of shopping} are given by

$$U_{O,n,t} = X_{O,n,t}\beta_O + LV_{z,n}\mu_{LV_z} + Z_{z,n}\Theta_z + f_{1,O,n,t} + f_{3,n,t} + \psi_{O,n} + \epsilon_{O,n,t} \quad (5.1)$$

$$U_{S,n,t} = X_{S,n,t}\beta_S + f_{1,S,n,t} + f_{2,n,t} + \epsilon_{S,n,t} \quad (5.2)$$

where

$$f_{1,i,n,t} = (\beta_{cost} + Z_{online,n}\Delta_{online,cost} + \psi_{cost,n}) \cdot cost_{i,n,t} + \varphi_{LV_{online},cost} \cdot LV_{online,n} \cdot cost_{i,n,t} \quad (5.3)$$

$$f_{2,n,t} = (\beta_{time,S} + Z_{pleasure,n}\Delta_{pleasure,time,S} + \psi_{time,S,n}) \cdot time_{S,n,t} + \varphi_{LV_{pleasure},time} \cdot LV_{pleasure,n} \cdot time_{S,n,t} \quad (5.4)$$

$$f_{3,n,t} = (\alpha^{M,L}_{size} + \alpha_{male} \cdot male_n + \alpha_{age} \cdot age_n) \cdot size^{M,L}_{n,t} \quad (5.5)$$

$X_{i,n,t}$ is a $(1 \times J)$ vector of alternative-specific choice attributes and β_i is a $(J \times 1)$ alternative-specific coefficient vector. Both LVs are directly affecting the constant of the online alternative (in-store shopping is defined as the reference alternative) and are interacted with shopping cost and in-store shopping time to reveal heterogeneity in respective attribute sensitivities: $LV_{z,n}$ is a zero-centered latent variable, μ_{LV_z} is the coefficient of latent variable z shifting the intercept of the online alternative, $\varphi_{LV_{online},cost}$ and $\varphi_{LV_{pleasure},time}$ are the coefficients of the interaction terms between the two LVs and some selected choice attributes (i.e. shopping cost × pro-online shopping attitudes; in-store shopping time × pleasure of shopping).

All choice attributes and both LVs were interacted with the shopping purpose (except for the size/weight of the shopping basket and shopping costs), with grocery shopping (G) as a reference, to allow for purpose-specific taste heterogeneity. This increases estimation efficiency compared to a segmented estimation approach by product category, mainly regarding the estimation of only one measurement model.

$Z_{z,n}$ is a $(1 \times Q_z)$ vector of the same observable, socioeconomic characteristics also included in the structural equations of the LVs (see also Equation (5.6)). To compare for the actual gains in model performance (regarding fit, behavioral insights, efficiency and forecasting) when including the LVs compared to a reduced form MIXL excluding them (Vij and

Walker, 2016), $Z_{z,n}$ directly affects heterogeneity in the same parameters as the two LVs do, with Θ_z and Δ_z representing ($Q_z \times 1$) coefficient vectors.

To account for the correlation across choices within individuals and unobserved (random) coefficient heterogeneity (e.g. Greene et al., 2006), three additional components were added to the utility function which vary across individuals but are constant over choice situations. $\psi_{O,n} \sim N(0, \sigma_O^2)$ is an individual-specific random error component with mean zero and standard deviation σ_O, for each individual shifting the intercept of the online alternative by the respective amount. $\psi_{cost,n} \sim N(0, \sigma_{cost}^2)$ and $\psi_{time,n} \sim N(0, \sigma_{time}^2)$ are two random components capturing unobserved heterogeneity in shopping cost and in-store shopping time to adequately compare the reduced form MIXL with the ICLV model (Vij and Walker, 2016): As indicated in Equation (5.6), each LV comprises error variance via the structural equations, which partly capture some unobserved heterogeneity in the choice model (Daziano and Bolduc, 2013a; Kløjgaard and Hess, 2014) through the constant, time and cost interaction effects.

The size/weight of the shopping basket was included using two dummy variables for medium (M) and large (L) size/weight (with small size as the reference), captured by $\alpha_{size}^{M,L}$. Including gender and age interactions allow for preference heterogeneity in varying levels of shopping inconvenience regarding physical conditions, assuming that larger shopping baskets are preferably purchased online, especially for older and female respondents. Finally, $\epsilon_{i,n,t}$ is the remaining alternative-specific IID extreme value type I disturbance term.

The LV structural equations for latent variable z are linear functions of observed socioeconomic characteristics $Z_{z,n}$ for individual n:

$$\begin{aligned} LV_{z,n} &= Z_{z,n}\rho_z + \eta_{LV_{z,n}} \\ \eta_{LV_{z,n}} &\sim N(0, \sigma_{LV_z}^2) \end{aligned} \tag{5.6}$$

where $Z_{z,n}$ is a ($1 \times Q_z$) vector of socioeconomic characteristics to define $LV_{z,n}$ (note that each LV is defined by a partially different set of socioeconomic characteristics) and ρ_z is a ($Q_z \times 1$) coefficient vector.

5.3.2 *Measurement model*

The latent variable measurement equations with responses to the attitudinal questions (items) $I_{w,n}$ with $w \in \{\text{onl1}, \text{onl2}, ..., \text{ple3}\}$ discussed in Section 5.2 are given by

$$\begin{aligned} I_{w,n} &= \overline{I}_w + \tau_{I_w} LV_{z,n} + \nu_{w,n} \\ \nu_{w,n} &\sim N(0, \sigma^2_{I_w}) \end{aligned} \tag{5.7}$$

where $\overline{I}_w$ are the mean ratings of the four-point-Likert scales of each item w calculated beforehand (Hess and Beharry-Borg, 2012; Kløjgaard and Hess, 2014), avoiding the estimation of unnecessary parameters. $I_{w,n}$ are the observed items for individual n, τ_{I_w} is the LV measurement coefficient for item w and σ_{I_w} is the corresponding standard deviation.

Finally, the choice of shopping channel i is modeled by maximizing the alternative-specific utility $U_{i,n,t}$ for each individual n and choice scenario t:

$$c_{i,n,t} = \begin{cases} 1 \text{ if } U_{i,n,t} > U_{j,n,t} \\ 0 \text{ if } U_{i,n,t} \leq U_{j,n,t} \end{cases} \tag{5.8}$$

5.3.3 *Estimation*

Assuming that the random components $\psi_{i,n}$[2] and the latent variables $LV_{z,n}$ are mutually independent and $\epsilon_{i,n,t}$ is IID extreme value type I, the unconditional joint probability $L_n(\cdot)$ – the expected value over all possible values of $\psi_{i,n}$ and $LV_{z,n}$ that individual n chooses alternative i among a sequence of choices T_n, and, simultaneously, stating his/her attitudes via the items $I_{w,n}$ only once – is defined by the integral of the product of conditional choice and item probabilities over the distributions of $\psi_{i,n}$ and $LV_{z,n}$ (e.g. Walker and Ben-Akiva, 2002):

$$\begin{aligned} L_n(\cdot) = \int\int \prod_i \prod_{t=1}^{T_n} & P(c_{i,n,t} = 1 | X_{i,n,t}, LV_{z,n}, \theta, \psi_{i,n})^{c_{i,n,t}} \\ & \times u(I_{w,n} | LV_{z,n}, \tau_{I_w}, \sigma_{I_w}) \; g(LV_{z,n} | Z_{z,n}, \rho_z, \Sigma_{LV_z}) \\ & \times h(\psi_{i,n} | \Sigma_\psi) \; dLV_{z,n} \; d\psi_{i,n} \end{aligned} \tag{5.9}$$

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2 Please note that $\psi_{cost,n}$ is not alternative-specific.

where θ is the set of fixed parameters of the discrete choice submodel, and $h(\psi_{i,n}|\Sigma_\psi)$ and $g(LV_{z,n}|Z_{z,n}, \rho_z, \Sigma_{LV_z})$ are the multivariate distributions of the random components and LVs, respectively, with the corresponding vectors of standard deviations Σ_ψ and Σ_{LV_z}.

$$P(c_{i,n,t} = 1|X_{i,n,t}, LV_{z,n}, \theta, \psi_n) = \frac{\exp(U_{i,n,t})}{\exp(U_{O,n,t}) + \exp(U_{S,n,t})} \tag{5.10}$$

is the conditional choice probability and, for the linear measurement model,

$$u(I_{w,n}|LV_{z,n}, \tau_{I_w}, \sigma_{I_w}) = \prod_{I_w} \left(\frac{1}{\sigma_{I_w}} \phi \left(\frac{I_{w,n} - \overline{I_w} - \tau_{I_w} LV_{z,n}}{\sigma_{I_w}} \right) \right) \tag{5.11}$$

is the item probability function with ϕ as the standard normal density function. Due to identification issues (e.g. Vij and Walker, 2014), the first τ_{I_w} of each LV was fixed to 1.

Using maximum simulated likelihood techniques, the integral in Equation (5.9) is approximated by calculating the joint probability for any given value of $\psi_{i,n}$ and $LV_{z,n}$ using a smooth simulator that is consistent and asymptotically normal (Train, 2009). This is done by drawing values from the $g(LV_{z,n}|Z_{z,n}, \rho_z, \Sigma_{LV_z})$ and $h(\psi_{i,n}|\Sigma_\psi)$ distributions, with superscript r referring to draw $r \in \{1, ..., R\}$: $\widetilde{L_n}(\cdot)$ shown in Equation (5.13) is the simulated likelihood for individual n, and the maximum simulated likelihood estimator contains the values in $\widehat{\Omega}$ and $\widehat{\Sigma}$ that maximize $\widetilde{LL}(\Omega, \Sigma)$, where Ω is the set of fixed parameter vectors of the full model:

$$\max \widetilde{LL}(\Omega, \Sigma) = \sum_{n=1}^{N} \log \left(\widetilde{L_n}(\cdot) \right) \tag{5.12}$$

$$\begin{aligned} \widetilde{L_n}(\cdot) = \frac{1}{R} \sum_{r=1}^{R} \prod_{i} \prod_{t=1}^{T_n} & P(c_{i,n,t} = 1|X_{i,n,t}, LV^r_{z,n}, \theta, \psi^r_n)^{c_{i,n,t}} \\ & \times u(I_{w,n}|LV^r_{z,n}, \tau_{I_w}, \sigma_{I_w}) \end{aligned} \tag{5.13}$$

Models were estimated in *R* 3.2.2 (CMC, 2017). Quasi-random draws were generated using Modified Latin Hypercube Sampling (MLHS) as proposed by Hess et al. (2006). The main criteria regarding identifiability and simulation bias as discussed in Vij and Walker (2014) were investigated: With 1'000 draws, estimates were carefully considered to be robust and stable. Cluster-robust (at the individual-level) standard errors were calculated using the Eicker-Huber-White sandwich estimator (e.g. Zeileis, 2006).

5.4 RESULTS

5.4.1 *Descriptive analysis of choice behavior*

The analyzed sample comprises 3'722 choice observations for 466 respondents (summary statistics of the choice attributes are shown in the Appendix, Table A.10): 37% were assigned to the groceries (G) and 63% to the standard electronic appliances (E) experiment. The market shares of online and in-store shopping choices depend on the shopping purpose: In the G experiment, 66% chose the in-store and 34% the online alternative, while in the E experiment, 38% chose the in-store and 62% the online alternative. In contrast to what is observed in reality[3], the total market share of online shopping is remarkably high for both shopping purposes partly resulting from the assumptions made to frame the respondents (most important, assuming that no private cars would be available for the in-store alternative), it clearly shows the tendency that for G, people prefer shopping in a store.[4] This is also reflected by the non-negligible share of respondents always choosing the same alternative within all choice situations, also referred to as "non-traders" (which, to some extent, is also explained by individuals' attitudes): While the overall share of non-traders is about 24%, the share of non-traders in the E experiment is substantially lower compared to the G experiment (19% and 31%, respectively; $p_{\Delta} < 0.01$). Almost 30% of participants that were assigned to the G experiment always chose the in-store alternative, whereas 14% that were assigned to the E experiment always chose the online alternative.

5.4.2 *Estimation results*

To have a first benchmark, to test the additional explanatory power of each LV in order to confine subsequent analyses and to compare results with the simultaneous approach, we estimate two sequential models[5] with random

3 Online shopping of books and electronic gadgets accounts for roughly 25% of total retail market shares, while for food products it accounts for roughly 5% (Verband des Schweizerischen Versandhandels VSV und GfK, 2015).

4 The imposed assumptions may have mainly led current car users to choose the online alternative more frequently. Note, however, that we tested whether car availability has an effect on the choice probability of online shopping, but it was not the case (the effect was positive with a t-value smaller than one).

5 There are essentially two ways how to include LVs in a choice model: Raveau et al. (2010) compared a sequential (first estimating a MIMIC model and predicting the distribution of attitudes, which then are included in the choice model) and a simultaneous (maximizing the

coefficients[6] (SM LV1; includes the pro-online shopping LV, and SM LV2; additionally adds the pleasure of shopping LV), where the predictions of a linear MIMIC model[7] are included as explanatory variables in the choice models according to the hypotheses discussed in Section 5.3.

These results are compared with the corresponding hybrid models (HCM LV1 and HCM LV2) with random coefficients (but without direct effects of socioeconomic characteristics; especially for the two-LV-specification, the model would become highly convoluted), as shown in the Appendix, Table A.12. The sequential approach implicitly takes into account the measurement items for assessing the goodness of fit, resulting in a choice model LL of more than 45 units higher compared to the hybrid models (which would be misleading, given that the items are typically not available for forecasting). All choice attributes with a $|\text{t-value}| < 1$ are excluded in subsequent analyses, which include travel cost and online/in-store shopping time, as well a their interactions with the shopping purpose.

The pleasure of shopping LV does not add substantial explanatory power: A likelihood-ratio (LR) test shows an insignificant increase in model fit when comparing SM LV1 with SM LV2 ($p = 0.16$), and there is even a slightly lower choice model LL in the HCM LV2 than the HCM LV1 model (by including an "uninformative" LV and given the joint estimation of the choice and indicator data, this result is not unexpected). Based on these

joint probability given the observed choices and indicators) estimation method. Although the sequential estimation approach is consistent and still often used in practice (e.g. Mokhtarian and Tang, 2013; Zhai et al., 2017), they emphasize the advantages of the simultaneous method in terms of bias and efficiency, which, in the former case, can have implications on valuation indicators. Apart from a better representation of the decision process and more efficient estimation properties (Daziano and Bolduc, 2013a), the simultaneous approach can also be better applied to predict the distribution of taste parameters and/or market shares for specific consumer segments based on socioeconomic characteristics.

6 Including random coefficients associated with the LVs helps to get unbiased parameter estimates by partly accounting for the LV measurement error (Yáñez et al., 2010).

7 We tested if an Ordered Logit (OL) measurement model shows different, potentially more accurate results, as suggested by Daly et al. (2012b), given the discrete nature of the items. However, the effects of the LVs in the choice models were almost identical up to a scaling factor, showing identical choice model fits, and the qualitative effects of socioeconomic characteristics on the LVs were indistinguishable. Furthermore, the correlations of conditional distributions of the LVs for these two specifications were above +0.994, which is also illustrated in the Appendix, Figure A.40 and Figure A.41. Therefore, even though the OL measurement model exhibited a much better fit, due to estimation time considerations we decided to use a linear specification. Results of the linear MIMIC model are presented in the Appendix, Table A.11.

findings, the decision was made to (i) focus on the pro-online shopping LV and (ii) also drop in-store shopping time from subsequent analyses.[8]

Four different models with increasing complexity are presented in Table 5.1 which were found to represent the different aspects of shopping channel choice appropriately. The first model (REDMNL) is a reduced form MNL model that explains choices with attributes specific to each shopping channel and includes the direct (= total) effects of socioeconomic characteristics: Given that the pro-online shopping LV is interacted with shopping purpose and shopping cost, the structure imposed by the ICLV model leads to a reduced form specification that has to include the same interactions for all socioeconomic characteristics that are part of the LV structural model. This includes the variables age, male, income, high education, married and store accessibility. To account for the error variance imposed by the ICLV model, the second model (REDMIX) is a reduced form MIXL model that additionally includes the random intercept and shopping cost parameter. The third model (HCMNL) is a hybrid choice model that includes the pro-online shopping LV and its interactions with shopping purpose and shopping cost. The fourth model (HCMIX) additionally adds the random intercept and shopping cost parameter. Results in Table 5.1 are organized in blocks: The choice model is presented first, followed by the direct/interaction effects of socioeconomic characteristics, the direct/interaction effects of the pro-online shopping LV, the LV structural model and the LV measurement model.

The improvement in AICc from the REDMNL to the REDMIX model is highly significant, with an increase in LL by 370 units by including two random parameters. This demonstrates that there is a substantial amount of unobserved heterogeneity in the preference for a shopping channel and shopping cost sensitivity.

8 In-store shopping time would become insignificant without including the pleasure of shopping LV.

TABLE 5.1: Estimation results: Reduced form and hybrid choice models.

Base category: In-store (S)	REDMNL Coef./(SE)	REDMIX Coef./(SE)	HCMNL Coef./(SE)	HCMIX Coef./(SE)
ASC (O)	−0.72***	−1.47***	−1.09***	−1.47***
	(0.17)	(0.30)	(0.23)	(0.29)
Shopping cost	−2.34***	−5.79***	−3.70***	−5.51***
	(0.27)	(0.67)	(0.42)	(0.61)
Delivery cost (O)	−0.10***	−0.18***	−0.15***	−0.18***
	(0.01)	(0.02)	(0.02)	(0.02)
Delivery cost × electr. (O)	0.07***	0.12***	0.11***	0.12***
	(0.02)	(0.02)	(0.02)	(0.02)
Delivery time (O)	−0.57***	−1.03***	−0.82***	−1.01***
	(0.09)	(0.14)	(0.13)	(0.14)
Delivery time × electr. (O)	0.50***	0.90***	0.72***	0.88***
	(0.09)	(0.14)	(0.13)	(0.14)
Travel time (S)	−2.42***	−4.71***	−4.86***	−5.60***
	(0.70)	(1.23)	(1.13)	(1.31)
Travel time × electronics (S)	0.56	1.36	2.60**	2.27*
	(0.81)	(1.34)	(1.19)	(1.37)
Size/weight medium (O)	1.07***	2.00***	1.52***	1.96***
	(0.10)	(0.18)	(0.15)	(0.18)
Size/weight large (O)	2.17***	3.99***	3.02***	3.94***
	(0.13)	(0.27)	(0.22)	(0.26)
Size/weight × age (O)	0.59	2.45*	1.73	2.58*
	(0.90)	(1.47)	(1.18)	(1.43)
Size/weight × male (O)	−0.58***	−0.95***	−0.87***	−0.96***
	(0.20)	(0.33)	(0.26)	(0.32)
Age (O)	−1.08	−3.33	1.70	−0.47
	(1.29)	(2.41)	(2.01)	(2.35)
Male (O)	0.13	0.22	−1.23**	−0.88
	(0.30)	(0.52)	(0.50)	(0.54)
Income (O)	0.54***	0.82***	0.41*	0.56**
	(0.17)	(0.30)	(0.23)	(0.26)
High education (O)	0.09	0.31	−0.63	−0.43

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Table 5.1 – *Continued from previous page*

Base category: In-store (S)	REDMNL Coef./(SE)	REDMIX Coef./(SE)	HCMNL Coef./(SE)	HCMIX Coef./(SE)
	(0.35)	(0.67)	(0.53)	(0.69)
Store accessibility (O)	−0.01	−0.04	0.44	0.37
	(0.44)	(0.79)	(0.50)	(0.64)
Married (O)	0.27	0.40	−0.32	−0.14
	(0.24)	(0.43)	(0.36)	(0.41)
Age × electronics (O)	0.44	0.64	−1.28	−0.89
	(1.37)	(2.55)	(2.06)	(2.47)
Male × electronics (O)	0.29	0.52	1.21**	1.22**
	(0.31)	(0.57)	(0.51)	(0.58)
Income × electronics (O)	−0.31	−0.41	−0.46*	−0.36
	(0.20)	(0.37)	(0.27)	(0.31)
High education × electr. (O)	−0.05	−0.22	−0.14	−0.03
	(0.42)	(0.80)	(0.61)	(0.81)
Store access. × electr. (O)	−0.50	−0.89	−0.56	−1.02
	(0.53)	(0.97)	(0.61)	(0.82)
Married × electronics (O)	0.17	0.35	0.51	0.69
	(0.30)	(0.56)	(0.41)	(0.51)
Age × shopping cost	7.10***	9.76**	4.77	5.72
	(2.23)	(4.11)	(3.00)	(3.85)
Male × shopping cost	−0.59	−1.55	0.06	−0.07
	(0.56)	(1.04)	(0.82)	(1.09)
Income × shopping cost	0.57	0.42	1.18**	0.92
	(0.40)	(0.77)	(0.54)	(0.67)
High education × shop. cost	−0.32	−0.74	0.27	0.20
	(0.72)	(1.37)	(0.99)	(1.38)
Store access. × shop. cost	0.31	−0.57	0.20	−0.55
	(0.83)	(1.50)	(1.08)	(1.41)
Married × shopping cost	−0.44	−0.96	−0.30	−0.39
	(0.56)	(1.04)	(0.73)	(1.00)
σ_{ASC} (O)	–	2.30***	–	1.93***
		(0.16)		(0.15)
$\sigma_{shopping\ cost}$	–	4.89***	–	4.19***
		(0.79)		(0.70)

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Table 5.1 – *Continued from previous page*

Base category: In-store (S)	REDMNL Coef./(SE)	REDMIX Coef./(SE)	HCMNL Coef./(SE)	HCMIX Coef./(SE)
Pro-online-shopping LV (O)	–	–	3.12^{***}	2.51^{***}
			(0.61)	(0.49)
Pro-online LV × electr. (O)	–	–	-0.91	-1.15^{**}
			(0.59)	(0.57)
Pro-online LV × shop. cost	–	–	-3.71^{***}	-3.84^{***}
			(1.25)	(1.12)
Pro-online shop. LV1: Age	–	–	-1.11^{***}	-1.02^{***}
			(0.29)	(0.30)
Male	–	–	0.32^{***}	0.31^{***}
			(0.07)	(0.07)
Income	–	–	0.14^{***}	0.12^{***}
			(0.04)	(0.04)
High education	–	–	0.33^{***}	0.31^{***}
			(0.09)	(0.09)
Store accessibility	–	–	-0.19^{*}	-0.18
			(0.10)	(0.12)
Married	–	–	0.20^{***}	0.20^{***}
			(0.07)	(0.07)
$\sigma_{pro-online\ shop.\ LV}$	–	–	0.52^{***}	0.60^{***}
			(0.04)	(0.03)
LV indicators: onl2	–	–	-0.54^{***}	-0.56^{***}
			(0.06)	(0.06)
onl3	–	–	-0.99^{***}	-1.05^{***}
			(0.08)	(0.08)
onl4	–	–	-0.58^{***}	-0.59^{***}
			(0.06)	(0.06)
onl5	–	–	-0.39^{***}	-0.38^{***}
			(0.06)	(0.06)
onl6	–	–	0.81^{***}	0.77^{***}
			(0.07)	(0.06)
onl7	–	–	-0.68^{***}	-0.74^{***}
			(0.07)	(0.07)
onl8	–	–	0.75^{***}	0.75^{***}

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Table 5.1 – *Continued from previous page*

Base category: In-store (S)	REDMNL Coef./(SE)	REDMIX Coef./(SE)	HCMNL Coef./(SE)	HCMIX Coef./(SE)
			(0.08)	(0.07)
onl9	–	–	-0.70^{***}	-0.71^{***}
			(0.05)	(0.05)
onl10	–	–	0.67^{***}	0.69^{***}
			(0.07)	(0.08)
SD onl1	–	–	0.64^{***}	0.59^{***}
			(0.03)	(0.02)
SD onl2	–	–	0.67^{***}	0.65^{***}
			(0.02)	(0.02)
SD onl3	–	–	0.81^{***}	0.74^{***}
			(0.03)	(0.03)
SD onl4	–	–	0.63^{***}	0.60^{***}
			(0.02)	(0.02)
SD onl5	–	–	0.76^{***}	0.75^{***}
			(0.03)	(0.03)
SD onl6	–	–	0.75^{***}	0.75^{***}
			(0.03)	(0.02)
SD onl7	–	–	0.76^{***}	0.72^{***}
			(0.03)	(0.03)
SD onl8	–	–	0.85^{***}	0.83^{***}
			(0.03)	(0.03)
SD onl9	–	–	0.60^{***}	0.56^{***}
			(0.02)	(0.02)
SD onl10	–	–	0.85^{***}	0.83^{***}
			(0.03)	(0.03)
# est. parameters	30	32	59	61
# respondents/choices		466/3722		
$\mathcal{LL}_{final}$	−2021.9	−1651.7	−7078.9	−6905.8
$\mathcal{LL}_{choicemodel}$	−2021.9	−1651.7	−1690.0	−1651.9
AICc	4108.1	3372.2	14293.2	13952.4

Note: Shopping cost, shopping time and travel time are scaled down by factor 100.

Robust standard errors (clustered by ID): $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

The final log-likelihood of the hybrid models is not directly comparable to the first two models, as it is jointly determined over the whole set of parameters. Thus, what is decisive for model comparison is the log-likelihood of the choice model only (Walker and Ben-Akiva, 2002). This approach is representing a forecasting methodology based on a restricted set of parameters $\widetilde{\Omega}$, in which the (unknown) indicators of the measurement model are not used for assessing the goodness of fit. Comparing the REDMNL with the HCMNL, the increase in LL of about 332 units is slightly lower compared to the REDMIX. This is expected, given that the random parameters in the REDMIX are estimated on the choice data only, while in the HCMNL, the random components entering via the LV structural equation also have to incorporate the MIMIC model variance.[9]

By including the two random components, the HCMIX model shows an identical choice LL as the REDMIX model. Clearly, in terms of model fit, this discards the benefits of a hybrid model (see also Vij and Walker (2016) for a more in-depth discussion on this topic). Nevertheless, there are several advantages of the HCM approach that may justify the complexity of the model: The inclusion of LVs allows to disentangle direct and indirect ("mediated" via the LV) effects of socioeconomic characteristics, it allows to decompose heterogeneity into a purely random and attitudinal part and typically comes along with a gain in efficiency by making use of all available data (e.g. Kløjgaard and Hess, 2014). Last but not least, the REDMIX model structure would not have been considered in the absence of LVs during the process of model development, given that the majority of direct socioeconomic effects are insignificant in the REDMIX model. These points are further addressed below.

9 The random disturbance term included in the LV structural model also contributes to the unobserved heterogeneity in shopping channel preference and shopping cost sensitivity. Given the coefficients of variation in the REDMIX model of 1.6 for the intercept (= $|2.30/-1.47|$) and 0.8 for shopping cost (= $|4.89/-5.79|$), these amounts drop in the HCMNL to 0.5 for the former (= $|0.52/-1.09|$) and 0.1 (= $|0.52/-3.70|$) for the latter, reflecting that any heterogeneity in the choice model must be perfectly correlated with the disturbance term in the LV model (Kløjgaard and Hess, 2014). In the HCMIX model, this constraint disappears by including the two additional random parameters, implying an overall amount of heterogeneity similar to the REDMIX model.

The choice attributes shopping cost[10], delivery cost, travel time and delivery time[11] all exhibit the expected negative effect. A larger size/weight of the shopping basket strongly increases the choice probability of online shopping, exhibiting a significant amount of preference heterogeneity conditional on physical conditions: Female ($p < 0.01$) and older ($p < 0.1$; only significant in the random coefficient models) respondents' choice probability of online shopping increases more with a larger size/weight of the shopping basket.

Most attributes were interacted with the shopping purpose, with grocery shopping (G) as a reference: While shopping costs and the size/weight attribute exhibit no significant difference between G and electronic household appliances (E), it is interesting to see that travel time, delivery time and delivery cost show much less strong negative effects on utility for E than for G (but are still significantly different from zero; $p < 0.05$)[12]. There are several psychological mechanisms in force that can explain these findings: Buying E is usually done on a much more irregular basis, it exhibits a longer planning horizon and goods are non-perishable, thus leading to both a lower disutility of delivery and travel time.

The effect of delivery cost is about three times larger for G than for E (which, for the latter, would imply the same average marginal disutility as for shopping cost). Possible explanations are that (i) delivery costs are at fixed levels and their share of total shopping cost is substantially larger for G than for E (see also Appendix, Table A.10), and thus are perceived as more negative and (ii) people could more easily avoid delivery costs for G by just visiting a nearby grocery store, perceiving them as an actual loss (also referred to as "money illusion"; see e.g. Tversky and Kahneman (1986)). Online retailers should take note of that when designing effective pricing strategies: From a behavioral perspective, incorporating delivery in shopping costs would increase consumers' utilities and therefore the market shares, as e.g. Amazon has been doing for years.

The pro-online shopping LV shows, not surprisingly, a strong and positive effect on the choice of online shopping which is lower for E than

10 Respondents did not react to travel costs, but were anchoring behavior with respect to shopping costs (given their much larger share of total costs), which was not the case for delivery costs. On the other hand, travel time was perceived as much more unpleasant than the time spent for online/in-store shopping, with the latter showing no significant and substantial effect.

11 For interpretation issues, it is more convenient to treat delivery time as a continuous variable, mainly to calculate valuation indicators (i.e. CHF/day) similar to Hsiao (2009). We used attribute level mid-points to approximate delivery time for both shopping purposes.

12 Standard errors were calculated using the delta method (Daly et al., 2012a).

for G (HCMIX: $p < 0.05$; note that in both hybrid models, the net effect is still positive and significant; $p < 0.01$). This confirms the hypothesis that it takes less overcoming to purchase typical search goods such as E online, whereas for G, only respondents with positive attitudes towards online shopping consider online shopping as an alternative. Also, there is a strong interaction effect of shopping cost and the pro-online shopping LV, indicating that participants with more positive attitudes towards online shopping exhibit a substantially higher shopping cost sensitivity. This can be explained by the expanded alternative set when not considering in-store shopping as the dominant purchase channel, leading to a stronger price-driven trade-off behavior than for "traditional" shoppers.

The LV structural model describes attitudes in terms of observable socioeconomic characteristics, exhibiting interesting relationships between respondent profiles: Younger and male respondents with high income and education exhibit a significantly ($p < 0.01$) higher pro-online shopping attitude, characterizing a technology-oriented generation of younger and well-educated men. While obtaining very similar user profiles as e.g. in Farag et al. (2005), the positive effect of being married is interesting, which, one may argue, is associated with a lower time budget, whereby online shopping can be seen as a good alternative (Bellman et al., 1999). Also, while Farag et al. (2005) finds a positive effect of urbanity, which, in our data, is positively correlated with store accessibility (see also Figure 5.2), we find a negative (though not significant) effect of store accessibility on pro-online shopping attitudes, indicating some sort of habitual self-selection.

Finally, the coefficients of the measurement model are all highly significant and show the expected signs, confirming the results of the factor analysis regarding the interpretation of the LV.

5.4.3 *Parameter decomposition*

There are some notable differences between the direct effects of socioeconomic characteristics when comparing the reduced form with the hybrid models: While in the reduced form model, we directly measure the total effects of socioeconomic characteristics on utility, in the hybrid models we allow for a mediation via the LV (see also Figure 5.3), which are the indirect effects. The sum of direct and indirect effect is the total effect (see also e.g. Vij and Walker, 2016). This decomposition, as shown in Table 5.2, leads to interesting behavioral insights:

TABLE 5.2: Direct, indirect and total effects in the HCMIX model.

Attribute (HCMIX)	Outcome	Direct eff.	Indir. eff.	Total eff.
Male	Utility of onl. shop. (G)	−0.88	**0.78**	−0.09
Male	Utility of onl. shop. (E)	0.34	0.42	0.77
Male	Shop. cost sensitivity	−0.07	**−1.19**	−1.27
Age	Utility of onl. shop. (G)	−0.47	**−2.56**	−3.04
Age	Utility of onl. shop. (E)	−1.36	−1.39	−2.75
Age	Shop. cost sensitivity	5.72	**3.92**	**9.65**
Income	Utility of onl. shop. (G)	**0.56**	**0.30**	**0.87**
Income	Utility of onl. shop. (E)	0.20	0.16	0.36
Income	Shop. cost sensitivity	0.92	**−0.46**	0.46
High education	Utility of onl. shop. (G)	−0.43	**0.79**	0.36
High education	Utility of onl. shop. (E)	−0.46	0.43	−0.03
High education	Shop. cost sensitivity	0.20	**−1.20**	−1.00
Store accessibility	Utility of onl. shop. (G)	0.37	−0.44	−0.07
Store accessibility	Utility of onl. shop. (E)	−0.64	−0.24	−0.88
Store accessibility	Shop. cost sensitivity	−0.55	0.68	0.13
Married	Utility of onl. shop. (G)	−0.14	**0.50**	0.36
Married	Utility of onl. shop. (E)	0.55	0.27	0.82
Married	Shop. cost sensitivity	−0.39	**−0.77**	−1.16

Note: Effects reported for the utility of onl. shop. measure deviations from the alt.-spec. constant.
Effects reported for shopping cost sensitivity measure deviations from the mean effect β_{cost}.
Bold: Effect significant at $p < 0.05$.

All effects of respondent characteristics on the LV are statistically significant (except store accessibility with $p = 0.12$ in the HCMIX model; see also Table 5.1), whereas all direct effects are not (except for income on the probability of online shopping when purchasing G, as respondents with higher income may face more stringent time constraints; in this case, the share of the total effect mediated via the pro-online shopping LV is 35%). It can be argued that the ICLV approach helps to structure the underlying sources of heterogeneity in a more efficient way, which can be seen as a dedicated type of interaction between socioeconomic variables and attitudes affecting utility mainly via the LV.[13]

Without the inclusion of attitudes, the significant and positive interaction effect between age and shopping cost in the reduced form models has a peculiar interpretation: Arguing that older respondents are less cost sensitive is, from a behavioral perspective, questionable. However, given the increased cost sensitivity of respondents with pro-online shopping attitudes, and that age exhibits a significant and negative effect (which can be explained by a general reluctance towards new technologies of older respondents; see also e.g. Lian and Yen (2014)), the total effect of age on cost sensitivity is mainly mediated via respondents' attitudes, whereby the direct effect is not significantly different from zero.

While in the reduced form models, gender shows no significant effects, conditional on attitudes, men exhibit a significantly stronger preference for online shopping when purchasing E compared to G ($p < 0.05$; the direct net effect for E is not significantly different from zero). Given that E are typical search goods, it can be seen as more efficient to buy them online, which men strongly consider in their decision process. However, the total effect of male is not significant, as men also have higher pro-online shopping attitudes: In fact, for E, all indirect (and total) effects are not significantly different from zero, reflecting the smaller effect of pro-online shopping attitudes when purchasing E as discussed in Section 5.4.2.

The total effect of income on shopping cost sensitivity is not significantly different from zero and half of size in the reduced form compared to the hybrid models, which stands in contrast to a typically observed decreasing marginal utility of income (but supports the findings in Chapter 4,

13 Note that a LR test between the HCMIX and the HCM LV1 model (which excludes all direct effects; see also Appendix, Table A.12) indicates an insignificant increase in choice model fit (increase in LL by 6.2 units with 18 additional degrees of freedom in the HCMIX model; $p = 0.83$). This is not the case when comparing the REDMIX with a simple MIXL model without any direct (= total) effects: The increase in LL by 23.6 units with 18 additional degrees of freedom is highly significant ($p < 0.01$).

where income exhibits no effect on the VTTS). The main explanation can be found in the LV structural model: People with high income have more positive attitudes towards online shopping (which can be explained by the increased accessibility to technological devices), which implies a higher cost sensitivity through the LV interaction, thus diluting the direct interaction effect between income and shopping cost. Including the pro-online shopping LV helps to more accurately identify the direct (positive) interaction effect of income with shopping cost (which even becomes significant in the HCMNL model; $p < 0.05$).

To summarize, including attitudes towards online shopping not only leads to more behaviorally sound interpretations, but also to a moderate increase in estimation efficiency for parameters jointly estimated on both the choice and attitudinal data. The ICLV approach helps to structure respondent heterogeneity via the LV efficiently and more intuitively, and excluding all direct effects would not lead to a significant decrease in choice model fit.

5.4.4 *Marginal probability effects*

The marginal probability effects (MPE) presented in Table 5.3 show the average responsiveness of choice probabilities (i.e. %-point changes) to a change in attribute k while keeping all other attributes fixed (see e.g. Winkelmann and Boes, 2006). Given our complex model structure, we approximate the derivative of the choice probability with respect to a marginal change in a continuous attribute (e.g. shopping cost) by taking the difference between the initial and predicted (simulated) probability after a 1% increase in that attribute, denoted by k^*:[14]

$$\begin{aligned} MPE_i^k = & \sum_{n=1}^{N} \sum_{t=1}^{T_n} \sum_{r=1}^{R} \frac{1}{NT_nR} \\ & \Big(P(c_{i,n,t} | X_{i,n,t}^{k^*}, Z_n, \widehat{\Omega}, \widehat{\Sigma}, \Gamma^r) - P(c_{i,n,t} | X_{i,n,t}^{k}, Z_n, \widehat{\Omega}, \widehat{\Sigma}, \Gamma^r) \Big) \end{aligned} \tag{5.14}$$

were Γ^r corresponds to $LV_{online,n}^r$ and $\psi_{i,n}^r$.

Although predicted changes in real-world market shares are not reliable when using SP data (e.g. Glerum et al., 2013), results give insights in how people trade-off shopping cost, travel and delivery time when directly fac-

14 The same concept applies to changes in dummy variables of socioeconomic characteristics, investigating a discrete change from Z_n^k to $Z_n^{k^*}$ while keeping $X_{i,n,t}$ fixed.

Table 5.3: Average marginal probability effects (MPE) in the REDMIX, HCMIX and HCM LV1 models.

Attribute (HCMIX)	G: Onl. [%]	G: Store [%]	E: Onl. [%]	E: Store [%]
Shopping cost (+ 1%)	−0.36	−0.38	−1.68	−1.65
Travel time (+ 1%)	–	−0.12	–	−0.08
Delivery time (+ 1%)	−0.15	–	−0.08	–
Delivery cost (+ 1%)	−0.12	–	−0.04	–
Male (dummy)	−7.38	–	3.27	–
Age (+ 10 years)	−5.08	–	−0.91	–
Income (+ 25%)	3.81	–	1.41	–
High education (dummy)	3.81	–	1.15	–
Store accessibility (dummy)	−0.72	–	−9.10	–
Married (dummy)	3.99	–	10.34	–

Attribute (REDMIX)	G: Onl. [%]	G: Store [%]	E: Onl. [%]	E: Store [%]
Shopping cost (+ 1%)	−0.37	−0.39	−1.73	−1.71
Travel time (+ 1%)	–	−0.11	–	−0.08
Delivery time (+ 1%)	−0.16	–	−0.07	–
Delivery cost (+ 1%)	−0.12	–	−0.04	–
Male (dummy)	−4.44	–	3.47	–
Age (+ 10 years)	−3.99	–	−0.82	–
Income (+ 25%)	3.67	–	1.56	–
High education (dummy)	3.37	–	2.00	–
Store accessibility (dummy)	−0.21	–	−8.36	–
Married (dummy)	4.31	–	8.92	–

Attribute (HCM LV1)	G: Onl. [%]	G: Store [%]	E: Onl. [%]	E: Store [%]
Shopping cost (+ 1%)	−0.39	−0.41	−1.95	−1.94
Travel time (+ 1%)	–	−0.12	–	−0.08
Delivery time (+ 1%)	−0.16	–	−0.07	–
Delivery cost (+ 1%)	−0.12	–	−0.04	–
Male (dummy)	0.14	–	0.53	–
Age (+ 10 years)	−0.66	–	−0.58	–
Income (+ 25%)	1.45	–	1.37	–
High education (dummy)	7.03	–	7.11	–
Store accessibility (dummy)	−4.25	–	−3.92	–
Married (dummy)	4.65	–	4.49	–

ing the attributes of these two alternative shopping channels under well-defined experimental conditions.

Ceteris paribus, for G, a 1% increase in shopping cost decreases the predicted choice probabilities of either in-store or online shopping by about 0.4%-points, while for E, the effects are substantially larger given the higher average costs for E, exhibiting MPEs of about 1.7%-points. Clearly, compared to other choice attributes, shopping costs can be seen as the strongest predictor of shopping channel choice relevant for policy making.

Most socioeconomic effects are substantially larger when purchasing G, which, as discussed above, can be attributed to the more unusual setting for online shopping, also reflected by the significantly larger effect of the LV in the case of G. However, being married and store accessibility become larger for E (and the effect of male even changes signs) compared to G: In-store shopping could more easily be avoided for E, for which these characteristics show a substantial discriminatory power.[15]

When comparing the above models in terms of choice attribute MPEs, there are no substantial differences, which is not the case for socioeconomic characteristics: Although results are qualitatively comparable, MPEs are slightly different in the HCMIX and REDMIX model, which can be attributed to the additional information entering via the LV structural model. This is also reflected by the superior out-of-sample forecasting performance, using a random training subsample with 70% of observations: While the in-sample hit-rate in both models is 88.3%, the out-of-sample hit-rate is 71.8% in the HCMIX and 71.6% in the REDMIX model, with the former exhibiting an out-of-sample choice model LL of 6.2 units larger (LR test: $p < 0.01$; note that the measurement model is not considered for forecasting; Yáñez et al. (2010); Daziano and Bolduc (2013b)), speaking in favor of the hybrid model.

5.4.5 *VTTS and the value of delivery time savings*

Our results are inconsistent with the traditional microeconomic framework of consumer behavior (see e.g. Jara-Diaz, 2007) in the sense that coefficients

15 Results should be interpreted more from a qualitative viewpoint, as the total effects of socioeconomic characteristics are in most cases not significant. For the sake of completeness, Table 5.2 also includes the MPEs derived for the HCM LV1 model. While the effects of choice attributes are again almost identical, now the effects of socioeconomic characteristics are solely mediated via the LV, with *all* indirect (= total) effects now being significant (also for E; $p < 0.05$; except for store accessibility), leading to more confident statements. The strongest effect now occurs for high education, showing an average increase in the probability of online shopping by more than 7%-points.

for travel, delivery and shopping cost significantly differ, raising the question of how the marginal utility of income (= minus the marginal disutility of cost) – typically resulting from a single cost coefficient in mode choice models – should be treated to calculate the valuation indicators in the current application. Thus, the perception of costs is not context-independent, and similar results have been found in marketing (e.g. Erdem et al., 2002) or other transportation studies (e.g. toll road or parking studies; see e.g. Hensher and Rose, 2009; Hess and Rose, 2009a; Weis et al., 2012), for which Hensher (2011) suggests using a weighted average of the different cost coefficients by the corresponding attribute levels.

Given that the utility contribution of shopping cost follows a distribution dictated by the random coefficient, the LV and socioeconomic interaction terms (Equation (5.15)), we first obtained the conditional estimates of the shopping cost coefficient $\widetilde{\lambda_{cost,n}}$ (Equation (5.16); see e.g. Revelt and Train, 2000), which we then inserted in Equation (5.17) to calculate the weighted average marginal disutility of cost C_n for each individual:

$$\lambda^r_{cost,n} = \widehat{\beta}_{cost} + Z_{online,n}\widehat{\Delta}_{online,cost} + \psi^r_{cost,n} + \widehat{\varphi}_{LV_{online},cost} LV^r_{online,n} \quad (5.15)$$

$$\widetilde{\lambda_{cost,n}} = \frac{\sum_{r=1}^{R}\left[\prod_i \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, Z_{z,n}, \widehat{\Omega}, \widehat{\Sigma}, \Gamma^r)^{c_{i,n,t}} \lambda^r_{cost,n}\right]}{\sum_{r=1}^{R} \prod_i \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, Z_{z,n}, \widehat{\Omega}, \widehat{\Sigma}, \Gamma^r)^{c_{i,n,t}}} \quad (5.16)$$

were Γ^r corresponds to $LV^r_{online,n}$ and $\psi^r_{i,n}$. Finally,

$$C_n = \sum_{t=1}^{T_n} \frac{1}{T_n} \frac{\widetilde{\lambda_{cost,n}} \sum_i cost_{i,n,t} + \widehat{\beta}^{G,E}_{delivery\ cost} delivery\ cost^{G,E}_{n,t}}{\sum_i cost_{i,n,t} + delivery\ cost^{G,E}_{n,t}} \quad (5.17)$$

Table 5.4 presents the key valuation indicators (WTP), focusing on the value of travel time (VTTS) and delivery time savings (VDTS) with C_n in the denominator. As suggested by Bliemer and Rose (2013), we present WTP values for a median respondent given their robustness to extreme outliers (see e.g. Hess, 2007), also resulting from our WTP distributions being theoretically unidentified (Daly et al., 2012c), wherefore we do not report the WTP standard deviations (for further discussion, see also e.g. Hensher and Greene, 2003; Sillano and Ortúzar, 2005; Hess, 2007). Note that the standard deviation of C_n slightly increases when including the LV, accounting for an additional amount of cost heterogeneity that is not captured by the random coefficient.

TABLE 5.4: Weighted average cost coefficients and median valuation indicators.

	MIXL Value	HCM LV1 Value	REDMIX Value	HCMIX Value
Mean of C_n	−6.26	−6.16	−6.04	−5.53
Median of C_n	−6.71	−6.63	−6.37	−6.22
SD of C_n	2.71	2.82	2.77	2.86
VTTS shop. trips (G) [CHF/h]	41.90	48.19	42.99	54.38
VTTS shop. trips (E) [CHF/h]	27.97	26.31	30.52	29.25
VDTS del. time (G) [CHF/day]	9.28	9.28	9.40	9.83
VDTS del. time (E) [CHF/day]	1.10	1.14	1.19	1.16

The current analysis reveals relatively high median VTTS of about 50 CHF/h for G and 30 CHF/h for E. Note that the VTTS for shopping trips in Switzerland is highly transportation mode, shopper-type, study and context dependent (see e.g. Erath et al., 2007; VSS Norm, 2009; Weis et al., 2017), ranging between 6 CHF/h for PT and 160 CHF/h for weekly grocery shopping trips. Noticeable differences even occur in the current study for roughly the same set of respondents: The mode-specific VTTS obtained in Chapter 4 for shopping trips are not significantly different from the sample means, roughly exhibiting the values reported in Table 4.6. The VTTS for car modes of about 30 CHF/h is close to the one obtained for E here, but substantially smaller than for G, while the VTTS for PT of about 14 CHF/h is substantially smaller in both cases. This nicely demonstrates that the context of a survey or SP experiment also matters a lot.

After all, the current analysis contributes new evidence for large potentials of ICT shopping services from a travel behavior perspective, especially in the case of E (i.e. a typical search good; see also Hsiao (2009)): With VDTS for G of about 9 CHF/day and for E of 1.20 CHF/day, even for G, delivery time of four days is still valued less than the average travel time of one grocery shopping round trip[16].

Results indicate that when not including attitudes in the choice model, valuation indicators remarkably change due to some sort of omitted variable bias, confirming the findings in Raveau et al. (2010) that not includ-

16 Note that average total travel time of 47 minutes for a home-based shopping trip corresponds to a monetary value of about 40 CHF for groceries and 25 CHF for electronic appliances.

ing attitudes (MIXL[17] and REDMIX) may lead to less appropriate results than the corresponding hybrid models (HCM LV1 and HCMIX). For example, VTTS for G increases by roughly 25% when comparing the HCMIX with the REDMIX model. Interestingly, this difference mainly results from a more negative utility of travel time when purchasing G in the HCMIX specification, while other coefficients mainly remain unchanged.[18] Findings also imply that respondents with pro-online shopping attitudes exhibit lower WTPs, as their cost sensitivity is higher while sharing identical (non-distributed) time coefficients[19], a result that – given the current experimental assumptions – has to be challenged.

5.4.6 *Connecting shopping preferences and the VoL*

Having obtained the conditional VTTS estimates for shopping trips, the VTAT can be obtained as shown in Section 4.5.2, representing the direct benefit/loss that results from the time assigned to travel. Given the relatively high median VTTS for G (54.4 CHF/h) and E (29.3 CHF/h; resulting from the HCMIX model) together with a VoL of 22.9 CHF/h (resulting form the TUMIX model), the median VTAT become negative and substantial in both cases: For G –34.1 CHF/h and for E –9.1 CHF/h (see Table 5.5).

TABLE 5.5: VTAT [CHF/h] and interquartile range (IQR) for shopping trips.

	Groceries (G)	Electronics (E)
Median VTAT [CHF/h]	−34.1	−9.1
IQR	(30.9)	(28.5)
N	133	211

The main implication of this result is that on average, the travel conditions of shopping trips (in the given experimental context) are perceived as very unpleasant, especially in the case of grocery shopping, where it (negatively) exceeds all the mode-specific VTAT as shown in Table 4.9. One explanation is that traveling to a store may be associated with a committed, often unpleasant activity (shopping), and/or negative associations related

17 Note that the MIXL is a Mixed Logit model without including socioeconomic characteristics, serving as a benchmark to compare with the hybrid model without any direct effects of socioeconomic characteristics (HCM LV1).

18 Similar findings are obtained when comparing the MIXL with the HCM LV1 model.

19 Interactions of pro-online shopping attitudes and travel/delivery time were tested, but were found to be insignificant and small.

to shopping trips (e.g. kids crying in the back of the car, searching for a rare parking space in front of the store, etc.). Clearly, this goes in line with our argumentation in Section 5.4.5, that for longer distances, avoiding a shopping trip produces more benefits than waiting for the delivery of the products.

Last but not least, we investigate if the individual shopping cost sensitivity (the negative of $\widetilde{\lambda_{cost,n}}$) is correlated with the VoL or one of its components. The argumentation is similar as in Section 4.5.3: One may hypothesize that an individual with a high VoL would also exhibit a lower shopping cost sensitivity, reflected by a low marginal utility of income, which – together with a fixed travel time coefficient – is associated with a higher VTTS for shopping trips (since $\widetilde{\lambda_{cost,n}}$ enters the denominator; see also Equation (5.17)).

A correlation analysis reveals that there is no such connection. However, it shows that the shopping cost sensitivity is negatively associated with the VoL component reflecting the preference for freely chosen goods relative to time (correlation = –0.14; $p < 0.01$): Respondents with a stronger preference for goods consumption care less about shopping costs, which is associated with a higher VTTS. This is counter-intuitive, and the opposite result has been obtained in Section 4.5.3: While the correlation between the VoL and mode-specific VTTS in most cases is negligible as well, the preference for freely chosen goods relative to time exhibits significant and negative correlations with all VTTS except for the active modes (see also Table 4.12). This again highlights the strong context-dependency of results obtained from SP experiments (see also e.g. the discussion in Schmid et al., 2019a), and the importance of a critical discussion of the findings when making policy recommendations.

Finally, while more available time and money for freely chosen activities and goods, respectively, exhibit no significant correlation with the shopping cost sensitivity, the expenditure rate (i.e. the purchasing power for freely chosen goods per unit of freely assigned time available to spend it) shows a weak and negative correlation (–0.09; $p < 0.1$): Intuitively, respondents with a high expenditure rate care less about shopping costs. Together with the above finding, both effects cancel out, so that the correlation with the VoL (+0.01) essentially becomes zero.

5.5 CONCLUSIONS

This chapter presents the first alternative-specific hybrid choice model using stated preference data in the field of shopping behavior research, presenting a sophisticated modeling approach to explore the trade-offs individuals face when choosing between online and in-store shopping for two distinctly different types of products: Groceries (G), typical experience goods, and standard electronic appliances (E), typical search goods.

The integrated choice and latent variable (ICLV) approach comes along with an enhanced estimation efficiency and helps to structure respondent heterogeneity via the latent variable efficiently and more intuitively. As we can show for the current application, this leads to a more behaviorally sound representation of individual decision making when comparing to the reduced form Mixed Logit model.

By including two latent variables (LVs) reflecting the attitudes towards online shopping and the pleasure of shopping, the LV structural model reveals information of individual attitudes conditional on observable socioeconomic characteristics, which in turn affect the choice of the shopping channel: Given a specific target consumer segment, one can predict alternative-specific market shares and/or the heterogeneity in attribute sensitivities such as shopping costs, and based on that, develop an effective retailing strategy.

Supporting the findings by Rudolph et al. (2015) that price advantages are a key factor for doing online shopping in Switzerland, respondents with more positive attitudes towards online shopping exhibit a higher cost sensitivity, which can be explained by the expanded choice set when effectively considering both purchasing channels. Interestingly, the interaction of income and shopping cost is not significantly different from zero, which stands in contrast to the expectations. The main explanation is that people with high income have more positive attitudes towards online shopping, implying an increased price-driven trade-off behavior and diluting the interaction effect. Furthermore, results from the LV structural model indicate that the strongest socioeconomic factor explaining attitudes is education: Well-educated respondents tend to have a better access to ICT in general, thus exhibit a higher choice probability for online shopping that is mainly mediated via the pro-online shopping LV.

Results show a clear pattern of purpose-specific shopping channel preferences, supporting the hypothesis for experience goods that grocery shopping is mainly conducted in stores, and that respondents with positive attitudes towards online shopping choose the online alternative more often. This effect is dampened in the case of purchasing standard electronic appliances, given the more common situation to purchase E online. To summarize, while all these findings confirm the hypotheses in Section 5.3, we find no evidence that the pleasure of shopping adds substantial behavioral insights in explaining the choice between in-store and online shopping.

From a travel behavior perspective, results reveal further potentials for online shopping services, given the relatively high value of travel time savings (VTTS) of about 50 CHF/h for G and 30 CHF/h for E compared to the value of delivery time (VDTS) ranging between 9 CHF/day for G and 1 CHF/day for E. For longer distances, avoiding a shopping trip thus produces more benefits than waiting for the delivery of the products, especially when purchasing E. However, as the experimental framing explicitly assumes home-based round trips, an assumption that might be plausible for weekly grocery shopping, the VTTS is possibly overestimated as the disutility of travel time may fade away for shopping trips chained with other activities (Adler and Ben-Akiva, 1979). However, our statement is robust in the sense that the mode-specific VTTS obtained in Chapter 4, although tendentially smaller, are still clearly exceeding the VDTS.

An important policy implication is that especially in the case of grocery shopping, shopping costs are perceived as less unpleasant relative to delivery costs. Online retailers should take note of that when designing an effective pricing strategy: From a behavioral perspective, incorporating delivery in shopping costs would increase customers' utilities and therefore the market shares of online shopping.

The main limitations result from the general nature of SP experiments and the limited, contrived and constrained experimental setting. First, the reader has to be aware that results are not easily generalizable to other scenarios than the ones presented to the respondents. Especially in terms of travel time, delivery time and cost, the current analysis shows a significant heterogeneity in attribute sensitivities between G and E. Other product categories might also ask for more differentiated choice attributes, as e.g. clothing, furniture or entertainment, which would require further investigations. Also the term "groceries" remains vague and might need further refinements. Second, by assuming (i) home-based and single purpose shopping trips, (ii) ignoring multi-channel shopping, (iii) ignoring store attributes, price, brand and quality perceptions, (iv) abstracting from social motives and (v) excluding private cars for the in-store alternative – although important for the coherence of choice situations and the overall project guidelines – might have affected choice behavior in an unpredictable way. Third, a general limitation of SP surveys one should always be aware of, is the difficulty of respondents to decide exclusively based on the presented attributes and to abstract from any hidden factors in their decision making process. Finally, the causality of the reported effects regarding the LVs should be interpreted with caution. Apart from the cross-sectional nature (i.e. attitudes were not observed over time) of the model assumptions to derive direct policy implications for *changes* in the attitudes (Chorus and Kroesen, 2014), it is not clear if e.g. positive attitudes towards online shopping lead to an increased cost sensitivity, or if respondents with an increased cost sensitivity have more positive attitudes towards online shopping.

6

ADAPTATIONS IN CAR USAGE

God is nothing but the power of the universe to organize itself.

— Lee Smolin

6.1 INTRODUCTION

Understanding peoples' reactions to changes in travel costs plays a key role when analyzing the effect of different pricing regimes, with mobility pricing serving as an important policy tool to shape and control travel demand. Several studies have elaborated theories and concepts of mobility and road pricing (e.g. Yang and Huang, 2005; Johansson and Mattsson, 2012), and a lot of research has been conducted to understand the behavioral reactions to different pricing regimes in several countries (e.g. Morrison, 1986; Mackett, 2001; Nielsen, 2004; Santos and Shaffer, 2004; Olszewski and Xie, 2005; Daunfeldt et al., 2009) including Switzerland (e.g. Vrtic et al., 2010), how to attract drivers out of their cars (e.g. Mackett, 2001; Banister, 2008) and to better understand the public acceptance of new pricing policies (e.g. Verhoef et al., 1997; Jakobsson et al., 2000; Viegas, 2001; Fujii et al., 2004; Jaensirisak et al., 2005).

Most studies have either used RP or "conventional" SP data to investigate the effects of travel costs (including fuel prices, road tolls and other pricing schemes) on demand, where the choice dimension often was limited (e.g. SP mode and route choice; see also e.g. Greene and Hensher, 2003; Hensher and Rose, 2009; Vrtic et al., 2010; Weis et al., 2010; Fröhlich et al., 2012; Weis et al., 2017), and/or the variation in costs was not substantial (e.g. aggregated time series data; see also e.g. Goodwin, 1992; Graham and Glaister, 2002; Burris, 2003; Goodwin et al., 2004). For the latter type of studies, following the definition in Goodwin (1992), the effects on travel demand are typically distinguished between short-run ($<$ 1 year) and long-run ($\geq$ 1 year) elasticities, and the general trend found in the literature is that the short-run elasticities (≈ -0.1) are, on average, about three times smaller than long-run elasticities (≈ -0.3). The intuition behind is that peoples' behavioral reactions to price changes are sticky and take some time to adapt.

To investigate radical changes in pricing schemes such as e.g. in the case of the central London congestion charging (e.g. Litman, 2005; Banister, 2008) or the vehicle registration and congestion fees in Singapore (e.g. Goh, 2002; Olszewski and Xie, 2005) for a country like Switzerland (where mobility pricing as such does not exist so far), a behavioral experiment that tries to reflect these effects should optimally allow respondents to change and adapt across multiple choice dimensions. This includes, apart from changes in the distance traveled, the modification of activity patterns including mode and location choices in the short- and medium-run, as well as adaptations in mobility tool ownership in the long-run.

Having collected this kind of data as part of the *Post-Car World* project, the main topic addressed by this chapter is, to what degree individuals would be changing travel behavior, specifically the distance traveled by MIV (private car and motorbike), assessing radical pricing effects from an activity-based perspective. The focus is to better understand and quantify the transition towards such a car-free society where privately owned vehicles may be substituted by PT season ticket ownership (see also e.g. Scott and Axhausen, 2006) and/or various forms of shared mobility services such as carsharing (CS) and carpooling (CP), and where pricing mechanisms are considered as the driving force to achieve substantial changes in behavior. The idea is to estimate aggregated response functions (by using highly disaggregate data) to obtain MIV travel cost elasticities for a daily and yearly time horizon, where most of the relevant choice dimensions are not modeled explicitly (given the relatively small sample size)[1], but considered by the respondents in their decision processes. We thus assume a cost-minimizing behavior, conditional on respondents' underlying preferences regarding their activity and mobility plans in the short- and long-run.[2]

The conceptual design for investigating the adaptations on a daily basis (see also Section 2.2.3.1) is built on the work of Weis (2012), where – instead of travel costs – radical changes in travel times were implemented. The decision process was very selective and respondents mostly changed the departure times from the home location[3], resisting major changes in be-

1 More advanced modeling approaches, such as the MDCEV model (see e.g. Bhat, 2005, 2008), where multiple choice dimensions (e.g. car type) and the related amounts consumed (e.g. distance traveled) can be modeled simultaneously, would require a substantially larger data set to get stable and meaningful results (see also the discussion in e.g. Erath and Axhausen, 2010). Therefore, the adaptations in car, fuel and engine types, as well as the substitution effects with PT, CS and CP are investigated using descriptive analyses.

2 Note that residential or work location choices were not considered in the experiments.

3 This was essentially the default option in the experiment.

havior. The conceptual design for investigating the adaptations on a yearly basis (see also Section 2.2.3.2) is built on the work of Erath and Axhausen (2010). Especially for fuel prices increasing up to 5 CHF/l, adaptation behavior was substantial, and respondents not only changed the yearly distance traveled, but also chose smaller engine or more fuel efficient cars to dampen the cost explosion. Finally, the obtained cost elasticity of about –0.15 for the overall demand was low, but in the expected range, concluding that the elasticity may be underestimated due to the survey approach (such that the substitution effect towards more energy-efficient vehicles is overestimated): In reality, expectations of the fuel prices are uncertain and e.g. in case of an oil price shock, people may be more likely to first restrain the distance traveled before reconsidering the car type.

A comparison between the MIV travel cost elasticities for these two related, but conceptually different approaches helps to shed light on the speed of adaptation towards a car-reducing society from a mobility pricing perspective. Clearly, our data may suffer from a hypothetical bias and for transportation policy appraisals we recommend to recognize the reported results more as qualitative indicators. In the case of adaptations in daily scheduling, given that we have chosen the busiest day reported in the travel diary as the reference day, elasticities should be interpreted as an upper bound (since the scope to adapt and savings potential is much higher compared to days where respondents do not travel as much), while in the case of yearly adaptations (as discussed above), the obtained elasticities should be seen as a lower bound.

Finally, we want to stress that this chapter only covers one specific aspect of the rich amount of information collected, focusing on the main topic also related to the primary goals of the project, namely the reduction in MIV usage towards a car-free society. Therefore, we focus our attention on those respondents/households who (i) have chosen MIV at least once in the reference day (in case of the daily scheduling experiment) and (ii) own a least one motorized vehicle (in case of the mobility tool ownership experiment). Further research may shed light on other interesting aspects that would go beyond the scope of this chapter.

The structure of this chapter is as follows: Section 6.2 presents the data obtained from the behavioral experiments used to model adaptation behavior and shows some descriptive analyses – apart from the main model variables also discussing the adaptation in car/fuel/engine types as well as the substitution patterns towards PT and shared mobility services. Section 6.3 discusses the modeling framework applied to obtain the travel cost elasticities of demand, while Section 6.4 shows the results and compares the elasticities obtained from the two stated adaptation experiments. Finally, Section 6.5 summarizes and discusses the main findings and limitations and gives an outlook on future work.

6.2 DATA DESCRIPTION AND DESCRIPTIVE ANALYSIS

6.2.1 *Daily scheduling experiment*

Table 6.1 presents the summary statistics of the relevant scheduling variables in the base scenario including all valid interviews (237 respondents). The experiment is described in Section 2.2.3.1. Given our survey approach based on the busiest day reported in the travel diary (where MIV has been preferably chosen at least once), it shows that the average number of trips is substantially larger than the global average (see also Table 2.16) which also positively affects the distance traveled, duration and related travel costs. Furthermore, the share of respondents who have chosen MIV at least once in the base scenario is 69.2%, leading to a sample size of N = 163 with 815 choice observations (after removing one influential outlier with a daily distance traveled of 488.5 km) which is relevant for subsequent analyses.

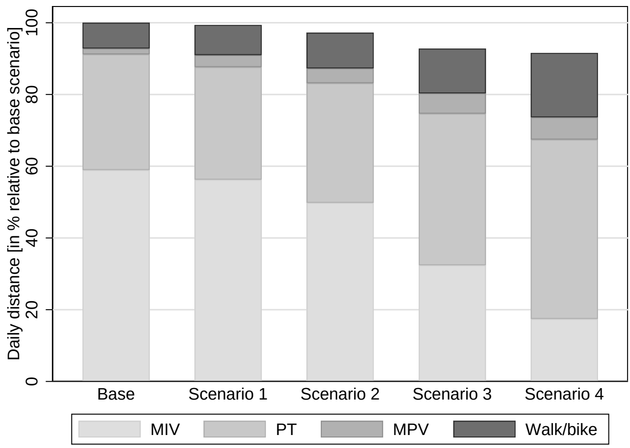
TABLE 6.1: Daily scheduling experiment: Summary statistics for the base scenario (N = 237).

Attributes	μ	σ	ν	min.	max.
Total trips [#]	5.1	2.2	1.1	2	15
Total travel duration [min.]	98.6	71.5	1.9	2	459
Total distance traveled [km]	69.6	84.0	2.2	0.0	488.8
Total travel cost [CHF]	12.8	83.8	2.8	0.0	107.0
MIV usage [%]	69.2	46.3	-0.8	0	100
PT usage [%]	48.9	50.1	0.0	0	100
MPV usage [%]	2.5	15.7	6.0	0	100

μ = mean, σ = standard deviation, ν = skewness.

Figure 6.1 provides an overview of how the increase in mode-specific travel cost affects the distance traveled. While in the first two scenarios (all scenarios are described in Section 2.2.3.1), the change in daily distance is relatively small, the decrease in MIV usage is highest between scenarios 2 and 3, and finally decreases by about 40%-points in scenario 4 relative to the base scenario. Relative to the base scenario, which already exhibits a relatively large mode share of PT typically observed in the metropolitan area of Zurich (e.g. Fröhlich et al., 2012; Becker et al., 2017; Weis et al., 2017), the shift from MIV to PT is steady throughout the scenarios and more than doubles in scenario 4. Although less substantial in absolute numbers, the increase in MPV (CS and CP) and active modes is noticeable as well. While bike and walk are only relevant for shorter distance trips, the contribution to the daily distance traveled becomes substantial and increases by about 11%-points relative to the base scenario. On the other hand, the mode share of only 6% for MPV in scenario 4 remains small, and in absolute terms, the substitution effect towards PT and active modes is much more pronounced. After all, the overall distance traveled decreases by about 8%-points in scenario 4 relative to the base scenario, mainly resulting from skipping some activities (average decrease in the daily number of trips by 0.4).[4] This also reflects the main adaptation preference, such that respondents mostly reacted by changing the travel modes, and activity locations as well as activity patterns were mostly kept fix.

FIGURE 6.1: Daily distance by mode [% relative to the base scenario].



Now focusing on MIV users who exhibited the most prominent increases in travel cost (see also Table 2.6), Figure 6.2 shows how the costs per kilo-

4 In terms of daily travel times, although respondents reduced overall travel, the average daily travel time increased by 18.5%-points in scenario 4 relative to the base scenario, as people mainly switched to slower modes, such as PT and bike.

meter [CHF/km] changed over the adaptation scenarios, on average increasing from 0.17 CHF/km in the base scenario up to 1.77 CHF/km in scenario 4. Behavioral reactions did not take long to happen: While scenario 1 exhibits almost the same distance traveled as in the base scenario (about 60 km on average), clearly visible drops in mileage are observed from scenario 2 onward, on average going down to 11 km in scenario 4. Interestingly, 21% of respondents did not make any changes at all to the distance traveled and additional analyses indicate that neither income nor any other socioeconomic characteristic is able to explain this intransigence (see Appendix, Table A.13, first column): The only significant and positive effect on respondents' willingness to adapt is the distance traveled in the base scenario (which, by design, is the upper bound of what respondents actually traveled by MIV during the reporting period).

FIGURE 6.2: Daily scheduling experiment: Average MIV costs per kilometer [CHF/km] and daily distance traveled by MIV [km].

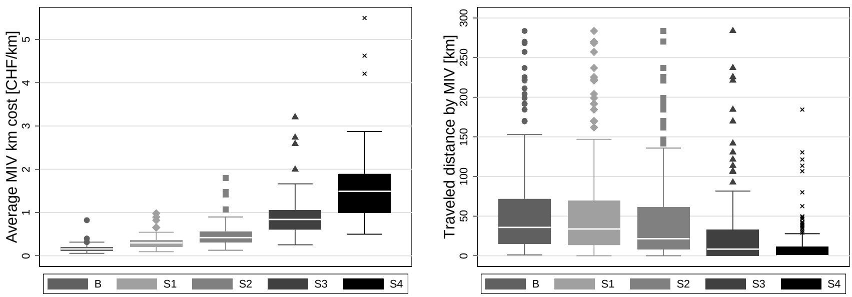


Figure 6.2 indicates that the distance traveled by MIV is highly right-skewed (skewness ν over all scenarios = 2.2), and that the occurrence of zeros increases for increasing travel costs (97 in total). In fact, this means that 60% of respondents at some point decided not to use MIV anymore (see also Appendix, Table A.13, second column). In those cases when reaching this point *before* the last scenario, respondents drop out from the panel, leading to a final estimation dataset with 741 choice observations.

One may be tempted to take the logarithm on the distance traveled, such that the elasticities can be easily estimated using a linear log-log regression model (e.g. Benoit, 2011). However, the dependent variable would be undefined in cases of observations with a zero, hence we would have to omit these observations, which is not appropriate as it would bias the results.

Therefore, a more suitable modeling approach is considered that can better handle the zeros, as further discussed in Section 6.3.

6.2.2 *Mobility tool ownership experiment*

Table 6.2 presents the summary statistics of the relevant choice/outcome variables in the base scenario including all valid interviews (187 households), consisting of aggregated travel demand and (fixed and variable) costs for MIV and PT. The experiment is described in Section 2.2.3.2. On average, households travel almost half as much with MIV than with PT, but experience substantially higher fixed (about four times) and variable (about two times) costs. This is mainly explained by the relatively high share of season ticket owners (47.8%), where the most frequent PT users (mainly for commuting) travel with zero variable costs within Switzerland or the covered region.

The share of households who have used MIV at least once in the base scenario is 88.2%, leading to a sample size of N = 165 with 825 choice observations that is relevant for subsequent analyses. Furthermore, while the share of PT usage is considerably high, it is not surprising that on a yearly basis, almost every household (99.5%) has used PT at least once. In case of MPV usage, on a yearly basis, 37.4% of households have used CS and/or CP at least once. However, as shown in Figure 6.4, the yearly distance traveled with these modes is almost negligible (1.7%).

Table 6.2: Mobility tool ownership experiment: Summary statistics for the base scenario (N = 187).

Attributes	μ	σ	ν	min.	max.
MIV distance traveled [km]	8'847	8'784	2.0	0	52'700
MIV variable cost [CHF]	1'719	1'820	2.6	0	12'848
MIV fix cost [CHF]	8'156	7'635	1.5	0	44'496
PT distance traveled [km]	15'197	17'930	2.4	0	106'920
PT variable cost [CHF]	985	1'085	2.7	0	7'932
PT fix cost [CHF]	2'091	2'439	2.1	0	12'225
MIV usage [%]	88.2	32.9	-0.8	0	100
PT usage [%]	99.5	7.3	-2.3	0	100
MPV usage [%]	37.4	48.5	0.5	0	100

μ = mean, σ = standard deviation, ν = skewness.

Focusing on households who own at least one car or motorbike, Figure 6.3 shows the main adaption behavior in terms of MIV fleet composition, fuel and engine type: Households tend to choose more fuel efficient cars and car ownership drops considerably from about 88% to 60% (Figure 6.3a). At the same time, although contributing little to the yearly distance traveled, households start using MPV (at least once on a yearly basis) considerably, increasing by more than 25%-points in scenario 4 relative to the base scenario (Figure 6.3a). Gasoline operated cars are substituted by hybrid and electric cars (Figure 6.3b), although the absolute change in behavior is moderate. Even in scenario 4, gasoline is still the preferred fuel type. A similar trend is observable for the engine type (Figure 6.3c), switching from normal and powerful cars to economical ones. The effects of behavior on households' fixed and variable cost composition for MIV and PT finally indicates that all these measures imply a cost-dampening effect on car usage (Figure 6.3d; increase in total cost by only about 5%-points in scenario 4 relative to the base scenario), where the variable costs increase considerably by design, while fixed costs decrease (decrease in MIV ownership). After all, the total yearly mobility costs increase by about 22%-points in scenario 4 relative to the base scenario.

Figure 6.4 gives a first overview of how the increase in mode-specific mobility costs affects the yearly distance traveled. While in the first two scenarios (all scenarios are described in Section 2.2.3.2), the change in demand indicators is relatively small, the decrease in MIV usage considerably drops in scenarios 3 and 4. Although the change in overall demand is similar as in the daily scheduling experiment (decrease by about 5%-points in scenario 4 relative to the base scenario), the decrease in MIV distance from about 38% to 21% is less pronounced than in the daily scheduling experiment by about factor two. Clearly, the main explanation for the less elastic demand is the substitution towards more fuel efficient cars and there is a trend observable that respondents mainly switch from large and medium cars towards PT and MPV. Similar as in the daily scheduling data, in absolute values, the increase in PT demand is most pronounced, while in relative terms, the demand for MPV increases remarkably.

Figure 6.5 shows how the MIV variable costs per kilometer [CHF/km] changed over the adaptation scenarios, on average increasing from 0.25 CHF/km in the base scenario up to 1.14 CHF/km in scenario 4, exhibiting a similar range and magnitude as in the daily scheduling experiment. However, as discussed above, the effects on yearly distance traveled is – in relative terms – less pronounced: While scenarios 1 and 2 exhibit almost

FIGURE 6.3: Adaptations in a) car fleet composition, b) fuel type, c) engine type, and d) the fixed and variable cost composition of MIV and PT (in % relative to the base scenario).

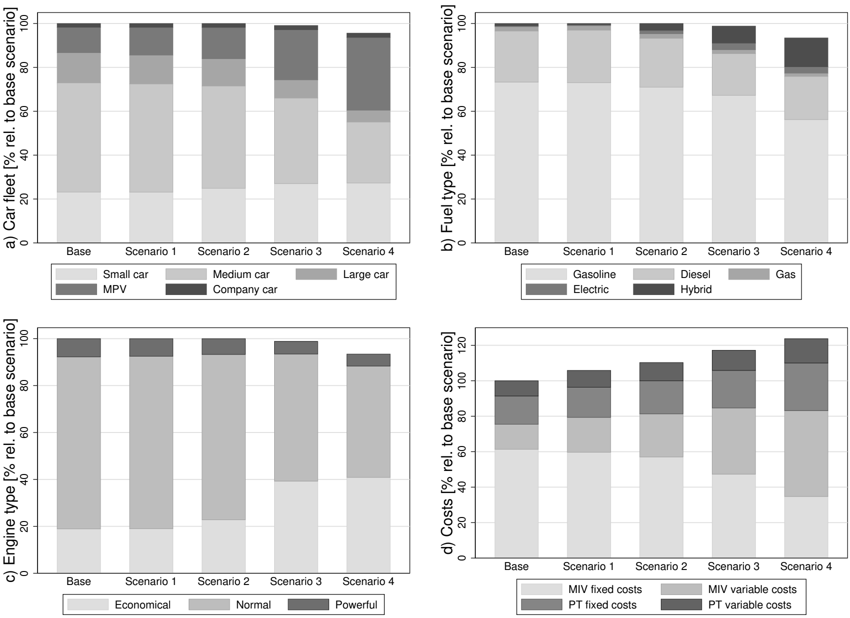


FIGURE 6.4: Yearly distance by mode (in % relative to the base scenario).

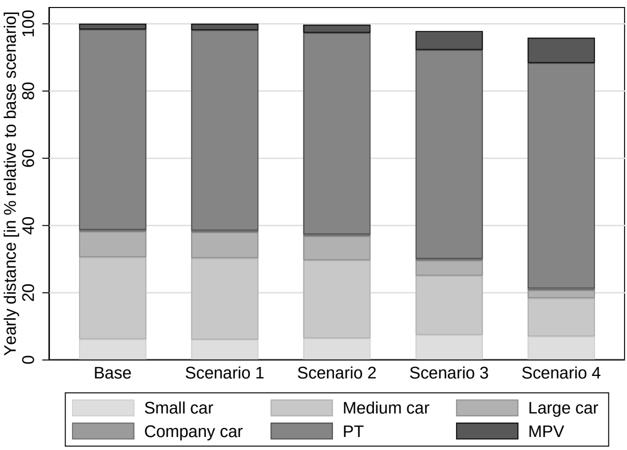
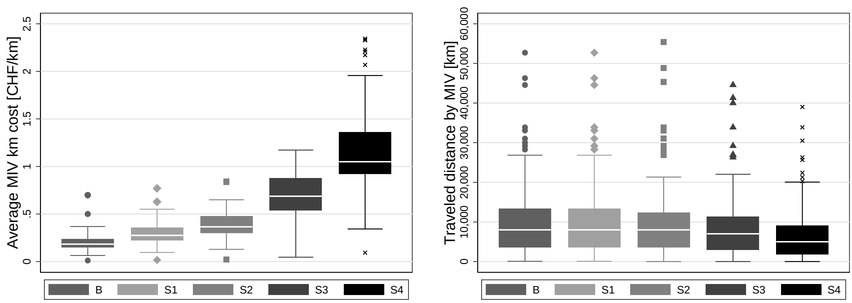


FIGURE 6.5: MIV variable costs [CHF/km] and yearly distance traveled by MIV [km].



the same distance traveled as in the base scenario (about 9'900 km on average), clearly visible drops in mileage are mainly observed in scenario 4, on average going down to 6'610 km.

43% of households did not make any changes in the yearly distance traveled by MIV, but mostly reacted by changing car (including MPV), fuel or engine type and only 7% of households decreased their yearly distance to zero (12 in total). The distance traveled is again very right-skewed (skewness ν over all scenarios = 2.0) and the occurrence of zeros (although much less pronounced than in the daily scheduling experiment) should be taken into account in the modeling framework.

Additional analyses again indicate that no household characteristic is able to explain this intransigence in distance traveled (see Appendix, Table A.14, left column): The only substantial, significant and positive effect on respondents' willingness to adapt, similar as in the daily scheduling experiment, is the distance traveled in the base scenario. On the other hand, mainly those households with low income and kids at some point decided not to use MIV at all, both exhibiting a strong effect (see Appendix, Table A.14, right column). In those cases when reaching this point *before* the last scenario, households drop out from the panel, leading to a final estimation dataset with 821 choice observations.

6.3 MODELING FRAMEWORK

The following modeling framework is applied to investigate the behavioral reactions in both adaptation experiments and finally allows a direct comparison between the obtained cost elasticties of travel demand.

The (exponential) regression model equation for individual/household $n \in \{1, 2, ..., N\}$ in adaptation scenario $t \in \{0, 1, ..., T_n \leq 4\}$ are, in case of the most exhaustive model with random parameters (EMIX), given by

$$y_{n,t} = \exp\left(\alpha + Z_n\rho + \psi_{\alpha,n} + \widetilde{\beta}_n \cdot \log(x_{n,t})\right) + \zeta_{n,t} \tag{6.1}$$

where $y_{n,t}$ is the daily/yearly distance traveled by MIV [km] when facing the average travel costs per km for MIV, $x_{n,t}$ [CHF/km]. α is the intercept, Z_n is a $(1 \times L)$ vector of socioeconomic characteristics and ρ is a $(L \times 1)$ parameter vector capturing observed heterogeneity and $\psi_{\alpha,n} \sim N(0, \sigma_\alpha^2)$ is a random component capturing unobserved heterogeneity in the intercept (e.g. Greene, 2003). $\zeta_{n,t}$ is the remaining error term. Since we are using maximum likelihood to estimate the parameters (i.e. by maximizing the density of error terms; see Equation (6.7)), we assume that $\zeta_{n,t} \sim N(0, \sigma_\zeta^2)$.

Among several possible modeling approaches that were tested beforehand (e.g. such as the fixed and random effects log-transformed linear regression, the Poisson and negative binomial regression model; see also Schmid and Axhausen, 2017), the exponential regression model – given the non-negativity and very right-skewed distribution of the dependent variable – was found to fit the data appropriately and led to robust and stable estimates when accounting for observed and unobserved heterogeneity. Compared to a log-transformed linear model, this functional form is not incompatible with the occurrence of zeros[5] and avoids the issue weather the error term is additive or multiplicative. Also, the direct specification and estimation of the conditional expectation function $E(y_{n,t}|x_{n,t}, ...)$ is preferred, as in general $E(\log(y)|x) < \log(E(y|x))$ holds (Wooldridge, 1992). The cost elasticity of distance traveled by MIV is given by

$$\epsilon_n = \frac{\partial E(y_{n,t}|x_{n,t}, ...)}{\partial x_{n,t}} \frac{x_{n,t}}{E(y_{n,t}|x_{n,t}, ...)} = \widetilde{\beta}_n \tag{6.2}$$

we define as

$$\widetilde{\beta}_n = -\exp(\beta_{cost} + Z_n\kappa + \psi_{\beta,n}) \cdot \left(\frac{dist_{n,0}}{\overline{dist}_0}\right)^{\omega_{dist}} \tag{6.3}$$

where β_{cost} is the fixed mean effect, Z_n is a $(1 \times M)$ vector of socioeconomic characteristics and κ is a $(M \times 1)$ parameter vector capturing observed het-

5 Adding a 1 to all $y_{n,t}$ and estimating a log-linear model is often done in practice. However, $y_{n,t}$ then becomes unit-dependent (e.g. diving $y_{n,t}$ by 1'000 would lead to different results).

erogeneity, and $\psi_{\beta,n} \sim N(0, \widetilde{\sigma}_{\beta}^{2})$ is a random component capturing unobserved heterogeneity in the cost elasticity. The log-normal distribution of $\widetilde{\beta}_n$ ensures that no sign violations occur, so that the cost elasticity is always negative.

The non-linear interaction term with trip distance $dist_{n,0}$ ($\overline{dist}_0$ represents the sample mean) additionally allows for heterogeneity in the cost elasticity with respect to the distance traveled in the base scenario (denoted by subscript 0), which, as discussed above, turned out to be a critical factor in explaining adaptation behavior: If the distance elasticity of travel cost, ω_{dist}, is positive, $\widetilde{\beta}_n$ increases (in absolute values) for increasing distance. As shown in Section 6.2, we expect this to be the case, given that respondents who do not travel much in the base scenario also have less savings potential and a lower scope to adapt their behavior when travel costs increase.

Assuming a full covariance matrix V of the random components

$$\psi \in \{\psi_{\alpha,n}, \psi_{\beta,n}\} \sim N(0, V) \tag{6.4}$$

we apply a Cholesky factor decomposition to V, where C is the lower triangular matrix such that $CC' = V$. A draw of ψ is calculated as

$$\begin{pmatrix} \psi^r_{\alpha,n} \\ \psi^r_{\beta,n} \end{pmatrix} = \begin{pmatrix} \sigma_\alpha & 0 \\ \sigma_{\alpha,\beta} & \sigma_\beta \end{pmatrix} \cdot \begin{pmatrix} \eta^r_\alpha \\ \eta^r_\beta \end{pmatrix} \tag{6.5}$$

such that $\psi^r_{\alpha,n}$ and $\psi^r_{\alpha,n}$ are correlated[6] due to the common influence of η^r_α on both of them, where η^r_α and η^r_β correspond to draws from two independent standard normal distributions. From this follows that $\mathrm{Var}(\psi_{\alpha,n}) = \sigma^2_\alpha$, $\mathrm{Var}(\psi_{\beta,n}) = \sigma^2_{\alpha,\beta} + \sigma^2_\beta$ and $\mathrm{Cov}(\psi_{\alpha,n}, \psi_{\beta,n}) = \sigma_\alpha \cdot \sigma_{\alpha,\beta}$ (see e.g. Train, 2009).

The unconditional likelihood $L_n(\cdot)$ – the expected value over all possible values of ψ that individual n chooses to travel $y_{n,t}$ kilometers among a sequence of adaptation scenarios T_n – is defined by the integral of the product of conditional densities $u(y_{n,t}|x_{n,t}, Z_n, \Omega, \psi)$ over the distributions of ψ and accounts for panel effects (e.g. Greene, 2003):

$$L_n(\cdot) = \int \prod_{t=1}^{T_n} u(y_{n,t}|x_{n,t}, Z_n, \Omega, \psi)\ h(\psi|\Sigma)\ d\psi \tag{6.6}$$

6 The random coefficient models turned out to be stable only when allowing $\psi_{\alpha,n}$ and $\psi_{\beta,n}$ to be correlated (see also the discussions in Section 6.4).

where

$$u(y_{n,t}|x_{n,t}, Z_n, \Omega, \psi) = \frac{1}{\sigma_\zeta} \cdot \phi\left(\frac{y_{n,t} - \exp\left(\alpha + Z_n\rho + \psi_{\alpha,n} + \widetilde{\beta}_n \cdot \log(x_{n,t})\right)}{\sigma_\zeta}\right) \tag{6.7}$$

and ϕ is the standard normal density function. Ω is the set of fixed parameter vectors, $h(\psi|\Sigma)$ is the multivariate distribution of the random components with the corresponding vector of distributional parameters Σ.

Using maximum simulated likelihood techniques, the integral in Equation (6.6) is approximated by calculating the probability density for any given value of ψ using a smooth simulator that is consistent and asymptotically normal (Train, 2009). This is done by drawing values from the $h(\psi|\Sigma)$ distributions, with superscript r referring to draw $r \in \{1, ..., R\}$: $\widetilde{L_n}(\cdot)$ shown in Equation (6.9) is the simulated likelihood for individual n, and the maximum simulated likelihood estimator contains the values in $\widehat{\Sigma}$ and $\widehat{\Omega}$ that maximize $\widetilde{LL}(\Omega, \Sigma)$:

$$\max \widetilde{LL}(\Omega, \Sigma) = \sum_{n=1}^{N} \log\left(\widetilde{L_n}(\cdot)\right) \tag{6.8}$$

$$\widetilde{L_n}(\cdot) = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_n} u(y_{n,t}|x_{n,t}, Z_n, \Omega, \psi^r) \tag{6.9}$$

Models were estimated in *R 3.2.2* (CMC, 2017). Quasi-random draws were generated using Modified Latin Hypercube Sampling (MLHS; Hess et al., 2006). The main criteria regarding identifiability and simulation bias as discussed in Vij and Walker (2014) were investigated: With 4'000 draws, estimates were carefully considered to be robust and stable. Cluster-robust (at the individual-level) standard errors were calculated using the Eicker-Huber-White sandwich estimator (e.g. Zeileis, 2006).

6.4 RESULTS

Four models with increasing complexity are presented in Table 6.4 (daily scheduling experiment) and Table 6.5 (mobility tool ownership experiment), which were found to represent the adaptations in daily/yearly distance traveled appropriately. All models are conditional on MIV usage/ownership in the base scenario. The base model (BASE) is a simple exponential regression model that includes an intercept and the effect of travel costs, the second model (DIST) adds the non-linear interaction term with the distance traveled in the base scenario, the third model (USER) adds the respondent/household characteristics and the fourth model (EMIX) additionally includes the random components, capturing unobserved heterogeneity in the intercept and cost elasticity. After each increase in complexity, all parameters with a $|\text{t-value}| < 1$ are removed for the final model specifications.

6.4.1 *Adaptations in daily distance*

The estimated cost effect reveals an average elasticity of $-\exp(-0.76) = -0.47$ in the BASE model (SE = 0.07; $p < 0.01$): If MIV travel costs per kilometer increase by 1%, the distance traveled by MIV decreases by 0.47%, as expected indicating that the demand is inelastic. This value, though, is relatively high and has to be seen as a main consequence of the survey design: By choosing the busiest day reported as the reference day respondents were facing in the experiment, the savings potential and scope to adapt is high and the elasticity should be interpreted as an upper bound.

Several other possible modeling approaches as mentioned in Section 6.3 have been tested for sensitivity analysis (models do not include any interaction terms and results should be compared to the BASE model)[7], for which the estimates of the cost elasticity, $\widehat{\epsilon}$, are presented in Table 6.3. For the sake of completeness, we also present the results of a model using first differences in levels (M1), where the effect of –1.08 measures the change in distance traveled [km] for a unit change in travel costs [CHF] (thus is not an elasticity). Although this model yields stable results (also when accounting for observed and unobserved heterogeneity) it is inconvenient, as it does not provide the elasticities directly. The fixed (M2) and random effects (M3) Poisson approach[8] yields $\widehat{\epsilon}$ of about –0.5 in both cases[9] very

7 All models for sensitivity analysis were estimated in *Stata 15.1*.

8 While in practice often used for (discrete) count data (Hausman et al., 1984), Gourieroux et al. (1984) show that the Poisson model can be applied to continuous dependent variables as well, allowing for consistent parameter estimation.

9 When testing the random (RE) against the fixed effects (FE) approach, a Hausman test (Hausman, 1978) did not reject H_0 of the RE approach being consistent ($p = 0.46$), i.e. the unobserved error component is uncorrelated with $\log(x_{n,t})$, which is a key assumption of the RE approach (as shown in Table 6.3, corresponding $\widehat{\epsilon}$ are essentially identical). If this holds true, the RE approach tends to be more efficient than the FE approach and also allows for the inclusion of time-invariant regressors (Winkelmann, 2008), which, in essence, was done in the final specification of the exponential regression model (EMIX).

TABLE 6.3: Daily scheduling experiment: Different model specifications to estimate the MIV travel cost elasticity. M1: First differences in levels ($\hat{\epsilon}$ corresponds to km/CHF; i.e is *not* an elasticity); M2: Fixed effects Poisson; M3: Random effects Poisson; M4: Fixed effects negative binomial; M5: Random effects negative binomial; M6; Zero-inflated Poisson.

	M1 Coef./(SE)	M2 Coef./(SE)	M3 Coef./(SE)	M4 Coef./(SE)	M5 Coef./(SE)	M6 Coef./(SE)
$\hat{\epsilon}$	-1.08^{***}	-0.50^{***}	-0.50^{***}	-0.59^{***}	-0.60^{***}	-0.43^{***}
	(0.16)	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)

Significance levels: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

close (and not significantly different; the 95% confidence intervals $\approx \pm 2$ SE are not overlapping) to the exponential regression model. The Poisson model has some convenient estimation properties (see e.g. Hausman et al., 1984; Winkelmann, 2008), but in our case led to peculiar results when increasing the model complexity.[10] Similar conclusions are made for the negative binomial models (M4 and M5): $\hat{\epsilon}$ of about –0.6 is not significantly different from the exponential model, but substantially larger (in absolute values) and adding further complexity was not successful either. Finally, the zero-inflated Poisson model (M6) specifically takes into account the zeros that occurred when respondents changed the distance traveled to zero, but again yields very similar results as the exponential regression model.

Going ahead with the exponential regression model, adding the distance traveled in the base scenario (DIST) substantially increases the model fit (AICc decreases by 524 units, and the R^2 increases from 0.11 to 0.57; see also Appendix, Figure A.42a-b), as expected showing an increasing cost elasticity for increasing distance. Importantly, by controlling for distance, the elasticity point estimate decreases substantially by more than 20% to –0.37, which already seems more reasonable with respect to previous research. However, one should note that no study can serve as a proper benchmark, as no work has ever been conducted using a comparable survey design.

10 By adding the interaction terms of respondent characteristics with travel costs, the increase in LL was substantial, but coefficients remained insignificant; after all, this also seems to be a problem of the relatively small sample size.

TABLE 6.4: Estimation results: Daily scheduling experiment.

	BASE Coef./(SE)	DIST Coef./(SE)	USER Coef./(SE)	EMIX Coef./(SE)
Constant ($\widehat{\alpha}$)	3.29***	3.36***	3.29***	2.91***
	(0.10)	(0.09)	(0.08)	(0.10)
Travel cost ($\widehat{\beta}_{cost}$)	−0.76***	−1.00***	−0.97***	−0.69***
	(0.12)	(0.10)	(0.10)	(0.09)
Model SD ($\widehat{\sigma}_{\zeta}$)	54.23***	38.02***	35.52***	25.74***
	(4.57)	(3.16)	(2.84)	(2.44)
Distance × cost ($\widehat{\omega}_{dist}$)	–	0.73***	0.78***	0.84***
		(0.05)	(0.05)	(0.11)
Driver × const. ($\widehat{\rho}_{driver}$)	–	–	0.04***	0.04***
			(0.01)	(0.01)
Male × const. ($\widehat{\rho}_{male}$)	–	–	0.23***	0.26***
			(0.07)	(0.08)
Income × const. ($\widehat{\rho}_{inc.}$)	–	–	0.34**	0.21***
			(0.14)	(0.07)
Kids × const. ($\widehat{\rho}_{kids}$)	–	–	−0.12	−0.11
			(0.08)	(0.10)
Male × cost ($\widehat{\kappa}_{male}$)	–	–	−0.19***	−0.17**
			(0.05)	(0.07)
High educ. × cost ($\widehat{\kappa}_{educ.}$)	–	–	0.12***	0.04
			(0.02)	(0.03)
Couple × cost ($\widehat{\kappa}_{couple}$)	–	–	−0.06***	−0.03
			(0.02)	(0.02)
Kids × cost ($\widehat{\kappa}_{kids}$)	–	–	0.08*	*n.r.*
			(0.04)	
Urban × cost ($\widehat{\kappa}_{urban}$)	–	–	0.04	*n.r.*
			(0.03)	
SD const. ($\widehat{\sigma}_{\alpha}$)	–	–	–	0.69***
				(0.06)
SD cost ($\widehat{\sigma}_{\beta}$)	–	–	–	0.15***
				(0.05)

Continued on next page

Table 6.4 – *Continued from previous page*

	BASE Coef./(SE)	DIST Coef./(SE)	USER Coef./(SE)	EMIX Coef./(SE)
Cov.(const.,cost) ($\widehat{\sigma}_{\alpha,\beta}$)	–	–	–	-0.55^{***} (0.12)
# estimated parameters	3	4	13	16
# respondents	163	163	163	163
# choice observations	741	741	741	741
# draws	–	–	–	4000
R^2	0.11	0.57	0.63	0.82
$\mathcal{LL}_{final}$	−4010.39	−3747.20	−3696.99	−3573.68
AICc	8026.93	7502.65	7422.42	7183.08

Note: Income is mean-normalized and zero-centered.

$-$: Not included in the model. *n.r.* : Not reported in the table because |t-value| < 1.

Robust standard errors (clustered by ID): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

The inclusion of respondent characteristics (USER) significantly increases the model fit (AICc decreases by 50 units; R^2 increases to 0.63; see also Appendix, Figure A.42c) and shows that high income and male respondents travel longer distances and that car passengers tend to travel smaller distances than drivers (all $p < 0.05$). Of greater interest are the effects on the cost elasticity, showing that male and low educated respondents living in a relationship without kids are less responsive to increases in travel costs than their counterparts. Especially in the case of gender (exhibiting the strongest effect), men tend to choose car more frequently (e.g. Becker et al., 2017) and typically exhibit a lower willingness to reduce car usage (e.g. Polk, 2004).

Importantly, income does not exhibit any effect on the cost elasticity, which – although contradicting the expectations – again supports our findings in Chapter 4 and Chapter 5, where choice behavior, the VTTS and shopping cost elasticities mostly remain unaffected by income. After all, the elasticity point estimate (–0.38) is only marginally affected when controlling for respondent characteristics.

Finally, adding the random components increases the model fit (AICc decreases by 123 units; R^2 increases to 0.82; see also Appendix, Figure A.42d)[11]. The estimated standard deviations of the random components all are significant ($p < 0.01$) and substantial. Importantly, including them does not contradict previous results regarding signs of other coefficients: In most cases, the USER and EMIX coefficients are not significantly different, except for the intercept (and the global model SD estimate). However, the effects of user characteristics to explain the heterogeneity in cost elasticity become less strong (only the effect of male remains significant) and the elasticity point estimate (–0.50) again moves towards the BASE model.[12]

The estimated covariance between the random intercept and cost component is significant ($p < 0.01$), negative and substantial, indicating that a higher distance traveled is associated with a lower (in absolute value) cost elasticity. The mechanism behind is that the non-linear interaction term with distance traveled in the base scenario is strongly and positively associated with the travel cost elasticity (correlation = +0.93 in the USER model) and accounting for the (unobserved) covariance dampens this effect, such that the correlation reduces to +0.72 in the EMIX model. In other words, by only including the distance interaction, its positive effect on the cost elasticity would be overestimated.[13]

To predict the sample distribution of the cost elasticity, the conditional elasticity estimates are obtained by calculating the most likely mean value for each respondent (using R = 4'000 draws), conditional on the observed sequence of choices and fitted elasticity distributions, by applying Bayes' rule (Equation (6.10); see e.g. Revelt and Train, 2000; Hess et al., 2005; Train, 2009; Schmid and Axhausen, 2019b; Schmid et al., 2019a):

$$\widehat{\epsilon}_n = \frac{\sum_{r=1}^{R}\left[\prod_{t=1}^{T_n} u(y_{n,t}|x_{n,t}, Z_n, \widehat{\Omega}, \widehat{\Sigma}, \psi^r)\widetilde{\beta}_n^r\right]}{\sum_{r=1}^{R}\prod_{t=1}^{T_n} u(y_{n,t}|x_{n,t}, Z_n, \widehat{\Omega}, \widehat{\Sigma}, \psi^r)} \tag{6.10}$$

Results are shown in Table 6.5 and illustrated in Figure 6.6: The mean and median cost elasticities decrease substantially when accounting for the distance traveled in the base scenario, but then again increase when

11 The R^2 in the EMIX model is defined as the square root of the correlation between observed and fitted values, with the latter being calculated by taking into account the conditional parameter estimates for each individual/household by using Bayes' rule (see also Equation (6.10)).

12 Note that the actual mean/median sample elasticities are presented below, accounting for the fitted distribution of the travel cost coefficient.

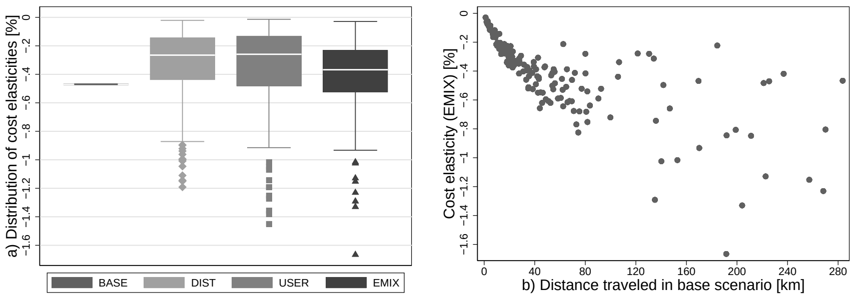
13 Note that when not including the non-linear interaction term with distance traveled in the base scenario, the estimated covariance would not be significantly different from zero.

accounting for unobserved heterogeneity, resulting in a sample median of –0.37. Elasticities exhibit a right-skewed distribution with a larger mean than median, and Figure 6.6b shows where this mainly comes from: As discussed above, the elasticity and distance traveled in the base scenario are positively correlated, with only a few respondents exhibiting very high daily distances and consequently adjusting more strongly to increasing travel costs.

TABLE 6.5: Adaptations in daily distance: Median cost elasticities [%] and interquartile range (IQR) for each model.

	BASE	DIST	USER	EMIX	N
Median $\widehat{\epsilon}_n$	-0.47	-0.27	-0.26	-0.37	163
Mean $\widehat{\epsilon}_n$	-0.47	-0.34	-0.36	-0.42	
IQR	(0.0)	(0.30)	(0.35)	(0.29)	

FIGURE 6.6: Adaptations in daily distance: Distribution of cost elasticities [%], and its visualization depending on the distance traveled in the base scenario (EMIX).



6.4.2 *Adaptations in yearly distance*

The estimated cost effect reveals an average elasticity of $-\exp(-1.86) = -0.16$ in the BASE model (SE = 0.04; $p < 0.01$): If MIV travel costs per kilometer increase by 1%, the yearly distance traveled by MIV decreases by 0.16%. This value is roughly three times smaller than in the daily scheduling experiment, such that MIV travel demand is substantially more inelastic in the long-run. After all, this value is relatively small compared to previous research on fuel price elasticity (≈ -0.3; see Section 6.1) which again has to be seen as a main consequence of the survey design: Households were able to adapt behavior in multiple dimensions and as shown in Section 6.2.2, households effectively made use of these options, so that the distance traveled is, in relative terms, much less affected than in the daily scheduling experiment (where no adaptation towards more efficient motorization was possible). However, our result is very close to what was reported in Erath and Axhausen (2010) (overall demand elasticity of –0.15) who essentially used the same survey approach for a similar geographical coverage (whole Switzerland).

TABLE 6.6: Mobility tool ownership experiment: Different model specifications to estimate the MIV travel cost elasticity. M1: First differences in levels ($\widehat{\epsilon}$ corresponds to km/CHF; i.e is *not* an elasticity); M2: Fixed effects Poisson; M3: Random effects Poisson; M4: Fixed effects negative binomial; M5: Random effects negative binomial; M6; Zero-inflated Poisson.

	M1 Coef./(SE)	M2 Coef./(SE)	M3 Coef./(SE)	M4 Coef./(SE)	M5 Coef./(SE)	M6 Coef./(SE)
$\widehat{\epsilon}$	-0.30^{***}	-0.21^{***}	-0.21^{***}	-0.34^{***}	-0.33^{***}	-0.17^{***}
	(0.07)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)

Significance levels: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

Again, several other possible modeling approaches as mentioned in Section 6.3 have been tested for sensitivity analysis, for which the estimates of the travel cost elasticity, $\widehat{\epsilon}$, are presented in Table 6.6. Starting with a model in first differences (M1), the effect of –0.30, measured in km/CHF (thus is not an elasticity), is roughly three times smaller than in the daily scheduling experiment, decreasing in the same relative magnitude as the BASE model elasticity. The fixed and random effects Poisson (M2 and M3) and negative binomial (M4 and M5) approaches go in the same direction, exhibiting elasticities substantially (roughly two times) below the ones reported above, with the latter models again exhibiting larger (but not significantly different) elasticities than the former. Similarly, the zero-inflated Poisson model (M6) exhibits an elasticity more than two times smaller than above and is very close to the current BASE model estimate. Results confirm our general finding that long-run elasticities are substantially and significantly below the ones obtained in the daily scheduling experiment and that in both cases, results are robust in the sense that the 95% confidence intervals of $\widehat{\epsilon}$ are never overlapping.

Going ahead with the exponential regression model, adding the distance traveled in the base scenario (DIST) substantially increases the model fit (AICc decreases by 483 units, and the R^2 increases from 0.02 to 0.46; see also Appendix, Figure A.43a-b), as expected again showing an increasing cost elasticity for increasing distance. By controlling for distance, the elasticity point estimate now increases by almost factor two to –0.29.

The inclusion of respondent characteristics (USER) significantly increases the model fit (AICc decreases by 120 units; R^2 increases to 0.54; see also Appendix, Figure A.43c) and shows that high income respondents and couples living in rural areas travel longer distances (all $p < 0.05$). The effects on the travel cost elasticity indicate that high income households living in rural areas are less responsive to increases in costs than their counterparts (both $p < 0.05$). Income finally shows the expected effect on cost sensitivity: One explanation is that the sum of yearly travel costs is much more affecting households' money budget than on a daily basis, and respondents start considering travel and mobility behavior with respect to their income only in the long-run. After all, the elasticity point estimate (–0.27) is only marginally affected when controlling for household characteristics.

Finally, adding the random components substantially increases the model fit (AICc decreases by 1'116 units; R^2 increases to 0.95; see also Appendix, Figure A.43d). The estimated standard deviations of the random components all are significant ($p < 0.01$) and substantial and including them does not contradict previous results regarding signs of other coefficients: In most cases, the USER and EMIX coefficients are not significantly different, except for the interaction of distance with travel cost (and the global model SD estimate σ_ζ) and the elasticity point estimate is only marginally affected.

Similar as in the daily scheduling experiment, the estimated covariance between the random intercept and cost component is significant ($p < 0.01$), negative and substantial, indicating that a higher distance traveled is associated with a lower (in absolute value) cost elasticity. At the same time, the non-linear interaction effect with distance traveled in the base scenario almost doubles in the EMIX model and the same mechanism is at play as discussed for the daily scheduling experiment, substantially dampening the correlation between the travel cost elasticity and distance (from +0.95 in the USER model to +0.35 in the EMIX model; see also Figure 6.7b).

TABLE 6.7: Estimation results: Mobility tool ownership experiment.

	BASE Coef./(SE)	DIST Coef./(SE)	USER Coef./(SE)	EMIX Coef./(SE)
Constant ($\widehat{\alpha}$)	2.05***	1.90***	1.88***	1.72***
	(0.09)	(0.08)	(0.07)	(0.03)
Travel cost ($\widehat{\beta}_{cost}$)	−1.86***	−1.23***	−1.30***	−1.36***
	(0.37)	(0.14)	(0.14)	(0.06)
Model SD ($\widehat{\sigma}_{\zeta}$)	8.13***	6.05***	5.59***	2.00***
	(0.87)	(0.62)	(0.54)	(0.26)
Distance × cost ($\widehat{\omega}_{dist}$)	–	0.94***	1.05***	1.91***
		(0.08)	(0.08)	(0.05)
HH income × const. ($\widehat{\rho}_{inc.}$)	–	–	0.38**	0.67**
			(0.16)	(0.31)
Couple × const. ($\widehat{\rho}_{couple}$)	–	–	0.06**	0.03*
			(0.03)	(0.02)
Urban × const. ($\widehat{\rho}_{urban}$)	–	–	−0.18***	−0.22***
			(0.05)	(0.05)
HH income × const. ($\widehat{\kappa}_{inc.}$)	–	–	−0.28**	−1.36**
			(0.14)	(0.68)
Urban × const. ($\widehat{\kappa}_{urban}$)	–	–	0.19***	0.44***
			(0.05)	(0.15)
SD const. ($\widehat{\sigma}_{\alpha}$)	–	–	–	0.80***
				(0.02)
SD cost ($\widehat{\sigma}_{\beta}$)	–	–	–	0.28***
				(0.04)
Cov.(const.,cost) ($\widehat{\sigma}_{\alpha,\beta}$)	–	–	–	−1.52***
				(0.09)
# estimated parameters	3	4	9	12
# households	165	165	165	165
# choice observations	821	821	821	821
# draws	–	–	–	4000
R^2	0.02	0.46	0.54	0.95

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Table 6.7 – *Continued from previous page*

	BASE Coef./(SE)	DIST Coef./(SE)	USER Coef./(SE)	EMIX Coef./(SE)
$\mathcal{LL}_{final}$	−2885.36	−2642.64	−2577.22	−2015.49
AICc	5776.86	5293.53	5173.60	4057.04

Note: Distance traveled by MIV is scaled down by factor 1000. Household (HH) income is mean-normalized and zero-centered.

− : Not included in the model. *n.r.* : Not reported in the table because |t-value| < 1.

Robust standard errors (clustered by ID): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

The conditional elasticity estimates are again calculated according to Equation (6.10) and results are shown in Table 6.8 and illustrated in Figure 6.7: The mean and median cost elasticities now increase substantially when accounting for the distance traveled in the base scenario, but then again decrease when accounting for unobserved heterogeneity, resulting in a sample median of –0.13 (EMIX). Again, elasticities exhibit a right-skewed distribution and Figure 6.7b shows where this mainly comes from: As discussed above, the elasticity and distance traveled are positively correlated, with only a few respondents exhibiting very high daily distances and consequently adjusting more strongly to increasing travel costs. However, the pattern is much less pronounced than in the daily scheduling experiment, while the amount of unobserved heterogeneity is much more predominant here.

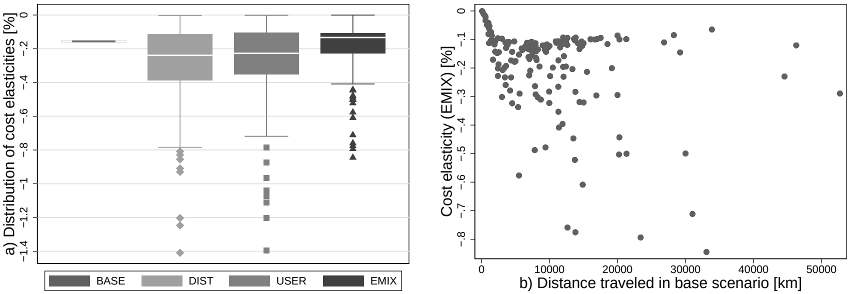
TABLE 6.8: Adaptations in yearly distance: Median cost elasticities [%] and interquartile range (IQR) for each model.

	BASE	DIST	USER	EMIX	N
Median $\widehat{\epsilon}_n$	−0.16	−0.24	−0.23	−0.13	165
Mean $\widehat{\epsilon}_n$	−0.16	−0.29	−0.27	−0.19	
IQR	(0.0)	(0.27)	(0.25)	(0.12)	

6.5 CONCLUSIONS

To what degree individuals would be changing travel behavior when mobility costs are reaching unprecedented proportions, is an important ques-

FIGURE 6.7: Adaptations in yearly distance: Distribution of cost elasticities [%], and its visualization depending on the yearly distance traveled in the base scenario (EMIX).



tion that may not only help researchers and policy makers to develop and implement efficient pricing regimes, but also forecast travel demand e.g. in case of an exogenous price shock. Radical pricing effects are assessed from an activity-based perspective on a daily and yearly basis within two hypothetical behavioral experiments, where respondents were able to adapt behavior in multiple dimensions: How would individuals reorganize their daily activity patterns and mode choice, and how would households react within a longer time horizon when adaptations in mobility tool ownership are possible as well?

Given the relatively small sample size and rich amount of data collected, the current analysis focuses on one key aspect, namely the effect of MIV travel costs on the distance traveled by MIV. The main attempt addressed by this chapter is to better understand and quantify the transition towards a car-free society, estimating response functions – i.e. cost elasticities of travel demand – for highly disaggregate data. Specifically, estimates could be used as a first input to simulate travel behavior by using tools such as the agent-based transport simulation software *MATSim* (Horni et al., 2016), evaluating different mobility pricing regimes for the Canton of Zurich or whole of Switzerland – currently a hot topic in Swiss policy.[14] Further research using these two datasets is encouraged and may shed light on other, more specific aspects, such as the quantitative assessment of the behavior of PT users or the choice of shared mobility services.

Results indicate that elasticities differ substantially between the daily scheduling and mobility tool ownership experiment: If MIV travel costs in-

14 See e.g. www.astra.admin.ch (last access: July 11, 2019).

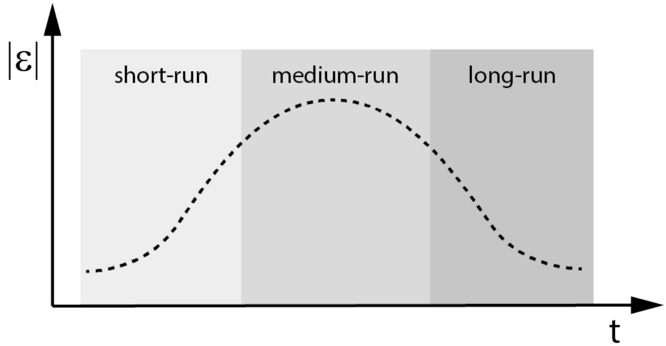
crease by 1%, median respondents reduce the distance traveled by roughly 0.37% in case of the former, which drops to about 0.13% in case of the latter. Both results have to be interpreted critically and, to some extent, seen as a logical consequence of the survey design: By choosing the busiest day reported as the reference day in the daily scheduling experiment, the obtained elasticity may be interpreted as an upper bound, whereas in the mobility tool ownership experiment, the substitution effect towards more efficient mobility tools may impose a smaller effect. In reality, one may be more likely to first restrain the distance traveled before reconsidering the car type. In both cases, a hypothetical bias may add an additional layer of uncertainty and the herein presented results should be seen more from a qualitative perspective.

Other sensible model specifications have been tested for sensitivity analysis, indicating that there are some noticeable differences and that the decision was made in favor of the exponential regression model mainly for reasons of simplicity, estimation stability and robustness. The ordering and magnitude of effects are not much affected though and the elasticities in the daily scheduling experiment are always above the ones in the mobility tool ownership experiment. Importantly, in both experiments, the effects are not significantly different from each other. Last but not least, there are some econometric issues to be critically challenged, such as the inclusion of distance traveled in the base scenario as an interaction variable. We have shown that it strongly and intuitively affects the elasticities (i.e. the more individuals travel by MIV, the more they adapt their behavior). However, controlling for it interferes with the random effects and also may lead to an endogeneity problem. Attempts to tackle these issues are left for further research.

One important issue that remains to be challenged is the opposite direction of short- and long-term elasticities reported in the literature, arguing that peoples' reaction to changes in travel costs is sticky and needs some time to adapt, thus implying a more elastic response in the long-run. A possible attempt to synthesize our results with previous research is discussed as follows and depicted in Figure 6.8.

In the daily scheduling experiment, although the focus lies on one reference day, the task may be perceived more as a longer-term decision (which is conditional on current mobility tool ownership). Remember the way how respondents were introduced to the experiment: Future policies, such as road tolls and congestion taxes for MIV are introduced and fuel prices increase substantially. One may argue that if respondents know with cer-

FIGURE 6.8: Hypothesized pathway of the cost elasticity of travel demand (ϵ) over time (t).



tainty that they have to pay these higher prices on a regular basis, they will also change their behavior in a more pronounced way. In reality, however, the world is uncertain and it is more than plausible that individuals take some time to adapt their daily activity and mobility plans, including location decisions and mode choice. Therefore, the obtained results may be better interpreted as a *medium-run* elasticity and our definition of *medium-run* seems related to what is meant by long-run in previous research (e.g. Dix and Goodwin, 1982; Goodwin, 1992).

Adaptations in mobility tool ownership – towards more efficient engine types, hybrid or electric cars – may then be seen as an actual *long-run* decision, most presumably exceeding the long-run definition according to previous research substantially (note, however, that potentially important long-run decisions, such as residential or work location choices, were not considered in the experiments). The resulting travel cost elasticity does reflect those substitution patterns, so that ultimately the overall distance traveled by MIV is not decreasing that much. In fact, our respondents could easily change the vehicle type and take other measures to efficiently dampen the variable costs. After all, the purchasing price they would have to pay for a more ecological vehicle was not explicitly considered in the experiment, as only the yearly fixed costs matter.

7 CONCLUSIONS

Millions saw the apple fall, but Newton was the one who asked why.

— Bernard M. Baruch

7.1 DISCUSSIONS AND POLICY IMPLICATIONS

One main objective of this thesis is to investigate and synthesize different key aspects of the comprehensive *Post-Car World* project. The data collection described in Chapter 2 covers a broad range of topics, and one goal of this thesis is to demonstrate how different research fields and data collection methods play together to come up with a deeper understanding of human behavior in general and travel behavior in particular. The following discussion summarizes the results of each chapter, provides some concluding remarks and implications for policy and research.

Chapter 2 demonstrates several issues that may occur when dealing with long-duration and burdensome studies, presenting useful tools and analyses to get an idea of the respondents' motivation for participating in a survey and to further improve the survey process. Importantly, we show that incentive payments exhibit an ambiguous effect on response behavior: A high incentive level leads to a significantly higher initial participation rate, but the net-effect on completion is zero. One explanation might be that when realizing the high response burden, high incentives might convince people who are actually not interested in the survey topic to participate, but when realizing the enormous response burden, they may decide to drop-out. We also present a quantitative model to predict response rates based on previous studies conducted at the IVT, where we show that decreasing the response burden by 100 points ($\approx$ 8-9 minutes response time) increases the expected response rate by about 6%. Our findings may support and inspire researchers when designing and conducting future studies – not only in the field of transportation research.

Chapter 3 describes how the data on respondents' travel (used to infer time-use), non-physical entertainment activities (used to infer in-home leisure) and expenditure behavior are used to estimate the value of leisure (VoL). This is an important measure in transportation research, as it builds the microeconomic foundation of the value of travel time savings (VTTS). However, estimating the VoL is difficult: It requires, apart from sophisticated econometric skills and data preparations, high-quality data on a variety of activities and expenditures over a sufficiently long period to be considered as a long-run equilibrium (clearly, our one week reporting period might not be enough, but provides a bearable, although still substantial, response burden).

These efforts are rewarded by the clear and intuitive results: The obtained VoL of 23 CHF/h is roughly half of the wage rate, and comprehensive sensitivity analyses have shown – although sometimes the results are affected substantially – that the VoL lies always below the wage rate. This means that the consumption of goods – apart from fixed income, affordable through labor supply – exhibits a high importance relative to leisure for our Zurich respondents which goes in line with the Swiss mentality.

Chapter 4 presents a pooled RP/SP choice model, where the RP mode choice data obtained from the travel diary is joined with the SP mode and route choice data, making use of the benefits of both data types. The obtained median VTTS for walk (24.9 CHF/h), bike (16.9 CHF/h), private car and motorbike (MIV; 28.9 CHF/h), public transportation (PT; 13.8 CHF/h), CS (27.3 CHF/h) and CP (31.3 CHF/h) indicate that there is a substantial difference between modes, which can only partly be attributed to characteristics of the users: In case of PT, the mode effect (i.e. the VTTS difference between MIV and PT) always dominates the user type effects, remaining more or less persistent for all investigated user groups.

An important implication is that the value of time assigned to travel (VTAT) – the difference between the VoL and VTTS – has inverse signs for different modes, following the reverse ranking in mode-specific VTTS: The VTAT is negative for CP (-8.9 CHF/h), MIV (-4.8 CHF/h), CS (-2.7 CHF/h) and walk (-0.7 CHF/h), and positive for bike (6.9 CHF/h) and PT (10.3 CHF/h). Together with MIV, the two emerging modes CS and CP exhibit the worst performance in terms of VTAT which indicates that the value of time assigned to travel in car modes is substantially lower than in PT. This seems to capture well the outstanding service quality of PT in Switzerland in general, and Zurich in particular and is also reflected in the alternative-specific constants: Even in the complete absence of private cars, respondents clearly prefer to choose PT rather than CS or CP.

How are the enormous efforts of obtaining the VoL justified from a policy perspective? We argue that a shift of focus from the VTTS to its two components, i.e. the VoL and the VTAT, would help assessing options under a budget constraint, as it would allow a comparative evaluation of investments in (i) faster connections (captured by the VoL) or (ii) the conditions of in-vehicle travel (captured by the VTAT). For example, from a PT operator's point of view, our results indicate that investing in speed may exhibit a higher marginal impact on user benefits (by eventually decreasing the travel time), while for a CS or CP operator, investing in the quality of travel may be suggested (by eventually decreasing the VTTS).

Having obtained the VTTS and VoL for each individual, we show that both measures exhibit relatively low correlations: Mode-specific VTTS are primarily depending on individual travel preferences that are mostly uncoupled with the opportunity value of time. One main component of the VoL – income – does not exhibit any effects on the mode-specific VTTS. This is an important finding of this thesis, asking for further research that is needed to verify this result for other user segments, regions or countries which exhibit a larger heterogeneity in income, and/or where travel exhibits a substantially larger share of total expenditures.

In Chapter 5, we change the topic by investigating respondents' purchasing preferences for two types of goods: Groceries (G), typical experience goods and standard electronic appliances (E), typical search goods. Based on the SP data obtained from the shopping channel choice experiment and the attitudes towards shopping and ICT related aspects, we estimate the first alternative-specific hybrid choice model in the field of shopping behavior research.

The main methodological implication of the applied modeling framework is an enhanced estimation efficiency and intuitive structure of respondent heterogeneity via the latent variable. As we can show with the current application, this leads to a more behaviorally sound representation of individual decision making when comparing to the reduced form model without respondents' attitudes.

From a travel behavior perspective, results reveal a further potential for online shopping services, given the relatively high VTTS of about 50 CHF/h for G and 30 CHF/h for E compared to the value of delivery time (VDTS) ranging between 9 CHF/day for G and 1 CHF/day for E. For longer distances, in both cases, avoiding a shopping trip thus produces more benefits than waiting for the delivery of the products – a finding that is further supported by the negative VTAT for the in-store alternative. Also, in the case of grocery shopping, shopping costs are perceived as less unpleasant relative to delivery costs. Online retailers should take note of that when designing an effective pricing strategy: From a behavioral perspective, incorporating delivery in shopping costs would increase customers' utilities and therefore the market shares of online shopping.

Chapter 6 presents the results obtained from the two SA experiments, where we estimate cost elasticities of travel demand (i.e distance traveled by MIV) for increasing variable MIV travel costs. To what degree individuals would be changing travel behavior when mobility costs are reaching unprecedented proportions, is an important question that may not only help researchers and policy makers to develop efficient pricing regimes, but may also forecast travel behavior in case of an exogenous price shock.

The cost elasticities of travel demand differ substantially between the daily scheduling and mobility tool ownership experiment: If MIV travel costs increase by 1%, median respondents reduce the distance traveled by 0.37% in case of the former, which drops to about 0.13% in case of the latter. We argue that in the short/medium-run, people may adapt more strongly, since substitution effects towards more energy efficient vehicles are unlikely. In the long-run, however, the elasticity does reflect those substitution patterns, such that ultimately the overall distance traveled by MIV may not be decreasing that much. This finding may be important for elaborating future congestion policies: In case of increasing fuel prices, for example, results indicate that in the long-run this would only lead to a relatively small effect on the overall traffic volume.

7.2 LIMITATIONS

A wide range of data have been collected as part of this project and many issues that were unclear or insufficient when doing the study design should be mentioned at this point. As discussed in Chapter 2, after all the survey became extremely and almost unreasonably burdensome. Apart from investigating behavioral experiments with the focus on car-reducing or car-free scenarios (which still remained rather vague when starting with the project), the survey should also include ICT related aspects of travel behavior and allow to estimate the VoL which turned out to be a very time consuming endeavor: Not only for the respondents, but also while conducting the fieldwork. At the same time, the data quality was suffering, respondents were overwhelmed when completing all different kinds of questionnaires and the drop-out rate was substantial. This should be avoided in future studies: The topic should be narrowed down and the response burden reduced to a reasonable level. In the end, this is also reflected in the PCW sample characteristics – apart from other potentially important, but unobserved characteristics of respondents participating in such a survey – showing a clear trend towards highly educated, upper class and very PT affine respondents. Also, a major problem involved the recruitment of all eligible (older than 18 years) household members, simultaneously affecting the age distribution in the PCW sample: Although larger households are overrepresented, mostly fractions (e.g. parents or the addressed household heads) of all eligible household members actually participated in the survey.[1] To what extent the results and policy implications may be affected by this sampling bias remains rather vague and is left for further research.

When designing the questionnaires and behavioral experiments, it would have been helpful to involve focus groups to raise the awareness which choice attributes are considerably important for respondents' decision making. In fact, the survey was designed under time pressure mainly due to organizational reasons[2], and several inconsistencies were found after the fieldwork has been finished already. The most important ones are discussed as follows:

– The design of the daily and long-run expenditure questionnaires should have put more emphasis on the distinction between committed and uncommitted goods (which is a crucial issue when estimating the VoL), instead of complying with the Swiss household budget survey. Either way, their inclusion in the survey led to a substantial drop-out rate, since many respondents could not see the connection of expenditures and travel behavior.[3]

– A finer grained distinction of activities would have been very helpful, especially secondary activities at home, to obtain a clearer distinction between committed and uncommitted time and therefore more confident VoL estimates. Many assumptions were imposed that cannot be tested, including e.g. the definition of committed time at home.

1 Last but not least, this also affected the final sample size and one should keep in mind, that the cross-sectional dimension of the *Post-Car World* dataset is not very large.
2 Basil Schmid started his PhD five months after the official kick-off meeting of the *Post-Car World* project.
3 Similar complains were made for the personality questionnaire.

- In case of the SP mode, route and shopping channel choice experiments, a crucial issue that has been missed is the inclusion of MIV (as part of the scenario description, or additional choice alternative) to obtain more meaningful statements relative to current modes, instead of insisting on our definition of the *Post-Car World* scenario (which still includes cars, but not private ones). After all, the main limitations of some parts in this thesis result from the general nature of SP experiments and the limited, contrived and constrained experimental settings. The reader has to be aware that the results are not easily generalizable to other scenarios than the ones presented to the respondents. We further demonstrate, that our results are context-dependent, which – in the case of cost sensitivities – violates the assumptions of the traditional microeconomic framework of consumer behavior. Further research in this direction would be beneficial in the context of valuation studies.

- Similarly, the results of the two SA experiments have to be interpreted critically and, to some extent, seen as a logical consequence of the survey design: By choosing the busiest day reported as the reference day in the daily scheduling experiment, the obtained cost elasticity of travel demand may be interpreted as an upper bound, whereas in the mobility tool ownership experiment, the substitution effect towards more efficient mobility tools may impose a lower bound. In reality, however, one may be more likely to first restrain the distance traveled before reconsidering the car type. In both cases, a hypothetical bias may add an additional layer of uncertainty, and the herein presented results should be seen more from a qualitative perspective.

7.3 OUTLOOK

The data collected as part of this project is exceeding the scope to analyze each aspect in this thesis. While each chapter independently provides discussions and topics for further research in the conclusion sections, the goal here is to provide an non-exhaustive outlook on what kind of additional analyses could be done with the current dataset.[4]

A sophisticated mobility tool ownership model à la Becker et al. (2017) would shed light on the actual (RP) mode preferences and substitution

4 Note that the PCW dataset will be properly archived for public use at the ETH online library by the end of 2019: www.library.ethz.ch

patterns conditional on socioeconomic characteristics and respondents' attitudes. Such a model could be stand-alone or integrated in the RP/SP choice model presented in Chapter 4 using a simultaneous estimation approach similar as in Mabit and Fosgerau (2009), accounting for self-selection in a dedicated way when estimating the VTTS.

The interrelations between travel behavior and ICT usage could be further investigated using a SEM approach (e.g. Farag et al., 2007), linking out-of-home with related online activities of the same purpose (e.g. shopping and leisure), as already done in Fuchs (2016) for a preliminary (incomplete) version of the current dataset. It would allow to investigate these interrelations for a one week reporting period (by accounting for the panel structure in a dedicated way), which is rarely found in the literature. Furthermore, a comparison with the results obtained from the shopping channel choice model in Chapter 5 could validate possible substitution patterns between in-store and online shopping on a RP basis.

A broad range of attitudes and personality traits (including risk aversion, environmental awareness, love of variety, and mode-specific attitudes) were collected, which were included only to a small extent in the shopping channel choice model in Chapter 5. Results have shown that including attitudes allows to structure respondent heterogeneity more efficiently and in a more intuitive way, and allows deeper behavioral insights when explaining choice behavior (which would not have been obtained when applying a reduced form specification only). Therefore, it might be of great interest how the inclusion of attitudes may improve the behavioral insights of results in the other chapters.

Finally, results of the activity-based models (i.e. the estimated LOS utility weights from the RP/SP models, the cost elasticities and/or the planning and scheduling styles from the SA experiments) could be incorporated into the agent-based transport simulation *MATSim*, creating scenarios for different adaptations in supply and policy changes for the Canton of Zurich.

A

APPENDIX

FIGURE A.1: Household questionnaire I.

Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

1 Household

Welcome to our mobility survey and thank you for participating!

We ask one household member to fill in the following household and vehicle forms for general information about your household.

All information will be treated in the strictest confidence and will not be handed to persons not involved in the project. The data is exclusively serving scientific purposes and statistical analyses. The persons engaged in the survey are committed to absolute discretion.

Given name and surname: ☐

Number of adult household members participating in the survey: ☐

Residential address: Street ☐ No. ☐
ZIP ☐ City ☐

Which services are within a 10 minute walking distance from your home?

- ☐ School
- ☐ Doctor
- ☐ Grocery store
- ☐ Bank
- ☐ Bus or tram stop
- ☐ Post office
- ☐ Train station
- ☐ Restaurant / bar

Do you have a secondary residence?

- ☐ No
- ☐ Yes, address:

Street ☐ No. ☐
ZIP ☐ City ☐

How many persons live in the household, including yourself?

☐ Children (0- 6 yrs.) ☐ Adolescents (6 - 18 yrs.) ☐ Adults

Do you have dogs in your household?

- ☐ No
- ☐ Yes, ☐ dogs

How would you characterise your household?

- ☐ Single person
- ☐ Couple without children
- ☐ Couple with children
- ☐ Single parent
- ☐ Other (e.g. shared flat)

Figure A.2: Household questionnaire II.

What is the gross income of your household per month (before tax)?

- ☐ Less than 2'000 CHF
- ☐ Between 2'000 and 4'000 CHF
- ☐ Between 4'000 and 6'000 CHF
- ☐ Between 6'000 and 8'000 CHF
- ☐ Between 8'000 and 10'000 CHF
- ☐ Between 10'000 and 12'000 CHF
- ☐ Between 12'000 and 14'000 CHF
- ☐ Between 14'000 and 16'000 CHF
- ☐ More than 16'000 CHF
- ☐ No answer

Monthly expenses for yor primary residence:

Residence type ☐ Rented ☐ Owned

Rented:

Rent (per month): ______ CHF

incl. extra costs? (heating, electricity, water) ☐ Yes ☐ No

If not included, extra costs (per month): ______ CHF

Owned:

Repayment costs: (per month; e.g. mortgage or loan) ______ CHF

Extra costs: (per month; heating, electricity, water) ______ CHF

Maintenance: (per year; repairs, garden etc.) ______ CHF

Size of appartment/house, rooms (w/o kitchen/bathroom): ______ Square meters: ______

What is the building does your home belongs to? ☐ New ☐ Old ☐ Renovated

Does your home include exterior spaces? ☐ No ☐ Garden ☐ Balcony

Type of residence? ☐ Single family house ☐ Apartment buidling ☐ High rise

Type of location? ☐ City centre ☐ Suburban ☐ Rural

How many of the following vehicles are owned by your household?

- ______ Car(s)
- ______ Motorbike(s)
- ______ Bicycle(s)

If other vehicles, please specify: ______ ______

Where do you park your bicycles and how would you describe the security/accessibility?

- ☐ Courtyard/garden
- ☐ (Sheltered) driveway
- ☐ On-street
- ☐ (Underground) garage
- ☐ Appartment/basement
- ☐ Other: ______

Security: ☐ High ☐ Medium ☐ Low

Accessibility from the street: ☐ High ☐ Medium ☐ Low

2

Figure A.3: Vehicle questionnaire I.

Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

2 Motorized vehicles

We ask you now to give detailed information about all motorized vehicles in your household. If your household does not possess motorized vehicles, please skip this form and continue with the next questionnaire.

Please fill in the required information about motorized vehicles available in your household (Car, van, motorbike, SUV, jeep, truck, etc.).

	Vehicle 1	Vehicle 2	Vehicle 3
Make			
Model			
Displacement (ccm)			
Year of manufacture			
Year of purchase			
Effective price (CHF)			
Company car	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No
Fuel type	Gasoline ☐ Diesel ☐ Hybrid ☐ Other ☐	Gasoline ☐ Diesel ☐ Hybrid ☐ Other ☐	Gasoline ☐ Diesel ☐ Hybrid ☐ Other ☐
Fuel consumption	l/100km	l/100km	l/100km
Mileage per year (estimate)			
Motorway toll sticker	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No
Available parking	Courtyard ☐ Driveway ☐ On-street ☐ Garage ☐ Other ☐	Courtyard ☐ Driveway ☐ On-street ☐ Garage ☐ Other ☐	Courtyard ☐ Driveway ☐ On-street ☐ Garage ☐ Other ☐
Monthly cost	CHF	CHF	CHF
Distance from home (estimate)	m	m	m
Used vehicle	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No
Motorbike	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No

3

Figure A.4: Vehicle questionnaire II.

Please fill in the required information about motorized vehicles available to your household (Car, van, motorbike, SUV, jeep, truck, etc.).

	Vehicle 1	Vehicle 2	Vehicle 3
Brand			
Make			
Displacement (ccm)			
Year of manufacture			
Year of purchase			
Effective price (CHF)			
Company car	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No
Fuel type	Gasoline ☐	Gasoline ☐	Gasoline ☐
	Diesel ☐	Diesel ☐	Diesel ☐
	Hybrid ☐	Hybrid ☐	Hybrid ☐
	Other ☐	Other ☐	Other ☐
Fuel consumption	l/100km	l/100km	l/100km
Mileage per year (estimate)			
Motorway toll sticker	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No
Available parking	Courtyard ☐	Courtyard ☐	Courtyard ☐
	Driveway ☐	Driveway ☐	Driveway ☐
	On-street ☐	On-street ☐	On-street ☐
	Garage ☐	Garage ☐	Garage ☐
	Other ☐	Other ☐	Other ☐
Monthly cost	CHF	CHF	CHF
Distance from home (estimate)	m	m	m
Used vehicle	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No
Motorbike	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No

Thank you for your information.

4

FIGURE A.5: Person questionnaire I.

IVT Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

ETH Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

3 Person

Each participating household member is asked to complete his or her own (provided) copy of this form. It contains detailed questions about the person.

Given name: ______	Year of birth: 19 ___
Sex:	☐ Female ☐ Male
What is your citizenship?	☐ Swiss ☐ Other: ______
What is your marital status? ☐ Single ☐ Married ☐ Widowed	☐ Divorced ☐ Civil union ☐ Cancelled civil union ☐ Married, separated
What is you highest education level? ☐ Mandatory school not completed ☐ Mandatory school ☐ Commercial school ☐ Apprenticeship	☐ Vocational school ☐ High school ☐ Master certificate / diploma ☐ Technical school ☐ Higher vocational college ☐ Polytechnic institute ☐ University degree ☐ Other: ______
What is your current professional status? (Multiple answers possible) ☐ Retired ☐ Disabled	☐ In education ☐ Working as: ______ ☐ Job-seeking due to: ______ ☐ Engaged in own household
In case you are working or are in education: How many hours per week do you spend for this activity on average? ______ hours	
Address or location of work or education:	Street ______ No. ___ ZIP ___ City ______ Locality (e.g. Paradeplatz): ______ ______

1

Figure A.6: Person questionnaire II.

In case you are working/employed: Since when are you employed by your current employer?	Since (month/year):
In case you are working/employed: What is your position? ☐ Permanent ☐ Formally fixed-term with rollover option	☐ Fixed-term, less than 1 year ☐ Fixed-term, 1 to 2 years ☐ Fixed-term, ___ years
In case you are working/employed: How would you describe the status of your current position in terms of long-term committments? ☐ Long-term position with specified goals ☐ Temporary position with career opportunities ☐ Job without long-term perspectives/goals ☐ Other:	
Does your job or education offer the possiblity for home office?	☐ No ☐ Yes, on average ___ days per week
Do you have parking available at your work/education location?	☐ No ☐ Yes, at monthly cost of: ___ CHF
Do you have a car driving license?	☐ Yes ☐ No
How often do you have a car available?	☐ Always ☐ Frequently ☐ Rarely / upon prior agreement ☐ Never
Dou you have a motorbike driving license?	☐ Yes ☐ No
How often do you have a motorbike available?	☐ Always ☐ Frequently ☐ Rarely / upon prior agreement ☐ Never
Please estimate the distance you covered with any private (road) vehicles as a driver (car, motorbike etc.) during the last 12 months: ___ km per year	

2

Figure A.7: Person questionnaire III.

Are you memeber in a car-sharing organisation (e.g. Mobility)?
- ☐ No
- ☐ Yes, privately
- ☐ Yes, for work

If you are member of a car-sharing organisation: Since (month/year): ______

Name of organisation (multiple entries possible): ______

How frequently do you use the services? ______ times per ☐ month ☐ year

For what purpose do you use the car-sharing services primarily (multiple entries possible)?
- ☐ Passenger transport (including yourself)
- ☐ Goods (e.g. furniture, equipment etc.)
- ☐ Groceries
- ☐ Leisure (e.g. excursions, visits etc.)

What is the average duration of a car-sharing trip? ______ hour(s)

Do you own a travel card for public transport?

☐ Yes ☐ No

If yes, please indicate the type and number of zones if applicable:

☐ National season ticket
- ☐ Standard ☐ 1st Class
- ☐ Student ☐ 2nd Class
- ☐ Partner ☐ Monthly*
- ☐ Senior *(min. 4 months)
- ☐ Handicap ☐ Yearly

☐ Half-fare travel card

☐ Regional season ticket (e.g. ZVV)
- ☐ Monthly ☐ Local
- ☐ Yearly ☐ Regional

☐ Gleis 7

☐ Multiple trips ticket

☐ Corridor ticket

☐ Other: ______

Total price: ______ CHF

Number of zones: ______

☐ Unknown

How many trips with public transport did you undertake in the last 7 days (rides with transfers count as 1 trip; round trips as 2 trips): ______ trips

On how many days in the last 7 days did you use public transport? ______ days

Do you have one or more of the following devices available for usage?
- ☐ Smartphone ☐ Tablet PC
- ☐ Desktop ☐ Laptop

3

FIGURE A.8: Person questionnaire IIII.

What is your personal gross income per month (before tax)?

- ☐ No income
- ☐ Less than 250 CHF
- ☐ 250 CHF to 500 CHF
- ☐ 500 CHF to 850 CHF
- ☐ 850 CHF to 1’200 CHF
- ☐ 1’200 CHF to 1’600 CHF
- ☐ 1’600 CHF to 2’000 CHF
- ☐ 2’000 CHF to 2’300 CHF
- ☐ 2’300 CHF to 2’600 CHF
- ☐ 2’600 CHF to 3’000 CHF
- ☐ 3’000 CHF to 3’500 CHF
- ☐ 3’500 CHF to 4’000 CHF
- ☐ 4’000 CHF to 4’500 CHF
- ☐ 4’500 CHF to 5’000 CHF
- ☐ 5’000 CHF to 5’600 CHF
- ☐ 5’600 CHF to 6’300 CHF
- ☐ 6’300 CHF to 7’000 CHF
- ☐ 7’000 CHF to 7’900 CHF
- ☐ 7’900 CHF to 8’800 CHF
- ☐ 8’800 CHF to 9’700 CHF
- ☐ 9’700 CHF to 10’500 CHF
- ☐ 10’500 CHF to 11’400 CHF
- ☐ 11’400 CHF to 12’300 CHF
- ☐ 12’300 CHF to 13’200 CHF
- ☐ 13’200 CHF to 17’500 CHF
- ☐ 17’500 CHF to 32’000 CHF
- ☐ More than 32’000 CHF

Thank you for your information.

4

Figure A.9: Travel diary I.

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Institute for Transport Planning and Systems

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Swiss Federal Institute of Technology Zurich

4.1 Travel diary

Thank you for participating in our survey!

In this part, we ask you to report all trips you undertake during the reporting week indicated in the cover letter.

Each trip represents exactly one change in location in order to undertake one activity at this location. Please indicate the day of the week that the trips on each page refer to.

All information will be treated in the strictest confidence and will not be handed to persons not involved in the project. The data is exclusively serving scientific purposes and statistical analyses. The persons engaged in the survey are committed to absolute discretion.

Given name: ______ Year of birth: 19__

Did you **not** leave your home for one of the following days during the reporting week?

If you did not leave your home for one day during the reporting week, please indicate this in the following list, and add the reason.

- ☐ Monday — Reason: ______
- ☐ Tuesday — Reason: ______
- ☐ Wednesday — Reason: ______
- ☐ Thursday — Reason: ______
- ☐ Friday — Reason: ______
- ☐ Saturday — Reason: ______
- ☐ Sunday — Reason: ______

Please fill in this part of the questionnaire at the end of the reporting week.

Figure A.10: Travel diary II.

Travel diary: Explanation of the fields in the diary

Start address	**Please indicate the address of the location from where you started your first trip of the reporting week.** If it is your home address, just tick the box. Start address: **Abbr.:** ___ Str. ___ Nr. ___ PLZ ___ Ort ___ ☐ Home
Start time	Please indicate the time you started your trip.
Travel mode	**Tick the modes you used for undertaking the trip and give** the estimated travel times with each of the travel modes used. **Please also include the parts of the trip that included walking, e.g. from the parking lot or the bus stop to the destination.**
Waiting time	Please indicate how much time you spent waiting at a train station or tram/bus stop.
Time of arrival	Please indicate the arrival time.
Covered distance	Please provide an estimate of the covered distance (as accurate as possible).
Destination address	Please provide the address of the destination of your trip, e.g. **Zürich HB** or **home**. Here, you can indicate up to 4 locations that you visit most frequently during your reporting week, and then just use these abbreviations later in the questionnaire (e.g. **"work"** in the "location" or "address" field).

Address 1: **Abbr.:** ___ Str. ___ No. ___ ZIP ___ City ___	Address 2: **Abbr:** ___ Str. ___ No. ___ ZIP ___ City ___
Address 3: **Abbr:** ___ Str. ___ No. ___ ZIP ___ City ___	Address 4: **Abbr:** ___ Str. ___ No. ___ ZIP ___ City ___

Trip purpose	Please indicate what type of activity you performed at the destination (examples are given on the following page).
Number of persons	**Please indicate how many member of your household or other persons (e.g. friends)** accompanied your trip **or participated in the** activity at the destination.
Planning horizon	Please indicate how much in advance you planned the trip.
Expenses / travel costs	Please report the out-of-pocket cost that occurred for each reported trip (e.g. tickets, fares, parking cost etc.). Please do not report season ticket costs, fuel costs, monthly parking costs etc. here.

2

Figure A.11: Travel diary III.

Examples of trip purposes

For each conducted trip you are asked to indicate exactly one purpose.
The following examples should help you to assign your trip purpose to one of the categories. If you cannot find an appropriate category, please tick “Other” and specify.

Return home: → From outside Bring/pick up someone: → Train station, airport → Kindergarden, school → Doctor, hospital → etc. Work / education → Work location → Study location	Errands → Administration, bank → Post office → Hairdresser, nail studio → Doctor, hospital → Optician → Repair service → Tailor, laundry service → Police station → Gas station → Travel office → Fotographer → etc.
Shopping (daily needs): → Food, drinks → Sanitary articles → Cleaning products → Tobacco, cigarettes → Newspapers, magazines → Medicine → etc. Shopping (long term needs): → Clothing, shoes → Devices → Furniture, decoration → Sports equipment, bikes → Construction, gardening → Tableware → CD’s, books, stationery → etc.	Leisure: → Private meetings or visits → Cinema, theater, concert, museum → Restaurant, cafe, bar, club → Personal sports exercise → Public swimming pool → Sports event → Walk, promenade → Botanical garden → Park, zoo, recreational area → Excursions, bike tours → Markets, exhibitions → Religion/church → Hospital visits → etc.

Important notes:
- One trip describes the travel to one single location, where a single activity is conducted. Don’t forget: Going home (i.e. “Return home”) is a separate trip and should be indicated accordingly.
- If the expenses occur in foreign currencies (e.g. Euro), please indicate the currency.
- Please write clearly and in block letters.

Thank you!

FIGURE A.12: Travel diary IIII.

Travel diary (day of week):	☐ Mon	☐ Tue	☐ Wed	☐ Thu	☐ Fri	☐ Sat	☐ Sun

Trip number	1	2
Start time	hh:mm	hh:mm
Travel mode	☐ Walk min. ☐ Bicycle min. ☐ Motorbike min. ☐ Car (as driver) min. ☐ Car (as passenger) min. ☐ Tram / bus min. ☐ Train min. ☐ Other min. Wating time: min.	☐ Walk min. ☐ Bicycle min. ☐ Motorbike min. ☐ Car (as driver) min. ☐ Car (as passenger min. ☐ Tram / bus min. ☐ Train min. ☐ Other min. Wating time: min.
Arrival time	hh:mm	hh:mm
Total distance	km (estimated)	km (estimated)
Destination (address or location)	Str. No. ZIP City Location	Str. No. ZIP City Location
Trip purpose: Please choose **only 1 activity**!	☐ Return home ☐ Drop off / pick up someone ☐ Work / education ☐ Shopping (daily needs) ☐ Shopping (long term needs) ☐ Errands ☐ Business ☐ Leisure, specify: ☐ Other, specify:	☐ Return home ☐ Drop off / pick up someone ☐ Work / education ☐ Shopping (daily needs) ☐ Shopping (long term needs) ☐ Errands ☐ Business ☐ Leisure, specify: ☐ Other, specify:
Number of involvevd persons / dogs	Trip (**Please do not include yourself**) Activity Household memebers Other persons dogs	Trip (**Please do not include yourself**) Activity Household memebers Other persons dogs
Planning horizon	☐ Routine activity / return home trip ☐ One or several days in advance ☐ During the same day ☐ Spontaneous	☐ Routine activity / return home trip ☐ One or several days in advance ☐ During the same day ☐ Spontaneous
Expenses / Travel cost	☐ PT fare CHF ☐ Parking fees CHF ☐ Taxi fees CHF ☐ Rental costs (e.g. for car, bike etc.) CHF ☐ No travel expenses for this trip	☐ PT fare CHF ☐ Parking fees CHF ☐ Taxi fees CHF ☐ Rental costs (e.g. for car, bike etc.) CHF ☐ No travel expenses for this trip

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Figure A.13: Online diary I.

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4.2 Online diary

In this part, we ask you to keep track on your **private online- and/or telecommunication activities** during the reporting week. Please specify **what activities** you have undertaken and **how much time** you have spent for each of them. For each day, there is one separate form with a selection of predefined and open categories.

All information will be treated in the strictest confidence and will not be handed to persons not involved in the project. The data is exclusively serving scientific purposes and statistical analyses. The persons engaged in the survey are committed to absolute discretion.

Given name: ____ Year of birth: 19__

1

Figure A.14: Online diary II.

Online and telecommunication diary:	**Monday**

	Duration	Amount spent
(Online-)Shopping: Purchase / bookings of (please also indicate *phone* orders) ...		
☐ Tickets for events, flights, train tickets, hotel bookings (e.g. starticket.ch, ebookers.com, SBB.ch, etc.)	min.	CHF
☐ Clothes or sports equipment (e.g. zalando.ch, sportxx.ch, etc.)	min.	CHF
☐ Electronic appliances (e.g. digitec.ch, hshop.ch, melectronics.ch, distrelec.ch, exlibris.ch, etc.)	min.	CHF
☐ Furniture and accessoires (e.g. möbel-online.home24.ch, micasa.ch, etc.)	min.	CHF
☐ Books and magazines (e.g. amazon.de, etc.)	min.	CHF
☐ Groceries (e.g. leshop.ch, nespresso.ch, coopathome.ch, muesli.ch, etc.)	min.	CHF
☐ Other:	min.	CHF
(Online-)Entertainment: Download / stream / watch / play ...		
☐ Music	min.	CHF
☐ TV / movies / TV shows / youtube	min.	CHF
☐ Computer games	min.	CHF
☐ Other:	min.	CHF
☐ E-Banking / bank transactions	min.	
☐ Social networks (e.g. facebook.com, twitter.com, etc.)	min.	
☐ Non-work communication (e.g. phone calls, SMS, Email, WhatsApp, online-chatting; with friends, acquaintances, etc.)	min.	
☐ Inquiries and education (e.g. google, online-news, vacation planning, restaurants, hotels, online-tutorials, blogs, price comparison, etc.)	min.	
☐ Online dating (e.g. parship.ch, c-date.ch, etc.)	min.	
☐ Other:	min.	CHF
	min.	CHF
☐ No online- and/or telecommunication activities on this day		

Figure A.15: Short-term expenditures.

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4.3 Short- and long-term expenses

In this part, we ask you to keep track on your short-term daily expenses (e.g. groceries, restaurant, clothes etc.). Please specify the expenses separately for each day of the week.

On the last page, we ask you to specify your longer-term and/or regularly occurring expenses. Please do not try too hard to get a perfect estimate and provide the numbers as accurately as possible.

All information will be treated in the strictest confidence and will not be handed to persons not involved in the project. The data is exclusively serving scientific purposes and statistical analyses. The persons engaged in the survey are committed to absolute discretion.

Given name: ______ Year of birth: 19__

Expenses form: **Monday**

	Amount spent
Short-term cost of living: Expenses for ...	
☐ Groceries (z.B. Drinks, food, tobacco etc.)	CHF
☐ Leisure and entertainment (e.g. movie theatre, club, concert, sports, swimming pool entrance, etc.)	CHF
☐ Food and accomodation (e.g. cafe, restaurant, hotel, etc.)	CHF
☐ Newspapers and magazines	CHF
☐ Clothing, shoes, accessoires	CHF
☐ Other:	CHF
	CHF
☐ No expenses on this day	

Figure A.16: Long-term expenditures.

Expenses form for longer-term and/or regularly occurring expenses and savings

Please enter estimates of your **average longer-term and/or regularly occurring expenses for the given categories for the last** 12 months. You can give the amount per year or month, whatever is more convenient for you.
Here is an example for the category "Communication":

- Mobile phone subscription of **75 CHF per month**
- Land-line phone, TV- and internet subscription costs incl. concession (Billag) of **100 CHF per month**
- Homepage-fees of **60 CHF per year**

→ 75 CHF + 100 CHF + 60 CHF / 12 = **200 CHF per month**

You can use a different temporal basis for each category!
Don't think too long and just give a rough estimate!
In case the expenses apply to the household (and not only to you as a person), please only indicate the amount once!

Longer-term and/or regularly occurring expenses: Summarised expenses for ...	Amount spent	per
☐ Eletronic devices and appliances (e.g. computer, tablet, laptop, HiFi set, smartphone, CD's, DVD's, household appliances, camera, spare parts, etc.)	CHF	
☐ Clothing, accessoires, apparel, sports equipment (e.g. shoes, jeans, skis, rollerblades, tennis racket, snowboard, etc.)	CHF	
☐ Communication (e.g. mobile phone or combined subscription (Phone, internet, TV), Fees, etc.)	CHF	
☐ Services (e.g. hairdresser, technician, custaodian, pedicure, etc.)	CHF	
☐ Vacation (e.g. flight, hotel, etc.)	CHF	
☐ Appartement decoration (e.g. furniture, lamps, etc.)	CHF	
☐ Education (e.g. university fees, advanced training, books, private lessons, etc.)	CHF	
☐ Health (e.g. dentist, therapy, medication, etc.)	CHF	
☐ Health insurance (e.g. base insurance plus special policies)	CHF	
☐ Other insurance (e.g. car, liability, accident, retirement arrangements, etc.)	CHF	
☐ Newspaper and magazine supscriptions (e.g. Tagesanzeiger, NZZ, Annabelle, Weltwoche, etc.)	CHF	
☐ Sports and leisure subscriptions (e.g. fitness card, yearly subscriptions for football games, etc.)	CHF	
☐ Association fees, alimony and other payments to third parties (e.g. Rega, church, sports club, professional organisation, etc.)	CHF	
☐ Private vehicle leasing (e.g. car, motorbike, bike, etc.)	CHF	
☐ Other:	CHF	
	CHF	

Savings: How much do you have left at the end of a month on average?
The number can be negative, which means that your savings decrease.

CHF ☐ positive balance ☐ negative balance

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Figure A.17: Mode choice SP introduction.

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1 Mode choice

This questionnaire addresses the following person in your household. We ask this person to fill in the forms on the following pages:

Given name: **Andreas**	Year of birth: **1967**

In this part, we ask you about your choice of travel modes under different conditions. Imagine you live in the near future. The weather is friendly with a outdoor temperature of about 15 °C. You plan to make a trip for the purpose of:

Shopping

The distance relates to one of the trips you reported in the first part of the study. Assume you have the following modes available:

- **Walk**
- **Carpooling** as passenger (a carpooling member located nearby is driving in the same direction as your destination. You register online. Assume that you have never met the driver before.
- **Carsharing** (flexible use of vehicles parked nearby that can be parked at any location after use)
- **Public transportation (PT)**

On the following two pages you find eight choice situations. In each situation, the available alternatives are described with the following attributes:

- **Travel cost:** Share of expenses for carpooling, cost for carsharing (based on duration and distance travelled) or ticket cost for public transportation usage (2nd class)
- **Travel or walking time**
- **Access and egress time:** Time you spend walking to the mode or from the mode to your destination
- **Risk of missing carpooling driver:** The driver may not show up, despite the appointment
- **Number of transfers in PT**
- **Headway:** Regularity of PT service

Attribute levels of the available modes differ from situation to situation. Please imagine yourself in these situations and try to **make your choices solely based on the values and characteristics shown**. Carefully trade-off the attributes against each other and for each situation, choose one mode that you consider best.

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FIGURE A.18: Example choice situation: Mode choice SP.

Situation 1
Purpose: **Shopping**

	Walk	Carpooling passenger	Carsharing driver	PT
Travel cost		3.50 CHF	8.60 CHF	1.90 CHF
Travel time	38 min.	14 min.	10 min.	15 min.
Access and egress time		8 min.	4 min.	7 min.
Risk of missing the driver		10 %		
Number of transfers				0 x
Headway				3 min.

☐ ☐ ☐ ☐

Your choice

Situation 2
Purpose: **Shopping**

	Walk	Carpooling passenger	Carsharing driver	PT
Travel cost		2.00 CHF	6.70 CHF	1.90 CHF
Travel time	38 min.	18 min.	17 min.	15 min.
Access and egress time		8 min.	4 min.	6 min.
Risk of missing the driver		5 %		
Number of transfers				0 x
Headway				6 min.

☐ ☐ ☐ ☐

Your choice

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Figure A.19: In-store vs. online shopping SP introduction.

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2 In-store or online shopping

This questionnaire addresses the following person in your household. We ask this person to fill in the forms on the following pages.

Given name: **Jonathan**	Year of birth: **1960**

Imagine you live in the near future and decide about doing your purchases either by **ordering online** or by **traveling to a store nearby** that you can only access by means of public transportation, carsharing or carpooling. Hence, you experience either delivery cost or travel cost.

Please note that you do not have a private car available and that shopping is for one single purpose: Buying **standard electronic devices for entertainment** or **household appliances**.

Assume that the products are identical, regardless of whether you order or buy them in the shop (same brand, quality, etc.). On the following two pages you find eight choice situations. In each situation, the available alternatives are described with the following attributes:

- **Delivery cost** (incl. possible custom fees) or **travel cost** for the trip to the store
- **Travel time** to the store
- **Delivery time** (incl. possble delays)
- Approximate **Size / Weight** of the purchases
  - : Easy to carry (e.g. water kettle, smartphone, hairdryer, etc.)
  - : Heavy / inconvenient to carry (e.g. computer, TV set, coffee machine, etc.)
  - : Very heavy or inconvenient to transport (e.g. large Hifi set, lawn mower, fridge, etc.)
- **Time** for **ordering** or for **purchase** in the shop (incl. waiting time at the cashier)
- **Cost** of purchase

Please consider that the attribute values shown in the choice situations only partly relate to the information you declared in the first part of the study and can therefore be different to situations of your personal experience. Please try to **make your choices solely based on the values and characteristics shown**. Carefully trade-off the attributes against each other and choose the one alternative you consider best, i.e. ordering online or travel to the store.

Figure A.20: Example choice situations: In-store vs. online shopping SP.

Situation 1 Purpose: **Electronic appl.**	Order	Travel to store
Delivery cost / travel cost	**0.00** CHF	**5.20** CHF
Travel time to store		**39** min.
Delivery time (incl. possible delays)	min. 1 week	
Size / weight of the goods basket		
Ordering time / shopping time	**48** min.	**54** min.
Shopping cost	**540.00** CHF	**600.00** CHF
	☐	☐
	⟵ Your choice ⟶	

Situation 2 Purpose: **Electronic appl.**	Order	Travel to store
Delivery cost / travel cost	**0.00** CHF	**9.10** CHF
Travel time to store		**21** min.
Delivery time (incl. possible delays)	2-3 days	
Size / weight of the goods basket		
Ordering time / shopping time	**54** min.	**66** min.
Shopping cost	**600.00** CHF	**600.00** CHF
	☐	☐
	⟵ Your choice ⟶	

Situation 3 Purpose: **Electronic appl.**	Order	Travel to store
Delivery cost / travel cost	**0.00** CHF	**5.20** CHF
Travel time to store		**21** min.
Delivery time (incl. possible delays)	mind. 1 week	
Size / weight of the goods basket		
Ordering time / shopping time	**63** min.	**54** min.
Shopping cost	**600.00** CHF	**630.00** CHF
	☐	☐
	⟵ Your choice ⟶	

Situation 4 Purpose: **Electronic appl.**	Order	Travel to store
Delivery cost / travel cost	**10.00** CHF	**9.10** CHF
Travel time to store		**39** min.
Delivery time (incl. possible delays)	min. 1 week	
Size / weight of the goods baskett		
Ordering time / shopping time	**63** min.	**66** min.
Shopping cost	**600.00** CHF	**600.00** CHF
	☐	☐
	⟵ Your choice ⟶	

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Figure A.21: Route choice SP introduction.

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3 Route choice

This questionnaire addresses the following person in your household. We ask this person to fill in the forms on the following pages:

Given name: **Barbara**	Year of birth: **1967**

In this part, we ask you about your choice of different route alternatives. Imagine you live in the near future. The weather is friendly with an outdoor temperature of about 15 °C. You think about undertaking a public transportation trip for the purpose of

Leisure

The distance is related to one of the trips you specified in the first part of the study.

On the following pages you find four choice situations. In each situation, the available route alternatives are described with the following attributes:

- **Travel cost**
- **Travel time**: Time spent in the vehicle
- **Access and egress time:** Time you spend walking to the mode or from the mode to your destination
- **Number of transfers**
- **Headway:** Regularity of PT service

Attribute levels of the available routes differ from situation to situation. Please imagine yourself in these situations and try to **make your choices solely based on the values and characteristics shown**. Carefully trade-off the attributes against each other and for each situation, choose one route that you consider best.

FIGURE A.22: Example choice situations: In-store vs. online shopping SP.

Situation 1

Purpose: **Leisure**

	Route A	Route B	Route C
Travel cost	2.90 CHF	2.90 CHF	2.40 CHF
Travel time	4 min.	4 min.	2 min.
Access and egress time	16 min.	9 min.	13 min.
Number of transfers	1 x	0 x	1 x
Headway	3 min.	10 min.	6 min.

☐ ☐ ☐

← Your choice →

Situation 2

Purpose: **Leisure**

	Route A	Route B	Route C
Travel cost	1.90 CHF	2.40 CHF	2.90 CHF
Travel time	3 min.	2 min.	2 min.
Access and egress time	13 min.	16 min.	9 min.
Number of transfers	1 x	0 x	1 x
Headway	10 min.	10 min.	3 min.

☐ ☐ ☐

← Your choice →

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Figure A.23: Attitudinal questionnaire I.

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4 Attitudinal questionnaire

In this questionnaire we present different statements about several topics related to your attitudes towards mobility, your shopping behavior and other personal traits. Each statement is followed by four boxes forming a scale from “completely agree” to “completely disagree”. Please give your opinion to each of these statements.

Please do not think too long about your opinion - there is no correct or wrong answer. Please note that there will be no political or other kind of judgement of your opinion.

All information will be treated in the strictest confidence and will not be handed to persons not involved in the project. The data is exclusively serving scientific purposes and statistical analyses. The persons engaged in the survey are committed to absolute discretion.

Given name: ______________ Year of birth: 19____

Figure A.24: Attitudinal questionnaire II.

Attitudes towards car usage

		completely disagree			completely agree
1.	One is less worth without owning a car in today's society.	☐	☐	☐	☐
2.	In my opinion it is a status symbol to own a car.	☐	☐	☐	☐
3.	To reduce emissions, as a first step the whole road traffic should be slowed down.	☐	☐	☐	☐
4.	I support the idea of radically increasing fuel prices in order to improve the public transportation infra-structure.	☐	☐	☐	☐
5.	My car should stand out from the big crowd and should be something special.	☐	☐	☐	☐
6.	I would not be able to organize my daily life without a car.	☐	☐	☐	☐
7.	Car driving is a criminal offence against the environment.	☐	☐	☐	☐

Figure A.25: Attitudinal questionnaire III.

Attitudes towards public transportation

		completely disagree			completely agree
1.	I think it is right that public transportation gets prioritized accross the whole city.	☐	☐	☐	☐
2.	It bothers me that when using public transportation, one often is confronted with unpleasant people.	☐	☐	☐	☐
3.	The public transportation infrastructure in Zurich is amazing.	☐	☐	☐	☐
4.	I am a very outgoing person.	☐	☐	☐	☐
5.	The complicated timetables discourage me from using public transportation.	☐	☐	☐	☐
6.	I often prefer to be by myself.	☐	☐	☐	☐
7.	Public transportation is not flexible enough.	☐	☐	☐	☐

Attitudes towards walk and bike

		completely disagree			completely agree
1.	I walk as often as possible because it is healthy.	☐	☐	☐	☐
2.	There are plenty of places in Zurich where it is life-threatening to walk.	☐	☐	☐	☐
3.	The noise and smell of the road traffic make life of pedestrians hard.	☐	☐	☐	☐
4.	When driving a bike I feel independent and free.	☐	☐	☐	☐
5.	Driving a bike is the best means of transportation for me.	☐	☐	☐	☐

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Figure A.26: Attitudinal questionnaire IIII.

Attitudes towards emerging modes

		completely disagree			completely agree
1.	I like the humming of a gasoline engine.	☐	☐	☐	☐
2.	I could totally imagine to completely go without a car.	☐	☐	☐	☐
3.	Car-sharing schemes (such as e.g. Mobility) should be increasingly provided and promoted.	☐	☐	☐	☐
4.	I would be happy to share my car with others, if all users would equally share the costs.	☐	☐	☐	☐
5.	It should be more invested into the development of self-driving cars (which are equipped with a high number of sensors and cameras and thus are able to detect their surroundings) with an environmentally friendly engine.	☐	☐	☐	☐
6.	Autonomous cars that could be ordered online to a desired location would be a good alternative to a privately owned vehicle.	☐	☐	☐	☐
7.	Preferably everything should stay as it is.	☐	☐	☐	☐
8.	Moving pathways (as e.g. at the airport) are worth investigating to be the main means of transportation within a city.	☐	☐	☐	☐
9.	The most obvious instrument to decrease urban traffic in the future is a strict reduction of the immigration quota.	☐	☐	☐	☐
10.	I would like to become a member of a car-sharing scheme that allows the free usage of available cars, and, after usage, the vehicle can be placed at any free parking space within the city.	☐	☐	☐	☐
11.	A city like Zurich without any cars is inconceivable.	☐	☐	☐	☐
12.	I dream of a calm life without any nasty surprises.	☐	☐	☐	☐
13.	Self-driving cars are scary.	☐	☐	☐	☐

Figure A.27: Attitudinal questionnaire V.

Attitudes towards online and in-store shopping

		completely disagree			completely agree
1.	I often order products on the Internet.	☐	☐	☐	☐
2.	Online shopping is associated with risks.	☐	☐	☐	☐
3.	Credit card fraud is one of the reasons why I don't like online shopping.	☐	☐	☐	☐
4.	The internet has more cons than pros.	☐	☐	☐	☐
5.	A disadvantage of online shopping is that I cannot physically examine the products.	☐	☐	☐	☐
6.	Online shopping facilitates the comparison of prices and products.	☐	☐	☐	☐
7.	The risk of receiving a wrong product is one of the main reasons why I don't like online shopping.	☐	☐	☐	☐
8.	I like to visit shops, even if I don't want to buy something, just for looking around.	☐	☐	☐	☐
9.	Shopping is exhausting and does not make fun.	☐	☐	☐	☐
10.	Shopping usually is an annoying duty.	☐	☐	☐	☐
11.	I like to follow the new developments in the tech industry.	☐	☐	☐	☐
12.	All what I need, I find in the shops.	☐	☐	☐	☐

Figure A.28: Attitudinal questionnaire VI.

Risk-taking behavior

		completely disagree			completely agree
1.	I admit if my taste differs from that of my friends.	☐	☐	☐	☐
2.	I would openly disagree with my boss in front of my co-workers.	☐	☐	☐	☐
3.	I also speak my mind about unpopular issues at social events.	☐	☐	☐	☐
4.	I often cheat in my daily life.	☐	☐	☐	☐
5.	I would drive home even if I was feeling a little tipsy.	☐	☐	☐	☐
6.	I have shoplifted a small item (e.g. a lipstick or a pen) once.	☐	☐	☐	☐
7.	I would accept a job that is paid solely based on commission.	☐	☐	☐	☐
8.	I start my trip earlier if I have to drive an unfamiliar route.	☐	☐	☐	☐
9.	I always try to be at the airport at the latest possible time.	☐	☐	☐	☐
10.	I would gamble in casinos with an amount worth my daily income.	☐	☐	☐	☐
11.	Risky sports such as parachuting or bungee jumping are too dangerous for me.	☐	☐	☐	☐
12.	I prefer public transportation connections with short transfer times.	☐	☐	☐	☐

Figure A.29: Attitudinal questionnaire VII.

Environmental sensitivity

		completely disagree			completely agree
1.	Too much attention is paid to environmental problems.	☐	☐	☐	☐
2.	The ongoing discussions about the greenhouse effect are totally exaggerated.	☐	☐	☐	☐
3.	Environmental pollution affects health.	☐	☐	☐	☐
4.	Environmental pollution is a threat to the future of our children.	☐	☐	☐	☐
5.	Saving threatened species is an unnecessary luxury.	☐	☐	☐	☐
6.	We should care for our environment because we depend on it.	☐	☐	☐	☐
7.	Behavorial change requires a good example by the government.	☐	☐	☐	☐
8.	Environmental protection is too costly.	☐	☐	☐	☐
9.	Stricter vehicle exhaust gases control should be enforced.	☐	☐	☐	☐
10.	The price of gasoline should be increased to reduce pollution.	☐	☐	☐	☐
11.	Behavorial change requires more environmentally friendly products.	☐	☐	☐	☐
12.	The one who causes environmental damage should also pay to repair it.	☐	☐	☐	☐

Figure A.30: Attitudinal questionnaire VIII.

Love of variety

		completely disagree			completely agree
1.	I like to experience novelty and change in my daily life.	☐	☐	☐	☐
2.	I like to have lots of activity around me.	☐	☐	☐	☐
3.	I prefer a clearly structured, repetitive daily schedule.	☐	☐	☐	☐
4.	I do not like surprises.	☐	☐	☐	☐
5.	When eating outside I like to try the most unusual things.	☐	☐	☐	☐
6.	Cultures completely different from my own fascinate me.	☐	☐	☐	☐
7.	I always keep an open door for surprise visitors.	☐	☐	☐	☐
8.	I like to explore new places.	☐	☐	☐	☐
9.	I like to choose new routes to known destinations.	☐	☐	☐	☐
10.	I like to drive around just for the fun of it.	☐	☐	☐	☐
11.	I like to meet new people while traveling by public transportation.	☐	☐	☐	☐
12.	I travel a lot in order to experience new cultures.	☐	☐	☐	☐

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Table A.1: Assignment of the different mode choice SP questionnaire types.

Driving license	Bike availability	Distance	Chosen mode	Choice alternatives	SP type
Yes	Yes/No	< 5 km	Walk	W/TA/CP/CS/PT	1
	Yes	< 15 km	Bike	B/TA/CP/CS/PT	2
	No	< 5 km	MIV/PT	W/TA/CP/CS/PT	1
	Yes	< 5 km	MIV/PT	B/TA/CP/CS/PT	2
	Yes	$5 \leq ... < 15$ km	MIV/PT	B/TA/CP/CS/PT	2
	No	$5 \leq ... < 15$ km	MIV/PT	TA/CP/CS/PT	3
	Yes/No	≥ 15 km	MIV/PT	TA/CP/CS/PT	3
No	Yes/No	< 5 km	Walk	W/TA/CP/PT	4
	Yes	< 15 km	Bike	B/TA/CP/PT	5
	No	< 5 km	MIV/PT	W/TA/CP/PT	4
	Yes	< 5 km	MIV/PT	B/TA/CP/PT	5
	Yes	$5 \leq ... < 15$ km	MIV/PT	B/TA/CP/PT	5
	No	$5 \leq ... < 15$ km	MIV/PT	TA/CP/PT	6
	Yes/No	≥ 15 km	MIV/PT	TA/CP/PT	6

CP = carpooling, CS = carsharing, PT = public transportation, TA = taxi, W = walk, B = bike.

Figure A.31: Example choice situation: Adaptations in daily scheduling (tool I).

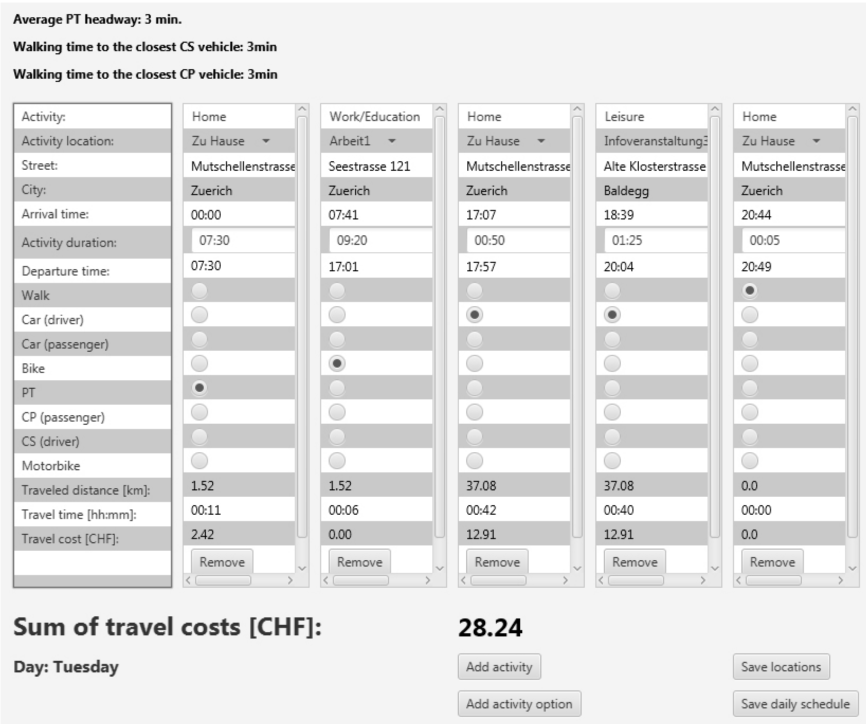


Figure A.32: Mobile persons in household: Adaptations in mobility tool ownership (tool II).

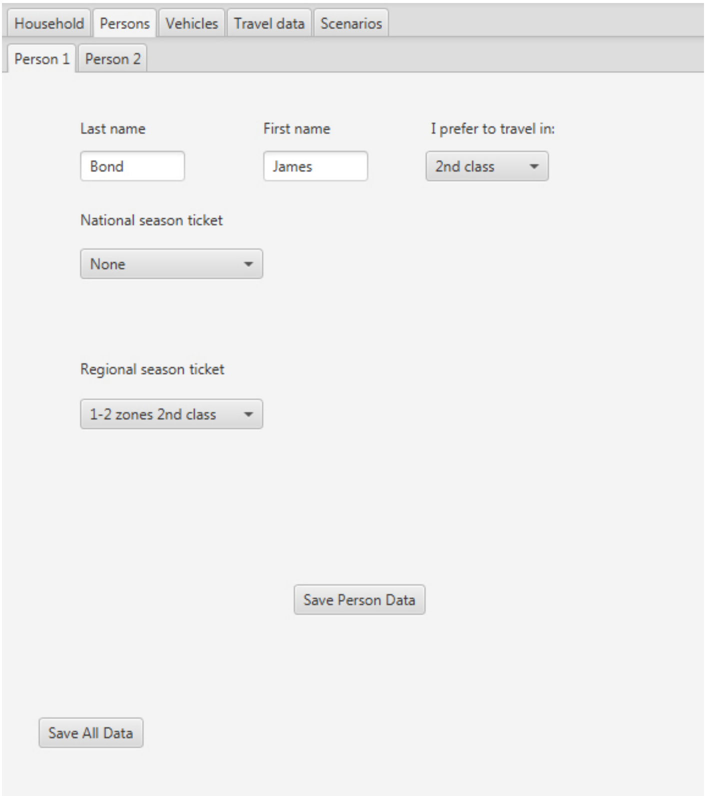


FIGURE A.33: Vehicle information: Adaptations in mobility tool ownership (tool II).

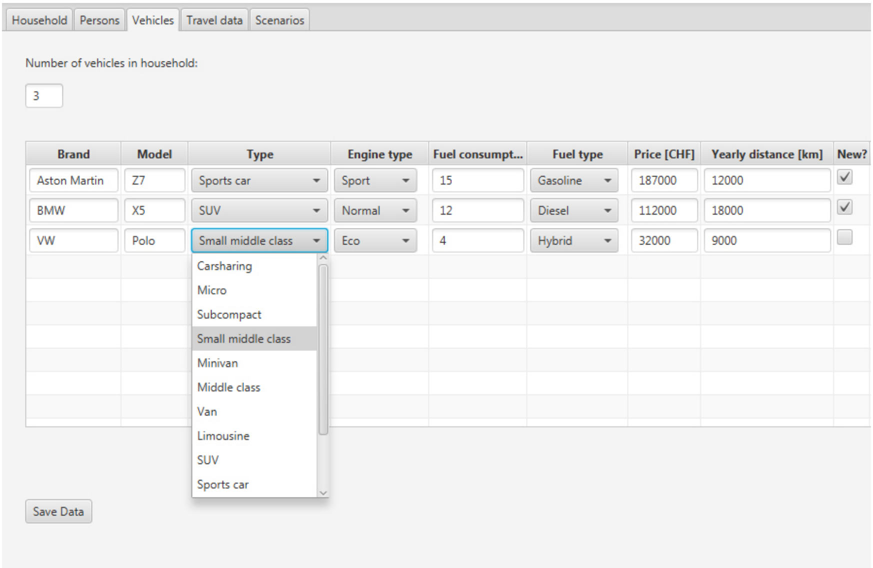


Figure A.34: Example choice situation (base scenario): Adaptations in mobility tool ownership (tool II).

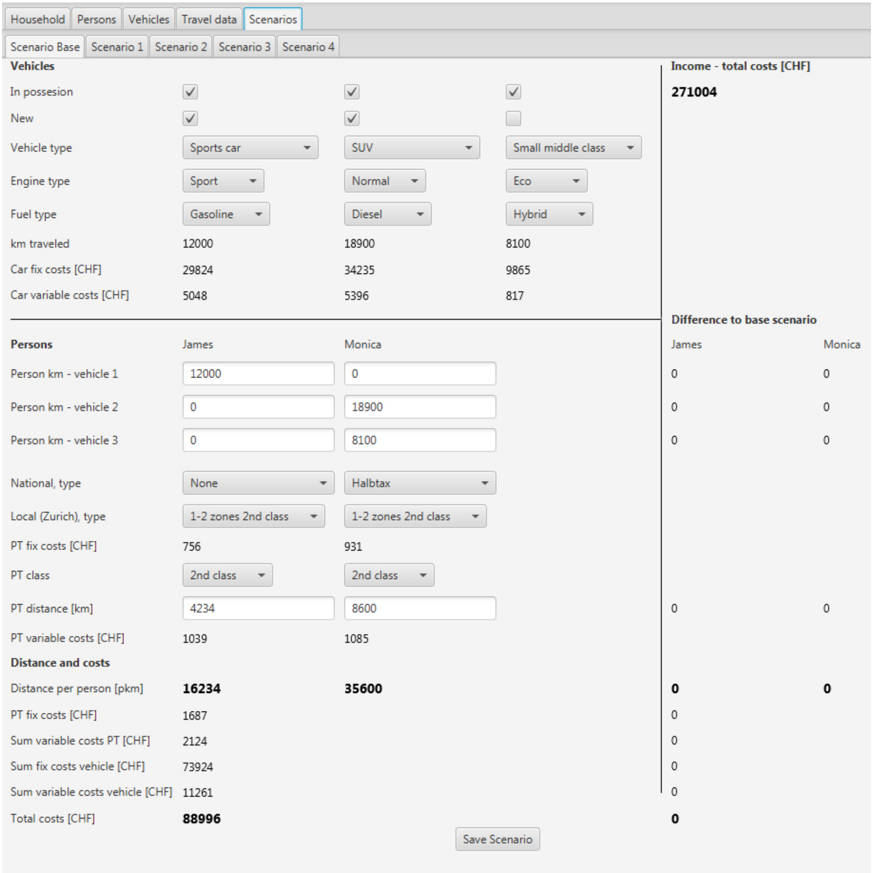


Table A.2: OLS models for the adjustment of activity durations. The dependent variable in both models is the effective minus the observed (from the travel diary) working time.

	$T_{w_{obs.}} < T_w$ Coef./(SE)	$T_{w_{obs.}} > T_w$ Coef./(SE)
Home	0.144***	0.333***
	(0.05)	(0.06)
Accompanying activities	0.186	0.550**
	(0.20)	(0.23)
Grocery shopping	0.181	−0.327
	(0.53)	(0.37)
Durable goods shopping	0.261	−0.625
	(0.25)	(0.44)
Errands	0.416	0.392***
	(0.31)	(0.11)
Travel	0.189	0.434**
	(0.14)	(0.18)
Out-of-home leisure (Tf1)	0.172***	0.261***
	(0.06)	(0.06)
Online/entertainment (Tf2)	0.212***	0.273***
	(0.08)	(0.09)
Other activities	−0.264	1.019***
	(0.21)	(0.23)
# est. parameters	9	9
# respondents (N)	174	193
R^2	0.11	0.23

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

Constant not reported in the table.

Figure A.35: Sample distributions of time-use model variables (N = 369).

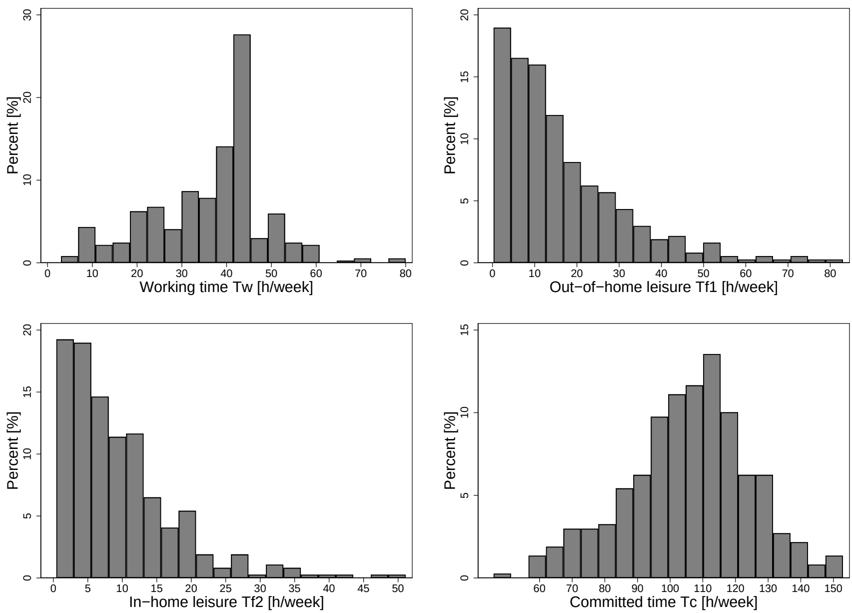


TABLE A.3: OLS model for the adjustment of expenditures in the PCW dataset.

	Monthly savings [CHF]
	Coef./(SE)
Constant	325.300
	(1054.53)
Male	359.464
	(287.70)
Age [years]	−24.274*
	(13.20)
Personal income [CHF]	0.285***
	(0.04)
Single	*Base*
Married	−312.860
	(302.31)
Widowed	103.018
	(751.51)
Divorced	−375.104
	(454.16)
Civil union	−1194.840
	(752.48)
Married, separated	−1056.072
	(1036.31)
Obligatory school	*Base*
Commercial school	−1122.039
	(708.84)
Apprenticeship	−218.710
	(441.11)
Vocational school	−358.310
	(501.16)
High school	−1489.455***
	(554.17)
Master certificate	−593.437
	(549.74)

Continued on next page

Table A.3 – *Continued from previous page*

	Monthly savings [CHF] Coef./(SE)
Technical school	283.166
	(586.69)
Higher vocational college	−682.531
	(458.04)
Polytechnic institute	494.615
	(697.96)
University degree	−931.598**
	(422.31)
Single person household	*Base*
Couple without kids	195.428
	(427.09)
Couple with kids	−208.459
	(454.24)
Single parent	−588.707
	(617.34)
Other (shared flat, etc.)	661.686
	(627.82)
House/apartment owner	256.093
	(365.02)
Area of house/apartment [m^2]	−0.938
	(1.54)
More than 5 room house/apartment	−619.819*
	(333.16)
New building	*Base*
Old building	−729.487**
	(362.23)
Renovated building	−408.944
	(312.18)
Living in: House	*Base*
Living in: Apartment	−152.981
	(382.79)
Living in: High rise building	−216.657

Continued on next page

Table A.3 – *Continued from previous page*

	Monthly savings [CHF] Coef./(SE)
	(917.92)
Urban residential loc.	*Base*
Suburban residential loc.	−453.130
	(295.24)
Rural residential loc.	43.177
	(420.57)
Car availability: Always	*Base*
Car availability: Frequently	412.740
	(362.80)
Car availability: Rarely	717.838**
	(300.94)
Car availability: Never	169.670
	(307.35)
PT season ticket in possession	850.697*
	(442.56)
Tablet computer in possession	15.874
	(11.49)
# est. parameters	36
# respondents	369
R^2	0.37

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

TABLE A.4: OLS model for the imputation of $Ec - Y$ in cases where respondents exhibit a negative money balance (i.e. $Ec - Y > w \cdot T_w$). Only those respondents are included in the model who exhibit a positive money balance (i.e. $w \cdot T_w + Y - Ec \geq 0$).

	$Ec - Y \leq w \cdot T_w$
	Coef./(SE)
Constant	−93.878
	(145.75)
Male	105.988***
	(38.20)
Age [years]	−5.178**
	(2.18)
Personal income [CHF]	0.182***
	(0.00)
Single	*Base*
Married	−45.718
	(50.08)
Widowed	18.077
	(187.99)
Divorced	92.179
	(73.09)
Civil union	94.439
	(163.83)
Married, separated	586.475**
	(233.73)
Single person household	*Base*
Couple without kids	0.380
	(65.42)
Couple with kids	52.175
	(68.91)
Single parent	−209.247**
	(104.31)
Other (shared flat, etc.)	11.308
	(107.44)

Continued on next page

Table A.4 – *Continued from previous page*

	$Ec - Y < w \cdot T_w$ Coef./(SE)
PT season ticket	90.707
	(58.83)
# cars in HH	11.664
	(24.39)
Smartphone in possession	14.734
	(56.67)
Tablet in possession	15.332
	(35.97)
Desktop in possession	−16.988
	(36.90)
Laptop in possession	26.267
	(44.49)
Urban residential loc.	*Base*
Suburban residential loc.	15.393
	(39.68)
Rural residential loc.	28.837
	(55.25)
# est. parameters	21
# respondents	335
R^2	0.92

Robust standard errors: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

TABLE A.5: Exponential regression model for the imputation of fixed income: EVE 2005 dataset for Eastern Switzerland and the greater region of Zurich.

	Fixed income [CHF] Coef./(SE)
Constant	5.306***
	(0.40)
Age [years]	0.027***
	(0.00)
Weekly working hours	−0.006**
	(0.00)
Male	−0.637***
	(0.11)
Single/widowed/separated/civil union	*Base*
Married	−0.121
	(0.10)
Divorced	−0.188**
	(0.09)
Household income/1000 [CHF]	−0.119***
	(0.02)
Household income^2/1000	2.605***
	(0.66)
# rooms in house/apartment	0.117***
	(0.03)
Single HH, couple w/o kids, other	*Base*
Single parent	−0.438**
	(0.17)
Couple with kids	−0.806***
	(0.16)
# household members	1.144***
	(0.23)
# household members^2/1000	−129.555***
	(34.68)
# est. parameters	13
# respondents	689
R^2	0.35

Robust standard errors: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

FIGURE A.36: Sample distributions of labor income, fixed income and expenditure model variables (N = 369).

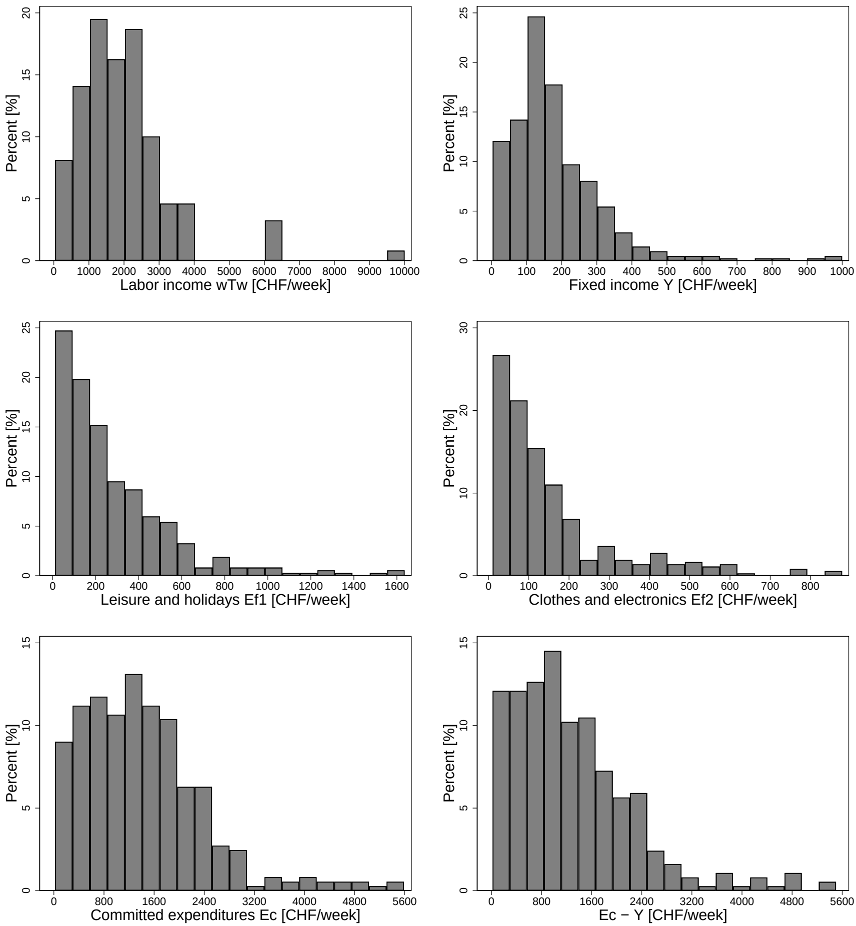


FIGURE A.37: Schematic illustration of the utility function: A baseline utility parameter corresponds to the slope of the utility function (i.e. the marginal utility) when the first unit is consumed.

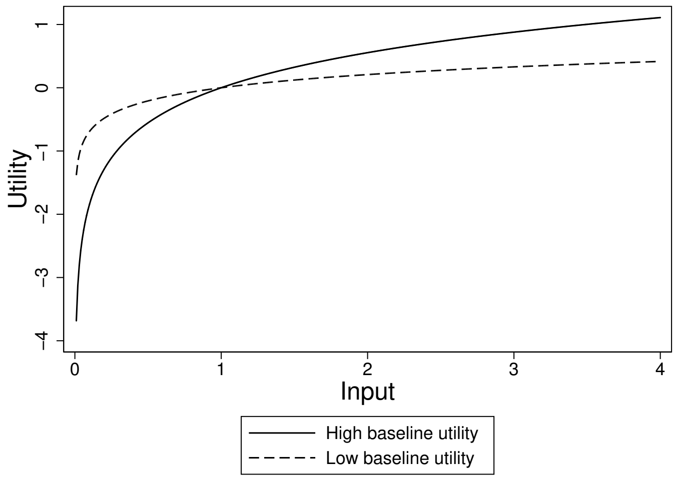


FIGURE A.38: Distributions of residuals and residuals vs. fitted values in the TU-MIX model.

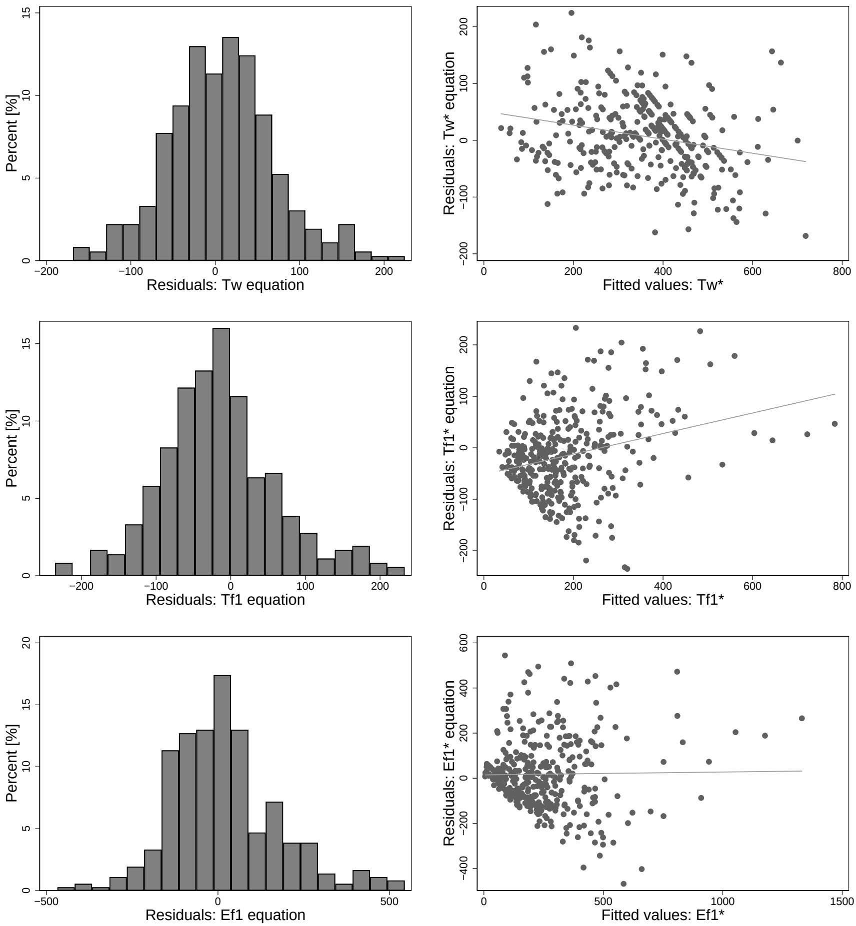


TABLE A.6: Summary statistics of RP mode choice attributes (MC_RP; for available alternatives).

Attributes	Obs.	μ	σ	ν	min.	max.
Crowfly dist. [km]	8'962	7.4	15.9	5.6	0.0	227.6
Dist. if choice = walk [km]	1'571	0.6	0.8	4.8	0.0	9.0
Dist. if choice = bike [km]	1'315	2.2	2.7	4.1	0.1	22.3
Dist. if choice = MIV [km]	2'961	8.4	12.6	4.5	0.0	142.1
Dist. if choice = PT [km]	2'845	12.4	23.3	4.0	0.3	227.6
Purpose = work/educ.	8'962	0.3	0.5	0.7	0	1
Purpose = shopping	8'962	0.1	0.3	2.8	0	1
Purpose = leisure	8'962	0.2	0.4	1.8	0	1
Purpose = other	8'962	0.5	0.5	0.1	0	1
Weekend trip	8'962	0.2	0.4	1.5	0	1
Travel time walk [min.]	7'053	39.4	35.9	1.4	0.0	391.6
Travel time bike [min.]	7'624	23.8	28.0	2.0	0.0	221.4
Travel time MIV [min.]	7'609	14.8	16.4	3.8	0.1	191.4
Travel cost MIV [min.]	7'609	2.3	4.1	7.0	1.0	66.0
Travel time PT [min.]	7'313	17.8	20.8	3.4	0.1	227.8
Travel cost PT [min.]	7'313	2.2	3.5	4.8	0.0	54.5
Transfers PT [#]	7'313	0.7	0.9	1.4	0	7
Access + egress PT [min.]	7'313	12.8	8.4	2.1	0.4	79.3
Headway PT [min.]	7'313	10.0	8.6	4.0	1.0	164.7

μ = mean, σ = standard deviation, ν = skewness.

TABLE A.7: Summary statistics of SP mode choice attributes (MC_SP; for available alternatives).

Attributes	Obs.	μ	σ	ν	min.	max.
Crowfly dist. [km]	2'710	20.7	28.3	2.9	0.7	222.2
Purpose = work/educ.	2'710	0.4	0.5	0.4	0	1
Purpose = shopping	2'710	0.2	0.4	1.7	0	1
Purpose = leisure	2'710	0.4	0.5	0.3	0	1
Travel time walk [min.]	208	44.5	15.6	-0.4	14	208
Travel time bike [min.]	1'216	35.7	16.8	0.3	5	71
Travel time CP [min.]	2'710	33.3	30.9	2.9	3	223
Travel cost CP [min.]	2'710	4.6	4.7	3.6	2	48.6
Access + egress CP [min.]	2'710	6.6	3.3	1.9	3	20
Risk miss. driver CP [%]	2'710	11.8	6.3	0.3	5	20
Travel time CS [min.]	2'567	31.9	29.7	2.9	2	240
Travel cost CS [min.]	2'567	13.7	11.1	3.1	2.4	92.7
Access + egress CS [min.]	2'567	6.6	3.3	1.9	3	20
Travel time PT [min.]	2'710	35.1	34.7	2.7	2	232
Travel cost PT [min.]	2'710	6.6	7.5	4.5	1.9	77.5
Transfers PT [#]	2'710	1.3	1.2	0.6	0	4
Access + egress PT [min.]	2'710	11.7	5.8	0.8	2	36
Headway PT [min.]	2'710	15.1	13.1	2.6	3	90

μ = mean, σ = standard deviation, ν = skewness.

Table A.8: Summary statistics of SP route choice attributes (RC_CS).

Attributes	Obs.	μ	σ	ν	min.	max.
Crowfly dist. [km]	612	22.6	32.4	3.0	0.7	222.2
Purpose = work/educ.	612	0.4	0.5	0.5	0	1
Purpose = shopping	612	0.2	0.4	1.8	0	1
Purpose = leisure	612	0.5	0.5	0.1	0	1
Travel time R1 [min.]	612	34.6	33.9	2.8	4	231
Travel cost R1 [min.]	612	13.3	11.7	3.2	2.7	90.9
Access + egress R1 [min.]	612	7.8	3.9	1.2	3	22
Congestion R1 [min.]	612	4.5	5.1	3.3	1	36
Travel time R2 [min.]	612	32.5	31.6	2.8	4	231
Travel cost R2 [min.]	612	13.6	12.2	3.2	2.7	90.9
Access + egress R2 [min.]	612	8.4	4.0	0.8	3	22
Congestion R2 [min.]	612	4.3	4.5	3.4	1	36
Travel time R3 [min.]	612	33.8	34.1	3.0	4	231
Travel cost R3 [min.]	612	13.8	12.5	3.2	2.7	90.9
Access + egress R3 [min.]	612	7.0	4.0	1.1	3	22
Congestion R3 [min.]	612	4.3	4.4	3.5	1	36

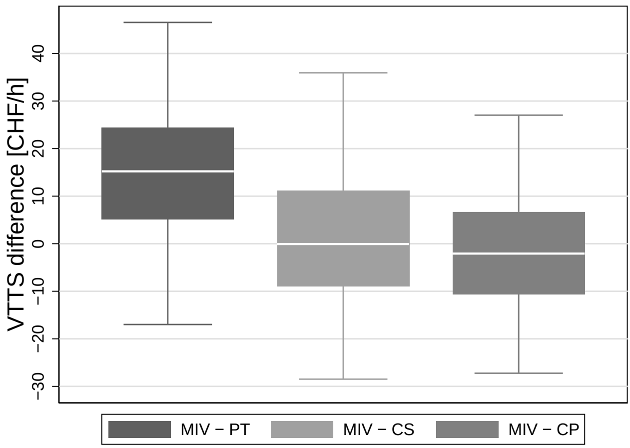
μ = mean, σ = standard deviation, ν = skewness.

TABLE A.9: Summary statistics of SP route choice attributes (RC_PT).

Attributes	Obs.	μ	σ	ν	min.	max.
Crowfly dist. [km]	580	20.8	26.8	2.2	0.9	133.7
Purpose = work/educ.	580	0.4	0.5	0.2	0	1
Purpose = shopping	580	0.2	0.4	1.5	0	1
Purpose = leisure	580	0.4	0.5	0.6	0	1
Travel time R1 [min.]	580	33.6	32.7	2.8	2	250
Travel cost R1 [min.]	580	6.1	6.4	3.6	1.9	53.5
Access + egress R1 [min.]	580	11.9	5.9	0.8	2	34
Transfers R1 [#]	580	1.2	1.3	0.7	0	4
Headway R1 [min.]	580	14.5	13.4	3.0	3	90
Travel time R2 [min.]	580	34.3	31.4	1.9	2	195
Travel cost R2 [min.]	580	6.1	6.5	3.8	1.9	53.5
Access + egress R2 [min.]	580	11.9	6.0	0.8	2	34
Transfers R2 [#]	580	1.3	1.2	0.7	0	4
Headway R2 [min.]	580	17.3	14.9	3.0	3	90
Travel time R3 [min.]	580	34.6	32.9	2.7	2	250
Travel cost R3 [min.]	580	6.3	6.9	3.7	1.9	53.5
Access + egress R3 [min.]	580	11.8	5.9	0.9	2	34
Transfers R3 [#]	580	1.4	1.2	0.5	0	4
Headway R3 [min.]	580	15.1	13.2	2.7	3	90

μ = mean, σ = standard deviation, ν = skewness.

Figure A.39: Sample distributions of individual VTTS differences between MIV and PT, CS and CP of respondents who have chosen both modes in comparison at least once.



VTTS AND VTAT: EQUIVALENCE OF MODE AND USER-TYPE EFFECTS

Given our definitions of the total mode effect in Equation (4.21) and the VTAT in Equation (4.23), it directly follows that the weighted average of the differences in the VTTS between mode i and j (the total mode effect) can also be expressed as the weighted average of differences in the VTAT between mode j and i, as the VoL cancels out (Jokubauskaite et al., 2019):

$$\begin{aligned} \text{Total } \Delta VTTS_{i-j} &= \frac{N_a(VTTS_{i,a} - VTTS_{j,a}) + N_b(VTTS_{i,b} - VTTS_{j,b})}{N_a + N_b} \\ &= \frac{N_a(VTAT_{j,a} - VTAT_{i,a}) + N_b(VTAT_{j,b} - VTAT_{i,b})}{N_a + N_b} \end{aligned} \tag{A.1}$$

Therefore, the mode effects $\Delta VTTS_{i-j}$ reported in Table 4.7 for a given user group correspond to the VTAT difference between mode i and j, but with the opposite sign. To give an example, while urban residents exhibit a mode effect $\Delta VTTS_{MIV-PT}$ of 5.9 CHF/h, their VTAT difference is –5.9 CHF/h, saying that their value of time assigned to travel is higher in PT than MIV. Rural residents have a substantially higher VTAT difference of –19.3 CHF/h, thus exhibiting an even higher VTAT for PT relative to MIV.

The same trick can be applied to the total user-type effects:

$$\begin{aligned} \text{Total } \Delta VTTS_{i-j,a-b} &= \Delta VTTS_{a-b,i} - \Delta VTTS_{a-b,j} \\ &= \Delta VTAT_{a-b,j} - \Delta VTAT_{a-b,i} \end{aligned} \tag{A.2}$$

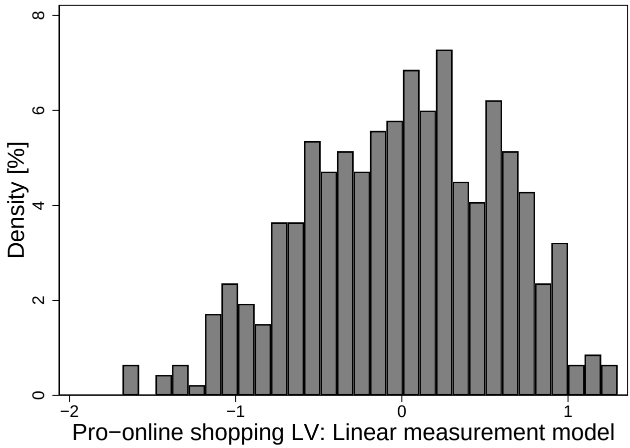
Therefore, the total user-type effects $\Delta VTTS_{i-j,a-b}$ reported in Table 4.8 correspond to the VTAT difference between mode i and j, but with the opposite sign. To give an example, when comparing MIV and PT, the total user-type effect of the difference between rural and urban residents, $\Delta VTTS_{MIV-PT,rural-urban}$, is 13.6 CHF/h, which, in terms of VTAT, corresponds to –13.6 CHF/h, saying that the value of time assigned to travel is 13.6 CHF/h higher in PT than MIV for rural compared to urban residents.

TABLE A.10: Summary statistics of attributes in the in-store or online shopping choice experiment.

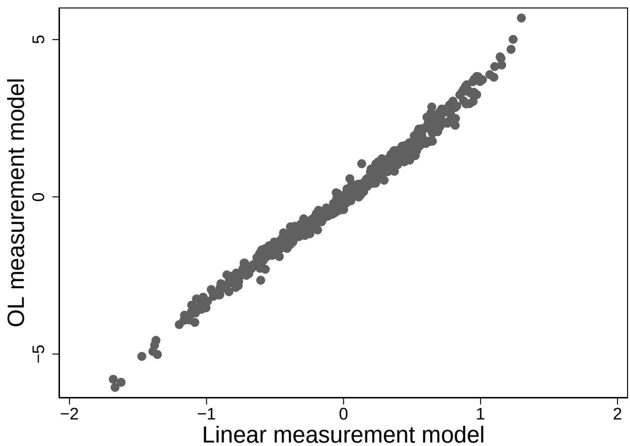
Attributes	μ	σ	ν	min.	max.
Shopping cost O [CHF]	237.8	184.4	0.7	21.6	700
Shopping cost S [CHF]	250.5	193.7	0.7	22.8	665
Time for shop. O [min]	38.5	14.8	1.2	10.0	112.0
Time for shop. S [min]	42.2	16.3	1.3	11.0	123.0
Del. cost incl. duty O [CHF]	7.6	5.6	0.0	0.0	15.0
Travel cost S [CHF]	5.3	3.3	3.0	1.8	33.0
Del. time groceries O [d]	1.6	0.6	0.5	0.8	2.5
Del. time electronics O [d]	5.4	2.5	0.0	2.5	9.0
Travel time S [min]	23.6	16.6	2.2	3.0	196.0
Size/weight of the good basket O/S	1.9	0.8	0.1	1.0	3.0

O = online, S = in-store, μ = mean, σ = standard deviation, ν = skewness.
Note: Summary statistics for delivery time are based on an attribute level mid-point approximation.

FIGURE A.40: Conditional distribution of pro-online shopping latent variable.

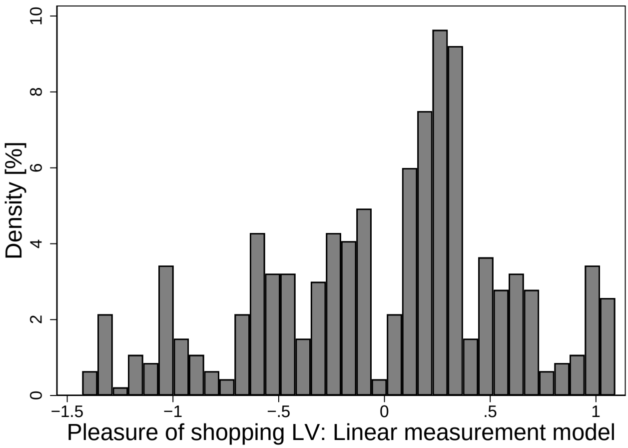


(a) Pro-online shopping LV (linear measurement model).

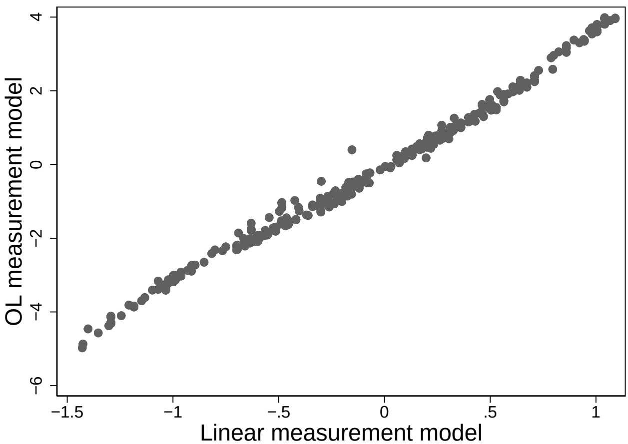


(b) Pro-online shopping LV (linear vs. Ordered Logit measurement model).

FIGURE A.41: Conditional distribution of the pleasure of shopping latent variable.



(a) Pleasure of shopping LV (linear measurement model).



(b) Pleasure of shopping LV (linear vs. Ordered Logit measurement model).

TABLE A.11: Estimation results: MIMIC model for the two latent variables.

Variable	Pro-online shopping Coef./(SE)	Pleasure of shopping Coef./(SE)
Male	0.31***	−0.28***
	(0.07)	(0.05)
Age	−1.05***	–
	(0.28)	
High education	0.33***	0.19***
	(0.08)	(0.07)
Income	0.19***	–
	(0.06)	
Store accessibility	−0.17*	0.24***
	(0.10)	(0.09)
Married	0.18***	−0.11**
	(0.06)	(0.05)
Non-working	–	0.19**
		(0.08)
Car available	–	0.05*
		(0.03)
σ_{LV_z}	0.57***	0.50***
	(0.04)	(0.04)
onl1	1	–
onl2	−0.59***	–
	(0.06)	
onl3	−1.10***	–
	(0.08)	
onl4	−0.62**	–
	(0.06)	
onl5	−0.39***	–
	(0.06)	
onl6	0.77***	–
	(0.07)	
onl7	−0.77***	–
	(0.07)	

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Table A.11 – *Continued from previous page*

Variable	Pro-online shopping Coef./(SE)	Pleasure of shopping Coef./(SE)
onl8	0.77^{***}	–
	(0.08)	
onl9	-0.73^{***}	–
	(0.06)	
onl10	0.72^{***}	–
	(0.08)	
ple1	–	1
ple2	–	-1.34^{***}
		(0.10)
ple3	–	-1.37^{***}
		(0.10)
# parameters	38	
# respondents	466	
# draws	1000	
$\mathcal{LL}_{final}$	-6698.7	

Robust SE's: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

Note: Item-SD's not reported in the table.

Table A.12: Estimation results: Sequential and hybrid choice models w. two LVs.

Base category: In-store (S)	SM LV1 Coef./(SE)	SM LV2 Coef./(SE)	HCM LV1 Coef./(SE)	HCM LV2 Coef./(SE)
Alt.-spec. constant (O)	-1.47^{***}	-2.10^{***}	-1.47^{***}	-1.58^{***}
	(0.29)	(0.42)	(0.29)	(0.30)
σ_{ASC} (O)	2.08^{***}	2.06^{***}	1.99^{***}	1.86^{***}
	(0.15)	(0.15)	(0.16)	(0.17)
Shopping cost	-5.94^{***}	-6.02^{***}	-5.85^{***}	-6.10^{***}
	(0.62)	(0.65)	(0.61)	(0.74)
$\sigma_{shopping\ cost}$	4.87^{***}	4.90^{***}	4.55^{***}	4.36^{***}
	(0.74)	(0.79)	(0.75)	(0.87)
In-store shopping time (S)	–	-2.47^{**}	–	-2.35^{**}
		(1.18)		(1.15)
$\sigma_{in-store\ shop.\ time}$ (S)	–	0.34	–	1.70^{**}
		(0.42)		(0.70)
Delivery cost (O)	-0.18^{***}	-0.18^{***}	-0.18^{***}	-0.18^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Delivery cost × electr. (O)	0.13^{***}	0.13^{***}	0.13^{***}	0.13^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Delivery time (O)	-1.03^{***}	-0.99^{***}	-1.03^{***}	-1.01^{***}
	(0.14)	(0.14)	(0.14)	(0.14)
Delivery time × electr. (O)	0.90^{***}	0.86^{***}	0.90^{***}	0.88^{***}
	(0.14)	(0.14)	(0.14)	(0.14)
Travel time (S)	-5.28^{***}	-5.46^{***}	-5.34^{***}	-5.21^{***}
	(1.27)	(1.28)	(1.26)	(1.29)
Travel time × electr. (S)	2.15	2.45^{*}	2.31^{*}	2.42^{*}
	(1.34)	(1.35)	(1.34)	(1.39)
Size/weight medium (O)	1.30^{**}	1.38^{**}	1.99^{***}	2.01^{***}
	(0.55)	(0.55)	(0.18)	(0.18)
Size/weight large (O)	3.30^{***}	3.36^{***}	3.98^{***}	3.97^{***}
	(0.60)	(0.60)	(0.26)	(0.27)
Size/weight × age (O)	2.43^{**}	2.35^{**}	2.46^{**}	2.17^{*}
	(1.15)	(1.15)	(1.16)	(1.14)
Size/weight × male (O)	-0.93^{***}	-0.98^{***}	-0.94^{***}	-1.04^{***}

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Table A.12 – *Continued from previous page*

Base category: In-store (S)	SM LV1 Coef./(SE)	SM LV2 Coef./(SE)	HCM LV1 Coef./(SE)	HCM LV2 Coef./(SE)
	(0.27)	(0.27)	(0.27)	(0.27)
Pro-online-shopping LV (O)	2.31***	2.23***	2.21***	1.88***
	(0.36)	(0.36)	(0.36)	(0.38)
Pro-online LV × electr. (O)	−0.63	−0.55	−0.57	−0.16
	(0.44)	(0.44)	(0.44)	(0.47)
Pro-online LV × shop. cost	−3.26***	−3.31***	−3.49***	−3.33***
	(0.82)	(0.85)	(1.25)	(1.17)
Pleasure of shopping LV (O)	–	1.15	–	1.82**
		(1.11)		(0.91)
Pleasure LV × electr. (O)	–	−1.15	–	−1.68
		(1.46)		(1.10)
Pleasure LV × shop. time (S)	–	4.50	–	6.04***
		(2.99)		(2.34)
Pleasure LV × shop. time × electronics (S)	–	−3.89	–	−5.52**
		(3.54)		(2.68)
Pro-online shop. LV1: Age	–	–	−1.13***	−0.98***
			(0.30)	(0.31)
Male	–	–	0.31***	0.26***
			(0.07)	(0.07)
Income	–	–	0.14***	0.15***
			(0.04)	(0.04)
High education	–	–	0.31***	0.29***
			(0.08)	(0.09)
Store accessibility	–	–	−0.18*	−0.23**
			(0.11)	(0.12)
Married	–	–	0.20***	0.07
			(0.07)	(0.05)
$\sigma_{pro-online\ shop.\ LV}$	–	–	0.59***	0.59***
			(0.03)	(0.04)
Pro-online shop. LV: onl2	–	–	−0.56***	−0.54***
			(0.06)	(0.07)
onl3	–	–	−1.04***	−1.02***

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Table A.12 – *Continued from previous page*

Base category: In-store (S)	SM LV1 Coef./(SE)	SM LV2 Coef./(SE)	HCM LV1 Coef./(SE)	HCM LV2 Coef./(SE)
			(0.08)	(0.08)
onl4	–	–	−0.59***	−0.58***
			(0.06)	(0.06)
onl5	–	–	−0.38***	0.08
			(0.06)	(0.07)
onl6	–	–	0.77***	0.78***
			(0.06)	(0.06)
onl7	–	–	−0.74***	−0.72***
			(0.07)	(0.07)
onl8	–	–	0.75***	0.74***
			(0.07)	(0.08)
onl9	–	–	−0.71***	−0.71***
			(0.05)	(0.05)
onl10	–	–	0.69***	0.69***
			(0.07)	(0.07)
SD onl1	–	–	0.59***	0.59***
			(0.02)	(0.03)
SD onl2	–	–	0.65***	0.66***
			(0.02)	(0.02)
SD onl3	–	–	0.74***	0.75***
			(0.03)	(0.03)
SD onl4	–	–	0.60***	0.61***
			(0.02)	(0.02)
SD onl5	–	–	0.75***	0.79***
			(0.03)	(0.03)
SD onl6	–	–	0.74***	0.74***
			(0.02)	(0.02)
SD onl7	–	–	0.71***	0.72***
			(0.03)	(0.03)
SD onl8	–	–	0.83***	0.83***
			(0.03)	(0.03)
SD onl9	–	–	0.56***	0.56***
			(0.02)	(0.02)

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Table A.12 – *Continued from previous page*

Base category: In-store (S)	SM LV1 Coef./(SE)	SM LV2 Coef./(SE)	HCM LV1 Coef./(SE)	HCM LV2 Coef./(SE)
SD onl10	–	–	0.83***	0.83***
			(0.03)	(0.03)
Pleasure of shop. LV: Sex	–	–	–	−0.31***
				(0.07)
High education	–	–	–	0.23***
				(0.08)
Store accessibility	–	–	–	0.23
				(0.15)
Non-working	–	–	–	0.17**
				(0.08)
Married	–	–	–	−0.11**
				(0.05)
Car available	–	–	–	0.05*
				(0.03)
$\sigma_{pleasure\ of\ shop.\ LV}$	–	–	–	0.51***
				(0.04)
Pleasure of shop. LV: ple2	–	–	–	−1.38***
				(0.11)
ple3	–	–	–	−1.31***
				(0.10)
SD ple1	–	–	–	0.74***
				(0.03)
SD ple2	–	–	–	0.33***
				(0.04)
SD ple3	–	–	–	0.37***
				(0.03)
# estimated parameters	17	23	43	61
# respondents/choices		466/3722		
$\mathcal{LL}_{choicemodel}$	−1614.7	−1610.1	−1658.1	−1659.1
AICc	3264.8	3268.8	13921.5	16777.2

Robust standard errors (clustered by ID): $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

TABLE A.13: Binary Logit models investigating the effect of respondent characteristics on the willingness to adapt (i.e. respondents have adapted the distance traveled by MIV, and respondents have adapted the distance traveled by MIV to zero at some point during the experiment).

	Adapt something	Adapt to zero
	Coef./(SE)	Coef./(SE)
Constant	2.376**	1.135
	(1.16)	(1.11)
Male	0.040	0.505
	(0.43)	(0.39)
Age [years]	−0.036	−0.029
	(0.02)	(0.02)
High educ.	0.563	0.376
	(0.43)	(0.39)
Urban	0.463	0.558
	(0.43)	(0.36)
Kids	−0.732	−0.218
	(0.51)	(0.44)
Income [CHF/1000]	−0.022	−0.038
	(0.03)	(0.03)
Couple	0.301	−0.021
	(0.48)	(0.40)
MIV distance base scenario [km]	0.012**	0.008**
	(0.01)	(0.00)
# est. parameters	9	9
# respondents (N)	163	163
ρ^2	0.08	0.08

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

TABLE A.14: Binary Logit models investigating the effect of household characteristics on the willingness to adapt (i.e. households have adapted the distance traveled by MIV, and households have adapted the distance traveled by MIV to zero at some point during the experiment).

	Adapt something Coef./(SE)	Adapt to zero Coef./(SE)
Constant	-0.156	-1.267
	(0.62)	(0.82)
Urban	0.314	-0.228
	(0.34)	(0.68)
Kids	0.693^{*}	1.831^{***}
	(0.36)	(0.59)
HH income [CHF/1000]	-0.061	-0.209^{***}
	(0.05)	(0.07)
Couple	-0.708	-0.652
	(0.44)	(0.61)
MIV distance base scenario [km/1000]	0.138^{***}	0.045^{*}
	(0.04)	(0.03)
# est. parameters	6	6
# respondents (N)	165	165
ρ^2	0.13	0.16

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

FIGURE A.42: Daily scheduling experiment: Goodness of fit.

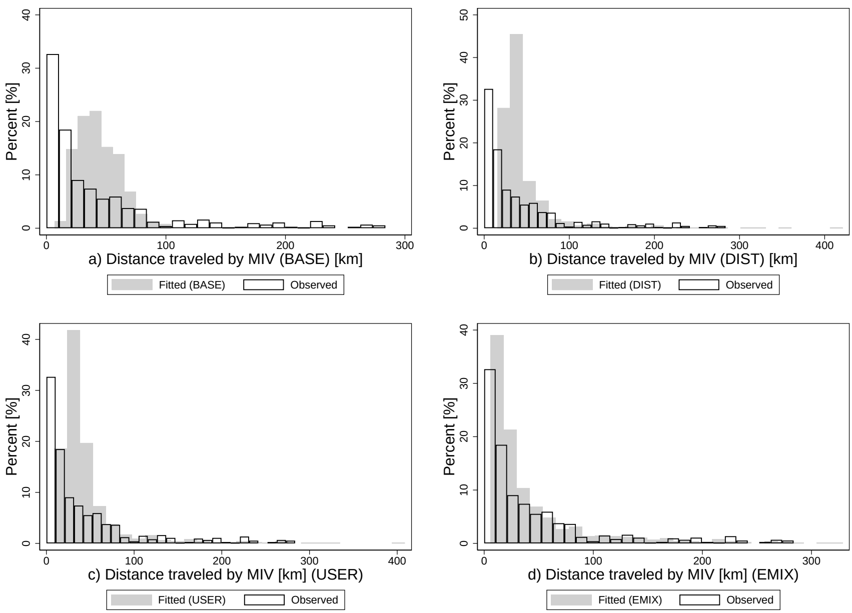
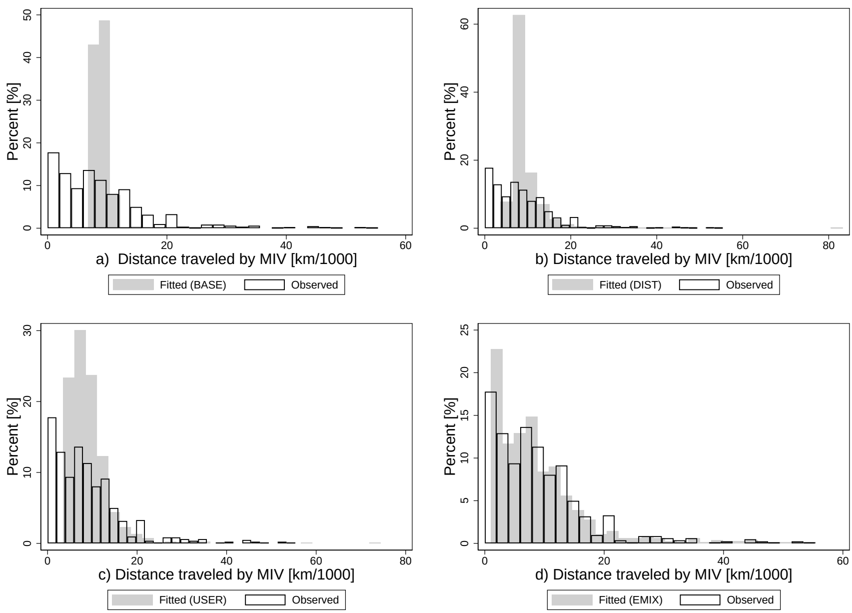


Figure A.43: Mobility tool ownership experiment: Goodness of fit.



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CURRICULUM VITAE

PERSONAL DATA

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EDUCATION

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2007 – 2010	University of Zurich, Zürich, Switzerland *Final degree:* Bachelor of Arts in Economics *Title of Bachelor Thesis:* Business Cycles and Marriage Formation
2000 – 2004	Kantonsschule Romanshorn, Thurgau, Switzerland *Final degree:* University entrance qualification

EMPLOYMENT

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PUBLICATIONS

FIRST AUTHOR JOURNAL PUBLICATIONS

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