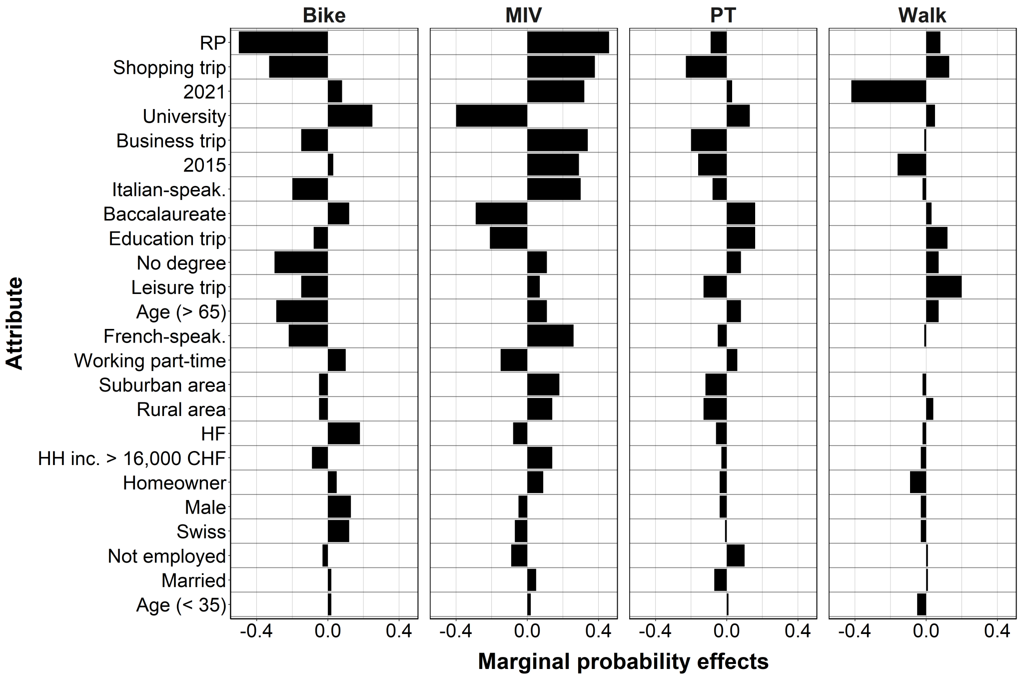

Influence of socioeconomic variables on mode choice in Switzerland

A comparison of three large-scale RP/SP data sets

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Abstract

This thesis observes the effects of socioeconomic variables on mode choice behavior using three large-scale RP/SP data sets. Multiple models (multinomial logit and mixed logit) are estimated and contrasted. This thesis finds that education is the most influential socioeconomic variable. However, compared to level-of-service (LOS) variables, the average effect of socioeconomic variables is found to be substantially smaller. The partworth of the highest-ranking LOS variable, travel time walk, is approximately 15 times larger than that of the highest-ranking socioeconomic variable, education. Furthermore, the largest socioeconomic marginal probability effect (MPE), university degree, affects the choice probability by a mere absolute value of 0.40 percentage points. This thesis concludes that the impacts of socioeconomic variables are (i) substantially smaller than those of LOS variables and (ii) inconclusive. Due to merely marginal changes in different groups, it is hard to justify larger actions in transport policy based on socioeconomic main effects alone.

Keywords

Socioeconomic variables, Swiss mode choice, marginal probability effects, partworth analysis

Suggested Citation

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Abbreviations

ASC Alternative-specific constant

BIC Bayesian information criterion

BMS Federal vocational baccalaureate

FMS Specialized baccalaureate

GA National public transport season ticket

HF College of higher education

HH Household

iia Independence of irrelevant alternatives

iid Independent and identically distributed

inc Income

LOS Level-of-service

MC Mode choice

MCM Mode choice models

MIV Motorized individual vehicle(s) (car and motorbike)

MNL Multinomial logit

MPE Marginal probability effects

MTMC Mobility and Transport Microcensus

Nbr. of trns. Number of transfers

PT Public transport

RP Revealed preference

SP Stated preference

Swiss fed. dipl. Swiss federal diploma

VoT Value of time

WTP Willingness-to-pay

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Swiss Federal Institute of Technology Zurich

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1 Introduction

Transport modeling is an essential tool with which transport planners assess the impact of mobility trends, travel behavior changes in the population, new transport technologies, and different policy measures (Ortúzar and Willumsen, 2011). Mode choice models (MCM) are an important component of transport modeling. Variables, such as land-use patterns, level-of-service (LOS) attributes, socioeconomic variables, or personal attitudes, are chosen according to the model, the modeling purpose, and the data available (e.g., Axhausen *et al.* (2004); Naveen and El-Geneidy (2012); Yang *et al.* (2018); Ha *et al.* (2020)).

LOS attributes, for example, travel time or travel costs, affect mode choice (e.g., Naveen and El-Geneidy (2012); Yang *et al.* (2018); Ha *et al.* (2020)) and improve model quality (e.g., Axhausen *et al.* (2004); Schmid (2019); Schmid *et al.* (2019b)). However, the effects of socioeconomic variables, such as gender or education, are not as conclusive (De Witte *et al.*, 2013). Compared to LOS variables, their explanatory power appears limited, given that models including socioeconomic variables do not necessarily have a substantially better goodness-of-fit (e.g., Schmutz (2015); Schmid *et al.* (2021)).

The inclusion of socioeconomic variables in MCM can provide valuable insight into which population groups prefer certain modes of transport. Socioeconomic variables in MCM may help benefit these groups with the right policy (Ha *et al.*, 2020). A shift towards sustainable modes of transport seems desirable due to climate change. Understanding the travel behavior of varying socioeconomic groups can aid the design of policies to shift their choices to more sustainable modes such as walking or cycling (Ko *et al.*, 2019). Furthermore, marginal probability effects and elasticities can help better understand the impact of specific policies on different socioeconomic groups and to observe which group profits from which measure most.

Many high-quality data sets are found in Switzerland. These data sets include LOS variables, socioeconomic variables, and in some cases, detailed information about the residents, location, workplace, and attitudes towards certain topics of transport policy. The Mobility and Transport Microcensus (MTMC), collected by the federal government every five years since 1974 (Federal Office for Spatial Development ARE, 2022), is an example of these Swiss high-quality data sets. Furthermore, there are various studies conducted by the Institute for Transport Planning and Systems (IVT) of ETH Zurich, for example, the Swiss value of time study (Axhausen and Schmid, 2021) or the Post-Car World study (Schmid *et al.*, 2019a).

This thesis uses three of the aforementioned data sets and aims to address the following questions:

- What is the effect of socioeconomic variables on mode choice in Switzerland?
- Is it possible to make consistent statements regarding the importance of socioeconomic variables across different data sets?
- What recommendations can be made for future mode choice studies regarding the importance of socioeconomic variables?

The answers to these questions might support future (Swiss) mode choice studies

- when data is collected.
- in the model building process.
- when future results are discussed.
- in putting the socioeconomic characteristics in the right context regarding their importance compared to LOS attributes.

This thesis proceeds with a review of the most relevant literature in chapter 2, followed by a detailed description (chapter 3) of the methods applied and the data used (chapter 4). Chapter 5 discusses the results and in chapter 6 these results are placed into a greater context.

2 Socioeconomic variables in literature

The first part of this literature review observes the general influence of socioeconomic variables on mode choice in a primarily European context. The second part focuses on socioeconomic variables in Swiss studies and their contribution to model fits.

2.1 General influence of socioeconomic variables on mode choice in a primarily European context

Some of the most commonly found socioeconomic variables in MCM are (see, for example, De Witte *et al.* (2013); Ortúzar and Willumsen (2011); Naveen and El-Geneidy (2012); Yang *et al.* (2018)):

- age
- gender
- education
- occupation
- income
- household structure
- mobility tools (e.g., car ownership or PT season ticket)

The results of the literature review regarding these socioeconomic variables are presented below. These variables correlate in some instances.

2.1.1 Age

The life expectancy and the median age of the European population have been increasing over the past decades (Federal Statistical Office for FSO, 2022b; Statistics Explained, 2021). As people age, their needs regarding transportation also change. Work-related trips decrease, leisure trips increase (Hjorthol *et al.*, 2010), the ability to use certain modes may decrease, or the time-use patterns may change.

In Switzerland, car drivers aged 75 years or older must prove their driving capability every two years to retain their driver's license (TCS, 2022). Before 2018, motorists were required to take such tests upon turning 70 years old (SRF, 2022). Regular tests may decrease the number of people driving after a certain age, which, in turn, will influence their mode choice behavior. In addition, the Swiss Federal Railways (SBB) offer financial incentives for specific age groups. For example, women over the age of 64 years (for men 65 years) pay approximately 25% less for a national season ticket than adults between 26 and 64/65 years (SBB, 2022). Such financial incentives may influence the travel behavior of specific age groups.

Fröhlich *et al.* (2012) include age as a linear term into the utility equation of MIV and find a positive and significant effect for age in Switzerland. However, the variable age is not included in the utility equations of PT, bike, or walking. This indicates that an increase in age positively affects MIV usage relative to the other modes.

Both Weis *et al.* (2017) and Weis *et al.* (2021) find that as age increases, the likelihood of using either walking or cycling as means of transportation decreases in Switzerland. Weis *et al.* (2017) further find that the older the individual, the more likely they use PT. The authors include age as a quadratic effect, with a linear and a quadratic term, into the different utility functions. While the linear terms are positive, the quadratic terms are negative for bike, walking, and PT (MIV is the reference case). Weis *et al.* (2017) state that at age 40, cycling and walking have their highest implicit utility, while the utility continues to increase for PT with age.

Contrary to the studies mentioned above, Böcker *et al.* (2017) state that for the elderly in the Netherlands, walking is more important than for the non-elderly. Furthermore, they also find in their study that the group of non-elderly uses MIV more often than the elderly. Moreover, Scheiner and Holz-Rau (2012) state that people in Germany who are older than their partner use MIV less, bringing a possible interdependence between (relative) age, relationship status, and MC into play.

De Witte *et al.* (2013) find in their literature review that there is no consensus regarding the effect of age on MC. While some studies suggest that older people use PT more often, other studies suggest that MIV use increases with age. The four studies cited by De Witte *et al.* (2013) which show a positive correlation between age, and MIV usage are all from the USA or Canada (Pucher and Renne, 2003, 2005; Kim and Ulfarsson, 2008; Nurul Habib *et al.*, 2009). Meanwhile, of the three studies indicating a positive correlation between age and PT usage, only one is from the USA (Bhat, 1998). The other two are from Switzerland (de Palma and Rochat, 2000) and Germany (Cirillo and Axhausen, 2006). The two European studies both focus on individual cities. de Palma and Rochat (2000) look at work trips in Geneva, and Cirillo and Axhausen (2006) at the travel behavior in Karlsruhe and Halle. This may be problematic since land use has an influence on mode choice. Walking and transit usage dominate traditional urban settings (Ewing and Cervero, 2001). This may also affect the results from Böcker *et al.* (2017) since the study is conducted for Greater Rotterdam. Nationwide studies such as Fröhlich *et al.* (2012) or Weis *et al.* (2017) better represent the effects of specific variables on MC in a certain country.

Beige and Axhausen (2012) find that there are interdependencies between life events and long-term mobility tool ownership decisions. Life events such as buying a car or a PT season ticket affect long-term decisions. Some life events usually happen during certain life stages (e.g., moving out of the parent's house, getting married, having children). This hints at the interdependencies between life events, age, and long-term mobility decisions. Section 2.1.7 discusses the impact of mobility tool decisions.

Hjorthol *et al.* (2010) find that over time, older people in Denmark, Norway, and Sweden tend to hold on to their driving licenses longer into advanced age than was previously the case. Furthermore, the authors state that older people also tend to increase their number of leisure and shopping trips, for which they tend to rely on their cars. In addition, they add that there is a distinction between the different age cohorts regarding driving license ownership. This is due to women of older generations having less opportunity to obtain a driving license. This pertains to gender and mobility tool ownership, which will be discussed in the chapters 2.1.2 and 2.1.7. Hjorthol *et al.* (2010) differentiate between varying generations of older people instead of between the young and old.

Kuhnimhof *et al.* (2012) find that in Germany, since 1997, young adults (aged 18-29 years) have exhibited the use of increasingly various modes of transportation. This is particularly true for people with access to cars. Their use of other modes has been increasing over the past years. Also, since 1997, the share of train (for national) and airplane (for international travel and tourism) has been increasing. Due to this increase, fewer car trips for distances above 50 km are recorded among young Germans. The authors' results indicate that the reduction in car usage is limited to young men, indicating a possible correlation between age, gender, and car use.

In addition to the results above, Focas and Christidis (2017) state that although car-driving rates have either ceased to grow or are already declining in many European countries, this trend might not necessarily be due to the age of people. This trend may be due to the economic situation as GDP and the number of driving licenses correlate within the study. Furthermore, they also express that there is not yet enough evidence to state whether effects such as change in work situations (e.g., more part-time or work from home), as well as extended education durations and shifting attitudes towards the role of cars, cause a long-term change in car usage. This is also supported by Colli (2020).

To summarize the aforementioned findings, the effect of age may be divided into two aspects. The effect of age, as described in Böcker *et al.* (2017); De Witte *et al.* (2013); Fröhlich *et al.* (2012); Scheiner and Holz-Rau (2012); Weis *et al.* (2017, 2021), comprises the first aspect. This effect may be related to life events, which affect mobility decisions (Beige and Axhausen, 2012).

Second, there is also the aspect of changes between generations/age cohorts, as reported by Colli (2020); Focas and Christidis (2017); Hjorthol *et al.* (2010); Kuhnimhof *et al.* (2012). Different generations may have diverse attitudes. Sometimes societal values evolve over time, in turn affecting mobility choices. Several studies mention the effects of attitudes on mode choice (e.g., Widmer *et al.* (2020); Becker *et al.* (2017)). The differences between generations can, for example, be seen in the possibility of acquiring a driver's license (Hjorthol *et al.*, 2010) or by the economic effects on a generation's feasible opportunities (Focas and Christidis, 2017; Colli, 2020). Since travel behavior is most easily influenced in youth (Beige and Axhausen, 2012), formative events occurring in youth may impact long-term travel behavior and influence the effect of age on MC. However, Weis (2012) finds the cohort effect to be insignificant on the trip generation. He states that travel behavior is greater influenced by life cycle events than cohort effects.

2.1.2 Gender

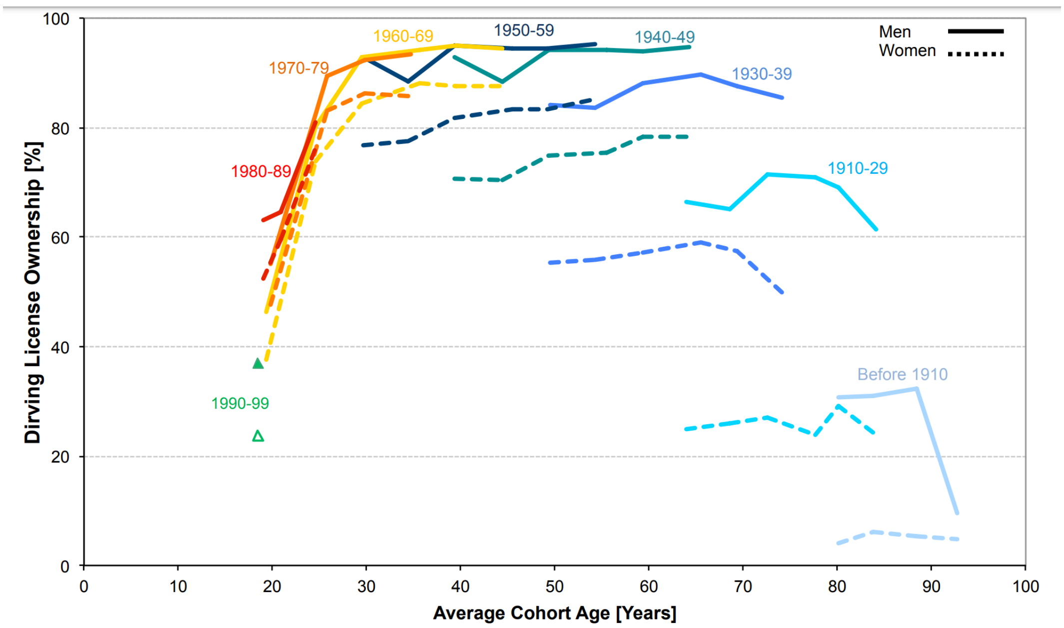
Gender is a regular variable in MCM. The available literature primarily distinguishes between male and female, not including any other genders in the analyses. Therefore, the following section differentiates only between male and female.

Their analysis of the commute mode choice in Barcelona, Spain, leads Braun *et al.* (2016) to conclude that women are less likely to use bikes for commuting. This is supported by Dėdelė *et al.* (2020) for the city of Kaunas in Lithuania, as well as by Commins and Nolan (2011) for the Greater Dublin Area and Weis *et al.* (2021) for the analysis of the 2010 and the 2015 MTMC.

However, evidence from the seven European cities, Antwerp, Barcelona, London, Örebro, Rome, Vienna, and Zurich, indicates that women are more willing to use sustainable modes of transportation like PT or bike than men (Gascon *et al.*, 2020). Although Commins and Nolan (2011) do not agree regarding cycling, they agree that women are more likely to take PT to work. Simma and Axhausen (2001) also find that men rely less on PT than women.

Regarding driver's licenses, the difference is more evident in older age cohorts between men and women. Substantially more men than women in the oldest age group have a driver's license. This difference is diminishing in younger age groups (Hjorthol *et al.*, 2010). Hjorthol *et al.* (2010) find a strong increase in women with driver's licenses between 1981/85 and 2005/06 for Denmark, Norway, and Sweden. The increase in female driver's license ownership can also be seen in Switzerland (see figure 1).

Figure 1: Driving license ownership by cohort and gender in Switzerland.



Source: van Eggermond (2020)

However, few studies conclude that women are currently more likely to drive than men. De Witte *et al.* (2013) mention that they do not find a consensus regarding the influence of gender on MC. Some studies suggest that females use cars more often, while others say that females use public transportation more often. Yet, De Witte *et al.* (2013) only mention one study which states that women are less likely to use PT (Brown *et al.*, 2003) compared to four studies supporting the statement that women are more likely to use PT (Bhat, 1998; Limtanakool *et al.*, 2006; O'Fallon *et al.*, 2004; Schwanen *et al.*, 2001).

The correlation between gender and other factors, such as occupation, appears to have a stronger effect on mode choice than gender itself. Regarding the correlation between gender and other factors, Lucas *et al.* (2016) find that the UK displays a strong interaction between single parenthood, presence of a child, income, and gender.

In their study, Kuhnimhof *et al.* (2012) do not find significant differences between car use in young German men and women. Moreover, a significant contribution of gender to MC in the 2010 MTMC could not be identified in Fröhlich *et al.* (2012).

Overall, it seems that gender not only influences MC but also correlates with other variables, such as family structure or income. As seen in figure 1, gender effects vary from generation to generation. This complicates an attempt to distinguish the effects of gender and ascertain a conclusive result. However, more literature appears to support that women are more likely to use PT than MIV (Bhat, 1998; Limtanakool *et al.*, 2006; O'Fallon *et al.*, 2004; Schwanen *et al.*, 2001; Gascon *et al.*, 2020; Commins and Nolan, 2011; Simma and Axhausen, 2001).

2.1.3 Education

Similar to age and gender, the effect of education as a variable on MC is not conclusive. While some sources state that highly educated people prefer MIV to PT, other studies claim the opposite (De Witte *et al.*, 2013). However, De Witte *et al.* (2013) provide only one source in favor of a positive correlation between car usage and education.

Among those who identify a positive impact of higher education on MIV use are Dėdelė *et al.* (2020). They express that people with high socioeconomic status (i.e., high education level, high income, employed) are more likely to use MIV as a mode of transport in Kaunas, Lithuania. Conversely, people who are unemployed and/or have a low level of income/education are more likely to use public transport.

In contrast, Dingil and Esztergár-Kiss (2022) find that in 29 countries, societies with higher education levels tend to buy fewer cars and use more alternative modes. Gascon *et al.* (2020) support these findings and state that higher educated participants use PT more often. Chidambaram and Scheiner (2021) mirror these results by stating that an increase in education leads to an increase in the likelihood of using PT in Germany.

Hudde (2022) states a positive correlation between cycling and education in the German population. The author also finds that highly educated people in medium- and large-sized cities cycle more than less educated people in medium- and large-sized cities and even more than low-educated people in rural areas. Hudde (2022) is not alone in finding a positive correlation between education and cycling. Braun *et al.* (2016) find a positive correlation between education beyond high school and cycling for the city of Barcelona. This is also supported by the findings of Commins and Nolan (2011) for the Greater Dublin Area. They state that people with higher education are more likely to walk, use a bike, or take PT to commute to work. Dėdelė *et al.* (2020), in their Lithuanian based study, identify that people with lower education tend to use the bike more often. In comparison, people with higher education tend to travel longer distances by bike.

According to Weis *et al.* (2017), education level has no significant effect on MC. However, Weis *et al.* (2017) also remark that education level correlates with income, a variable which will be discussed in chapter 2.1.5. In addition, De Witte *et al.* (2013) state that education in conjunction with other factors seems to have a higher effect on the mode choice than education itself.

In conclusion, more evidence seems to point toward a negative correlation between MIV usage and education. However, the findings are not conclusive.

2.1.4 Occupation

In their study on car deficient households, Scheiner and Holz-Rau (2012) find that neither paid work, nor unpaid work, increases the likelihood of driving. However, Dėdelė *et al.* (2020) find that in Kaunas, Lithuania, employed people are more likely to use MIV as a mode of transport, while unemployed people are more likely to use PT. Simma and Axhausen (2001) also find a positive correlation between employment and MIV usage.

Chidambaram and Scheiner (2021) state that flexible work schedules or long commutes increase the probability of using PT for German men and women. According to De Witte *et al.* (2013), people who work part-time or are self-employed are more likely to use MIV in their commute.

Overall, it appears that employed people are more likely to use MIV as a mode of transport.

2.1.5 Income

Many studies conclude that a higher income is associated with higher MIV use than PT (Fröhlich *et al.*, 2012; Dėdelė *et al.*, 2020; Chidambaram and Scheiner, 2021; De Witte *et al.*, 2013). Weis *et al.* (2021) and Weis *et al.* (2017) further state that higher income decreases the probability of going by foot or using PT. Furthermore, Chidambaram and Scheiner (2021) state that an increase in *personal* income increases the probability of both men and women commuting with MIV. In contrast, an increase in *household* income increases the likelihood of women using PT or walking.

In their analysis of cycling behavior and socioeconomic disadvantages, Vidal Tortosa *et al.* (2021) state that people in the highest income quintile make four times as many cycling trips as people in the lowest income. Furthermore, people within the highest income group are found to be significantly more likely to utilize cycling for their commute.

No effect at all is found by Böcker *et al.* (2017). Their study finds that household income does not significantly influence MC in either of the analyzed age groups.

As mentioned in 2.1.3, there is an interaction between income and education (Weis *et al.*, 2017), as people with higher education also tend to have higher-paying jobs.

2.1.6 Household structure/size

Regarding household size and structure, Commins and Nolan (2011) state that households containing young children are less likely to use modes other than MIV for their work commute. Chidambaram and Scheiner (2021) partially agree, as they find that women with young children are more inclined to use MIV instead of PT than women without young children. However, men with young children are more likely to use PT over MIV compared to men without young children.

Böcker *et al.* (2017) find that the size of a household matters, especially for elderly people. Walk, bike, and PT are more likely to be used by older people living in a large household. Living in a small household correlates stronger with MIV usage. This stands in contrast to the findings from De Witte *et al.* (2013), who say that bigger households and households with children are more likely to use MIV. Simma and Axhausen (2001), too, state that the number of children has a positive impact on the availability of MIV and their usage.

Similarly, the number of children negatively influences the usage of PT. By contrast, according to Weis *et al.* (2017), the household size is not significant at all.

2.1.7 Mobility tools

Nearly unanimous literature demonstrates mobility tools as clear influencers of MC. These tools have a positive influence on the selection of respective modes. For example, a PT season ticket positively influences the use of PT (Fröhlich *et al.*, 2012; Weis *et al.*, 2021; Böcker *et al.*, 2017). Similarly, having access to a car and possessing a driver's license increases the likelihood of using MIV (Böcker *et al.*, 2017; Simma and Axhausen, 2001). Moreover, the higher the ratio of cars per driver in a household, the more likely for MIV to be chosen as the mode of transportation (De Witte *et al.*, 2013). Furthermore, having a car in a household is a strong prohibitive factor in using PT (Gascon *et al.*, 2020; Simma and Axhausen, 2001).

Overall, owning a mobility tool increases the likelihood of primarily choosing this particular mode (Simma and Axhausen, 2001). However, mobility tools can facilitate the problem of endogeneity in MCM if not corrected.

2.2 Socioeconomic variables in a primarily Swiss context

2.2.1 Socioeconomic variables included in Swiss models

The following section compares the socioeconomic variables included in the MCM of five different Swiss studies.
The five studies are:

- Axhausen *et al.* (2004)
- Fröhlich *et al.* (2012)
- Schmutz (2015)
- Weis *et al.* (2017)
- Weis *et al.* (2021)

Some studies include multiple MCM, but the focus lies on the models which include socioeconomic effects. The socioeconomic variables included are:

- age
- household income
- gender
- occupation
- mobility tools

Of the five studies only Axhausen *et al.* (2004) use occupation and find it to be insignificant. Additionally, Weis *et al.* (2017) and Weis *et al.* (2021) use a quadratic function for both age and income. The linear terms are positive for age, while the quadratic terms have negative signs. This shows that age has an initially increasing effect with decreasing rate, and after a certain age, the effect decreases with an increasing rate.

It is further worth mentioning that none of the socioeconomic variables used in Axhausen *et al.* (2004) are significant. Consistently, Axhausen *et al.* (2004) do not include any socioeconomic variables in their recommended model other than the income elasticity.

The comparison between Weis *et al.* (2017) and Weis *et al.* (2021) shows that the quadratic effect of age on PT transitioned from significant to not significant. This is of interest, since Weis *et al.* (2021) use data from Fröhlich *et al.* (2012) and Weis *et al.* (2017). Otherwise, the socioeconomic variables in Weis *et al.* (2017) and Weis *et al.* (2021) are comparable regarding significance.

The comparison also shows that mobility tools, when included, are significant. Furthermore, their effect on the respective modes is positive.

2.2.2 Model fit

Several studies like Schmid (2019); Schmutz (2015); Schmid *et al.* (2019b, 2021) have built various MCM with increasing complexity. This allows the assessment of improvement in goodness-of-fit with each addition.

Schmid (2019) and Schmid *et al.* (2021) both analyze the same data, i.e. the Post-Car World data (Schmid *et al.*, 2019a). They estimate four different MNL models, increasing in complexity. The first model is the base model (RMNL), the second model contributes trip characteristics (TMNL), the third model further adds user characteristics (UMNL), and the fourth model additionally includes random components (MIXL). While there is a substantial increase in the Akaike information criterion (AIC) from the RMNL to the TMNL and from the UMNL to the MIXL, the increase in AIC from the TMNL to the UMNL is not substantial.

Schmutz (2015) analyzes the 2010 MTMC data. The author estimates several MNL models. The first model (MNL1) is a generic model, but without travel costs for PT and MIV. MNL2 contains these travel costs, MNL3 additionally contains mobility tools and MNL4 includes the aforementioned variables in addition to socioeconomic characteristics. The improvement in model fit from MNL1 to MNL2 is insubstantial, while the increase to MNL3 is substantial. Then again, the increase in model fit from MNL3 to MNL4 is minor. Similar to Schmid (2019); Schmid *et al.* (2021), adding socioeconomic characteristics does not lead to a substantial increase in model quality, even though they have significant estimates for certain socioeconomic variables (Schmutz, 2015).

Schmid *et al.* (2019b) analyze data from Austrian workers. Similar to Schmid (2019), they also estimate four different MNL models. BMNL is the base model, including alternative-specific attributes. TMNL adds the trip characteristics to BMNL. UMNL adds user characteristics and MIXL random components. Like Schmid (2019), and Schmutz (2015), Schmid *et al.* (2019b) also find that adding user characteristics does not bring a substantial increase in explanatory power, especially compared to the TMNL and MIXL models. Nevertheless, some of the user-specific coefficients are significant.

2.3 Conclusions

In general, there is a high interdependencies between different socioeconomic variables. Omitting certain variables leads to over- or underestimating the effect of other variables. For example, the exclusion of occupation may lead to false assumptions regarding the effect of age (Simma and Axhausen, 2001). Furthermore, other variables, such as land use (Ewing and Cervero, 2001) or attitudes (Becker *et al.*, 2017; Widmer *et al.*, 2020), also influence the effects of socioeconomic variables in MCM. Observed socioeconomic effects can manifest themselves differently dependent on the culture and country (Buehler, 2011).

Regarding the increase in model quality, it is observed that adding socioeconomic characteristics does not substantially increase the model fit in the studies above, despite individual coefficients sometimes being significant.

The sections above mainly discuss the influence of socioeconomic variables on the four modes MIV, PT, bike, and walk. Other modes, such as micro-mobility, autonomous vehicles, or urban air mobility were excluded from the overview above. Due to these being relatively recent forms of transportation, they are absent in the data sets utilized in this thesis. The interested reader could refer to Reck and Axhausen (2021) for additional information on users of shared micro-mobility, Fu *et al.* (2019) for further material on MC with urban air mobility, or Hörl *et al.* (2019) for modeling the effect of autonomous vehicles in Zurich.

3 Methodology

This chapter consists of three parts. The first part, section 3.1, lists the various R packages and software applied in this thesis. The second part explains the theory behind the models used (section 3.2), and the third part, section 3.3, briefly explains goodness-of-fit and four aspects of the post-estimation process.

3.1 Applied tools and software

For the data processing, modeling, and analysis, version 4.0.2 of the language and open-source software R (R Core Team, 2020) is used. The following packages are used in R:

- mixl (Molloy *et al.*, 2021)
- missRanger (Mayer, 2021)

The missRanger package is used to impute missing data. For the imputation process, all columns except the ID column are used. The mixl package is used to estimate models and perform post-estimation analysis.

3.2 Discrete choice model

This chapter describes the two types of model used: multinomial logit models and mixed logit models. As their names indicate, both belong to the family of logit models. The following section briefly introduces discrete choice models based on Train (2009).

Discrete choice models (DCM) have a finite, exhaustive, and mutually exclusive set of alternatives. According to the random utility theory, a person chooses the alternative with the highest utility (U).

This utility is decomposed into two parts: the part which can be observed by the researcher (V) and the part which is not observed (ε), hence treated as random by the researcher. The utility of a person n if choosing alternative j is then given as

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{1}$$

The probability of person n choosing alternative j over alternative i is given by

$$
\begin{aligned}
P_{nj} &= Prob(U_{nj} > U_{ni} \quad \forall j \neq i) \\
&= Prob(V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni} \quad \forall j \neq i) \\
&= Prob(\varepsilon_{ni} - \varepsilon_{nj} < V_{nj} - V_{ni} \quad \forall j \neq i)
\end{aligned}
\tag{2}
$$

This, in turn, is the cumulative probability that each $\varepsilon_{ni} - \varepsilon_{nj}$ is below $V_{nj} - V_{ni}$, which can be written in the following way:

$$P_{nj} = \int_{\varepsilon} I(\varepsilon_{ni} - \varepsilon_{nj} < V_{nj} - V_{ni} \quad \forall j \neq i) f(\varepsilon_n) d\varepsilon_n \tag{3}$$

The function $I(.)$ equals 1 if (.) is true and 0 otherwise. One can obtain different DCM from different specifications of $f(\varepsilon_n)$, which is the density of the unobserved utility part. The MNL model, for example, can be derived if ε is assumed to be independent and identically extreme value distributed (iid). The mixed logit model can be derived by assuming any distribution (containing all heteroskedasticity and correlation) plus an iid extreme value part.

3.2.1 Multinomial logit model

For an MNL model, the probability of person n choosing alternative j is

$$P_{nj} = \frac{e^{V_{nj}}}{\sum_i e^{V_{ni}}} \tag{4}$$

This is based on the assumption that the error terms ε_j are iid. This means that the unobserved part of utility j (ε_j) is not related to the unobserved part of utility i (ε_i). This may be true if the researcher has sufficiently defined the systemic part of utility V_{nj}. However, the iid assumption may not hold true in any other case. The observed factor can be represented by

$$V_{nj} = \beta' x_{nj} \tag{5}$$

x_{nj} is a vector containing observed variables, and β' is a vector with the estimated parameters. This then gives the logit choice probability (i.e., the probability of a person choosing an alternative) as:

$$P_{nj} = \frac{e^{\beta' x_{nj}}}{\sum_i e^{\beta' x_{ni}}} \tag{6}$$

A key characteristic of the MNL model is the independence from irrelevant alternatives (iia). This means that the probability ratio between two alternatives only depends on the two alternatives and not on any other alternative. This can lead to unrealistic predictions in the case of very similar alternatives.

Due to its iid nature, an MNL model only accounts for systematical taste variation, but no random taste variation. Random taste variation can be due to unobserved factors. In order to account for random taste variation, a mixed logit model should be used. The iid nature is also problematic when dealing with sequences of choices. According to the iid, unobserved factors affecting a choice at one point have to be independent of the unobserved factors affecting a choice at another point. This can be problematic when dealing with panel data.

3.2.2 Mixed logit model

For the mixed logit model, the probability of person n choosing alternative j is given by

$$P_{nj} = \int L_{nj}(\beta) f(\beta) d\beta \tag{7}$$

L_{nj} is the logit probability which is evaluated at parameters β:

$$L_{nj} = \frac{e^{V_{nj}(\beta)}}{\sum_i e^{V_{ni}(\beta)}} \tag{8}$$

For the mixed logit model used in this thesis, the density function $f(\beta)$ is continuous.

The density function $f(\beta)$ can be specified in different ways, for example to be normally distributed:

$$f(\beta) = N(\beta|b, W) \tag{9}$$

where b is the mean and W the covariance. Since β depends on the parameters describing its distribution, the mixed logit probabilities also depend on these parameters.

Other than for the MNL model, β contains not only observed attributes but also a random component to account for random taste variations in the sample, which are unknown to the researcher. So, where the MNL assumes fixed β parameters in the population, the mixed logit model allows for taste variation over the population. The mixed logit probability is essentially a weighted logit choice probability, where the logit choice probability is weighted by $f(\beta|\theta)$.

In the case of mixed logit models, the utility of person n derived from choice j is

$$U_{nj} = x_{nj}\beta_j + \eta_{nj} + \varepsilon_{nj} \tag{10}$$

where η_{nj} is a individual-specific random shift, accounting for unobserved taste heterogeneity. In this work η_{nj} is an individual- and mode-specific random component:

$$\eta_{nj} \sim N(0, \sigma^2_{ASC,j}) \tag{11}$$

As mentioned, the MNL model assumes that the error terms are iid. Hence, MNL models cannot account for unobserved factors correlated over a sequence of choice situations. However, mixed logit models can allow unobserved factors to correlate over a sequence of choice situations through random coefficients. This feature of the mixed logit model makes it more suitable for panel data settings.

3.2.3 Interaction terms

According to Louviere *et al.* (2000), main effects can explain up to 90% of the variance, while two-way interaction effects may explain 5 to 15%. So while interaction effects can give interesting insights into the valuation of LOS variables by different socioeconomic groups, they do not necessarily improve model quality substantially.

Because a goal of this thesis is to observe the effects of socioeconomic variables relative to LOS variables, this thesis primarily uses models containing only main effects and no interaction terms.

3.3 Goodness-of-fit and post-estimation

The following sections comprise a brief theory on goodness-of-fit for models and different parts of the post-estimation process.

3.3.1 Goodness-of-fit

There are several different criteria for goodness-of-fit. One of them is McFadden's Pseudo-R2 which is calculated as follows:

$$\rho = 1 - \frac{LL(\hat{\beta})}{LL(0)} \tag{12}$$

$LL(0)$ is the log-likelihood function when parameters are zero, and $LL(\hat{\beta})$ is the log-likelihood function at the estimated parameters. If the model predicted perfectly, the log-likelihood for $\hat{\beta}$ would be 0 and ρ 1 (Train, 2009). This indicator is problematic in that neither the number of parameters nor the population size is included. This makes comparing different data and choice sets impossible. Introducing too many parameters can lead to overfitting a model.

An indicator that takes into account the number of parameters and the sample size is the Bayesian information criterion (BIC):

$$BIC = -2LL + log(N)K \tag{13}$$

where LL is the log-likelihood, N the sample size, and K the number of parameters (Train, 2009).

A further indicator is the Akike information criterion (AIC), which accounts for the number of parameters K:

$$AIC = -2LL + 2K \tag{14}$$

The AICc is the AIC, but corrected for small sample sizes.

Unlike McFadden's Pseudo-R2, smaller values of AIC and BIC are better than large ones. In both models, $-2 * LL$ is the "reward" for increasing the log-likelihood, while $2K$ ($log(N)K$ respectively) is the "penalty" for increasing the model complexity. Both criteria cannot determine how well a model fits the data. However, they can demonstrate whether a model has a better balance between explanatory power and complexity than another.

Due to the BIC penalizing the number of parameters K with log(N)K and the AIC penalizing with 2K, BIC typically chooses the more parsimonious model (as log(N) is in most cases larger than 2).

The two criteria also differ in their underlying assumptions: The BIC tries to find the "correct" model, assuming it is part of the set of candidates. Meanwhile, the AIC tries to select the model which predicts an unknown distribution best (Bhattacharya and Burman, 2016).

3.3.2 Value of time and willingness-to-pay

The marginal rate of substitution between money and an attribute k at constant utility defines the subjective value attributed to an increase in attribute k of alternative i (Schmid, 2021a):

$$MRS_{k,i} = -\frac{\partial V_i/\partial Q_{k,i}}{\partial V_i/\partial c_i} \tag{15}$$

where ∂V_i is the change in utility, $\partial Q_{k,i}$ the change in attribute k of alternative i and ∂c_i the monetary change.

In the case of the number of transfers, for example, this would be the average amount that people are willing to pay to reduce the number of transfers.

3.3.3 Partworth

The partworth is the average contribution of an attribute to the overall utility. The partworth can be calculated as follows, where VI_k is the variable importance (i.e. partworth) of attribute x_k and $\hat{\beta}_k$ is the estimated parameter for attribute x_k (Schmid, 2021b):

$$VI_k = \frac{|\hat{\beta}_k| \cdot \bar{x}_k}{\sum_l |\hat{\beta}_l| \cdot \bar{x}_l} \tag{16}$$

3.3.4 Elasticity values

Elasticity is the change in probability P after a change in an attribute x. Own-elasticities are the change in probability P_i for a mode after an attribute x_i^k is changed, while cross-elasticities are the change in probability P_j for a mode after an attribute of a different mode x_i^k is changed. According to Schmid (2021b), the own-elasticity (E^{ik}) and the cross-elasticity (E^{jik}) can be calculated as follows:

$$E^{ik} = \frac{\% - change \quad in \quad P_i}{\% - change \quad in \quad x_i^k} = \frac{\frac{\bar{P}_{i,after} - \bar{P}_{i,before}}{0.5 \cdot (\bar{P}_{i,after} - \bar{P}_{i,before})}}{\frac{\bar{x}_i^{k*} - \bar{x}_i^k}{0.5 \cdot (\bar{x}_i^k + \bar{x}_i^{k*})}} \tag{17}$$

$$E^{jik} = \frac{\% - change \quad in \quad P_j}{\% - change \quad in \quad x_i^k} = \frac{\frac{\bar{P}_{j,after} - \bar{P}_{j,before}}{0.5 \cdot (\bar{P}_{j,after} - \bar{P}_{j,before})}}{\frac{\bar{x}_i^{k*} - \bar{x}_i^k}{0.5 \cdot (\bar{x}_i^k + \bar{x}_i^{k*})}} \tag{18}$$

where $\bar{x}_i^{k^*}$ is the attribute after the change.

For this work, the elasticity values are calculated as mode-specific averages over the three RP utility functions. The averages are weighted by the number of choices of each alternative. Only the elasticity values from RP utility functions are used since they are the observed choices and are thus crucial for policy analyses because they provide each mode's "true" market shares.

3.3.5 Marginal probability effects

Marginal probability effects (MPE) are the average change in probability before and after an attribute change. MPE are expressed in percentage-points and typically used for discrete attributes (Schmid, 2021b).

The MPE for changing attribute x^k of alternative i are hence given as:

$$MPE^{ik} = \bar{P}_{i,after} - \bar{P}_{i,before} \tag{19}$$

Similar to the elasticity values, the MPE are calculated as mode-specific averages over the three RP utility functions.

4 Data description

Chapter 4.1 describes the data sets, while chapter 4.2 presents the mode shares according to different variables, such as gender, age, or income. Chapter 4.3 gives insight into the relation between mobility tools. Chapter 4.4 investigates the relationship between household income and education level. Chapter 4.5 looks at the correlation between PT waiting time and other PT LOS variables. Finally, chapter 4.6 summarizes the insights gained in chapter 4.

4.1 Descriptive statistics of the data sets

Standardizing the data sets includes the removal of all observations not related to mode choice, as this thesis solely focuses on mode choice. Table 1 shows the number of observations and participants before the removal of all observations unrelated to mode choice.

Table 1: Observations and participants before the removal of observations unrelated to mode choice

	MTMC 2010	MTMC 2015	VSS 2021
Observations	52,208	67,365	47,842
Participants	3,605	6,099	1,797

Table 2 shows the number of observations after removing all observations unrelated to mode choice. The number of participants is the same as in table 1. About one-third of the VSS data set are mode choice observations. Of the MTMC 2010 data set, two-thirds are mode choice observations, and of the MTMC 2015 data set, around 58% are mode choice observations. While the observations for both MTMC data sets are either regarding mode or route choice, the VSS data set also includes residential and workplace location choices.

Table 2: Observations after the removal of observations unrelated to mode choices

	MTMC 2010	MTMC 2015	VSS 2021
Observations	35,167	38,901	15,496

After the removal of all data unrelated to mode choice, additional observations are removed. These removed observations include data when travel time is zero, as well as all trips for walk, when the travel time is above one hour. Additionally, all trips for bike are removed when the travel distance is above 15 km. If walk or bike are available alternatives yet are not selected and their travel time is above one hour (respectively travel distance above 15 km), these modes are intentionally excluded from the specific choice situation. Subsequently, the unified data contains 11,272 participants with a total of 87,326 observations. In table 3, the number of observations and participants per study are displayed. As can be observed, the MTMC 2010 data contains the highest average number of observations per participant (9.7), followed by the VSS 2021 data (8.5) and finally, the MTMC 2015 data (6.4). Furthermore, only a few observations have to be removed due to zero travel time or too high travel times for walk (respectively travel distances for bike). From the MTMC 2010 data set 964 observations and 80 individuals are removed. The MTMC 2015 data set has 941 observations and 145 individuals fewer than in table 2. Meanwhile, from the VSS 2021 data set, 333 observations and four individuals are removed.

Table 3: Observations and participants per year

	MTMC 2010	MTMC 2015	VSS 2021
Observations	34,203	37,960	15,163
Participants	3,525	5,954	1,793

The data sets contain both RP and SP data. Table 4 shows the proportions of RP and SP data. The VSS 2021 data set entails about twice as much RP data as the other two data sets.

Table 4: Percentage of RP and SP data

Data type	MTMC 2010 [%]	MTMC 2015 [%]	VSS 2021 [%]
RP	10.1	15.4	30.6
SP	89.9	84.6	69.4

Table 5 contains descriptive statistics about the participants of the three studies after the coding was unified. The values refer exclusively to the participants and not the observations. This is to be kept in mind since not all participants have the same amount of observations. Thus, observations of certain socioeconomic groups may prevail over other groups.

Table 5: Descriptive statistics

Variable	Value	MTMC 2010 [%]	MTMC 2015 [%]	VSS 2021 [%]
Sex	Female	51.0	49.5	49.9
	Male	49.0	50.5	50.1
Age	18 - 35	20.5	25.8	43.2
	36 - 50	30.1	30.1	26.2
	51 - 65	29.6	27.7	29.2
	$\geq$ 66	19.8	16.4	1.5
Swiss citizen	Yes	88.1	82.2	95.3
	No	11.9	17.7	4.7
	Not reported	0.0	0.1	0.0
Education	No degree	0.4	1.5	0.1
	Mandatory sch.	9.2	8.8	2.4
	Apprenticeship	38.3	34.5	27.7
	BMS/FMS	7.3	8.3	8.4
	Baccalaureate	7.2	8.0	10.2
	HF	3.7	3.3	18.0
	Swiss fed. dipl.	8.3	8.5	7.5
	University	25.5	26.8	25.7
	Not reported	0.2	0.2	0.0
PT season ticket	GA	12.4	11.1	15.3
	Halbtax	46.4	40.0	52.5
	Other	6.4	8.8	5.3
	None	34.8	40.1	26.8
Resident location area	Urban	44.5	42.4	22.6
	Suburban	37.4	38.6	28.4
	Rural	18.1	19.0	49.0
Employment level	Full time	43.2	43.5	53.9
	Part time	26.2	28.5	46.1
	Not employed[1]	30.6	27.9	0.0
	Not reported	0.0	0.1	0.0
Household income [CHF]	< 2,000	1.7	1.3	1.2
	2,000 - 4,000	11.1	7.9	3.6
	4,000 - 6,000	21.3	16.2	11.5

[1] This does not mean that these people do not work at all. They are not (officially) employed but could well be working in the household or taking care of family members.

Table 5 (continued)

Variable	Value	MTMC 2010 [%]	MTMC 2015 [%]	VSS 2021 [%]
	6,000 - 8,000	19.3	18.5	16.5
	8,000 - 10,000	14.8	15.4	16.6
	10,000 - 12,000	9.1	10.9	14.4
	12,000 - 14,000	5.4	6.4	11.3
	14,000 - 16,000	3.8	5.3	7.2
	> 16,000	5.7	8.1	11.5
	Not reported	7.8	9.9	6.2
Civil status	Single	26.7	29.9	48.0
	Civil union	0.2	0.4	1.2
	Cancelled civil union	0.0	0.1	0.1
	Married	54.4	56.8	41.0
	Married, separated	1.2	0.0	1.2
	Divorced	10.9	9.4	7.6
	Widowed	6.6	3.5	0.9
Household size	1	26.5	17.4	17.0
	2	39.1	37.0	36.4
	3	12.7	16.4	17.6
	$\geq$ 4	21.7	29.3	29.0
HH with kids	Yes	35.2	46.4	31.0
	No	64.8	53.6	69.0
Owns home	Yes	50.1	49.5	49.2
	No	49.9	50.3	50.8
	Not reported	0.0	0.2	0.0
Language	German	70.4	61.6	100.0
	French	24.3	31.4	0.0
	Italian	5.4	7.0	0.0
Number of cars per HH	0	15.1	12.2	13.8
	1	50.8	45.9	42.5
	2	27.8	32.4	34.1
	$\geq$ 3	6.2	9.5	9.6
	Not reported	0.0	0.1	0.0
Number of bikes per HH	0	23.1	21.2	7.2
	1	19.7	17.8	17.4
	2	24.5	23.6	23.8

Table 5 (continued)

Variable	Value	MTMC 2010 [%]	MTMC 2015 [%]	VSS 2021 [%]
	≥ 3	32.7	37.4	51.6
Number of motorbikes per HH	0	81.0	80.5	75.9
	1	15.1	15.2	17.7
	2	2.9	3.2	4.5
	≥ 3	1.0	1.0	1.9
	Not reported	0.0	0.1	0.0
Car license	Yes	89.0	89.5	94.0
	No	11.0	10.5	6.0
Motorbike license	Yes	36.1	32.8	37.8
	No	63.9	66.6	62.2

Overall, the two MTMC data sets display very similar descriptive statistics, while the VSS 2021 data set shows some differences compared to the MTMC data. The MTMC data sets include all trips from a randomly selected day, while the VSS 2021 data set includes the three most frequent trips for work, shopping, and leisure. The following paragraphs describe and explain the individual variables in greater detail.

Sex All three data sets show strong similarities in this variable. While the MTMC 2010 data set has marginally more women, men narrowly comprise the majority in the other two data sets.

Age As can be seen, the MTMC 2010 and 2015 data sets contain highly similar shares of different age groups. The VSS 2021 data set has fewer people older than 65 years, which is most likely due to the VSS 2021 data only including people who work at least part-time. In addition, the VSS 2021 data set displays more than double the share of people between 18 and 35 years compared to MTMC 2010. The share of people between 36 and 50 years is slightly lower than the MTMC data, while the share of people between 51 and 65 years is comparable.

Swiss citizen As can be seen, only 4.7% of participants in the VSS 2021 data set are not Swiss citizens. Meanwhile, both MTMC data sets have more than 10% non-Swiss participants. However, the MTMC 2010 data set has an about six percentage points larger share of Swiss citizens than the MTMC 2015 data set. Because the non-Swiss population comprises about a quarter of the population living in Switzerland (Federal Department of Foreign Affairs FDFA, 2022), all three data sets display disproportionately low shares of foreigners.

Education In the case of education, the MTMC 2010 data set has 17 levels, the MTMC 2015 data set has 19 levels, and the VSS 2021 data set has 11 levels. The education has been aggregated to eight levels for all three data sets. For example, the level of university includes people with degrees from universities of applied sciences (FH), pedagogical colleges, universities, and institutes. It can be seen that the MTMC data sets are very analogous. Meanwhile, the VSS 2021 data set differs mainly on three levels: mandatory school, apprenticeship, and college of higher education (HF). While the VSS data set has lower shares for the first two cases, it has a substantially higher share of people with an HF degree. Similar to other studies (e.g., Widmer *et al.* (2020)), the VSS 2021 data set includes an above-average number of individuals with higher education[2].

PT season ticket The category titled "other" includes public transport subscriptions such as a regional or route season ticket. Once again, similar to other studies, the VSS 2021 data set contains above-average shares of national season ticket (GA) and half-fare card (Halbtax) owners. Consequently, the proportion of people without a PT season ticket is substantially smaller in the VSS 2021 data set.

Residential location area As is displayed, nearly half of the people in the VSS 2021 data set live in rural areas. Contrarily, in the other two data sets, rural residence comprise less than one-fifth of all participants. In the MTMC data sets, the largest proportion of the population lives in urban areas.

Employment level Since the VSS 2021 data set contains only individuals who work either full- or part-time, it is clear why the classification for employment level varies so greatly from the MTMC data sets. While the MTMC data sets include the categories full-time, part-time, multiple part-times, and not employed, the VSS data set only shows the average number of hours worked per week. Furthermore, the VSS 2021 data set only includes people who work at least one hour per week. Therefore, in this paper, based on Federal Statistical Office for FSO (2022a), all individuals in the VSS 2021 data set who work 41 or more hours per week are assigned to the full-time category, and all those below that are assigned to the part-time category. The distribution of weekly hours worked in the VSS 2021 data set shows that most individuals work between 41 and 44 hours per week.

[2] In appendix A.1, there is a more detailed description of the different education levels used in this thesis.

In this thesis, participants of the MTMC data sets are categorized as part-time based on their workloads since there are no average weekly work hours for full-time workers. All those with workloads over 90% are categorized as full-time. In some cases, people working multiple part-time jobs have a workload above 100%. Thus they are categorized as full-time workers.

Household income The MTMC 2015 data set tends to show slightly higher proportions of individuals in the income categories above 8,000 CHF compared to the MTMC 2010 data set. The VSS 2021 data set has substantially higher proportions of persons with incomes above 8,000 CHF than the two MTMC data sets. Unlike the previous variables, all three data sets include a perceptible proportion of people who do not report their household income.

Civil status For the MTMC data sets, the civil status "married" clearly accounts for the largest share, with over 50% in each case. This is followed by "single" with less than 30%. In the VSS 2021 data set, however, the civil status "single" accounts for the largest share (48%), followed by "married" (41%). The share of divorced and widowed persons is also higher in the MTMC data sets than in the VSS 2021 data set.

Household size In terms of household size, the MTMC 2015 and VSS 2021 data sets are more resemble each other more than the two MTMC data sets. The MTMC 2010 data set has higher shares of single-person households than the other two data sets.

Household with kids Both the MTMC 2010 and VSS 2021 data sets have a similar proportion of households including children. The MTMC 2015 data set has a substantially higher share of households with children (46.4%). Although the VSS data differentiates between children younger and children older than six years, both MTMC data sets do not. They only indicate whether or not children are present in the household. Hence, this variable includes all children younger than 18.

Owns home This variable does not distinguish between apartment or house. It is only a question whether someone is an owner or pays rent. As one can see, the three data sets hardly vary when compared.

Language Since the survey for the VSS 2021 data set was only conducted in German-speaking Switzerland, the proportion of German speakers is 100%. The MTMC 2015 data set has a larger proportion of French and Italian speakers than the MTMC 2010 data set.

Number of cars, bikes, and motorbikes The three data sets are very similar in the number of cars per household. However, the MTMC 2010 data set contains slightly more households with one car, while the other two data sets have higher proportions of households with multiple cars. Regarding the number of bicycles, the VSS 2021 data set differs primarily in the proportion of households without bicycles and the proportion of households with three or more bicycles. In each MTMC data set, just over one-fifth of individuals do not have a bicycle at home, compared to just under 7% of individuals in the VSS data set. Moreover, in the VSS data set, slightly more than half of the individuals live in a household with three or more bicycles. Compared to the MTMC data sets, the VSS 2021 data set has a slightly higher proportion of households with motorcycles. In general, however, at least three-fourths of individuals do not have a motorcycle in their household, compared to a maximum of 15% who do not have cars.

Car and motorbike license In all three data sets, just under 90% or more of the individuals have a driver's license. The proportion of people with a driver's license in the VSS 2021 data set is nearly six percentage points higher than in the MTMC data sets. The shares of motorcycle licenses are similar across the three data sets. The MTMC 2015 data set has a slightly smaller proportion of people with motorcycle licenses than the other two data sets. Overall, the proportion of individuals with motorcycle licenses is below 40% in all three data sets.

4.2 Mode shares

From this point on, the combined data set is used where all missing values have been imputed using the missRanger package (Mayer, 2021).

The general mode shares can be seen in table 6. As can be observed, MIV has the highest mode share, almost triple of the next highest share (PT). Walk has, overall, the lowest share of all four modes. Furthermore, the table also displays the mode shares according to the type of data (i.e., RP or SP). While walk and MIV have higher shares in the RP data, bike and PT have higher shares in the SP data.

Table 6: Mode shares

	Bike [%]	MIV [%]	PT [%]	Walk [%]
Average	11.7	60.2	21.1	7.1
RP	9.4	63.2	18.3	9.1
SP	12.1	59.6	21.6	6.7

4.2.1 Mode shares and year

The mode shares per year and data type can be seen in table 7. It can be observed that the average share of walk is highest in 2010. While the share of walking is highest in 2010, the share of bike is highest in 2021. That year, the share is almost double its share in 2010. MIV has the highest share in 2015, and PT shares decrease from year to year.

Moreover, the SP and RP shares for PT in 2010 are nearly identical. Furthermore, it can be seen that the bike share for RP in 2021 is lower than the SP share but still the second-highest in the data. In addition, the share for PT is almost ten percentage points lower for RP 2021 compared to SP 2021. In other years, the difference for PT is not as strong. In 2015, the share for PT is higher for RP data than SP data. The juxtaposition between SP and RP walk is highest in 2021, with walk SP being only 3.5%, whereas walk RP is 11.8%. These are simultaneously the highest and lowest values for walk across all three years. The differences between RP and SP are generally more dominant in 2021 than in 2010 or 2015. This may also be due to the 2021 data set not being an MTMC data set and thus structured differently than the 2010 and 2015 data sets.

Table 7: Mode shares according to the year

Year		Bike [%]	MIV [%]	PT [%]	Walk [%]
2010	Average	10.2	57.5	22.8	9.5
	RP	6.3	60.7	22.4	10.6
	SP	10.6	57.2	22.8	9.4
2015	Average	9.8	64.4	20.5	5.3
	RP	7.0	65.7	21.1	6.1
	SP	10.3	64.2	20.4	5.1
2021	Average	19.8	55.6	18.6	6.0
	RP	14.7	61.8	11.7	11.8
	SP	22.0	52.8	21.6	3.5

4.2.2 Mode shares and gender

Table 8 shows the mode shares per gender and year. Females generally comprise a higher share of PT users, while males make up a higher share of MIV users. Moreover, in 2010 and 2015, males make up higher bike shares, while this changes in 2021.

Table 8: Mode shares according to gender and year

Gender	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
Female	2010	10.2	54.3	23.8	11.7
	2015	9.5	62.0	22.2	6.3
	2021	21.9	53.2	19.1	5.8
Male	2010	10.2	60.7	21.8	7.3
	2015	10.1	66.7	18.9	4.3
	2021	17.7	57.9	18.0	6.3

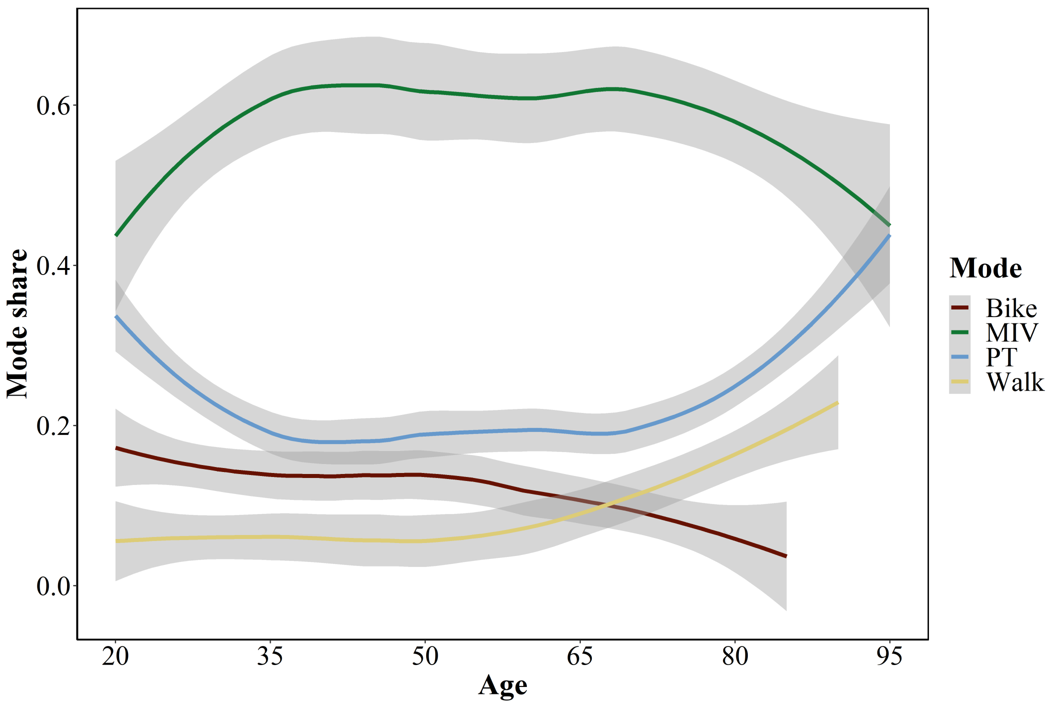
4.2.3 Mode shares and age

The mode shares according to age and year can be seen in 2. The gray areas account for the variation according to the year. As can be seen, both the mode shares of MIV and PT follow a quadratic function, even though with different signs. While the parabola for MIV would have a positive linear term and a negative quadratic term, it would be the opposite for PT.

The first turning point for the quadratic functions seems to be shortly after 35 years, while the second turning point is probably between 70 and 75 years. 75 (and 70 before) happens to be the age at which regular check-ups are mandatory to keep one's driver's license.

It can be noted that the share of walk increases with age while the share for bike decreases with age, especially after age 55. In addition, bike and walk are not chosen as modes after a certain age. However, it needs to be said that there are few observations for people older than 75.

Figure 2: Mode shares according to age

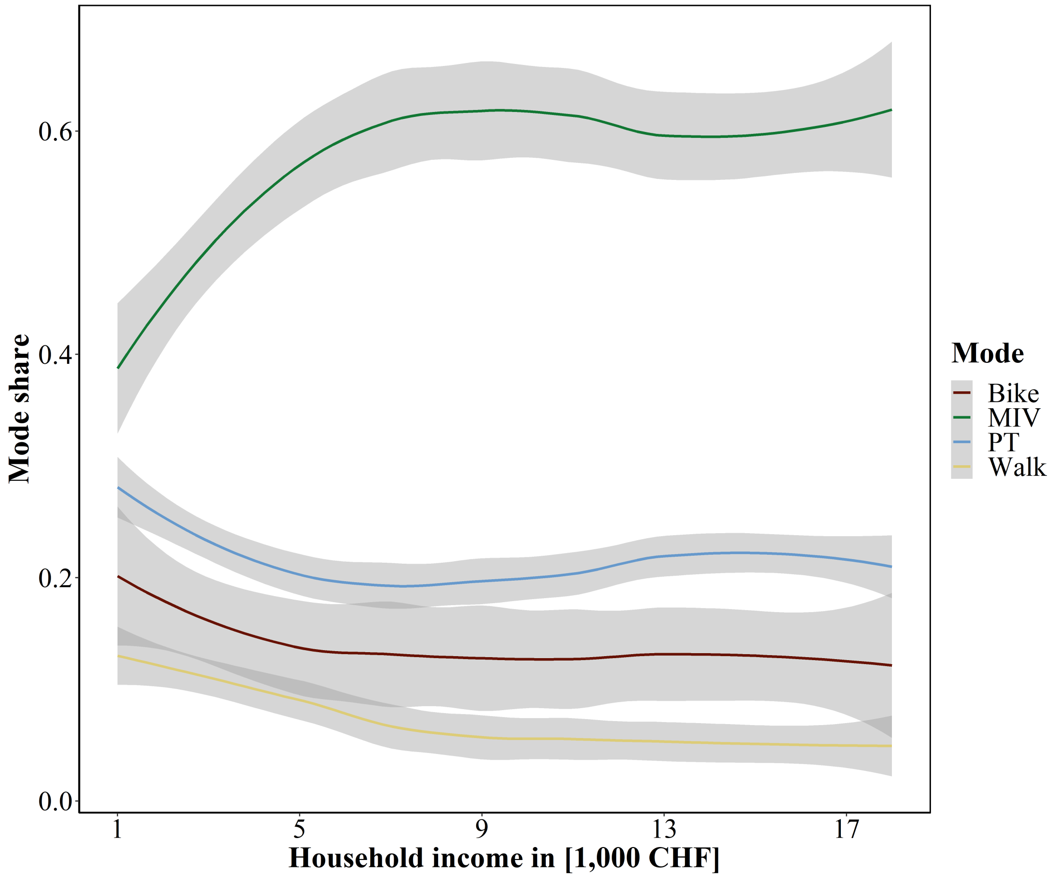


4.2.4 Mode shares and household income

Figure 3 shows the mode shares according to household income and the gray areas account for the variation according to the year. As can be seen, the mode share of MIV increases approximately linear to the logarithm of household income, while for other modes, it decreases before remaining constant.

In addition, above a monthly household income of about 9,000 CHF, there does not appear to be much shift in mode shares. Moreover, 9,000 CHF is also the median household income for the MTMC 2015 and VSS 2021 data sets, while the median household income for the MTMC 2010 data set is 7,000 CHF. Hence, the household income influences people in the lower-income half more than people above the median household income.

Figure 3: Mode shares according to household income



4.2.5 Mode shares and education

To analyze the mode shares, eight different education levels are used. These eight levels are displayed in table 9.

The final three education levels in the table (HF, Swiss federal diploma, and university) comprise the tertiary education level. However, the mode shares differ. For example, people with a university degree have higher shares of bike, walk, and PT compared to people with a Swiss federal diploma.

Furthermore, people with a baccalaureate reveal similar mode choice behavior to people with a university degree. This may be explained by the fact that most people with a baccalaureate continue their education by attending university. At the time of the surveys, some people with a baccalaureate were perhaps studying at university without yet having obtained a degree.

In addition, the education levels of apprenticeships and BMS/FMS also show similarities in mode choice behavior. Moreover, they, too, are similar to the Swiss federal diploma. Again, this may not come as a surprise because obtaining a Swiss federal diploma is a possible career path for people with an apprenticeship.

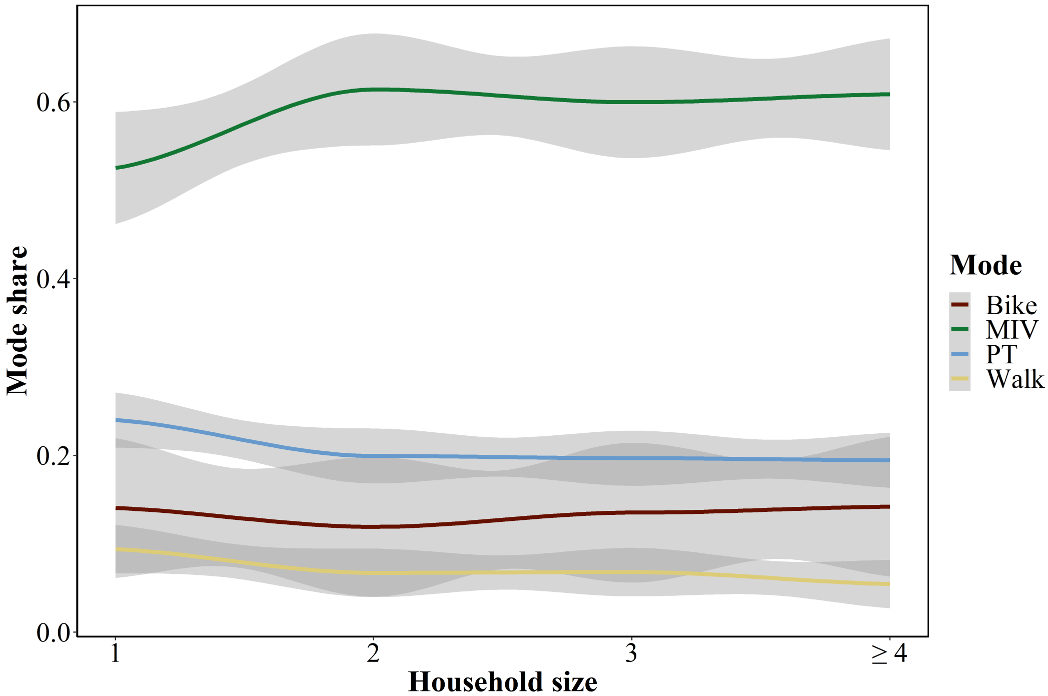
Table 9: Mode shares according to education level and year

Education	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
No degree	2010	4.5	73.2	16.1	6.2
	2015	5.4	52.8	21.5	20.3
	2021	0.0	88.9	0.0	11.1
Mandatory school	2010	9.6	53.1	22.7	14.6
	2015	8.4	60.8	23.0	7.8
	2021	15.4	47.4	29.7	7.6
Apprenticeship	2010	8.3	61.3	21.0	9.4
	2015	8.6	70.2	16.9	4.3
	2021	14.8	65.8	14.2	5.3
BMS/FMS	2010	7.2	62.1	20.5	10.2
	2015	6.3	67.6	20.9	5.2
	2021	16.3	61.7	16.7	5.2
Baccalaureate	2010	13.7	51.7	25.6	9.0
	2015	10.8	55.8	26.4	6.9
	2021	26.8	39.3	26.6	7.3
HF	2010	5.1	68.9	20.6	5.4
	2015	13.4	63.6	17.8	5.2
	2021	18.7	60.7	16.3	4.3
Swiss federal diploma	2010	9.9	66.3	17.3	6.6
	2015	4.6	77.1	14.8	3.6
	2021	13.8	70.6	11.9	3.6
University	2010	13.8	49.0	27.4	9.8
	2015	13.7	56.1	24.8	5.5
	2021	26.7	41.3	23.6	8.5

4.2.6 Mode shares and household size

The mode shares according to the household size can be seen in figure 4. The gray areas account for variation according to the year. As can be observed, households with more than two members have a similar mode choice pattern overall. However, one-person households slightly favor walk, bike, and PT as transport modes compared to the other household sizes.

Figure 4: Mode shares according to household size



4.2.7 Mode shares and kids in household

Table 10 shows mode shares according to whether a household has children or not. As can be seen, households with kids appear to have slightly higher shares of MIV and bike while having slightly lower shares of PT and walk. However, the difference is not as substantial as with other variables, such as education level.

The presence of kids in a household is probably also correlated with certain life stages. It may be assumed that if children still live at home, the parents may be of a specific age.

Table 10: Mode shares according to kids in the household and year

Kids in HH	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
Yes	2010	10.3	60.1	21.5	8.2
	2015	10.8	64.4	20.1	4.6
	2010	21.2	58.1	15.3	5.4
No	2010	10.1	56.0	23.6	10.2
	2015	8.9	64.4	20.8	5.8
	2021	19.1	54.5	20.1	6.3

4.2.8 Mode shares and Swiss citizenship

Table 11 shows mode shares according to Swiss citizenship. It can be seen that the difference between Swiss and non-Swiss individuals is relatively small. Generally, it appears that non-Swiss people demonstrate a trend in their mode choices. The shares for MIV and bike tend to increase, while the shares for PT and walk tend to decrease. Similarly, the PT and walk shares for Swiss people decrease from 2010 to 2021. In contrast to non-Swiss people, Swiss people demonstrate neither a trend in MIV nor in bike.

Table 11: Mode shares according to Swiss citizenship and year

Swiss citizen	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
Yes	2010	10.1	57.5	23.1	9.2
	2015	9.7	65.0	20.5	4.8
	2021	20.1	55.2	18.6	6.1
No	2010	10.6	57.4	20.3	11.7
	2015	10.4	61.3	20.6	7.8
	2021	13.9	63.5	17.5	5.1

4.2.9 Mode shares and language

The mode choices are also put in relation to the participants' language. As can be observed in table 12, people from the German-speaking part of Switzerland tend to use bike and PT more often than their French and Italian counterparts. Moreover, the Italian-speaking respondents use MIV even more than the French-speaking respondents. Furthermore, walking has higher shares among French- and Italian-speaking people.

Table 12: Mode shares according to language and year

Language	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
German	2010	11.2	54.9	25.2	8.7
	2015	11.4	61.9	22.5	4.2
	2021	19.8	55.6	18.6	6.0
French	2010	7.6	62.9	17.6	11.9
	2015	7.1	68.1	17.4	7.4
	2021	0.0	0.0	0.0	0.0
Italian	2010	8.0	67.7	14.8	9.4
	2015	6.3	72.2	15.2	6.3
	2021	0.0	0.0	0.0	0.0

4.2.10 Mode shares and home ownership

The mode shares according to whether a person owns their home or not can be seen in table 13. As displayed below, homeowners appear to choose MIV more often, by approximately ten percentage points. The main explanation is that homeowners tend to live in less urban locations.

Table 13: Mode shares according to homeowner and year

Homeowner	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
Yes	2010	8.4	63.3	21.1	7.2
	2015	8.9	69.8	17.8	3.5
	2021	18.1	60.6	17.6	3.8
No	2010	12.0	51.6	24.5	11.8
	2015	10.7	58.6	23.4	7.2
	2021	21.5	50.7	19.5	8.3

4.2.11 Mode shares and residential location area

Table 14 shows mode shares according to the residential location area. It can be observed that for urban residential locations, the shares of walk, bike, and PT are higher. The shares of MIV are lower compared to the other two residential location areas.

Moreover, the shares of walk, bike, and PT decrease further from a suburban area to a rural area. However, the decrease is not as substantial as before. Hence, the difference in mode choice between suburban and rural location areas is not as big as between these two and an urban location area.

Furthermore, the highest mode share in urban areas in 2021 is bike and no longer MIV. From 2015 to 2021, the MIV share is halved. In suburban areas, MIV also sees a substantial decrease in share by almost 20 percentage points. In rural areas, the decrease is still substantial, but with just eight percentage points, it is not as high as in urban or suburban areas.

Table 14: Mode shares according to residential location area and year

Residential location area	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
Urban	2010	13.5	45.7	26.4	14.4
	2015	13.8	51.3	26.3	8.7
	2021	34.9	25.7	26.6	12.8
Suburban	2010	7.4	67.0	19.9	5.7
	2015	7.9	70.7	18.0	3.4
	2021	21.1	53.0	20.1	5.8
Rural	2010	8.0	66.0	20.3	5.7
	2015	5.5	78.6	13.8	2.1
	2021	12.2	70.6	14.1	3.1

4.2.12 Mode shares and employment level

As shown in table 15, the full-time employment level contains higher shares for MIV than the other two employment levels. Furthermore, part-time workers and not employed individuals have similar shares for PT and MIV. However, the shares for walking are higher for the not employed individuals while the shares for bike are lower.

Table 15: Mode shares according to employment level and year

Employment level	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
Full-time	2010	9.1	63.6	21.4	5.9
	2015	9.0	68.3	19.0	3.7
	2021	16.1	61.2	17.0	5.7
Part-time	2010	13.6	53.5	24.1	8.9
	2015	11.3	62.1	22.1	4.4
	2021	24.2	48.9	20.5	6.5
Not employed	2010	8.6	51.9	23.7	15.8
	2015	9.4	60.5	21.3	8.8
	2021	0.0	0.0	0.0	0.0

4.2.13 Mode shares and civil status

Table 16 shows mode shares according to civil status. As can be seen, people who are married or have been married show similarities in mode shares. They tend to have higher MIV shares than other people. However, there are differences within the group of married / previously married people. For example, in 2010, widowed people have a walk share of about 20%, which clearly surpasses the walk shares of other married / previously married people. People in a civil union or who are single also display some similarities. Both groups have somewhat lower MIV shares while having slightly elevated PT shares.

Table 16: Mode shares according to civil status and year

Civil status	Year	Bike [%]	MIV [%]	PT [%]	Walk [%]
Single	2010	13.7	49.0	28.8	8.6
	2015	12.2	54.3	27.6	5.9
	2021	22.1	49.6	21.5	6.9
Civil union	2010	16.7	24.2	30.3	28.8
	2015	4.5	54.5	27.6	13.4
	2021	14.4	63.9	19.4	2.2
Cancelled civil union	2010	0.0	0.0	0.0	0.0
	2015	0.0	25.0	0.0	75.0
	2021	0.0	83.3	11.1	5.6
Married	2010	9.0	62.6	19.6	8.8
	2015	9.2	69.2	17.1	4.5
	2021	17.9	61.4	16.0	4.7
Married, separated	2010	11.6	61.8	18.4	8.2
	2015	0.0	0.0	0.0	0.0
	2021	12.6	53.0	19.7	14.8
Divorced	2010	9.6	56.4	24.7	9.4
	2015	7.2	65.8	20.9	6.1
	2021	18.8	59.0	14.7	7.6
Widowed	2010	6.0	50.3	23.1	20.6
	2015	6.7	62.2	19.4	11.6
	2021	11.7	66.4	18.2	3.6

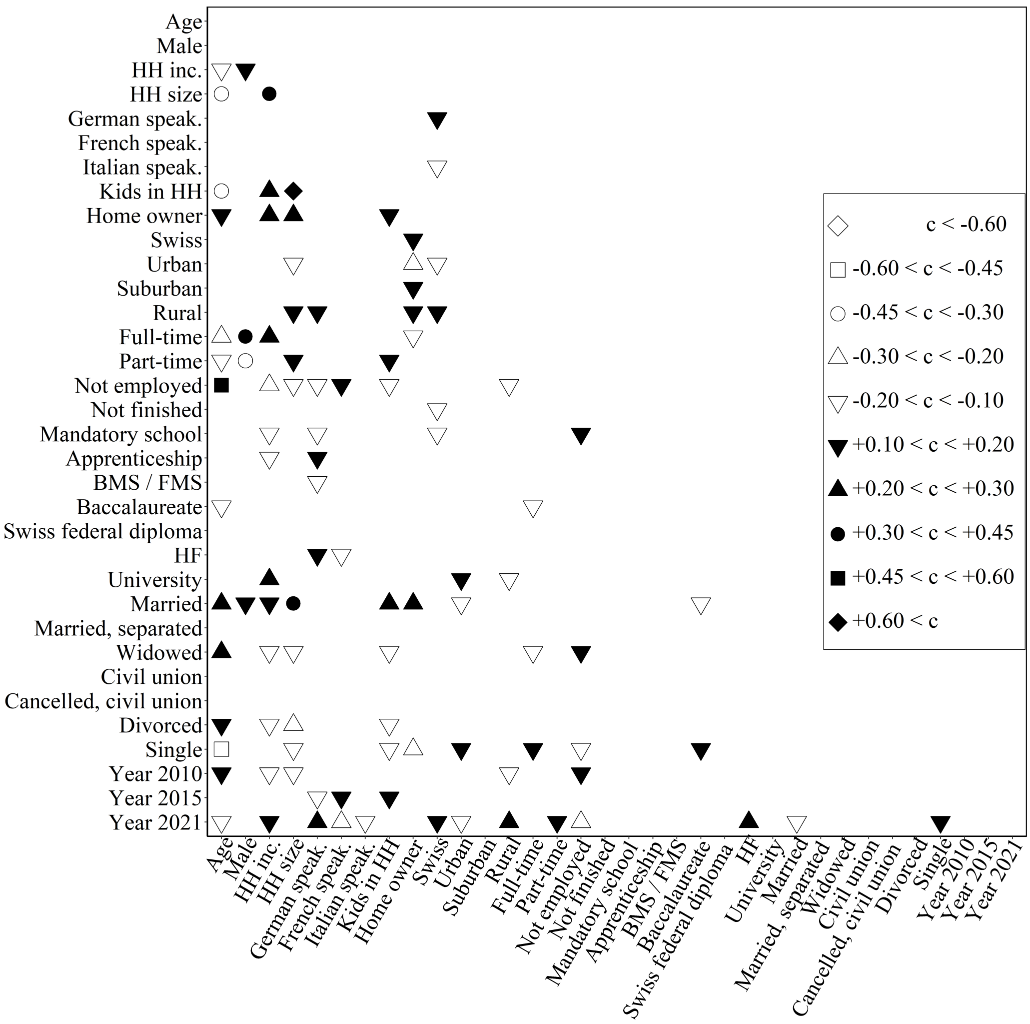
4.2.14 Correlation patterns

In order to avoid collinearity issues, the correlations between the different socioeconomic variables, presented in chapters 4.2.2 to 4.2.12, are analyzed. Figure 5 shows the corresponding correlation patterns.

The correlation between kids in a household and household size is the highest of all the variables and has a value of 0.76. The second and third highest correlation magnitudes are between age and being single (-0.53) and age and not being employed (0.45). No other pair of variables has an absolute correlation greater or equal to 0.45.

Apart from kids in a household and household size, there appears to be no pair with a critical magnitude of correlation. To avoid collinearity, kids in a household and household size will not be included in the same models.

Figure 5: Correlation patterns of different socioeconomic variables



4.3 Mobility tools

This chapter observes the relationship between mobility tools. The mobility tools considered are listed below.

- National season ticket (GA)
- Half-fare card
- other form of PT ticket
- no PT ticket
- car (if a person has a car license and the household has at least one car)
- bike (if there is at least one bike in the household or not)
- motorbike (if a person has a motorbike license and the household has at least one motorbike)

Table 17 provides an overview of the mobility tools for each year. As can be seen, more people own some PT subscription, own a bike, and have access to a motorbike in 2021 than in the other years. Moreover, in 2010 and 2015, more people have access to a car than a bike.

Table 17: Mobility tools according to the year

Year	GA	Half-fare card	Other ticket	No ticket	Car	Bike	Motorbike
2010	12.4	46.4	6.4	34.8	80.5	76.9	11.4
2015	11.1	40.0	8.8	40.1	82.7	78.8	10.5
2021	15.3	52.5	5.3	26.8	83.4	92.8	16.5

The shares of PT season ticket owners according to bike, motorbike access, and car access can be seen in table 18. It can be observed that the shares of people who do not own PT tickets are highest for people with access to a motorbike, followed by people with access to a car.

Table 18: PT season tickets according to bike / motorbike / car

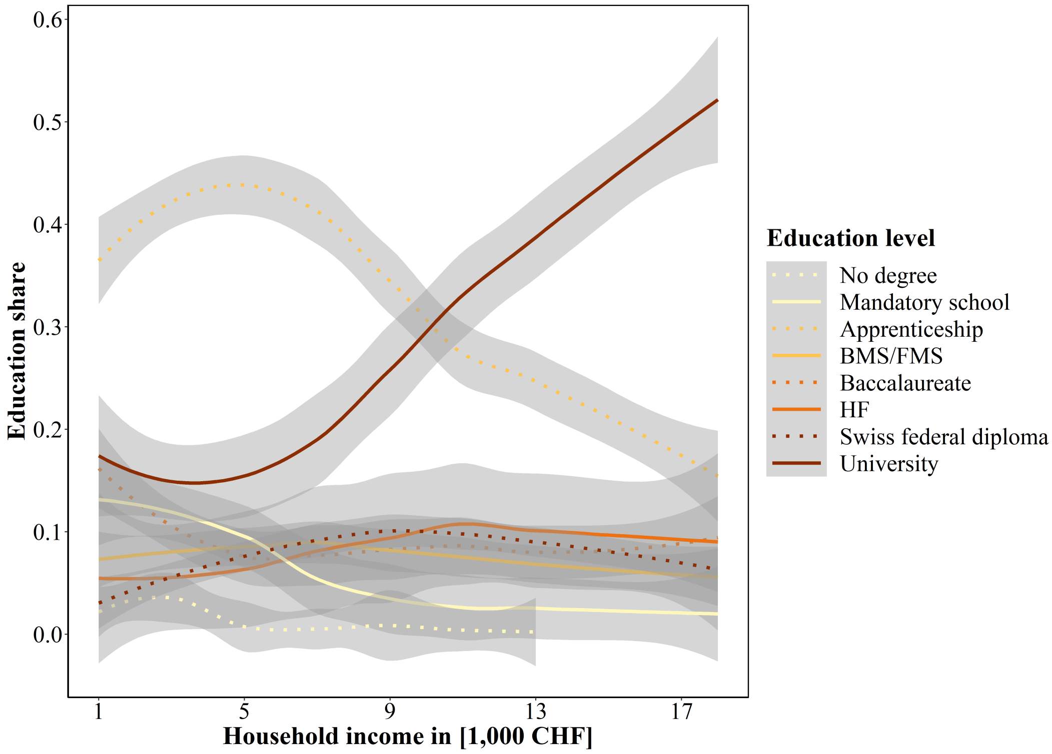
(Motor)Bike/Car	Year	GA	Half-fare card	Other ticket	No ticket
Bike	2010	12.3	48.8	5.5	33.4
	2015	11.7	41.7	7.4	39.2
	2021	15.6	53.5	5.0	25.8
Motorbike	2010	9.0	44.0	4.5	42.5
	2015	9.3	35.1	6.4	49.3
	2021	10.5	53.4	2.7	33.4
Car	2010	7.9	45.9	5.6	40.6
	2015	8.2	39.5	6.7	45.6
	2021	11.8	51.7	4.9	31.5

4.4 Household income and education level

As mentioned above, people with higher incomes appear to have higher MIV shares, while people with higher education may prefer modes such as PT or bike. In order to investigate this, the relationship between household income and education is examined.

In figure 6, education share according to household income can be seen. The gray areas account for variation according to the year. The two highest education shares are apprenticeship and university degree. Under a monthly household income of 11,000 CHF, people with an apprenticeship make up the largest education share, whereas, for income classes above this sum, people with a university degree comprise the largest education share. Although people with a university degree have lower shares of MIV (see table 9), high-income groups seem to have higher MIV shares (see figure 3). Given figure 6, this is probably due to the remaining 50% of high-income groups who do not possess a university degree.

Figure 6: Share of education degrees according to household income and year



4.5 Public transport waiting time

The PT waiting time is only available for RP data from 2015 and 2021. In order to avoid collinearity, the correlation of the waiting time with other LOS variables of PT is investigated. The highest observed correlation is between waiting time and the number of transfers (0.59). The next highest correlation is between waiting time and frequency (0.29). Except for the waiting time and the number of transfers, there is no pair of variables that shows a critical correlation.

4.6 Conclusions

Compared to the MTMC data, the VSS data has a younger, higher educated, and wealthier sample, which tends to live more in rural areas of the German-speaking part of Switzerland. This sample is also more likely to be single than married. Furthermore, the population from the VSS data has higher shares of mobility tools (PT season tickets, cars, bikes, and motorbikes).

There is a difference between mode shares when it comes to RP and SP data. Compared to SP data, MIV and walk have higher shares in RP data. Being male seems to increase the shares for MIV, while age appears to affect MIV and PT primarily. Whereas MIV use increases with age up to about 50 years and then decreases, the opposite seems to be the case for PT. Moreover, monthly household income mainly influences MIV usage. Increasing monthly household income appears to raise the likelihood of choosing MIV. The increase in likelihood exists up to a monthly household income of about 9,000 CHF. Above this sum, the likelihood appears impervious to monthly household income. Furthermore, the assumption that a higher monthly household income automatically leads to higher MIV shares in mode choice may not necessarily hold true. This is due to people with a university degree utilizing MIV less, despite making up the largest group of high-income classes. Hence, to obtain a more differentiated insight, the inclusion of various education levels appears to be necessary.

In addition, combining education degrees into only three levels may not be useful for modeling, given the differences in mode shares and mobility tool ownership across different education levels. The education levels belonging to the tertiary tier[3], for example, show differences in mode choice, even though they belong to the highest tier.

Household size only appears important if it is either a one-person household or a household with more people. Furthermore, the presence of kids seem to positively influence the likelihood of choosing MIV. The impact of Swiss citizenship does not appear to be substantial. The same cannot be said about language. A clear distinction between German-, French-, and Italian-speaking people is observed. German-speaking people appear to have higher shares of bike and PT. Moreover, home ownership seems to substantially increase the odds of choosing MIV, as does living in suburban or rural areas, working full-time, or being married. In terms of correlation, the highest correlation can be found between the presence of kids in a household and the household size. Furthermore, having access to a car negatively impacts the likelihood of owning a PT season ticket.

[3] According to Swiss Conference of Cantonal Ministers of Education (EDK) (2022), the levels HF, Swiss federal certificate, and university belong to this tier.

5 Modeling results

As seen in chapter 4, there are multiple variables, each with different effects on mode choice. Various models combine the variables discussed above to find the most suitable models. In the following chapter, the process and results from the model building process will be presented. It is important to note that the results are always seen relative to the reference levels and are not absolute.

Section 5.1 describes the steps of the model building process as well as the different variables included in the models. Section 5.2 compares the main models and section 5.3 presents the results from post-estimation.

5.1 Model building process

5.1.1 Steps

Initially, a basic model (MNL1) uses only LOS attributes (e.g., travel time and cost) and the years 2015 and 2021. In a second step, the trip purposes (e.g., shopping trip) are added to the model (MNL2). For the third model, socioeconomic variables are included. Multiple models are built in this third step because multiple socioeconomic variables can be included in various ways (e.g., continuous, dummy-coded, piecewise-linear). The incorporation of the two variables, age, and income, will be described in further detail in sections 5.1.2 and 5.1.3. From the model which emerges as the most suitable, the parameters insignificant at a 10% level are removed[4] (MNL3). In a fourth step, the LOS variables are removed from MNL3 and a model without them is estimated (MNL4). The fifth model (MIXL1) is based on the third model, but is a mixed logit model with random components added to the ASC. In a sixth step, interaction effects of socioeconomic variables with LOS variables are introduced in an MNL model. Afterward, all variables not significant at a 10% level are removed, and a new MNL model is estimated (MNL5) as well as a mixed logit model (MIXL2).

Among the different models estimated, one with interaction effects between gender and other socioeconomic variables exists. This is based on De Witte *et al.* (2013). The authors assume that more substantial effects probably arise from interaction terms between gender and other socioeconomic variables.

[4]This excludes control variables, such as RP, and the alternative specific constants (ASC).

Many variables and combinations are tested and shown to be not significant at the 10% level. For example, whether a household has children or not is not significant for any mode. Hence, it does not appear in any model.

The first comparison is between MNL2, MNL3, MNL4, and MIXL1 (see table 21). Afterward, MNL5 and MIXL2 are compared. MNL1 can be found in appendix B.1.

5.1.2 Age

Based on chapter 4.2, three models (MNLA.1, MNLA.2, and MNLA.3) involve age in different ways:

- As two dummy variables: 34 years or younger and 66 years or older (age 35 - 65 = reference)
- As two piecewise-linear effects: 34 years or younger and 66 years or older (age 35 - 65 = reference)
- As a continuous variable with age divided by ten

MNLA.1 is the model including age in the form of two dummies (age $<$ 35 and age $>$ 65). MNLA.2 is the model with age as two piecewise-linear effects (linear for age $<$ 35 and linear for age $>$ 65). MNLA.3 is the MNL that uses age as a continuous variable. The three models include LOS and control variables, trip attributes, residential location area, gender, and age. Although mode shares for MIV and PT seem to follow quadratic functions regarding age (see figure 2), age is not included as a quadratic function. This is due to the high correlation between linear and quadratic terms with the quadratic function.

As can be seen in appendix B.2, both, MNLA.1 and MNLA.2 perform better than MNLA.3. The differences in model fit between MNLA.1 and MNLA.2 are minimal, but with a slight advantage for MNLA.2. However, age will be included in the form of two dummy variables in subsequent models, as this is both easier to interpret and the difference in goodness-of-fit is negligible.

5.1.3 Income

Similar to age, different models include income in various ways.

- As a continuous variable in steps of 1,000 CHF
- As two dummy variables: income up to 5,000 CHF and income from 11,000 upward. These correspond to the 25% and the 75% quantiles for income in the data set.
- As two piecewise-linear effects: income below 5,000 CHF and income above 11,000 CHF.
- One dummy: Income below 10,000 CHF. This corresponds to the median.
- As four dummies (income $<$ 2,000 CHF, 2,000 - 4,000 CHF, 4,000 - 6,000 CHF, and $>$ 14,000 CHF).
- As five dummies (income $<$ 2,000 CHF, 2,000 - 4,000 CHF, 4,000 - 6,000 CHF, 14,000 - 16,000 CHF, and $>$ 16,000 CHF).

MNLI.1 includes income as a continuous variable, with income divided by 1,000. MNLI.2 includes income as two dummies, with the first dummy representing income in the lower 25% quantile and the second dummy representing income above the 75% quantile. MNLI.3 incorporates income piecewise-linear. Income is continuous below the 25% and above the 75% quantile. MNLI.4 has one dummy variable for income below the median (i.e., below 10,000 CHF). MNLI.5 and MNLI.6 include income with four or five dummies. Both have dummy variables for income categories $<$ 2,000 CHF, 2,000 - 4,000 CHF, and 4,000 - 6,000 CHF. While MNLI.5 has one dummy variable for income above 14,000 CHF, MNLI.6 has a dummy variable for income between 14,000 and 16,000 CHF and one for income above 16,000 CHF.

As seen in appendix B.3, MNLI.6 has the best goodness-of-fit. Hence, this model is chosen for further steps.

5.1.4 Utility functions

As shown in table 19, utility functions include travel times of the four modes. For MIV and PT, they also include travel costs. In the case of PT, access and egress time, frequency, and the number of transfers are also part of utility functions[5].

[5]Because of the correlation of waiting time with the number of transfers and because in preparatory models, the estimate for waiting time was positive, the waiting time is not part of the utility functions.

Table 19: Overview of LOS-attributes included in this work.

Attribute	Bike	MIV	PT	Walk
Travel time	✓	✓	✓	✓
Travel cost		✓	✓	
Access + egress time			✓	
Frequency			✓	
Number of transfers			✓	

In total, there are 28 different utility functions. Both MTMC 2010 and MTMC 2015 have ten utility functions (4 RP, 6 SP[6]). VSS 2021 has eight utility functions (4RP, 4 SP).

Table 20 shows the various socioeconomic and trip attributes, control variables, alternative specific constants (ASC), and random components used in the following models.

Table 20: Overview of socioeconomic attributes, trip attributes, control variables, ASC, and random components included in this work.

Socioeco. attribute	Trip attribute	Control variable/ASC	Random component
Residential location	Purpose	RP	Error components
area		Year	
Gender		ASC	
Age			
Income			
Language			
Education			
Employment level			
Civil status			
Citizenship			
Homeowner			

- RP: dummy variable with levels "RP" and "SP" (= reference)
- Year: dummy variables with levels "2010" (= reference), "2015", and "2021"
- Purpose: dummy variables with levels "work" (= reference), "education", "shopping", "business", "leisure", and "other"

[6]There are six SP utility functions from the MTMC data, because there are two attribute clauses for MIV and PT, containing different LOS variables. In the case of PT, the first attribute clause does not contain access time and the second does not contain frequency. There are also further differences for MIV. However, these are not relevant in the scope of this thesis. In the case of MIV, search time for a parking space has been added to travel time. The costs for a parking space have been added to the travel costs, since this is true for the VSS 2021 data set. Hence, there are not any separate parameters for these two LOS-attributes.

- Residential location area: dummy variables with levels "urban" (= reference), "suburban", and "rural"
- Gender: dummy variable with levels "male" and "female" (= reference)
- Age: dummy variables with levels "18 - 34", "35 - 65" (= reference), and "> 65"
- Income: dummy variables with levels "< 2,000 CHF", "2,000 - 4,000 CHF", "4,000 - 6,000 CHF", "6,000 - 14,000 CHF" (= reference), "14,000 - 16,000 CHF)", "> 16,000 CHF"
- Language: dummy variables with levels "German" (= reference), "French", and "Italian"
- Education: dummy variables with levels "no degree at all", "only finished mandatory school", "apprenticeship" (= reference), "BMS/FMS", "baccalaureate", "HF", "Swiss federal diploma", and "university"
- Employment level: dummy variables with levels "working full-time" (= reference), "working part-time", and "not employed"
- Civil status: dummy variable with levels "married" and "other" (= reference)
- Citizenship: dummy variable with levels "Swiss" and "other" (= reference)
- Homeowner: dummy variable with levels "Home owner" and "other" (= reference)

The utility functions for MXIL1 are in appendix B.4. As mentioned in chapter 4, the data sets are structurally different. The years 2015 and 2021 serve as a control variables. They capture these structural differences between data sets, e.g., in selected trips.

5.2 Model comparison

Table 21 compares MNL2, MNL3, MNL4, and MIXL1. As can be observed, the ASC of PT is the only negative ASC in MNL2, MNL3, and MIXL1. However, in MNL4, all ASC are negative. This implies that ignoring LOS variables omits many effects that negatively affect modes' average utility. Furthermore, the ASC for walk is substantially larger in MIXL1 than in the other three models, while the other two ASC are insignificant ($p > 0.1$). Furthermore, accounting for unobserved taste heterogeneity leads to an insignificant ($p > 0.1$) difference in choice probability for bike and PT, relative to MIV. The RP dummy variables are all highly significant ($p < 0.01$) and negative in the case of MIXL1. All models indicate that the difference between RP bike and RP MIV is highly significant ($p < 0.01$) and the largest compared to the other modes.

The LOS estimates have the expected negative signs and all of them are highly significant ($p < 0.01$). The absolute values of the LOS estimates approximately double from MNL3 to MIXL1, indicating very strong negative effects for higher LOS variables. The effects of the control variables 2015 and 2021 are comparable for MNL2 and MNL3, except for 2021 bike, where the sign changes. For both MNL2 and MIXL1, the signs for the control variables 2015 and 2021 are negative. Furthermore, the previously (MNL3) significant ($p < 0.01$) control variable 2015 bike is not significant ($p > 0.1$) in MIXL1. The signs of trip purpose variables are the same across the four models. For education trips, walk and PT appear to more likely choices compared to PT. Meanwhile, for shopping and business trips, MIV is the most convenient mode. In the case of leisure trips, walk is preferred to MIV and MIV is preferred to PT and bike.

The residential location area variables are almost all highly significant ($p < 0.01$) and negative, indicating that in suburban and rural areas, MIV has an advantage over the other modes. The same effect can be observed for speaking French or Italian.

According to expectations, being male increases the probability of choosing bike over MIV. Furthermore, young people seem less inclined to walk, while older people are less likely to choose bike. Both are in line with expectations. In addition, estimates for incomes above 16,000 CHF align with expectations. Higher household incomes tend to prefer MIV, especially over bike. However, the absence of income effects under 9,000 CHF is not according to expectations.

The effects of education are in line with expectations. Individuals without a degree are more likely to choose MIV over bike, while individuals with a baccalaureate, HF, or university degree tend to prefer walk, bike, and PT. Moreover, the effects of education are strongest on bike. Similarly, the estimates for employment level correspond to expectations. Working part-time increases the likelihood of choosing walk, bike, or PT over MIV, while not being employed increases the likelihood of choosing either walk or PT over MIV.

As expected, being married has a negative effect on the probability of choosing PT. All models' estimates are also highly significant ($p < 0.01$). In addition, being a Swiss citizen positively affects choosing bike or PT in all models. The effects of home ownership on walk and PT are negative and significant ($p < 0.1$) in MNL3, MNL4, and MIXL1.

The scale parameter for RP is highly significant ($p < 0.01$) and positive in each model. In MIXL1, however, the value is barely half of what it is in MNL3. All four random components are substantial and highly significant ($p < 0.01$). The largest random component is for bike, meaning that the unobserved preference heterogeneity is largest for that mode, while it is smallest for PT.

Finally, the MIXL1 model has substantially better goodness-of-fit values. As can be seen, the McFadden R^2 increases from 0.33 (MNL3) to 0.56, while AIC and BIC both decrease by approximately 34%. The difference between MNL2 and MNL3 is noticeable, but the increase does not seem very substantial given that MNL3 has almost twice as many parameters. MNL4 has substantially worse goodness-of-fit values. Given that MNL4 has 23 additional parameters compared to MNL2, the goodness-of-fit values of MNL4 are even worse. However, these results are according to expectation, as MNL4 does not include any LOS variables.

Overall, the parameters of MIXL1 are almost always of a larger magnitude than the parameters of MNL3. The inclusion of random components does not change the signs of most coefficients. The increased magnitude of the estimates, the significant random components, and the better model fit imply a substantial amount of unobserved heterogeneity in the sample.

Table 21: Estimation results of MNL2, MNL3, MNL4, and MIXL1

Base cat.: MIV	MNL2	MNL3	MNL4	MIXL1
	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
ASC walk: α_{walk}	1.80***	1.73***	−0.23**	4.34***
	(0.16)	(0.15)	(0.11)	(0.43)
ASC bike: α_{bike}	0.63***	0.29*	−0.37**	0.60
	(0.11)	(0.16)	(0.14)	(0.49)
ASC PT: α_{PT}	−0.35***	−0.30***	−0.61***	−0.26
	(0.06)	(0.09)	(0.08)	(0.21)
RP walk	−0.17**	−0.13*	−0.05	−0.81***
	(0.07)	(0.06)	(0.05)	(0.17)
RP bike	−1.04***	−1.01***	−0.87***	−4.01***
	(0.08)	(0.07)	(0.06)	(0.18)
RP PT	0.10	0.08	−0.07	−1.21***
	(0.07)	(0.06)	(0.05)	(0.11)
Travel time walk	−6.22***	−6.02***		−15.03***
	(0.26)	(0.25)		(0.65)
Travel time bike	−5.85***	−5.88***		−13.06***
	(0.26)	(0.26)		(1.08)
Travel time MIV	−3.02***	−2.88***		−5.64***
	(0.12)	(0.12)		(0.34)
Travel time PT	−2.26***	−2.14***		−4.37***
	(0.11)	(0.11)		(0.35)
Travel costs	−0.11***	−0.10***		−0.16***
	(0.01)	(0.01)		(0.02)

Table 21 (continued)

Base cat.: MIV	MNL2 Coef./(SE)	MNL3 Coef./(SE)	MNL4 Coef./(SE)	MIXL1 Coef./(SE)
Access + egress time PT	−1.86***	−1.58***		−3.75***
	(0.18)	(0.17)		(0.35)
Frequency PT	−0.94***	−0.80***		−1.58***
	(0.08)	(0.08)		(0.14)
Number of transfers PT	−0.23***	−0.23***		−0.48***
	(0.02)	(0.02)		(0.03)
2015 walk	−0.34***	−0.38***	−0.66***	−2.14***
	(0.10)	(0.10)	(0.10)	(0.28)
2015 bike	0.23**	0.29***	−0.14*	−0.36
	(0.09)	(0.09)	(0.08)	(0.29)
2015 PT	−0.33***	−0.30***	−0.16***	−0.92***
	(0.05)	(0.05)	(0.04)	(0.11)
2021 walk	−1.45***	−1.44***	−1.39***	−4.08***
	(0.12)	(0.14)	(0.12)	(0.38)
2021 bike	0.35***	−0.22**	−0.52***	−0.99***
	(0.10)	(0.11)	(0.10)	(0.33)
2021 PT	−0.26***	−0.28***	−0.38***	−0.71***
	(0.07)	(0.07)	(0.06)	(0.17)
Education trip walk	0.75**	0.69**	0.47	1.65**
	(0.33)	(0.30)	(0.33)	(0.59)
Education trip bike	0.36			
	(0.23)			
Education trip PT	0.59***	0.34**	0.44***	0.92***
	(0.13)	(0.13)	(0.12)	(0.28)
Shopping trip walk	−0.18			
	(0.14)			
Shopping trip bike	−1.16***	−0.92***	−0.58***	−3.41***
	(0.10)	(0.09)	(0.08)	(0.27)
Shopping trip PT	−0.53***	−0.58***	−0.64***	−1.68***
	(0.06)	(0.06)	(0.06)	(0.14)
Business trip walk	−0.54**	−0.41*	−0.08	−1.23
	(0.25)	(0.24)	(0.25)	(0.86)
Business trip bike	−0.42*	−0.53**	−0.27	−2.20***
	(0.22)	(0.22)	(0.20)	(0.62)
Business trip PT	−0.78***	−0.76***	−0.65***	−1.57***
	(0.12)	(0.12)	(0.12)	(0.24)
Leisure trip walk	0.27**	0.40***	0.04	1.88***
	(0.13)	(0.10)	(0.08)	(0.24)
Leisure trip bike	−0.47***	−0.28***	−0.25***	−1.01***
	(0.09)	(0.09)	(0.08)	(0.22)
Leisure trip PT	−0.24***	−0.32***	−0.43***	−0.59***
	(0.05)	(0.05)	(0.05)	(0.12)

Table 21 (continued)

Base cat.: MIV	MNL2	MNL3	MNL4	MIXL1
	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
Other trip walk	0.18			
	(0.59)			
Other trip bike	−1.71*			
	(0.96)			
Other trip PT	0.16			
	(0.33)			
Suburban area walk		−0.33***	−0.44***	−0.69**
		(0.10)	(0.09)	(0.25)
Suburban area bike		−0.28***	−0.60***	−0.83***
		(0.08)	(0.08)	(0.26)
Suburban area PT		−0.32***	−0.48***	−0.80***
		(0.05)	(0.05)	(0.12)
Rural area bike		−0.15	−0.59***	−0.68**
		(0.10)	(0.09)	(0.30)
Rural area PT		−0.37***	−0.64***	−0.74***
		(0.06)	(0.05)	(0.14)
French speak. walk		−0.23**	−0.19*	−0.83***
		(0.11)	(0.10)	(0.29)
French speak. bike		−0.98***	−0.93***	−3.25***
		(0.11)	(0.10)	(0.30)
French speak. PT		−0.31***	−0.56***	−0.70***
		(0.06)	(0.05)	(0.13)
Italian speak. walk		−0.43**	−0.36*	−1.03**
		(0.21)	(0.18)	(0.48)
Italian speak. bike		−1.02***	−0.81***	−3.61***
		(0.21)	(0.20)	(0.61)
Italian speak. PT		−0.43***	−0.66***	−0.92***
		(0.11)	(0.10)	(0.25)
Male bike		0.36***	0.26***	1.08***
		(0.07)	(0.07)	(0.21)
Age (< 35) walk		−0.19*	−0.18*	−0.57**
		(0.10)	(0.09)	(0.26)
Age (> 65) bike		−0.93***	−0.77***	−2.86***
		(0.13)	(0.12)	(0.39)
Income (> 16,000 CHF) walk		−0.31*	−0.17	−0.84**
		(0.17)	(0.15)	(0.42)
Income (> 16,000 CHF) bike		−0.47***	−0.36***	−1.16***
		(0.12)	(0.11)	(0.35)
Income (> 16,000 CHF) PT		−0.24***	−0.14**	−0.42**
		(0.08)	(0.07)	(0.17)
No degree bike		−1.04*	−0.96*	−3.04**
		(0.52)	(0.52)	(1.09)

Table 21 (continued)

Base cat.: MIV	MNL2 Coef./(SE)	MNL3 Coef./(SE)	MNL4 Coef./(SE)	MIXL1 Coef./(SE)
Baccalaureate walk		0.38^{**}	0.32^{**}	1.15^{***}
		(0.16)	(0.14)	(0.40)
Baccalaureate bike		0.42^{***}	0.47^{***}	1.59^{***}
		(0.12)	(0.11)	(0.42)
Baccalaureate PT		0.33^{***}	0.44^{***}	1.08^{***}
		(0.08)	(0.07)	(0.18)
HF walk		0.27	0.12	0.15
		(0.20)	(0.16)	(0.44)
HF bike		0.52^{***}	0.50^{***}	1.45^{***}
		(0.13)	(0.12)	(0.36)
University walk		0.67^{***}	0.66^{***}	1.86^{***}
		(0.11)	(0.09)	(0.27)
University bike		0.87^{***}	0.91^{***}	2.76^{***}
		(0.09)	(0.08)	(0.26)
University PT		0.45^{***}	0.62^{***}	1.26^{***}
		(0.05)	(0.05)	(0.12)
Working part-time walk		0.16	0.17^{*}	0.50^{*}
		(0.11)	(0.09)	(0.27)
Working part-time bike		0.35^{***}	0.35^{***}	1.15^{***}
		(0.08)	(0.07)	(0.25)
Working part-time PT		0.23^{***}	0.26^{***}	0.52^{***}
		(0.05)	(0.05)	(0.11)
Not employed walk		0.12	0.30^{***}	0.31
		(0.12)	(0.11)	(0.31)
Not employed PT		0.25^{***}	0.29^{***}	0.50^{***}
		(0.06)	(0.06)	(0.14)
Married PT		-0.17^{***}	-0.23^{***}	-0.31^{***}
		(0.04)	(0.04)	(0.09)
Swiss bike		0.36^{***}	0.35^{***}	1.07^{***}
		(0.11)	(0.11)	(0.36)
Swiss PT		0.12^{*}	0.19^{***}	0.14
		(0.07)	(0.06)	(0.18)
Home owner walk		-0.34^{***}	-0.28^{***}	-1.21^{***}
		(0.09)	(0.08)	(0.24)
Home owner PT		-0.12^{**}	-0.08^{*}	-0.35^{***}
		(0.05)	(0.04)	(0.11)
Scale parameter RP: σ_{RP}	1.02^{***}	1.07^{***}	1.34^{***}	0.50^{***}
	(0.04)	(0.04)	(0.05)	(0.02)
$\sigma_{ASC,walk}$				3.73^{***}
				(0.18)
$\sigma_{ASC,bike}$				4.79^{***}
				(0.17)

Table 21 (continued)

Base cat.: MIV	MNL2 Coef./(SE)	MNL3 Coef./(SE)	MNL4 Coef./(SE)	MIXL1 Coef./(SE)
$\sigma_{ASC,MIV}$				3.05^{***}
				(0.12)
$\sigma_{ASC,PT}$				1.69^{***}
				(0.18)
Number of parameters	36	67	59	71
Number of respondents	11,272	11,272	11,272	11,272
Number of choice observations	87,326	87,326	87,326	87,326
LL(null)	−78,203.49	−78,203.49	−78,203.49	−78,203.49
LL(init)	−79,582.07	−78,422.36	−78,457.77	−45,665.47
LL(final)	−54,302.70	−52,601.22	−61,492.59	−34,328.06
LL(choicemodel)	−54,302.70	−52,601.22	−61,492.59	−34,328.06
McFadden R2	0.31	0.33	0.21	0.56
AIC	108,677.40	105,336.44	123,103.18	68,798.13
AICc	108,677.64	105,337.26	123,103.81	68,799.04
BIC	109,014.99	105,964.73	123,656.45	69,463.92
Number of draws				1,000

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 22 shows MNL5 and MIXL2. The ASC for walk and PT are comparable to those of MNL3 and MIXL1. However, the ASC for bike is larger in magnitude and highly significant ($p < 0.01$). The main effects of travel times and the number of transfers in MNL5 and MIXL2 are similar to those in MNL3 and MIXL1. However, the main effects for access and egress time see a substantial reduction in magnitude and are also insignificant ($p > 0.1$) in MNL5 and MIXL2. The main effects for frequency are slightly larger in magnitude in MNL5 and MIXL2 compared to MNL3 and MIXL1.

The interaction between LOS and socioeconomic attributes makes it possible to see the attribute sensitivity for different socioeconomic groups. The models show that people living in suburban areas, people with incomes below 6,000 CHF, and people working part-time are less sensitive regarding increases in travel time for walk. However, there are differences regarding the travel time sensitivity of these different income groups. The lower the income, the less sensitive people are to an increase in travel time. Furthermore, people younger than 35 years are more sensitive towards travel time for walk and bike. People with a household income of between 2,000 and 4,000 CHF per month are less sensitive regarding increases in travel time bike. Furthermore, people with a household income between 4,000 and 6,000 CHF are less sensitive regarding an increase in travel time for

MIV or PT. The interaction terms between travel time MIV and various education levels show that people with these education levels are more sensitive to increases in travel time MIV. Regarding people without a degree, this is not according to expectations. Moreover, people without a degree are more sensitive to changes in MIV travel time than people with higher degrees. This is in contrast to Schmid *et al.* (2021). Homeowners are more sensitive to changes in MIV travel time. Most groups exhibiting elevated attribute sensitivities for specific travel times also have lower probabilities of choosing these specific modes.

The interaction terms with travel costs show that people with Swiss federal diplomas, HF degrees, and people who are not employed are marginally less sensitive to changes in attributes, as their interaction terms are all negative.

Access + egress time, frequency, and the number of transfers have more insignificant ($p > 0.1$) interaction terms in MIXL2 compared to travel times. The introduction of random components appears to account for the variation previously covered by these terms. In MIXL2, there is only one highly significant ($p < 0.01$) estimate for access and egress time: the interaction with Swiss. As the interaction shows, Swiss are more sensitive regarding changes in access and egress time than non-Swiss. Males are less sensitive to changes in frequency. Apart from the main effect, the only significant ($p < 0.1$) term for frequency in MIXL2 is the interaction with male, unlike MNL5, where also the interactions with income above 16,000 CHF and with home ownership are significant ($p < 0.1$). In MIXL2, only the main effect for the number of transfers is significant ($p < 0.1$), while in MNL5, the interaction with HF is also significant ($p < 0.1$).

The effect of the control variables 2015 and 2021 are similar in MNL5 and MIXL2 compared to MNL3 and MIXL1. However, in the two interaction models, 2021 bike is not included. The magnitudes of the trip purpose variables in MNL3 and MIXL1 are similar to those in MNL5 and MIXL2, and the signs also correspond.

Most of the main socioeconomic effects in MNL3, MIXL1, MNL5, and MIXL2 are similar. However, there are some variations in magnitude and signs. While in MNL3 and MIXL1, the effect of age under 35 years on the probability of choosing walk is negative, it is positive in MNL5 and MIXL2. This is due to the negative interaction term between travel time walk and age under 35 years.

Furthermore, the interaction models contain main effects which are not in MNL3 and MIXL1 and vice versa. For example, MNL5 and MIXL2 contain the main effects for household incomes below 2,000 CHF and between 2,000 and 4,000 CHF.

The scale parameters for RP are very similar compared to MNL3 and MIXL1. The standard deviations for the random components are similar as well. However, $sigma_{ASC,PT}$ is the only one that is smaller in magnitude compared to MIXL1. All the other standard deviations are larger in magnitude in MIXL2. Hence, the interaction terms increase the unobserved taste heterogeneity for all modes but PT, where they decrease the unobserved taste heterogeneity.

Furthermore, the BIC of MNL3 to MNL5 and of MIXL1 to MIXL2 each differ by less than 1%. Moreover, the BIC of MNL3 and MIXL1 is lower than that of MNL5 and MIXL2. However, the AIC for MNL5 and MIXL2 are lower than for MNL3 and MIXL1. Once again, the differences are below 1%. This is in accordance with Louviere *et al.* (2000), and Ortúzar and Willumsen (2011), who state that most of the variance can be explained by main effects and that interactions do not account for a large portion of the variance explained. Due to this and the easier interpretation of the coefficients, post-estimation will be based on the MIXL1.

Table 22: Estimation results of MNL5 and MIXL2

Base cat.: MIV	MNL5	MIXL2
	Coef./(SE)	Coef./(SE)
ASC walk: α_{walk}	1.80^{***}	4.18^{***}
	(0.16)	(0.40)
ASC bike: α_{bike}	0.95^{***}	2.59^{***}
	(0.13)	(0.33)
ASC PT: α_{PT}	-0.13	-0.14
	(0.11)	(0.23)
RP walk	-0.18^{**}	-0.84^{***}
	(0.07)	(0.18)
RP bike	-1.09^{***}	-4.13^{***}
	(0.07)	(0.17)
RP PT	0.01	-1.40^{***}
	(0.06)	(0.12)
Travel time walk	-6.62^{***}	-16.84^{***}
	(0.38)	(0.85)
Travel time walk * suburban area	0.74	2.59^{**}
	(0.50)	(1.23)
Travel time walk * age (< 35)	-1.76^{***}	-5.00^{***}
	(0.53)	(1.07)
Travel time walk * income (< 2,000 CHF)	3.19^{**}	7.87^{***}
	(1.15)	(2.75)
Travel time walk * income (2,000 - 4,000 CHF)	1.19^{*}	3.12^{***}

Table 22 (continued)

Base cat.: MIV	MNL5 Coef./(SE)	MIXL2 Coef./(SE)
	(0.65)	(1.11)
Travel time walk * income (4,000 - 6,000 CHF)	0.86***	2.01*
	(0.30)	(1.00)
Travel time walk * working part-time	0.42*	1.71**
	(0.25)	(0.70)
Travel time bike	−5.69***	−13.34***
	(0.31)	(0.57)
Travel time bike * age (< 35)	−1.25**	−1.82
	(0.47)	(1.16)
Travel time bike * income (2,000 - 4,000 CHF)	1.43	6.81***
	(0.89)	(1.25)
Travel time MIV	−2.64***	−5.32***
	(0.15)	(0.41)
Travel time MIV * income (4,000 - 6,000 CHF)	0.57**	1.12**
	(0.25)	(0.41)
Travel time MIV * no degree	−1.73***	−2.42**
	(0.46)	(0.91)
Travel time MIV * baccalaureate	−0.73***	−1.25***
	(0.17)	(0.36)
Travel time MIV * HF	−0.46**	−1.24***
	(0.23)	(0.40)
Travel time MIV * university	−0.22	−0.42
	(0.13)	(0.31)
Travel time MIV * home owner	−0.37***	−0.43*
	(0.11)	(0.24)
Travel time PT	−2.28***	−4.65***
	(0.12)	(0.38)
Travel time PT * income (4,000 - 6,000 CHF)	0.58**	0.96**
	(0.22)	(0.37)
Travel costs	−0.09***	−0.14***
	(0.01)	(0.02)
Travel costs * Swiss federal diploma	−0.05**	−0.06**
	(0.02)	(0.03)
Travel costs * HF	−0.05**	−0.08**
	(0.02)	(0.03)
Travel costs * not employed	−0.04***	−0.10***
	(0.01)	(0.03)
Access + egress time PT	−0.53*	−0.13
	(0.27)	(0.66)
Access + egress time * Swiss fed. dipl.	−1.57***	−1.38
	(0.45)	(1.02)
Access + egress time * Italian speak.	−0.77	−1.44*

Table 22 (continued)

Base cat.: MIV	MNL5 Coef./(SE)	MIXL2 Coef./(SE)
	(0.50)	(0.84)
Access + egress time * Swiss	−1.17***	−4.22***
	(0.29)	(0.67)
Frequency PT	−1.16***	−1.99***
	(0.12)	(0.22)
Frequency * male	0.32**	0.40*
	(0.14)	(0.23)
Frequency * income (2,000 - 4,000 CHF)	0.48*	0.47
	(0.24)	(0.33)
Frequency * income (> 16,000 CHF)	−0.81***	−0.57
	(0.25)	(0.43)
Frequency * HF	0.34	0.22
	(0.26)	(0.40)
Frequency * home owner	0.30**	0.27
	(0.14)	(0.24)
Number of transfers PT	−0.21***	−0.35***
	(0.05)	(0.09)
Number of transfers * income (< 2,000 CHF)	0.18	0.31
	(0.14)	(0.22)
Number of transfers * HF	−0.17**	−0.17
	(0.07)	(0.10)
Number of transfers * Swiss	−0.01	−0.13
	(0.05)	(0.09)
2015 walk	−0.44***	−2.25***
	(0.11)	(0.29)
2015 bike	0.30***	−0.18
	(0.08)	(0.22)
2015 PT	−0.28***	−0.83***
	(0.05)	(0.11)
2021 walk	−1.32***	−3.39***
	(0.13)	(0.35)
2021 PT	−0.25***	−0.53***
	(0.07)	(0.16)
Education trip walk	0.79**	1.75
	(0.31)	(1.11)
Education trip PT	0.42***	1.10***
	(0.13)	(0.29)
Shopping trip bike	−0.97***	−3.50***
	(0.09)	(0.25)
Shopping trip PT	−0.52***	−1.55***
	(0.06)	(0.13)
Business trip walk	−0.46*	−1.24*

Table 22 (continued)

Base cat.: MIV	MNL5 Coef./(SE)	MIXL2 Coef./(SE)
	(0.25)	(0.73)
Business trip bike	-0.43^{*}	-1.89^{***}
	(0.23)	(0.60)
Business trip PT	-0.74^{***}	-1.56^{***}
	(0.12)	(0.24)
Leisure trip walk	0.41^{***}	1.98^{***}
	(0.10)	(0.25)
Leisure trip bike	-0.31^{***}	-1.04^{***}
	(0.09)	(0.22)
Leisure trip PT	-0.27^{***}	-0.46^{***}
	(0.05)	(0.11)
Suburban area walk	-0.75^{***}	-2.34^{***}
	(0.20)	(0.52)
Suburban area bike	-0.34^{***}	-1.03^{***}
	(0.09)	(0.25)
Suburban area PT	-0.34^{***}	-0.89^{***}
	(0.05)	(0.12)
Rural area walk	-0.28^{**}	-1.46^{***}
	(0.13)	(0.32)
Rural area bike	-0.22^{**}	-1.07^{***}
	(0.10)	(0.28)
Rural area PT	-0.39^{***}	-0.96^{***}
	(0.06)	(0.14)
French speak. bike	-0.96^{***}	-3.27^{***}
	(0.10)	(0.30)
French speak. PT	-0.30^{***}	-0.60^{***}
	(0.06)	(0.13)
Italian speak. bike	-1.06^{***}	-3.31^{***}
	(0.21)	(0.53)
Italian speak. PT	-0.34^{**}	-0.73^{***}
	(0.12)	(0.24)
Male PT	-0.18^{***}	-0.35^{***}
	(0.05)	(0.11)
Age (< 35) walk	0.58^{***}	1.63^{***}
	(0.20)	(0.46)
Age (< 35) bike	0.33^{**}	0.44
	(0.14)	(0.40)
Age (> 65) bike	-0.97^{***}	-3.05^{***}
	(0.13)	(0.38)
Income (< 2,000 CHF) walk	-1.33^{***}	-2.89^{**}
	(0.47)	(1.26)
Income (2,000 - 4,000 CHF) walk	-0.50^{*}	-0.92

Table 22 (continued)

Base cat.: MIV	MNL5 Coef./(SE)	MIXL2 Coef./(SE)
	(0.28)	(0.62)
Income (2,000 - 4,000 CHF) bike	-0.59^{**}	-2.24^{***}
	(0.25)	(0.48)
Income (> 16,000 CHF) bike	-0.43^{***}	-0.99^{***}
	(0.12)	(0.34)
No degree bike	-1.49^{***}	-3.63^{**}
	(0.52)	(1.35)
No degree PT	-0.59^{**}	-1.10^{**}
	(0.28)	(0.54)
Mandatory school PT	0.17^{*}	0.16
	(0.09)	(0.19)
HF bike	0.29^{**}	0.92^{**}
	(0.13)	(0.41)
University walk	0.57^{***}	1.60^{***}
	(0.11)	(0.29)
University bike	0.77^{***}	2.52^{***}
	(0.09)	(0.26)
University PT	0.37^{***}	1.04^{***}
	(0.07)	(0.16)
Working part-time PT	0.07	0.23^{**}
	(0.05)	(0.11)
Married PT	-0.14^{***}	-0.29^{***}
	(0.04)	(0.09)
Swiss PT	0.22^{**}	0.61^{***}
	(0.09)	(0.17)
Home owner PT	-0.27^{***}	-0.39^{***}
	(0.06)	(0.14)
Scale parameter RP: σ_{RP}	1.02^{***}	0.49^{***}
	(0.04)	(0.02)
$\sigma_{ASC,walk}$		3.94^{***}
		(0.17)
$\sigma_{ASC,bike}$		4.93^{***}
		(0.15)
$\sigma_{ASC,MIV}$		3.38^{***}
		(0.08)
$\sigma_{ASC,PT}$		0.85^{***}
		(0.14)
Number of parameters	88	92
Number of respondents	11,272	11,272
Number of choice observations	87,326	87,326
LL(null)	−78,203.49	−78,203.49
LL(init)	−78,923.35	−81,253.81

Table 22 (continued)

Base cat.: MIV	MNL5 Coef./(SE)	MIXL2 Coef./(SE)
LL(final)	−52,492.16	−34,218.73
LL(choicemodel)	−52,492.16	−34,218.73
McFadden R2	0.33	0.56
AIC	105,160.32	68,621.47
AICc	105,161.72	68,623.00
BIC	105,985.53	69,484.19
Number of draws		1,000

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

As previously mentioned, a model with interactions between gender and other socioeconomic variables is also estimated. According to expectations, some interaction terms have a larger absolute value than the main effect of gender. However, there is no substantial increase in goodness-of-fit. The model can be found in appendix B.5.

5.3 Post-estimation

This section discusses the post-estimation results for the MIXL1 model. The post-estimation consists of the value of time (VoT), the elasticity values, the partworth analysis, and the marginal probability effects (MPE).

5.3.1 Value of time and willingness-to-pay

Table 23 shows the value of time (VoT) and the willingness-to-pay (WTP) for the MIXL1 model. It can be seen that the VoT for walk is almost three times larger than the VoT for MIV. All of the VoT for the four modes are relatively high. This may be explained by the fact that the VoT is solely calculated based on mode choice and not also on route choice data. Furthermore, there are neither interactions with the trip distance or other variables, usually done in national valuation studies, nor are socioeconomic weights applied to account for over- or underrepresentation of different groups.

Weis *et al.* (2021) include interaction terms with trip distance. The VoT and WTP they obtain for MTMC 2010 and 2015 are substantially different from those in table 23. In most cases, they are less than half of the values in the table below. However, Weis *et al.* (2021) find significant differences in VoT and WTP between MTMC 2010 and 2015. The authors trace the differences, among other reasons, back to different lengths of trips in 2010 and 2015. The value most similar to Weis *et al.* (2021) is the WTP for the number of transfers. In Weis *et al.* (2021), the WTP hereof is 2.0 CHF/transfer (1.0 CHF/transfer respectively). Furthermore, according to the literature, the ranking of the different travel times is also comparable to Weis *et al.* (2021). Walk and bike travel times are valued highest, followed by MIV and PT.

Table 23: Value of time (VoT) and willingness-to-pay (WTP) for the MIXL model

	WTP		SE	t-value
Walk	93.91	[CHF/h]	9.84	9.54
Bike	81.58	[CHF/h]	9.93	8.21
MIV	35.23	[CHF/h]	2.40	14.69
PT	27.32	[CHF/h]	1.64	16.67
Access + egress time PT	23.40	[CHF/h]	2.67	8.76
Frequency PT	9.85	[CHF/h]	1.60	6.15
Number of transfers PT	2.97	[CHF/transfer]	0.32	9.35

5.3.2 Elasticity values

The own- and cross-elasticities can be seen in table 24. All the signs are according to expectation, and the highest absolute values for elasticity are the own-elasticities for travel times, with walk having the highest magnitude.

Bike benefits most highly from an increase in walk travel time. PT profits the most from an increase in both bike and MIV travel time, while MIV benefits most highly from an increase in PT travel time. PT reacts more sensitively to an increase in travel costs (-0.14) than MIV (-0.03). On the other hand, an increase in travel costs for MIV has a greater effect on PT (+0.08) than an increase in travel costs for PT has on MIV (+0.04).

Table 24: Own- and cross-RP-elasticities corresponding to a 1% increase in the attributes

Attribute	Walk	Bike	MIV	PT
Travel time walk	-0.86	0.19	0.05	0.15
Travel time bike	0.05	-0.67	0.05	0.12
Travel time MIV	0.03	0.08	-0.11	0.33
Travel time PT	0.03	0.06	0.09	-0.35
Travel cost MIV	0.01	0.01	-0.03	0.08
Travel cost PT	0.02	0.02	0.04	-0.14
Access time PT	0.03	0.05	0.03	-0.15
Frequency PT	0.02	0.02	0.02	-0.11
Nbr. of transfers PT	0.00	0.01	0.02	-0.06

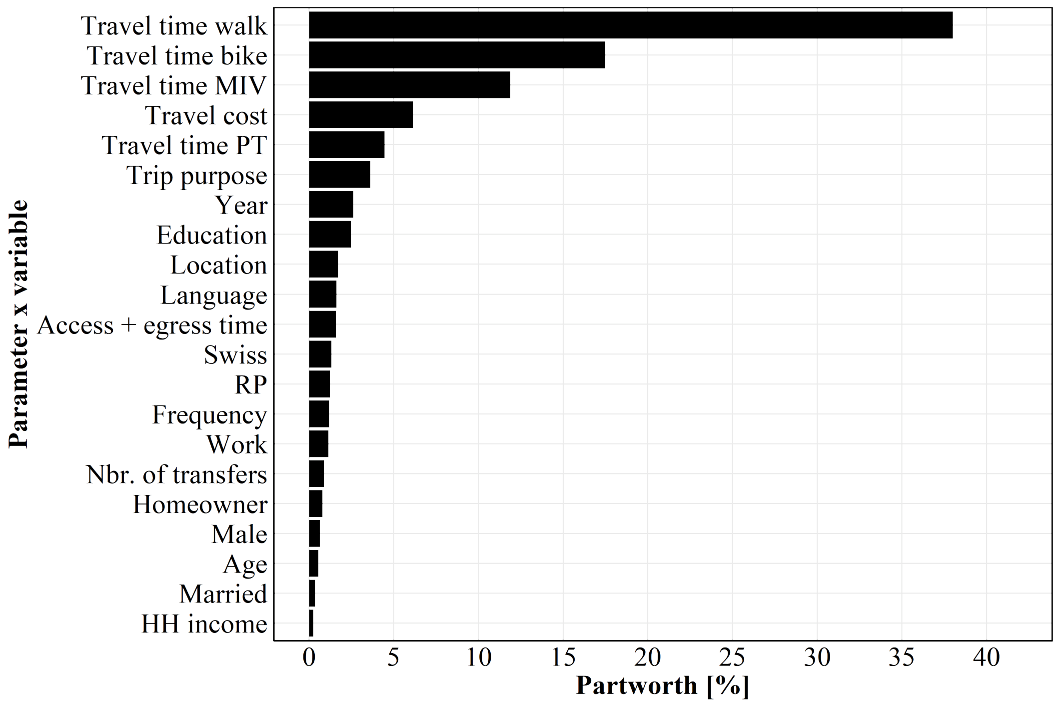
5.3.3 Partworth

Figure 7 shows the partworth of different attributes. The various attributes (except travel time) are aggregated using umbrella terms. For example, the effects of the control variables 2015 and 2021 are aggregated using the term year. In addition, the effects are not mode-specific but aggregated over all modes.

The decrease in partworth appears to follow a negative-reciprocal trend with an initial sharp decrease in partworth, followed by an increasingly slow decrease in partworth. On average, LOS variables have a higher impact on utility than socioeconomic variables. Furthermore, the three largest partworths all belong to travel time attributes. With approximately 38%, travel time walk shows the highest influence. With approximately

2.5%, education is the highest-ranking socioeconomic variable. Although this is about 15 times smaller than the partworth for travel time walk, it is still higher than the partworths of the LOS variables access time, frequency, and the number of transfers. The smallest average contribution stems from the household income, at less than 1%.

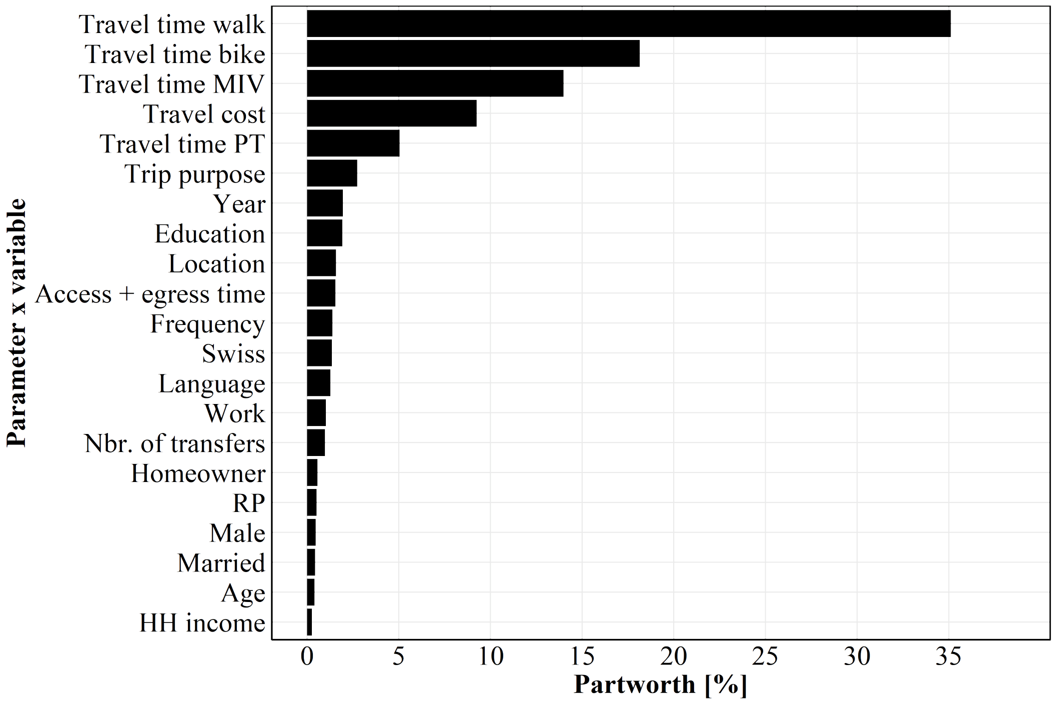
Figure 7: Partworth of different attributes for MIXL1



The ranking of partworths differs slightly for MNL3, as seen in figure 8. While the order of the nine highest-ranking attributes remains unchanged, the remaining LOS attributes rank higher for MNL3 than for MIXL1. Furthermore, RP is the fifth-lowest attribute for MNL3 and the ninth-lowest for MIXL1. Accounting for unobserved taste heterogeneity primarily increases the importance of language and RP. Overall, however, the nine most important attributes remain the same. In addition to the ranking, the partworth itself is also different. Travel time walk has a partworth of about 35%, which is slightly smaller than in MIXL1. Additionally, the differences between travel cost and travel time PT and between travel time PT and trip purpose are larger in figure 8.

Notably, partworths of socioeconomic attributes are small compared to those of LOS attributes in MIXL1 and MNL3. Thus, accounting for unobserved taste heterogeneity may change the order of some attributes slightly, but the overall contribution of socioeconomic attributes is neither substantially decreased nor increased.

Figure 8: Partworth of different attributes for MNL3



5.3.4 Marginal probability effects

Figure 9 shows the mode-specific MPE[7] for MIXL1. The largest absolute MPE result from the data type (RP vs. SP), followed by the control attribute for 2021. The three most influential socioeconomic attributes are having a university degree, speaking Italian, and having a baccalaureate.

Surprisingly, being male has negative MPE on MIV use, which contradicts table 8. Furthermore, male is only included for bike in MIXL1 (see table 21). Hence, the estimate of that parameter only displays the effect of male for bike relative to MIV. In addition, the MPE per attribute have to sum up to 0 over all alternatives. And since neither PT nor walk have a parameter for gender in MIXL1, the positive effect of male on the choice of bike has to be compensated by all three modes. As the probabilities of choosing a mode have to add up to one, increasing the probability of only one mode necessarily leads to decreasing the probabilities of the other modes. The MPE for age < 35 do not match expectations, as they increase the probability of choosing MIV, contradictory to figure 2. The positive effect of home ownership on the probability of choosing bike is also unexpected. The surprising signs may indicate interactions between various socioeconomic attributes that are not accounted for in the model. The effects of the other attributes

[7] A table containing the corresponding MPE values can be found in appendix B.6

mostly demonstrate the expected signs.

Figure 9: RP-MPE, mode specific, for MIXL1

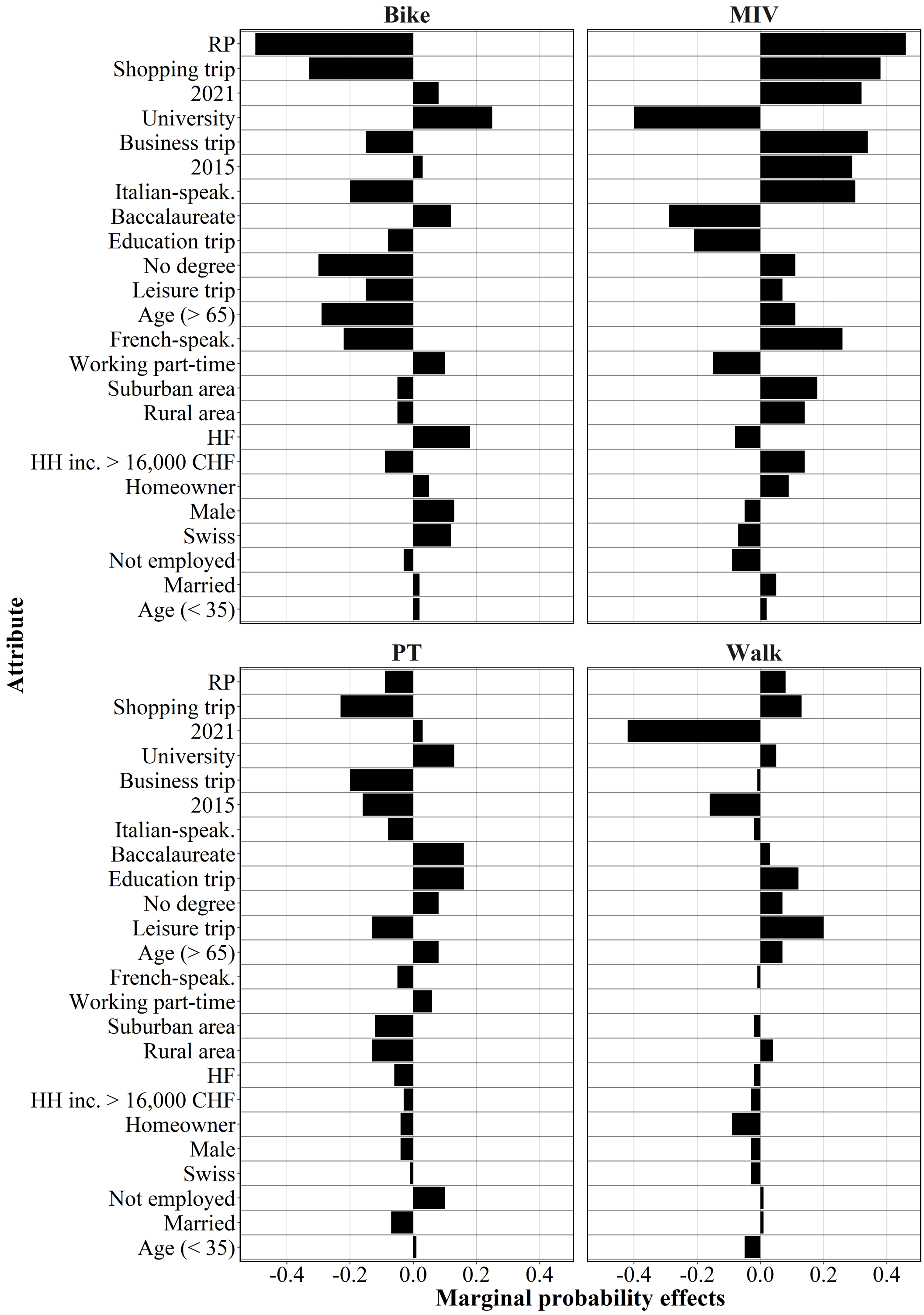
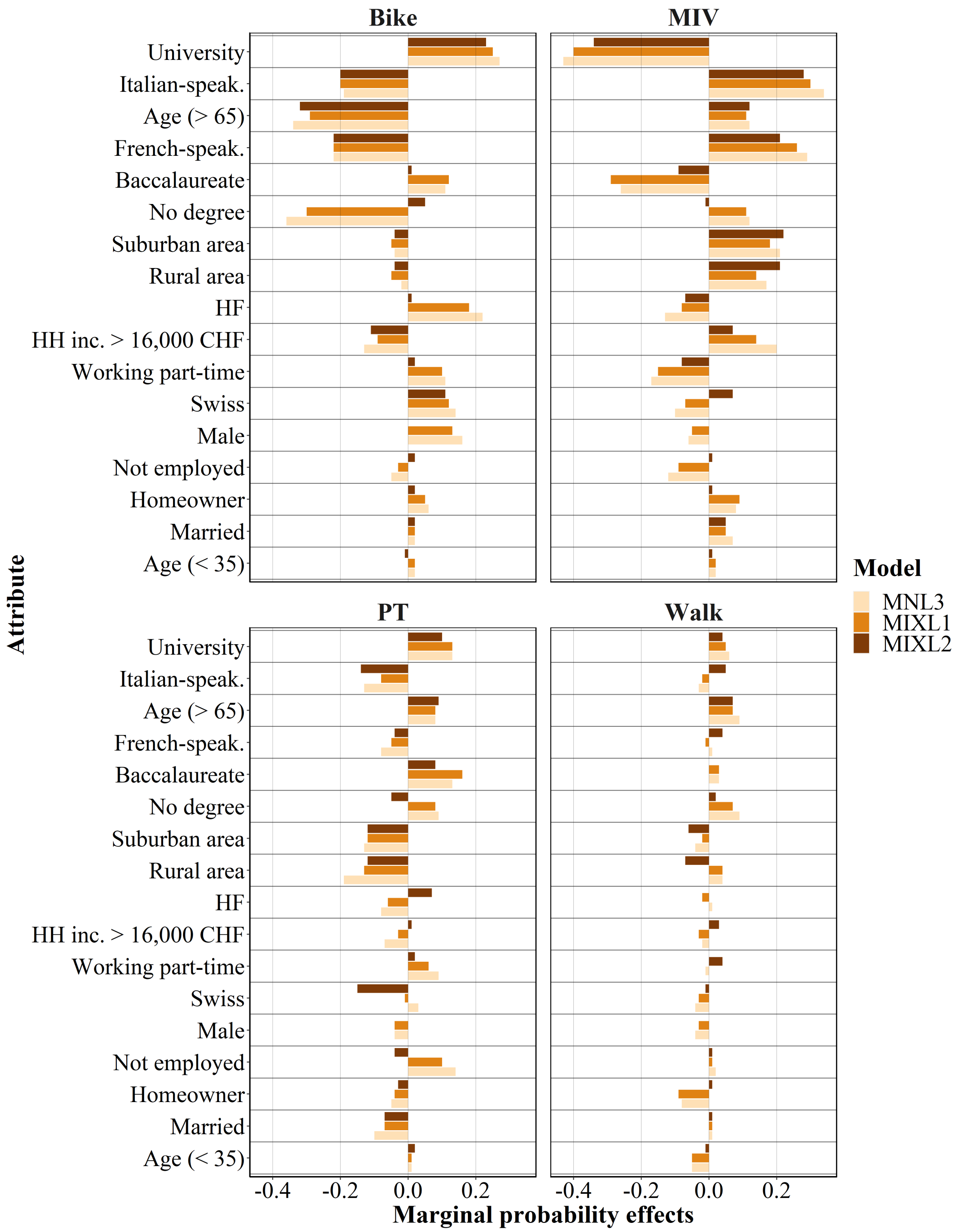


Figure 10 shows the MPE of the socioeconomic variables which appear in MNL3, MIXL1, and MIXL2. More often than not, the absolute MPE of MNL3 are greater than or equal to the absolute MPE of MIXL1 and MIXL2.

Figure 10: Mode- and model-specific MPE of socioeconomic characteristics



The signs of MPE differ three times between MNL3 and MIXL1 (Swiss citizen PT, French-speaking walk, and HF walk). MIXL1 and MIXL2 differ multiple times, the greatest difference shown is the effect of no degree on the mode bike. A similar pattern can be observed for PT and MIV. However, the pattern is not as pronounced as with bike and MIV.

Overall, there are differences between MNL3, MIXL1, and MIXL2. However, these differences do not seem to be fundamental. The models are mostly comparable in regard to the signs and values of the MPE.

Table 25 shows the percentage of absolute MPE per mode, differentiated by the variable type and the sum of absolute MPE per mode for MNL3, MIXL1, and MIXL2. For all modes but walk, the socioeconomic variables comprise more than 50% of the absolute MPE. This indicates that walk may be the mode whose choice is most difficult to explain through socioeconomic profiles. Moreover, walk is also the mode with the smallest sum of absolute MPE. Bike is the mode with the highest share of absolute socioeconomic MPE (62.7% in MIXL1). MIV is the mode with the highest sum of absolute MPE (4.60 in MIXL1). This indicates that the group of MIV users may be more homogeneous than the remaining modes' users. Due to the highly accessible and ubiquitous mode nature of walk, socioeconomic variables hardly factor into the heterogenic selection of this mode. PT poses a marginally less accessible mode in that its legal use requires the possession of a ticket. PT offers increased attractiveness in urban settings, due to its prevalence. PT is shown to be more attractive in urban settings, indicated by the negative MPE for suburban and rural areas for PT. As noted in a previous analysis (not reported), PT accessibility is strongly correlated with residential location area. Bike and MIV are comparatively more exclusive, not only requiring the availability of a vehicle, but also the ability to ride/drive it.

Compared to MIXL1, the MPE in MNL3 are greater. Additionally, the socioeconomic attributes make up 61.4% of MIV, being substantially higher than in MIXL1 or MIXL2. The introduction of interaction terms leads to a further reduction in the sum of absolute MPE for all modes except PT. The decrease in the sum of absolute MPE from MIXL1 to MIXL2 is largest for bike, followed by MIV. As seen above, the ASC for bike is substantially higher for MIXL2 than for MIXL1. The increase in the effect of unobserved factors may explain some of the reduction in MPE.

Overall, introducing random components and interaction terms reduces the influence of socioeconomic variables. However, not all modes are affected equally by this reduction. Walk is affected least, while bike is affected the most. In addition, the table and figures also show that even the largest effect of an attribute alters the probability by only 0.50 percentage points. Moreover, even the sum of absolute MPE per mode is less than a change of five percentage points.

Table 25: Percentage of absolute MPE according to mode and the variable type and sum of absolute MPE per mode for MNL3, MIXL1, and MIXL2

Model		Bike	MIV	PT	Walk
MNL3	Socioeconomic variables [%]	61.3	61.4	55.3	35.8
	Trip purpose/year/RP [%]	38.7	38.6	44.7	64.2
MIXL1	Socioeconomic variables [%]	62.7	55.0	55.6	34.1
	Trip purpose/year/RP [%]	37.3	45.0	44.4	65.9
MIXL2	Socioeconomic variables [%]	55.2	50.9	58.8	36.2
	Trip purpose/year/RP [%]	44.8	49.1	41.2	63.8
MNL3	Sum of absolute MPE	4.01	4.71	2.84	1.87
MIXL1	Sum of absolute MPE	3.54	4.60	2.25	1.70
MIXL2	Sum of absolute MPE	2.88	4.22	2.50	1.63

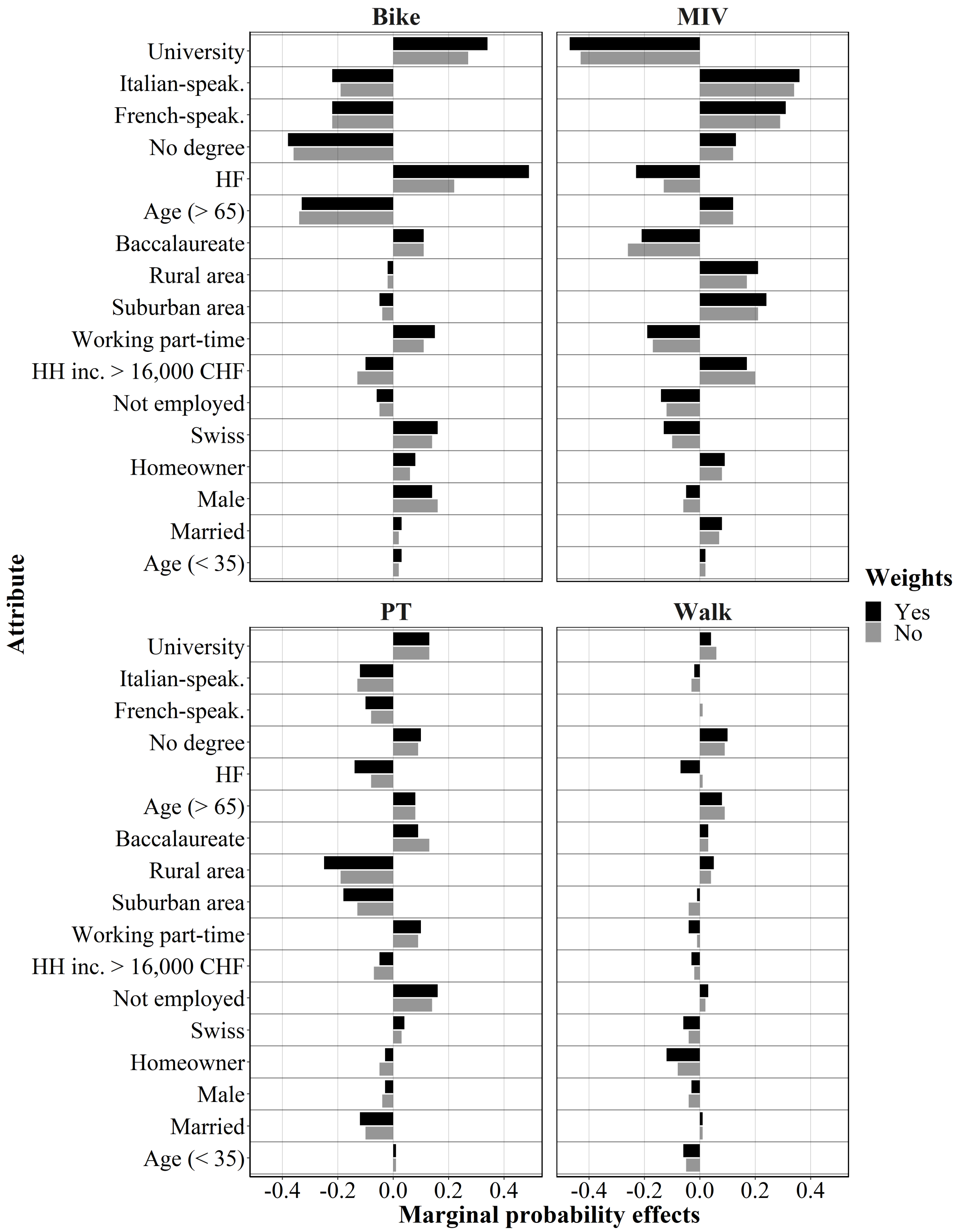
As mentioned above, the VSS data set differs in some characteristics from the other two. Therefore, a model is estimated but including weights to account for over- and underrepresentation of certain socioeconomic groups. The weights are applied to all observations of the unified data set. Because the inclusion of weights increases the computational cost, the weights are only used on MNL3. Table 26 presents both the percentage of absolute MPE according to the variable type and the sum of absolute MPE per mode for MNL3 with weights. Compared to the unweighted MNL3 in table 25, the sum of absolute MPE is higher for all modes except walk. Especially bike and PT are more affected by MPE in the model with weights. Moreover, the socioeconomic variables have higher MPE shares except for PT.

Table 26: Percentage of absolute MPE according to mode and the variable type and sum of absolute MPE per mode for MNL3, with weights

Model		Bike	MIV	PT	Walk
With weights	Socioeconomic variables [%]	67.5	64.7	53.7	43.3
	Trip purpose/year/RP [%]	32.5	35.3	46.3	56.7
With weights	Sum of absolute MPE	4.31	4.87	3.22	1.80

Figure 11 displays the MPE of MNL3 with and without weights. In some cases, the model with weights shows higher MPE. This is especially evident with the effect of HF. Moreover, the effect of HF on walk is also the only one where the two models differ regarding a potential increase or decrease in choice probability. In the model with weights, HF has a negative effect on the choice probability of walk. This effect is positive in the model without weights. Overall, including weights does not substantially affect the socioeconomic MPE.

Figure 11: Mode-specific socioeconomic MPE of MNL3 with and without weights



6 Conclusions

This chapter summarizes, interprets, and contextualizes the results of this thesis (sections 6.1). It further lists policy recommendations (6.2), limitations (section 6.3), and potential subjects for further research (section 6.4).

6.1 Discussion

This thesis estimates mode choice through the use of three Swiss large-scale RP/SP data sets, MNL, and mixed logit models. The results indicate that the overall contribution of socioeconomic variables on the explanatory power (goodness-of-fit) of a model is limited. While an increase in model fit can be observed, it is not substantial (AIC and BIC are about 3% smaller in MNL3 compared to MNL2). However, compared to the number of parameters that are introduced, the gain is minimal (31 more parameters in MNL3 than in MNL2). Furthermore, the introduction of random components in the alternative-specific constants substantially increases the model fit (AIC and BIC are about 34% smaller in MIXL1 than MNL3). Meanwhile, the omission of LOS variables results in a substantial loss in model fit (AIC and BIC are about 17% higher in MNL4 compared to MNL3). The introduction of interaction terms marginally affects the model fit, which is in accordance with Louviere *et al.* (2000) and Ortúzar and Willumsen (2011).

While some of the results agree with Fröhlich *et al.* (2012), Weis *et al.* (2017), and Weis *et al.* (2021), other results do not. For example, the authors find a negative correlation between age and the likelihood of choosing bike. Some results of this thesis, such as the significance of education, deviate from these three studies.

Moreover, the partworth shows that the variables with the highest contribution to the utility functions are travel time and travel costs. The highest-ranking socioeconomic variable is education. However, the ranking of the lower half variables is dependent on whether unobserved taste preferences are accounted for or not. Another interesting result is the inconsequential MPE of socioeconomic variables. The variable, university degree, results in the largest socioeconomic MPE (-0.40 percentage points on the choice probability of MIV). Additionally, the introduction of both random components and interactions between LOS and socioeconomic variables decreases the sum of absolute MPE of socioeconomic variables. The mode bike is most affected by this reduction and the mode walk the least. A possible interpretation is that bike users are more socioeconomically different from MIV users than PT or walk users from MIV users. Furthermore, the effects of socioeconomic variables in all models are less substantial than expected. This suggests that socioeconomic variables inherently contain more than is represented by their main effects. For example, the absence of latent variables mentioned by Widmer *et al.* (2020), or the interaction effects with other variables suggested by De Witte *et al.* (2013), could be responsible for this thesis's insubstantial results. These results concur with De Witte *et al.* (2013), who show that the effects of multiple socioeconomic variables are inconclusive and may be greater when interacting with other variables.

As both the estimates and MPE for the control variables 2015 and 2021 show, significant structural differences between the data sets exist. Nevertheless, the effect of those structural differences do not appear to compromise the results.

For future mode choice studies it is therefore recommended to include socioeconomic variables not solely through main effects, but also as interaction terms with other variables. Most notably, the inclusion of participants' attitudes may result in a more profound comprehension of the effect of socioeconomic variables.

6.2 Policy implications

Especially seen in the topic of equity in transport policy, differentiation by socioeconomic groups can help expand the view of the impact of various policy measures. However, this thesis shows that socioeconomic variables in the form of main effects do not provide a sufficient basis for policy decisions. While socioeconomic parameters are significant, their MPE are both insubstantial and inconclusive. Compared to LOS variables, socioeconomic variables are relatively ambiguous for policy analyses. However, socioeconomic variables may offer a better basis for policy applications in combination with LOS variables. MNL5 and MIXL2 show clear distinctions in attribute sensitivity for different socioeconomic groups. It is therefore important to consider various socioeconomic groups, especially in the case of national time valuation studies incorporated into norms and standards.

6.3 Limitations

Comparability of data As mentioned in chapter 4, the two MTMC data sets are similar, but the VSS 2021 data set differs from the MTMC data sets. While the MTMC data sets are a close approximation of the Swiss population, the VSS data set targets only the working population in the German-speaking part of Switzerland. However, including weights in MNL3 shows that the MPE do not substantially change. Overall, the MPE are slightly greater, but the differences between MNL3 with and without weights are minute. Moreover, the share of non-Swiss in VSS 2021 is substantially lower than in the MTMC data sets. Because the immigrant population comprises approximately a quarter of the population living in Switzerland (Federal Department of Foreign Affairs FDFA, 2022), all three data sets contain too low shares of non-Swiss. This is important because Swiss is a significant variable in the models and could affect the composition of the remaining socioeconomic variables.

Furthermore, the VSS 2021 data set was collected during the COVID-19 pandemic. This could partly explain the substantial discrepancies between RP- and SP-Data. For MTMC 2010 and 2015, the differences between mode shares in RP- and SP-Data are noticeable but not nearly as substantial as in VSS 2021. Hintermann *et al.* (2021) find that MIV has recovered mostly from reduction due to COVID-19 restrictions, but PT remains at lower usage levels. Table 7 shows that the RP-shares for MIV are similar to the MTMC, while the RP-shares for PT are uncharacteristically low. Therefore, one cannot dismiss the possibility that the COVID-19 pandemic has affected the mobility behavior of individuals in the VSS 2021 data set. Consequently, the three data sets possibly contain more dissimilarities. However, depending on the long-term impact on travel behavior, the inclusion of VSS 2021 may lend this work more credibility, also in the future.

Attitude variables This work contains LOS and socioeconomic variables but no attitude variables. However, the inclusion of attitudes has been shown to be a valuable addition to mode choice models and helps provide a more accurate view of the effects of socioeconomic variables (Widmer *et al.*, 2020).

Employment level As mentioned above, the population of the data sets are divided into full-, part-time working, and not employed. However, the average work hours per week could also be implemented instead of dividing the population into separate employment levels. The distribution of average weekly work hours is left-skewed for the VSS 2021 data set, with a wide range of work hours below the threshold of 41 hours a week. In addition, this work does not differentiate between students working part-time, familial caregivers who separately work part-time, and those who exclusively work part-time. Hence, accounting for whether or not part-time work is the main occupation of an individual could change results. Additionally, the category of not employed people encompasses the heterogeneous group of retired people, homemakers, and people unable to hold a job. Hence, their travel behavior likely differs.

Kids in household While a variable exists for children in a household, it encompasses all children under the age of 18. Thus, categorizing children into at least two groups, from 0 to 6 and 7 to 17 would have been more effective. Some literature points to travel behavior differing in the presence of young children (see, e.g., Commins and Nolan (2011)).

Work field and quality The VSS data set does not include any information on the various fields of work. This could be an interesting addition to the models, as work sectors have different requirements regarding work location and flexibility. Especially due to COVID-19 with the resulting increase in home-office, more information regarding the work sector and the work quality could prove a valuable asset in mode choice modeling. In the VSS 2021 data set, for example, MIV has a higher share of people who lack flexible work models compared to the other three modes. A differentiation between flexible and inflexible work could increase the information conveyed by the models.

Comparison across different models The effects of socioeconomic variables are compared across different models in this work (MNL3, MIXL1, and MIXL2). However, comparing additional models could provide additional insight since limitations bind each model. The MIXL1 and the MIXL2 model, for example, have normally distributed random components. Further models could have been estimated with error terms based on different distributions.

6.4 Further research

Potential elements for further research:

- One could use additional interaction models to determine significant differences between various socioeconomic groups. This thesis only tests the interactions of gender with other socioeconomic variables. However, the interactions of age, income, or education with other socioeconomic variables would provide more insights into the differences between socioeconomic groups.
- One could introduce the nature of work (e.g., office or construction jobs) as a variable into the model. It could be that education is an indicator of the nature of work a person pursues. Differentiating by work nature and sector may help clarify the role of education in MC further.
- One could include attitudes, choice of residential location area, and choice of mobility tools in models. Widmer *et al.* (2020) mention that not accounting for the interdependencies between mode choice, mobility tool choice, and residential location

area choice can distort the short- and medium-term parameters. Additionally, their approach allows a differentiation between the effects variables have on mode choice directly, the effects they have on mobility tool choice, and residential location area choice. Furthermore, accounting for attitudes substantially influences the MPE of socioeconomic attributes. Using an approach similar to Widmer *et al.* (2020) could affect the importance of socioeconomic variables used in this thesis and lead to more conclusive results. For example, it is assumed that education is the most significant variable in this thesis because it is a proxy for values and attitudes. This approach may gain further importance with long-term changes in land-use patterns and travel behavior, due to COVID-19 (Beck and Hensher, 2021).

- One could investigate the different mode choice patterns between Swiss and non-Swiss, as well as observing linguistic regions more intensely. All three data sets include a share of Swiss, which appears to be too large compared to the Swiss average. Moreover, increasing the share of the non-Swiss population may alter the composition of the remaining socioeconomic variables. Given the effect being Swiss seems to have on mode choice, further investigation into this topic may help understand existing differences better. Languages are also significant in this thesis. However, more research still needs to be conducted to conclusively present the difference between various language regions and whether or not they are significant.
- One could compare the differences in mode choice across additional MTMC data sets (e.g., 2000 and 2005). This could provide insight into how mode choice has changed over a larger period. Consequently, possible trends could be discovered.
- One could compare the effects and importance of socioeconomic variables over different model types (e.g., machine learning). This thesis utilizes MNL and mixed logit models to analyze the effects and importance of socioeconomic variables. However, based on machine learning, other model types have been implemented to analyze mode choice (Zhao *et al.*, 2020; Salas *et al.*, 2022). Machine learning is data-driven. Thus, models based on machine learning may help reveal previously obscured patterns and structures in data.

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A Appendix data description

A.1 Education levels

The eight education levels in this thesis are:

1. No degree: People who did not complete mandatory school
2. Mandatory school: People who completed only the mandatory school
3. Apprenticeship: People who completed an apprenticeship
4. BMS/FMS: People who have a specialized baccalaureate. This includes people who visited a vocational or business high school
5. Baccalaureate: People who either completed an academic high school (German: Gymnasium) or went to the teaching seminar (German: Lehrkräfe-Seminar)
6. HF: People who have a degree from a college of higher education or a technical high school
7. Swiss federal diploma: People with either a federal diploma of higher education or an advanced federal diploma of higher education
8. University: This includes people with a degree from a university, federal institute of technology (ETH), university of applied sciences (FH), university of teacher education (PH), or polytechnic institute (HTL)

B Appendix results

B.1 Base model

Table 27: Estimation results of MNL1

Base cat.: MIV	MNL1 Coef./(SE)
ASC walk: α_{walk}	1.86***
	(0.12)
ASC bike: α_{bike}	−0.01
	(0.09)
ASC PT: α_{PT}	−0.60***
	(0.05)
RP walk	−0.24***
	(0.07)
RP bike	−1.10***
	(0.09)
RP PT	0.00
	(0.08)
Travel time walk	−6.28***
	(0.26)
Travel time bike	−5.43***
	(0.25)
Travel time MIV	−3.12***
	(0.12)
Travel time PT	−2.30***
	(0.11)
Travel costs	−0.11***
	(0.01)
Access time PT	−1.87***
	(0.18)
Frequency PT	−0.95***
	(0.08)
Nbr. of transfers PT	−0.23***
	(0.02)
2015 walk	−0.33***
	(0.10)
2015 bike	0.22**
	(0.09)
2015 PT	−0.34***
	(0.05)
2021 walk	−1.47***

Table 27 (continued)

Base cat.: MIV	MNL1 Coef./(SE)
	(0.12)
2021 bike	0.18*
	(0.10)
2021 PT	−0.29***
	(0.07)
Scale parameter RP: σ_{RP}	0.95***
	(0.04)
Number of parameters	21
Number of respondents	11,272
Number of choice observations	87,326
LL(null)	−78,203.49
LL(init)	−78,484.46
LL(final)	−55,067.88
LL(choicemodel)	−55,067.88
McFadden R2	0.30
AIC	110,177.76
AICc	110,177.84
BIC	110,374.69

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

B.2 Age models

Table 28: Estimation results of models with different age variables

Base cat.: MIV	MNLA.1	MNLA.2	MNLA.3
	Coef./(SE)	Coef./(SE)	Coef./(SE)
ASC walk: α_{walk}	2.01***	2.00***	2.08***
	(0.17)	(0.18)	(0.22)
ASC bike: α_{bike}	0.74***	0.75***	1.35***
	(0.12)	(0.12)	(0.16)
ASC PT: α_{PT}	−0.16**	−0.15**	−0.06
	(0.07)	(0.07)	(0.10)
RP walk	−0.15**	−0.16**	−0.17**
	(0.07)	(0.07)	(0.07)
RP bike	−1.03***	−1.04***	−1.07***
	(0.08)	(0.08)	(0.08)
RP PT	0.07	0.07	0.04
	(0.06)	(0.06)	(0.07)
Travel time walk	−6.13***	−6.14***	−6.16***
	(0.26)	(0.26)	(0.26)
Travel time bike	−5.83***	−5.83***	−5.85***
	(0.26)	(0.26)	(0.26)
Travel time MIV	−2.97***	−2.97***	−2.97***
	(0.12)	(0.12)	(0.12)
Travel time PT	−2.20***	−2.20***	−2.21***
	(0.11)	(0.11)	(0.11)
Travel costs	−0.11***	−0.11***	−0.11***
	(0.01)	(0.01)	(0.01)
Access time PT	−1.64***	−1.64***	−1.66***
	(0.17)	(0.17)	(0.18)
Frequency PT	−0.83***	−0.83***	−0.83***
	(0.08)	(0.08)	(0.08)
Nbr. of transfers PT	−0.23***	−0.23***	−0.23***
	(0.02)	(0.02)	(0.02)
2015 walk	−0.34***	−0.34***	−0.34***
	(0.10)	(0.11)	(0.11)
2015 bike	0.21**	0.20**	0.19**
	(0.09)	(0.09)	(0.09)
2015 PT	−0.32***	−0.32***	−0.32***
	(0.05)	(0.05)	(0.05)
2021 walk	−1.33***	−1.34***	−1.36***
	(0.13)	(0.13)	(0.13)
2021 bike	0.23**	0.23**	0.24**
	(0.10)	(0.10)	(0.11)

Table 28 (continued)

Base cat.: MIV	MNLA.1 Coef./(SE)	MNLA.2 Coef./(SE)	MNLA.3 Coef./(SE)
2021 PT	−0.18**	−0.17**	−0.16**
	(0.07)	(0.07)	(0.07)
Education trip walk	0.79**	0.78**	0.74**
	(0.33)	(0.33)	(0.33)
Education trip bike	0.43*	0.43*	0.22
	(0.23)	(0.23)	(0.23)
Education trip PT	0.53***	0.55***	0.58***
	(0.13)	(0.13)	(0.13)
Shopping trip walk	−0.12	−0.12	−0.13
	(0.14)	(0.14)	(0.14)
Shopping trip bike	−0.95***	−0.95***	−1.04***
	(0.10)	(0.10)	(0.10)
Shopping trip PT	−0.55***	−0.55***	−0.52***
	(0.06)	(0.06)	(0.06)
Business trip walk	−0.50*	−0.50*	−0.48*
	(0.26)	(0.26)	(0.26)
Business trip bike	−0.44**	−0.44**	−0.41*
	(0.22)	(0.22)	(0.22)
Business trip PT	−0.75***	−0.75***	−0.76***
	(0.12)	(0.12)	(0.12)
Leisure trip walk	0.31**	0.31**	0.30**
	(0.14)	(0.14)	(0.14)
Leisure trip bike	−0.30***	−0.30***	−0.39***
	(0.09)	(0.09)	(0.09)
Leisure trip PT	−0.29***	−0.29***	−0.26***
	(0.05)	(0.05)	(0.05)
Other trip walk	0.24	0.25	0.21
	(0.60)	(0.60)	(0.62)
Other trip bike	−1.39	−1.39	−1.68*
	(0.86)	(0.86)	(0.87)
Other trip PT	0.06	0.06	0.11
	(0.33)	(0.33)	(0.33)
Suburban area walk	−0.51***	−0.51***	−0.51***
	(0.11)	(0.11)	(0.11)
Suburban area bike	−0.34***	−0.34***	−0.33***
	(0.08)	(0.08)	(0.08)
Suburban area PT	−0.39***	−0.39***	−0.40***
	(0.05)	(0.05)	(0.05)
Rural area walk	−0.34**	−0.34**	−0.33**
	(0.13)	(0.13)	(0.13)
Rural area bike	−0.22**	−0.23**	−0.19*
	(0.10)	(0.10)	(0.10)

Table 28 (continued)

Base cat.: MIV	MNLA.1 Coef./(SE)	MNLA.2 Coef./(SE)	MNLA.3 Coef./(SE)
Rural area PT	-0.46^{***}	-0.46^{***}	-0.47^{***}
	(0.06)	(0.06)	(0.06)
Male walk	-0.03	-0.03	-0.04
	(0.09)	(0.09)	(0.09)
Male bike	0.27^{***}	0.27^{***}	0.26^{***}
	(0.07)	(0.07)	(0.07)
Male PT	-0.11^{**}	-0.11^{**}	-0.10^{**}
	(0.04)	(0.04)	(0.04)
Age (< 35) walk	-0.10	-0.28	
	(0.10)	(0.38)	
Age (< 35) bike	-0.02	-0.13	
	(0.08)	(0.29)	
Age (< 35) PT	0.15^{***}	0.39^{**}	
	(0.05)	(0.19)	
Age (> 65) walk	-0.10	-0.15	
	(0.13)	(0.17)	
Age (> 65) bike	-0.95^{***}	-1.33^{***}	
	(0.13)	(0.18)	
Age (> 65) PT	0.16^{**}	0.21^{**}	
	(0.07)	(0.09)	
Age walk			-0.17
			(0.28)
Age bike			-1.42^{***}
			(0.23)
Age PT			-0.10
			(0.15)
Scale parameter RP: σ_{RP}	1.04^{***}	1.04^{***}	1.02^{***}
	(0.04)	(0.04)	(0.04)
Number of parameters	51	51	48
Number of respondents	11,272	11,272	11,272
Number of choice observations	87,326	87,326	87,326
LL(null)	−78,203.49	−78,203.49	−78,203.49
LL(init)	−78,697.29	−78,312.69	−78,696.52
LL(final)	−53,684.28	−53,683.55	−53,846.69
LL(choicemodel)	−53,684.28	−53,683.55	−53,846.69
McFadden R2	0.31	0.31	0.31
AIC	107,470.56	107,469.10	107,789.38
AICc	107,471.03	107,469.57	107,789.80
BIC	107,948.80	107,947.35	108,239.49

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

B.3 Income models

The tables 29 and 30 contain the six models with different income variables. Table 29 presents MNLI.1 to MNLI.3 and table 30 MNLI.4 to MNLI.6.

Table 29: Estimation results of models with different income variables, part 1

Base cat.: MIV	MNLI.1 Coef./(SE)	MNLI.2 Coef./(SE)	MNLI.3 Coef./(SE)
ASC walk: α_{walk}	2.05***	1.97***	1.96***
	(0.19)	(0.19)	(0.19)
ASC bike: α_{bike}	0.66***	0.81***	0.79***
	(0.14)	(0.13)	(0.13)
ASC PT: α_{PT}	−0.11	−0.16**	−0.14*
	(0.08)	(0.08)	(0.08)
RP walk	−0.15**	−0.15**	−0.15**
	(0.07)	(0.07)	(0.07)
RP bike	−1.03***	−1.04***	−1.04***
	(0.08)	(0.08)	(0.08)
RP PT	0.07	0.07	0.07
	(0.06)	(0.06)	(0.06)
Travel time walk	−6.14***	−6.14***	−6.14***
	(0.26)	(0.26)	(0.26)
Travel time bike	−5.84***	−5.85***	−5.84***
	(0.26)	(0.26)	(0.26)
Travel time MIV	−2.98***	−2.98***	−2.98***
	(0.12)	(0.12)	(0.12)
Travel time PT	−2.20***	−2.20***	−2.20***
	(0.11)	(0.11)	(0.11)
Travel costs	−0.11***	−0.11***	−0.11***
	(0.01)	(0.01)	(0.01)
Access time PT	−1.64***	−1.64***	−1.64***
	(0.17)	(0.17)	(0.17)
Frequency PT	−0.83***	−0.83***	−0.83***
	(0.08)	(0.08)	(0.08)
Nbr. of transfers PT	−0.23***	−0.23***	−0.23***
	(0.02)	(0.02)	(0.02)
2015 walk	−0.33***	−0.33***	−0.33***
	(0.11)	(0.11)	(0.11)
2015 bike	0.20**	0.19**	0.20**
	(0.09)	(0.09)	(0.09)
2015 PT	−0.31***	−0.32***	−0.32***
	(0.05)	(0.05)	(0.05)

Table 29 (continued)

Base cat.: MIV	MNLI.1 Coef./(SE)	MNLI.2 Coef./(SE)	MNLI.3 Coef./(SE)
2021 walk	-1.32^{***}	-1.31^{***}	-1.31^{***}
	(0.13)	(0.13)	(0.13)
2021 bike	0.21^{*}	0.19^{*}	0.21^{*}
	(0.11)	(0.11)	(0.11)
2021 PT	-0.17^{**}	-0.18^{**}	-0.17^{**}
	(0.07)	(0.07)	(0.07)
Education trip walk	0.79^{**}	0.80^{**}	0.81^{**}
	(0.33)	(0.33)	(0.33)
Education trip bike	0.44^{*}	0.44^{*}	0.42^{*}
	(0.23)	(0.23)	(0.23)
Education trip PT	0.53^{***}	0.53^{***}	0.53^{***}
	(0.13)	(0.13)	(0.13)
Shopping trip walk	-0.12	-0.12	-0.12
	(0.14)	(0.14)	(0.14)
Shopping trip bike	-0.95^{***}	-0.94^{***}	-0.95^{***}
	(0.10)	(0.10)	(0.10)
Shopping trip PT	-0.56^{***}	-0.56^{***}	-0.56^{***}
	(0.06)	(0.06)	(0.06)
Business trip walk	-0.49^{*}	-0.49^{*}	-0.49^{*}
	(0.26)	(0.26)	(0.26)
Business trip bike	-0.45^{**}	-0.45^{**}	-0.45^{**}
	(0.22)	(0.22)	(0.22)
Business trip PT	-0.74^{***}	-0.75^{***}	-0.75^{***}
	(0.12)	(0.12)	(0.12)
Leisure trip walk	0.31^{**}	0.31^{**}	0.32^{**}
	(0.14)	(0.14)	(0.14)
Leisure trip bike	-0.30^{***}	-0.29^{***}	-0.30^{***}
	(0.09)	(0.09)	(0.09)
Leisure trip PT	-0.29^{***}	-0.29^{***}	-0.29^{***}
	(0.05)	(0.05)	(0.05)
Other trip walk	0.24	0.26	0.26
	(0.60)	(0.59)	(0.59)
Other trip bike	-1.40	-1.42	-1.41
	(0.86)	(0.86)	(0.86)
Other trip PT	0.06	0.06	0.06
	(0.33)	(0.33)	(0.33)
Suburban walk	-0.51^{***}	-0.51^{***}	-0.51^{***}
	(0.11)	(0.11)	(0.11)
Suburban bike	-0.35^{***}	-0.35^{***}	-0.35^{***}
	(0.08)	(0.08)	(0.08)
Suburban PT	-0.39^{***}	-0.39^{***}	-0.39^{***}
	(0.05)	(0.05)	(0.05)

Table 29 (continued)

Base cat.: MIV	MNLI.1	MNLI.2	MNLI.3
	Coef./(SE)	Coef./(SE)	Coef./(SE)
Rural walk	−0.34**	−0.34**	−0.34**
	(0.13)	(0.13)	(0.13)
Rural bike	−0.22**	−0.23**	−0.23**
	(0.10)	(0.10)	(0.10)
Rural PT	−0.46***	−0.46***	−0.46***
	(0.06)	(0.06)	(0.06)
Male walk	−0.03	−0.03	−0.02
	(0.09)	(0.09)	(0.09)
Male bike	0.26***	0.26***	0.26***
	(0.07)	(0.07)	(0.07)
Male PT	−0.10**	−0.10**	−0.10**
	(0.04)	(0.04)	(0.04)
Age (< 35) walk	−0.10	−0.10	−0.09
	(0.10)	(0.10)	(0.10)
Age (< 35) bike	−0.02	−0.02	−0.02
	(0.08)	(0.08)	(0.08)
Age (< 35) PT	0.15***	0.15***	0.15***
	(0.05)	(0.05)	(0.05)
Age (> 65) walk	−0.12	−0.12	−0.14
	(0.13)	(0.13)	(0.13)
Age (> 65) bike	−0.92***	−0.89***	−0.92***
	(0.13)	(0.14)	(0.14)
Age (> 65) PT	0.14*	0.15**	0.15**
	(0.07)	(0.07)	(0.07)
Income [1,000 CHF] walk	−0.01		
	(0.01)		
Income [1,000 CHF] bike	0.01		
	(0.01)		
Income [1,000 CHF] PT	−0.01		
	(0.01)		
Income (< 6,000 CHF) walk		0.06	0.02
		(0.11)	(0.02)
Income (< 6,000 CHF) bike		−0.19**	−0.03
		(0.09)	(0.02)
Income (< 6,000 CHF) PT		0.01	−0.00
		(0.06)	(0.01)
Income (> 10,000 CHF) walk		−0.02	−0.00
		(0.11)	(0.01)
Income (> 10,000 CHF) bike		0.02	−0.00
		(0.08)	(0.01)
Income (> 10,000 CHF) PT		−0.03	−0.00
		(0.05)	(0.00)

Table 29 (continued)

Base cat.: MIV	MNLI.1 Coef./(SE)	MNLI.2 Coef./(SE)	MNLI.3 Coef./(SE)
Scale parameter RP: σ_{RP}	1.04^{***}	1.04^{***}	1.04^{***}
	(0.04)	(0.04)	(0.04)
Number of parameters	54	57	57
Number of respondents	11,272	11,272	11,272
Number of choice observations	87,326	87,326	87,326
LL(null)	−78,203.49	−78,203.49	−78,203.49
LL(init)	−80,420.96	−78,089.66	−77,250.56
LL(final)	−53,669.56	−53,655.17	−53,665.08
LL(choicemodel)	−53,669.56	−53,655.17	−53,665.08
McFadden R2	0.31	0.31	0.31
AIC	107,447.12	107,424.35	107,444.17
AICc	107,447.65	107,424.94	107,444.76
BIC	107,953.50	107,958.86	107,978.68

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 30: Estimation results of models with different income variables, part 2

Base cat.: MIV	MNLI.4	MNLI.5	MNLI.6
	Coef./(SE)	Coef./(SE)	Coef./(SE)
ASC walk: α_{walk}	1.96***	1.98***	1.98***
	(0.19)	(0.18)	(0.18)
ASC bike: α_{bike}	0.81***	0.86***	0.86***
	(0.13)	(0.13)	(0.13)
ASC PT: α_{PT}	−0.19**	−0.16**	−0.16**
	(0.08)	(0.07)	(0.07)
RP walk	−0.15**	−0.15**	−0.15**
	(0.07)	(0.07)	(0.07)
RP bike	−1.03***	−1.04***	−1.04***
	(0.08)	(0.08)	(0.08)
RP PT	0.07	0.07	0.07
	(0.06)	(0.06)	(0.06)
Travel time walk	−6.14***	−6.14***	−6.14***
	(0.26)	(0.26)	(0.26)
Travel time bike	−5.84***	−5.86***	−5.87***
	(0.26)	(0.26)	(0.26)
Travel time MIV	−2.98***	−2.98***	−2.98***
	(0.12)	(0.12)	(0.12)
Travel time PT	−2.20***	−2.20***	−2.20***
	(0.11)	(0.11)	(0.11)
Travel costs	−0.11***	−0.11***	−0.11***
	(0.01)	(0.01)	(0.01)
Access time PT	−1.64***	−1.64***	−1.63***
	(0.17)	(0.18)	(0.17)
Frequency PT	−0.83***	−0.83***	−0.83***
	(0.08)	(0.08)	(0.08)
Nbr. of transfers PT	−0.23***	−0.22***	−0.23***
	(0.02)	(0.02)	(0.02)
2015 walk	−0.33***	−0.33***	−0.33***
	(0.11)	(0.11)	(0.11)
2015 bike	0.20**	0.20**	0.20**
	(0.09)	(0.09)	(0.09)
2015 PT	−0.32***	−0.32***	−0.32***
	(0.05)	(0.05)	(0.05)
2021 walk	−1.32***	−1.31***	−1.30***
	(0.13)	(0.13)	(0.13)
2021 bike	0.21*	0.20*	0.20*
	(0.11)	(0.11)	(0.11)
2021 PT	−0.18**	−0.18**	−0.18**
	(0.07)	(0.07)	(0.07)
Education trip walk	0.78**	0.84**	0.83**

Table 30 (continued)

Base cat.: MIV	MNLI.4 Coef./(SE)	MNLI.5 Coef./(SE)	MNLI.6 Coef./(SE)
	(0.33)	(0.33)	(0.34)
Education trip bike	0.44*	0.47**	0.47**
	(0.23)	(0.23)	(0.23)
Education trip PT	0.53***	0.53***	0.52***
	(0.13)	(0.13)	(0.13)
Shopping trip walk	−0.12	−0.13	−0.13
	(0.14)	(0.14)	(0.14)
Shopping trip bike	−0.95***	−0.95***	−0.95***
	(0.10)	(0.10)	(0.10)
Shopping trip PT	−0.55***	−0.56***	−0.56***
	(0.06)	(0.06)	(0.06)
Business trip walk	−0.50*	−0.49*	−0.49*
	(0.26)	(0.26)	(0.26)
Business trip bike	−0.44**	−0.43*	−0.44*
	(0.22)	(0.22)	(0.22)
Business trip PT	−0.75***	−0.75***	−0.75***
	(0.12)	(0.12)	(0.12)
Leisure trip walk	0.31**	0.32**	0.32**
	(0.14)	(0.14)	(0.14)
Leisure trip bike	−0.30***	−0.29***	−0.29***
	(0.09)	(0.09)	(0.09)
Leisure trip PT	−0.29***	−0.29***	−0.29***
	(0.05)	(0.05)	(0.05)
Other trip walk	0.25	0.26	0.27
	(0.60)	(0.61)	(0.61)
Other trip bike	−1.38	−1.45*	−1.43*
	(0.87)	(0.86)	(0.85)
Other trip PT	0.06	0.07	0.08
	(0.33)	(0.33)	(0.33)
Suburban walk	−0.51***	−0.51***	−0.51***
	(0.11)	(0.11)	(0.11)
Suburban bike	−0.34***	−0.36***	−0.36***
	(0.08)	(0.08)	(0.08)
Suburban PT	−0.39***	−0.39***	−0.39***
	(0.05)	(0.05)	(0.05)
Rural walk	−0.34**	−0.34**	−0.34**
	(0.13)	(0.13)	(0.13)
Rural bike	−0.22**	−0.24**	−0.25**
	(0.10)	(0.10)	(0.10)
Rural PT	−0.46***	−0.46***	−0.46***
	(0.06)	(0.06)	(0.06)
Male walk	−0.03	−0.03	−0.03

Table 30 (continued)

Base cat.: MIV	MNLI.4 Coef./(SE)	MNLI.5 Coef./(SE)	MNLI.6 Coef./(SE)
	(0.09)	(0.09)	(0.09)
Male bike	0.26***	0.25***	0.25***
	(0.07)	(0.07)	(0.07)
Male PT	−0.11**	−0.11**	−0.11**
	(0.04)	(0.04)	(0.04)
Age (< 35) walk	−0.10	−0.10	−0.10
	(0.10)	(0.10)	(0.10)
Age (< 35) bike	−0.02	−0.03	−0.03
	(0.08)	(0.08)	(0.08)
Age (< 35) PT	0.15***	0.15***	0.15***
	(0.05)	(0.05)	(0.05)
Age (> 65) walk	−0.11	−0.11	−0.11
	(0.13)	(0.13)	(0.13)
Age (> 65) bike	−0.93***	−0.88***	−0.89***
	(0.13)	(0.13)	(0.13)
Age (> 65) PT	0.15**	0.16**	0.15**
	(0.07)	(0.07)	(0.07)
Income (< 2,000 CHF) walk		−0.07	−0.07
		(0.36)	(0.36)
Income (< 2,000 CHF) bike		−0.24	−0.24
		(0.31)	(0.31)
Income (< 2,000 CHF) PT		0.30	0.30
		(0.20)	(0.20)
Income (2,000 - 4,000 CHF) walk		−0.12	−0.12
		(0.16)	(0.16)
Income (2,000 - 4,000 CHF) bike		−0.49***	−0.49***
		(0.15)	(0.15)
Income (2,000 - 4,000 CHF) PT		−0.03	−0.03
		(0.09)	(0.09)
Income (4,000 - 6,000 CHF) walk		0.14	0.14
		(0.12)	(0.12)
Income (4,000 - 6,000 CHF) bike		−0.11	−0.11
		(0.10)	(0.10)
Income (4,000 - 6,000 CHF) PT		−0.00	−0.00
		(0.06)	(0.06)
Income (< 10,000 CHF) walk	0.06		
	(0.10)		
Income (< 10,000 CHF) bike	−0.09		
	(0.08)		
Income (< 10,000 CHF) PT	0.03		
	(0.05)		
Income (> 14,000 CHF) walk		−0.11	

Table 30 (continued)

Base cat.: MIV	MNLI.4 Coef./(SE)	MNLI.5 Coef./(SE)	MNLI.6 Coef./(SE)
		(0.14)	
Income (> 14,000 CHF) bike		-0.14	
		(0.10)	
Income (> 14,000 CHF) PT		-0.05	
		(0.06)	
Income (14,000 - 16,000 CHF) walk			0.03
			(0.22)
Income (14,000 - 16,000 CHF) bike			0.09
			(0.15)
Income (14,000 - 16,000 CHF) PT			0.11
			(0.09)
Income (> 16,000 CHF) walk			-0.19
			(0.17)
Income (> 16,000 CHF) bike			-0.28^{**}
			(0.12)
Income (> 16,000 CHF) PT			-0.15^{*}
			(0.08)
Scale parameter RP: σ_{RP}	1.04^{***}	1.04^{***}	1.04^{***}
	(0.04)	(0.04)	(0.04)
Number of parameters	54	63	66
Number of respondents	11,272	11,272	11,272
Number of choice observations	87,326	87,326	87,326
LL(null)	$-78,203.49$	$-78,203.49$	$-78,203.49$
LL(init)	$-78,696.74$	$-77,654.44$	$-79,045.51$
LL(final)	$-53,674.98$	$-53,617.19$	$-53,597.62$
LL(choicemodel)	$-53,674.98$	$-53,617.19$	$-53,597.62$
McFadden R2	0.31	0.31	0.31
AIC	107,457.97	107,360.37	107,327.25
AICc	107,458.50	107,361.09	107,328.04
BIC	107,964.35	107,951.15	107,946.16

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

B.4 Utility functions

The utility functions of MIXL1 for person $n \in 1, 2, ..., N$ in choice scenario $t \in 1, 2, ..., T$ are given by:

$$U^{RP,2010}_{walk,n,t} = \sigma_{RP} * (\alpha_{walk} + RP_{walk} + X_{walk,n,t}\beta_{walk} + P_{n,t}\gamma_{walk} + Z_n\lambda_{walk} + \eta_{walk,n}) \tag{20}$$

$$U^{RP,2010}_{bike,n,t} = \sigma_{RP} * (\alpha_{bike} + RP_{bike} + X_{bike,n,t}\beta_{bike} + P_{n,t}\gamma_{bike} + Z_n\lambda_{bike} + \eta_{bike,n}) \tag{21}$$

$$U^{RP,2010}_{MIV,n,t} = \sigma_{RP} * (X_{MIV,n,t}\beta_{MIV} + \eta_{MIV,n}) \tag{22}$$

$$U^{RP,2010}_{PT,n,t} = \sigma_{RP} * (\alpha_{PT} + RP_{PT} + X_{PT,n,t}\beta_{PT} + P_{n,t}\gamma_{PT} + Z_n\lambda_{PT} + \eta_{PT,n}) \tag{23}$$

$$U^{SP,2010}_{walk,n,t} = \alpha_{walk} + X_{walk,n,t}\beta_{walk} + P_{n,t}\gamma_{walk} + Z_n\lambda_{walk} + \eta_{walk,n} \tag{24}$$

$$U^{SP,2010}_{bike,n,t} = \alpha_{bike} + X_{bike,n,t}\beta_{bike} + P_{n,t}\gamma_{bike} + Z_n\lambda_{bike} + \eta_{bike,n} \tag{25}$$

$$U^{SP,A1,2010}_{MIV,n,t} = X_{MIV,n,t}\beta_{MIV} + \eta_{MIV,n} \tag{26}$$

$$U^{SP,A1,2010}_{PT,n,t} = \alpha_{PT} + X_{PT,n,t}\beta_{PT} + P_{n,t}\gamma_{PT} + Z_n\lambda_{PT} + \eta_{PT,n} \tag{27}$$

$$U^{SP,A2,2010}_{MIV,n,t} = X_{MIV,n,t}\beta_{MIV} + \eta_{MIV,n} \tag{28}$$

$$U^{SP,A2,2010}_{PT,n,t} = \alpha_{PT} + X_{PT,n,t}\beta_{PT} + P_{n,t}\gamma_{PT} + Z_n\lambda_{PT} + \eta_{PT,n} \tag{29}$$

$$U^{RP,2015}_{walk,n,t} = \sigma_{RP} * (\alpha_{walk} + RP_{walk} + 2015_{walk} + X_{walk,n,t}\beta_{walk} + P_{n,t}\gamma_{walk} + Z_n\lambda_{walk} + \eta_{walk,n}) \tag{30}$$

$$U^{RP,2015}_{bike,n,t} = \sigma_{RP} * (\alpha_{bike} + RP_{bike} + 2015_{bike} + X_{bike,n,t}\beta_{bike} + P_{n,t}\gamma_{bike} + Z_n\lambda_{bike} + \eta_{bike,n}) \tag{31}$$

$$U^{RP,2015}_{MIV,n,t} = \sigma_{RP} * (X_{MIV,n,t}\beta_{MIV} + \eta_{MIV,n}) \tag{32}$$

$$U^{RP,2015}_{PT,n,t} = \sigma_{RP} * (\alpha_{PT} + RP_{PT} + 2015_{PT} + X_{PT,n,t}\beta_{PT} + P_{n,t}\gamma_{PT} + Z_n\lambda_{PT} + \eta_{PT,n}) \tag{33}$$

$$U^{SP,2015}_{walk,n,t} = \alpha_{walk} + 2015_{walk} + X_{walk,n,t}\beta_{walk} + P_{n,t}\gamma_{walk} + Z_n\lambda_{walk} + \eta_{walk,n} \tag{34}$$

$$U^{SP,2015}_{bike,n,t} = \alpha_{bike} + 2015_{bike} + X_{bike,n,t}\beta_{bike} + P_{n,t}\gamma_{bike} + Z_n\lambda_{bike} + \eta_{bike,n} \tag{35}$$

$$U^{SP,A1,2015}_{MIV,n,t} = X_{MIV,n,t}\beta_{MIV} + \eta_{MIV,n} \tag{36}$$

$$U^{SP,A1,2015}_{PT,n,t} = \alpha_{PT} + 2015_{PT} + X_{PT,n,t}\beta_{PT} + P_{n,t}\gamma_{PT} + Z_n\lambda_{PT} + \eta_{PT,n} \tag{37}$$

$$U^{SP,A2,2015}_{MIV,n,t} = X_{MIV,n,t}\beta_{MIV} + \eta_{MIV,n} \tag{38}$$

$$U^{SP,A2,2015}_{PT,n,t} = \alpha_{PT} + 2015_{PT} + X_{PT,n,t}\beta_{PT} + P_{n,t}\gamma_{PT} + Z_n\lambda_{PT} + \eta_{PT,n} \tag{39}$$

$$U^{SP,2021}_{walk,n,t} = \alpha_{walk} + 2021_{walk} + X_{walk,n,t}\beta_{walk} + P_{n,t}\gamma_{walk} + Z_n\lambda_{walk} + \eta_{walk,n} \tag{40}$$

$$U^{SP,2021}_{bike,n,t} = \alpha_{bike} + 2021_{bike} + X_{bike,n,t}\beta_{bike} + P_{n,t}\gamma_{bike} + Z_n\lambda_{bike} + \eta_{bike,n} \tag{41}$$

$$U^{SP,2021}_{MIV,n,t} = X_{MIV,n,t}\beta_{MIV} + \eta_{MIV,n} \tag{42}$$

$$U^{SP,2021}_{PT,n,t} = \alpha_{PT} + 2021_{PT} + X_{PT,n,t}\beta_{PT} + P_{n,t}\gamma_{PT} + Z_n\lambda_{PT} + \eta_{PT,n} \tag{43}$$

$$U^{RP,2021}_{walk,n,t} = \sigma_{RP} * (\alpha_{walk} + RP_{walk} + 2021_{walk} + X_{walk,n,t}\beta_{walk} + P_{n,t}\gamma_{walk} + Z_n\lambda_{walk} + \eta_{walk,n}) \tag{44}$$

$$U^{RP,2021}_{bike,n,t} = \sigma_{RP} * (\alpha_{bike} + RP_{bike} + 2021_{bike} + X_{bike,n,t}\beta_{bike} + P_{n,t}\gamma_{bike} + Z_n\lambda_{bike} + \eta_{bike,n}) \tag{45}$$

$$U^{RP,2021}_{MIV,n,t} = \sigma_{RP} * (X_{MIV,n,t}\beta_{MIV} + \eta_{MIV,n}) \tag{46}$$

$$U^{RP,2021}_{PT,n,t} = \sigma_{RP} * (\alpha_{PT} + RP_{PT} + 2021_{PT} + X_{PT,n,t}\beta_{PT} + P_{n,t}\gamma_{PT} + Z_n\lambda_{PT} + \eta_{PT,n}) \tag{47}$$

where σ_{RP} is the scale parameter for RP data. α_i are the alternative-specific constants for alternative i, RP_i the control variables for RP data and mode i, 2015_i and 2021_i the control variables for the years 2015 and 2021 and mode i. $X_{i,n,t}$ is the vector of LOS attributes related to mode i and β_i the corresponding coefficient vector. $P_{i,n,t}$ is the vector denoting the trip purpose and γ_i is the corresponding coefficient vector related to mode i. Similarly, Z_n is the vector of socioeconomic attributes and λ_i the corresponding coefficient vector related to mode i. $\eta_{i,n}$ is the random component related to mode i.

B.5 Interaction model MNL6

Table 31: Estimation results of MNL6

Base cat.: MIV	MNL6 Coef./(SE)
ASC walk: α_{walk}	1.74^{***}
	(0.13)
ASC bike: α_{bike}	0.49^{***}
	(0.16)
ASC PT: α_{PT}	-0.08
	(0.08)
RP walk	-0.13^{**}
	(0.06)
RP bike	-1.02^{***}
	(0.07)
RP PT	0.08
	(0.06)
Travel time walk	-6.05^{***}
	(0.25)
Travel time bike	-5.96^{***}
	(0.26)
Travel time MIV	-2.89^{***}
	(0.12)
Travel time PT	-2.16^{***}
	(0.11)
Travel costs	-0.10^{***}
	(0.01)
Access time PT	-1.59^{***}
	(0.17)
Frequency PT	-0.81^{***}
	(0.08)
Nbr. of transfers PT	-0.23^{***}
	(0.02)
2015 walk	-0.42^{***}
	(0.10)
2015 bike	0.27^{***}
	(0.09)

Table 31 (continued)

Base cat.: MIV	MNL6 Coef./(SE)
2015 PT	−0.30***
	(0.05)
2021 walk	−1.34***
	(0.12)
2021 bike	−0.26**
	(0.11)
2021 PT	−0.30***
	(0.07)
Education trip walk	0.86***
	(0.30)
Education trip bike	0.45*
	(0.23)
Education trip PT	0.53***
	(0.14)
Shopping trip bike	−0.88***
	(0.09)
Shopping trip PT	−0.52***
	(0.06)
Business trip walk	−0.44*
	(0.24)
Business trip bike	−0.53**
	(0.22)
Business trip PT	−0.75***
	(0.12)
Leisure trip walk	0.39***
	(0.10)
Leisure trip bike	−0.21**
	(0.09)
Leisure trip PT	−0.25***
	(0.05)
Suburban area walk	−0.36***
	(0.11)
Suburban area bike	−0.23***
	(0.08)
Suburban area PT	−0.32***
	(0.05)
Rural area PT	−0.36***
	(0.06)
Rural area * male walk	−0.26
	(0.17)
French speak. bike	−1.18***
	(0.14)

Table 31 (continued)

Base cat.: MIV	MNL6 Coef./(SE)
French speak. PT	-0.29^{***}
	(0.06)
French speak. * male bike	0.51^{***}
	(0.18)
Italian speak. bike	-0.99^{***}
	(0.20)
Italian speak. PT	-0.42^{***}
	(0.10)
Male PT	-0.21^{***}
	(0.07)
Age (> 65) bike	-0.98^{***}
	(0.13)
Age (> 65) * male PT	0.04
	(0.09)
Income (< 2,000 CHF) * male walk	-0.80^{*}
	(0.43)
Income (< 2,000 CHF) * male bike	-0.49
	(0.36)
Income (2,000 - 4,000 CHF) bike	-0.23^{*}
	(0.13)
Income (> 16,000 CHF) walk	-0.35^{**}
	(0.17)
Income (> 16,000 CHF) bike	-0.47^{***}
	(0.12)
Income (> 16,000 CHF) PT	-0.27^{***}
	(0.08)
Mandatory school PT	0.37^{***}
	(0.11)
Mandatory school * male PT	-0.50^{**}
	(0.18)
Baccalaureate walk	0.28^{*}
	(0.15)
Baccalaureate bike	0.42^{***}
	(0.12)
Baccalaureate PT	0.35^{***}
	(0.08)
HF bike	0.47^{***}
	(0.13)
University walk	0.68^{***}
	(0.13)
University bike	0.87^{***}
	(0.08)

Table 31 (continued)

Base cat.: MIV	MNL6 Coef./(SE)
University PT	0.45^{***}
	(0.05)
University * male walk	-0.17
	(0.16)
Working part-time bike	0.35^{***}
	(0.08)
Working part-time PT	0.06
	(0.06)
Working part-time * male PT	0.23^{**}
	(0.10)
Married bike	-0.25^{**}
	(0.09)
Married PT	-0.25^{***}
	(0.06)
Married * male bike	0.44^{***}
	(0.11)
Married * male PT	0.19^{**}
	(0.09)
Swiss bike	0.31^{***}
	(0.11)
Home owner walk	-0.25^{**}
	(0.09)
Home owner PT	-0.08^{*}
	(0.05)
Scale parameter RP: σ_{RP}	1.06^{***}
	(0.04)
Number of parameters	71
Number of respondents	11,2720
Number of choice observations	87,326
LL(null)	$-78,203.49$
LL(init)	$-77,477.41$
LL(final)	$-52,574.63$
LL(choicemodel)	$-52,574.63$
McFadden R2	0.33
AIC	105,291.26
AICc	105,292.17
BIC	105,957.05

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

B.6 MPE for MIXL1

Table 32: RP-MPE, mode specific, for MIXL1

Attribute	Walk	Bike	MIV	PT
2015	-0.16	0.03	0.29	-0.16
2021	-0.42	0.08	0.32	0.03
Education trip	0.12	-0.08	-0.21	0.16
Shopping trip	0.13	-0.33	0.38	-0.23
Leisure trip	0.20	-0.15	0.07	-0.13
Business trip	-0.01	-0.15	0.34	-0.20
Suburban area	-0.02	-0.05	0.18	-0.12
Rural area	0.04	-0.05	0.14	-0.13
French speak.	-0.01	-0.22	0.26	-0.05
Italian speak.	-0.02	-0.20	0.30	-0.08
Male	-0.03	0.13	-0.05	-0.04
Age (< 35)	-0.05	0.02	0.02	0.01
Age (> 65)	0.07	-0.29	0.11	0.08
HH inc. $>$ 16,000 CHF	-0.03	-0.09	0.14	-0.03
No degree	0.07	-0.30	0.11	0.08
Baccalaureate	0.03	0.12	-0.29	0.16
HF	-0.02	0.18	-0.08	-0.06
University	0.05	0.25	-0.40	0.13
Home owner	-0.09	0.05	0.09	-0.04
Swiss citizen	-0.03	0.12	-0.07	-0.01
Working part-time	0.00	0.10	-0.15	0.06
Not employed	0.01	-0.03	-0.09	0.10
Married	0.01	0.02	0.05	-0.07
RP	0.08	-0.50	0.46	-0.09