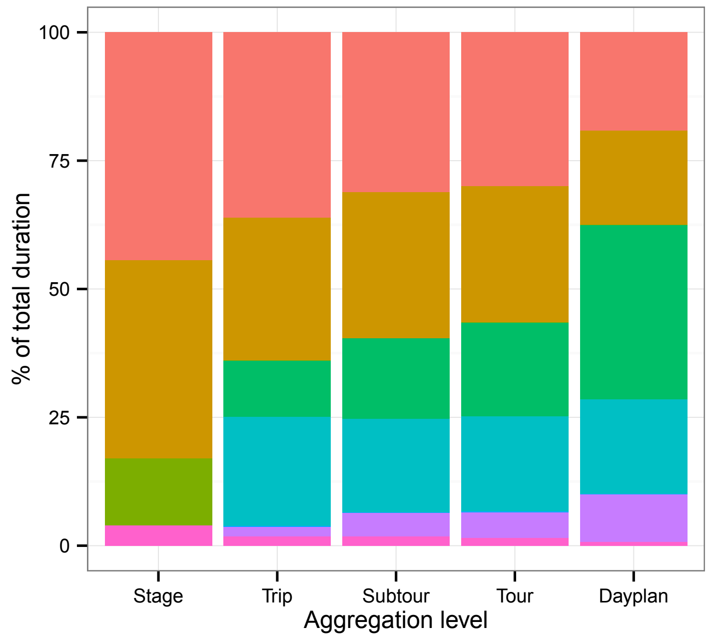

Effect of analytical units and aggregation rules on mode choice models

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Master thesis

Institute for Transport Planning and Systems

January 2015

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Glossary

Aggregated mode Mode categories derived through aggregation, i.e. all mode categories except for mode on stage level

Generated attributes Model derived attributes, e.g. through a routing algorithm, in differentiation to reported attributes

Microcensus If not otherwise specified: Swiss Mobility and Transportation Microcensus 2010

Mode group Group containing one or more mode categories like 'PT'

NM Non-motorized modes

PT Public transportation

Route-specific attributes Attributes that are specific for a certain observation, e.g. travel time

RP Revealed preference (in differentiation to stated preference (SP) data)

Travel time Time for travel (TT) from address to address if not otherwise specified

Master thesis

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Abstract

The quality of mode choice prediction is essential on the way to a resource efficient transport system. Commonly, mode choice is modelled on the trip or tour level, but a systematic evaluation of the definition of appropriate analytical units and aggregation rules is missing so far. This is in analogy to the 'modifiable areal unit problem' (MAUP) in statistical geography, in the sense that the definitions applied can effect the result. In order to find evidence for this issue with respect to mode choice, a choice set is generated on the basis of the Swiss Microcensus 2010 data, and multinomial logit-models are estimated for different aggregation levels. Results show that marginal substitution rates derived from coefficient estimates do not always show plausible values, which could be due to the known correlation between attributes in RP data. It can be concluded that regarding the trade-off between computation cost and prediction precision, the tour level might be the appropriate level for mode choice. It has to be noted however, that meaningful definitions will be subject to change with a more multi-modal behaviour.

Keywords
Travel demand, mode choice models, Swiss Microcensus, modifiable areal unit problem (MAUP), discrete choice, units of analysis, aggregation level, revealed preference

Preferred citation style

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Masterarbeit

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Zusammenfassung

Korrekte Verkehrsmittelwahlmodelle sind ein wichtiges Ziel in den Verkehrswissenschaften im Hinblick auf die Planung von effizienten Verkehrssystemen. Üblicherweise erfolgt die Modellierung der Verkehrsmittelwahl auf der Ebene von Wegen oder Touren. Eine systemische Auswertung der angemessenen Definition von Analyseeinheiten und Aggregationsregeln fehlt aber bisher. Die Aufgabe ist verwandt mit dem 'modifiable areal unit problem' (MAUP) in der statistischen Geographie, weil die getroffenen Annahmen die Resultate erheblich beeinflussen können. Um dies zu untersuchen, wurde auf der Grundlage der Daten aus dem Schweizerischen Mikrozensus 2010 Alternativensätze auf verschiedenen Auflösungsstufen erzeugt und anhand dieser multinomiale Logit-Modelle geschätzt. Ergebnisse zeigen, dass die Zeitwerte nicht immer im erwarteten Bereich liegen, was auf die Korrelation zwischen Attributen in den RP-Daten zurückzuführen sein könnte. Jedoch kann aus dem Vergleich von Modellgüte und Rechenzeit gefolgert werden, dass sich die Aggregationsebene 'Tour' für die Verkehrsmittelwahl eignet. Dabei muss jedoch berücksichtigt werden, dass diese Erkenntnis mit der Veränderung in Richtung multi-modalem Verkehrsverhalten in Zukunft nicht mehr ohne Weiteres gültig ist.

Schlüsselwörter

Verkehrsnachfrage, Verkehrsmittelwahlmodelle, Schweizerischer Mikrozensus, MAUP, discrete choice, Analyseeinheiten, Aggregationsstufe, reale Entscheidungen

Bevorzugter Zitierstil

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1 Introduction

The prediction of mode choice is essential for the performance of any travel demand model, because it determines user and social costs of travel. Facing the political trend towards less resource consuming transport systems, decisions makers need information about means to shift demand in the intended direction in a cost-efficient way.

Travel behaviour like mode choice have most commonly been analysed with trips as analytical units, and only recently tour-level model were implemented by researchers. The choice of the analytical unit for modelling, especially regarding the trade-off between modelling cost and precision has not been evaluated systematically. Recent surveys report individual travel behaviour in a stage resolution, which basically allows the generation of any higher-level units through allocation and aggregation.

Yet, the simplification of data through aggregation of categorical variables, and potential reduction of analysis cost, comes at the price of reduced resolution, or loss of prediction precision. For example, the aggregation of the mode choice variable from trip to tour level, when multiple modes are used within the trips, results in any possible combination of those modes and increases the categories that have to be allowed. Alternatively, rules have to be defined to allocate each combination to an original category, and thereby ideally reflecting the real choice process of the individual. Good model fit of the mode choice model estimated with aggregated observations could be evidence for the rules applied to be appropriate.

This work aims to address the following questions:

- How is individual mode choice different from other choices regarding time frame and explanatory variables?
- What concepts of analytical units of mode and movement have been discussed in the literature and how have they been applied in mode choice models?
- What effort is needed to generate the non-chosen mode attributes and how well is the reported behaviour reproduced?
- Is revealed preference (RP) data an appropriate basis for the review of analytical units in mode choice models?
- How does aggregation of choice sets influence model results and what can be inferred for the choice process, and for efficiency of travel demand prediction?

- What recommendations can be derived from this study for further research and application, especially facing a more dynamic mode use behaviour?

This thesis proceeds with a literature review, giving an overview of travel demand analysis and comparing the problem of defining units of analysis in transport behaviour analyis and statistic geography. Then, both formal concepts and analytical units, as well as empirical evidence of effects on mode choice are discussed in Chapter 2. For the practical part of this work, the reported behaviour from Swiss Mobility and Transport Microcensus 2010 on trip and stage level are supplemented with route-specific attributes for walk, bike, car and public transportation (Chapter 3). Performance of these procedures is evaluated in comparing observed stage attributes with generated values for the reported mode. Alternative sets are generated using attributes of the person, the reported behaviour and (supplemented) route-specific attributes aggregated from trip level alternatives. Moreover, invalid data is excluded (Chapter 4). In Chapter 5, alternative sets are described and compared. In a further step, different model specifications are developed for trips, before models are systematically estimated on other levels. Model estimation results are compared regarding explanatory power and estimated parameters like taste coefficients, and derived indices for relative valuation of variables are discussed (Chapter 6). Finally, Chapter 7 emphasises the relevant findings and the consequences with respect to the research questions. Recommendations for future research are given as well.

2 Literature review

This chapter examines the meaning of resolution in the prediction of mode choice behaviour in the current literature. To this end, methods and results of historical and recent research in mode choice prediction of passenger transport are reviewed. The concepts are discussed referring to the partly analogous 'Modifiable Area Unit Problem' in statistical geography, which is essentially the problem of how to aggregate observations in order to ensure meaningful representation of effects measured on the individual level. Previously reported dimensions of mode and adapted levels of movement are reviewed. Potentially relevant influences on mode choice are identified and it is discussed how they effect choice on different levels of resolution. Finally, the general procedure in order to quantify the effects based on available data is presented.

2.1 Explaining behaviour - Evolution of transport demand models

Since the beginnings of transportation demand models on a scientific basis in the middle of the 20th century, the distribution of the total transportation demand to different modes of supply has been an important step in modelling. Since then, with challenging phenomena like climate change and scarcity of resources on the agenda of transport policy, its importance has further increased.

In the same time the flexibility of models regarding behaviour, the level of detail and the precision of mode share prediction have increased, mainly based on the development of those determinants:

- (Dis)aggregation of explanatory social variables
- Availability of data
- Computational capacity
- Prediction methods and econometric theories
- Position in the overall prediction procedure
- Aggregation level of movement and modes

Throughout the 60s and 70s of the 20th century, an aggregated prediction procedure referred to as the classical 4-step model - with mode choice as the 3rd step - reflected the state of the art in this field. The starting point of mode choice procedure is the total or segmented trip matrices, which are split into the demand for each mode (i.e. network) for assignment (see for example Ortúzar and Willumsen (2011) for further references). Besides the weakness of missing time-of-day dependence and limited possibility of including detailed social variables, there is no integration which relates trips to their actual behavioural source, i.e. the activity in which individuals have the opportunity to derive satisfaction (or "utility"). In the beginning of the 80s, one of the first disaggregate demand models is documented by Gunn (1994) and enabled appropriate predictions with much higher requirements regarding behavioural variety and policy implications. Among other improvements, it allowed for chaining of trips in order to represent interaction between trips. Miller et al. (2005) mention various models that are sensitive to trip chaining. As the availability of data and computational capacity increased, Ben-Akiva et al. (1996) added the concept of activity to the disaggrated model techniques, which saw its first implementations for the cities of Boston and Portland.

2.2 Scales and units in travel behaviour

Travel means change in location, and the movement of an individual with time is continuously defined through explicit spatial coordinates, resulting in a continuous trajectory. Travel research is about explaining how the observed travel behaviour emerges and what the relevant influences are. In Western societies, travel as an aggregate phenomenon is eventually the result of individual's decisions, even if those decision may be restricted and influenced by other individuals or institutions. Accordingly, (travel) choice analysis assumes that the observed trajectories can be connected to preceding decisions of the travelling individuals. Thereby, causal relationships between the analytical objects like sections of a trajectory,(and their attributes), the individual itself or other objects it interacts with, are effective. It is further a quite plausible assumption that the individual does not consciously decide about every single point along the trajectory separately, but that a decision is taken for an entire section of the trajectory. Yet, those break points are not necessarily known a priori by the analyst, and neither is their relation to other objects used to explain decisions. In travel demand analysis, the respective concepts and rules are taken as a priori assumptions, and their effect on the results is often omitted. A background that is comparable to statistical geography, where the relation between individuals and higher levels of aggregation is known as the 'Modifiable Area Unit Problem' (MAUP). The next section discusses the essence of this problem.

2.2.1 The modifiable area unit problem (MAUP)

The partition of continuous space into discrete analytical units is inevitable for disciplines like statistical geography when results have to be derived on an aggregated level. Openshaw (1983) was the first to describe the problem comprehensively and proposed potential remedies, but some aspects of the problem had already been discussed decades before (Gehlke and Biehl, 1934).

Core of the problem is that results of aggregation are sensitive to the definition of aggregation units and the allocation of observations to them. Often, partly due to a lack of 'natural' units and partly due to practical circumstances, those units are defined without any meaning for the underlying processes or objects of analysis.

In spatial geography, the objects of analysis are often causal relationships between socio-economic variables, e.g. between crime rates and income. The base data is collected with surveys and has to be aggregated. The number of different possible configurations of aggregation units is dependent on the number and the aggregation rules, e.g. whether the basic units have to be spatially related neighbours or not. With large data sets, this number grows rapidly, and with it the range of potential outcomes in the results. Due to spatial auto-correlation, different zoning and grouping rules of aggregation can heavily influence the results.

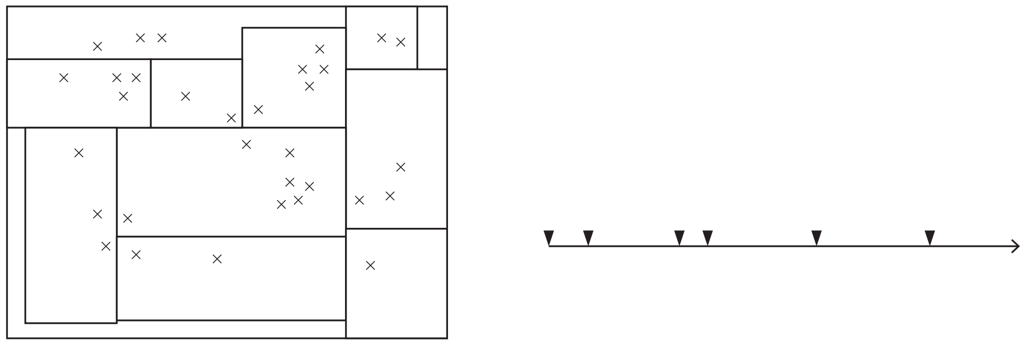
Openshaw (1983) highlights that due to the nature of the problem, the interdependence between aggregated data and a priori assumptions, cannot be avoided: Findings inferred from spatially aggregated data on natural objects are always prone to challenge (ecological fallacy problem). It is therefore an essential task of the analyst not only to evaluate the sensitivity of the results regarding independent variables, but also regarding his own a priori definitions.

An appropriate definition of aggregation units can be found using two general approaches: The search can either be started by a 'best guess' based on the known or assumed underlying processes that are identified by a priori data analysis. Or alternatively, the aggregation rules can be determined 'backwards', in defining a certain resolution, and iteratively searching for optimal aggregation rules in maximising the model fit. This process can even result in additional findings about the (spatial) structure of data.

2.2.2 Comparison of disaggregate travel behaviour with MAUP

While in statistical geography, an individual is usually the primary unit of analysis, it is the trajectory in time and space for travel analysis (Fig. 1). The derivation of zones as contiguous areas is analogous to the derivation of contiguous movement sections, which links the basic units, whether discrete like individuals or continuous like trajectories, to units of analysis. In analogy to the discussion of MAUP, the definition of analysis units should ideally lead to a maximum of homogeneity regarding the process under analysis. Or, in transferring the term of spatial auto-correlation mentioned above to choice analysis: Within an analytical unit of the trajectory, a high auto-correlation regarding the choice process of the individual should be present. The trajectory as the observable behaviour can be regarded as outcome of a sequences of decisions, during which the decision space is constantly narrowed, until the actual plan is enacted, and eventually observed. The appropriate definition of analytic unit is therefore dependent on the choice process under analysis. Secondly, as behaviour of individuals is subject to evolution, units might also require adaption across longitudinal analyses.

Figure 1: Comparison of zones and travel trajectory sections



Allocation of individuals to contiguous spatial zones

Partition of travel trajectory into sections

After defining the primary and other units of analysis, the rules for the transfer of attributes from one unit to another have to be defined. While some continuous variables like time and length are, in theory, calculated straightforwardly, it is a matter of definition for type of vehicle, ambience etc. In the case of choice analysis, non-linear or lexicographic effect can arise, e.g. if the number of considered aspect by the choice maker is limited, and minor aspects have to be omitted during aggregation.

The discussion so far has not necessarily put any restrictions on the number of sections; as with the number of analytical units approaching infinity, homogeneity within each unit does so as well. Therefore, the cost of processing information by the analyst, and the benefit of precision in prediction, have to be included when defining the number of units. With a constant number of basic units, the resolution of analysis is the reciprocal value of the number of analytical units. Consequently, the aggregation level on which mobility behaviour should be analysed in order to maintain a given level of precision, is dependent on the actual behaviour. The straightforward adaptation of the implications of MAUP to travel demand suggests that heterogeneity in data asks for higher complexity in analysis. The prediction error that is conceded by aggregation, is influenced by several aspects: The point of aggregation during the prediction process, the type of modelled effects (linear, quadratic etc.), and the heterogeneity of basic units regarding a given variable. For example, in disaggregate models, aggregation can be done as a last step, which allows to capture 'extreme' behaviour and non-linear effects.

To summarize, the following definitions have to be set prior to analysis: The target number of aggregated units (or resolution), the criteria to use in order to allocate the basic units to analytical units, and the rules to represent attributes of the basic unit on other analytical levels.

With this background, the following sections look at analytical units used for mode choice analysis.

2.3 Units in mode choice analysis

While the above mentioned aspects concern travel demand analysis in general, the scope of this work is limited to mode choice as the model step of highest relevance for research and policy makers. For mode choice, units for two dimensions are most relevant: The partition of an individual's trajectory in space, as the level of decision, and the alternatives of the mode choice, as the choice dimension. The following sections will inspect mode choice units regarding trends in behaviour and observation strategies, and the implications for (discrete) choice models.

2.3.1 Analytical units for movement

Reflecting the nature of travel demand as derived demand, the trip had been the basic unit in many past surveys and studies for the car-based society of the second half of the 20th century in the U.S. and elsewhere. The definition of the next-higher level of subtours and tours follows the logic that some places of basic activities are more important than others, and are therefore critical regarding the availability of vehicles. While up to tour level, unit definitions do not restrict the duration, higher levels are strictly defined periods like days, weeks etc. Little controversy is found in the literature about the principal definitions of the different levels. Yet, there is certain degree of freedom that still remains in their definition. And, most importantly, a systematic comparison of analytical units regarding their adequacy for certain kinds of analysis is missing so far.

Any analysis of travel behaviour relies on observations, coded and prepared following certain standards and for specific or general purposes. The survey design therefore predefines the purpose the data can be used for and how well actual behaviour is represented in the results. The discussion about analytical units therefore has its natural origin in the collection of data - namely travel surveys, as some assumptions are already made here, based on findings from previous surveys. Essentially, the resolution in which travel trajectories are reported defines the smallest possible units of analysis.

The numeric analysis in this work is based on data of the Swiss Microcensus 2010. The units applied in this survey are therefore taken as the ’base case’.

These units are discussed in greater detail below. An overview of the definitions used for this work is shown in Table 2.

The stage - a mode-specific unit of analysis While the trip has long been the basic unit in travel observation, Clifton and Muhs (2012) make recommendations for a better respresentation of multimodal trips in travel surveys, in especially enhancing the reporting of short and mainly non-motorized segments. The stage is defined as a section of the trajectory related to a single mode or vehicle, and is therefore essential for a high resolution in the observation of travel behaviour. The Swiss Microcensus adapted the stage concept with a minimum distance criterion of 25 meters for travel outside of buildings (Marconi et al., 2004). Even with this high level of resolution adapted, there are still hints to an underreporting of short segments, presumably done by walking (see Section 2.4.1). This case indicates evidence of the biasing effect of resolution on mode choice data, is already present at the step of data collection.

The trip - derived demand Trips as a unit relates travel demand to its purpose and is defined as a trajectory section between two activity locations. In simple cases, e.g. for direct home-work trips, a trip can easily be allocated to the purpose of work, which is usually defined as primary activity and is of a relatively long duration. When parents drop their children on the way to work, it is not straightforward any more. Depending on the detour for this intermediate stop, and whether it is close to home or close to work, the allocation of the trip to the preceding purpose can lead to misinterpretation. This issue is usually addressed by distinguishing purpose directly or through the duration of the following activity. Differing definitions are therefore found in literature. FHWA in the U.S. adopted the (additional) definition of trip chains, which consists of trips with only stops of 30 minutes or less. Trip-chains are termined by stops of 31 minutes or more (McGuckin and Nakamoto, 2004). Thus, the definition of trips adopted for Swiss Microcensus corresponds to the U.S. definition of trip-chains, which is also denoted as ’half-tour’ by Bowman et al. (1998). It is recommended to fully report every stop in the survey data, which can be recoded according to the purpose classification and the objective of the analysis.

Subtour and tours - from and to anchor points While the distinction between trips and trip-chains is dependent on the duration of the intermediate stop, further aggregation of those units relates to the definition of anchor points, usually home or work or other locations of primary activities that are mostly result of a long-term decision and relatively persistent. Often, those locations are both origin and destination throughout a day, and are related to the opportunity to change mode, for example because car parking is available at home and at work. Therefore, those points are important for mode choice. Again, different definitions are found, depending whether the focus is on mode choice or on allocation of travel to purpose. The Swiss Microcensus 2010 data is coded according to the definition that tours are chains of trips that start at home and end as soon as a trip ends at home. In contrast, trip chains from home to work are treated as tours in the U.S. (McGuckin and Nakamoto, 2004), as are any trip chains between two predefined anchor points (home or work). Subtour, not reported in the Microcensus data, is a special case of tour that also allows for other anchor points. For this work, subtours can be any sequence of trips that starts and ends at the same point.

Dayplan - natural rythm In travel surveys like for example the Swiss Microcensus 2010, the reported behaviour of an individuals generally covers one day, which can be denoted as 'dayplan'. This limits the maximum duration of the units discussed above, and dayplans that do not end at home leave tours or subtours incomplete. Moreover, day-based surveys restricts the analysis of behavioural patterns of an individual with longer cycles, for example the travel patterns connected with social networks, or habitual mode choice.

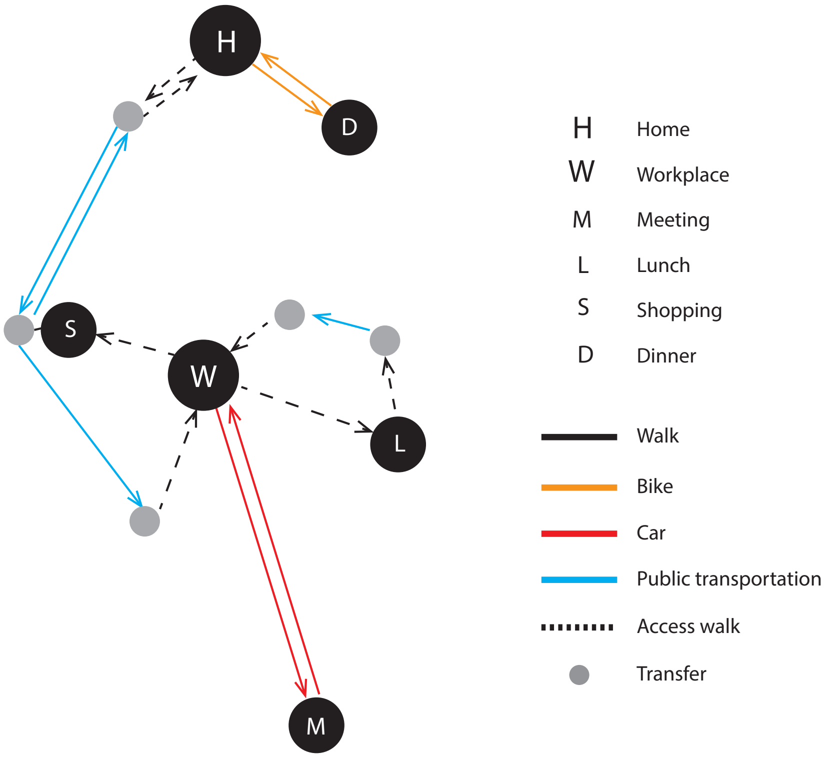
Table 1: Units of movement, definitions used for this work, based on Swiss Microcensus 2010

Name	Delimitation criterion	Related to
Stage	Vehicle/mode change, walk > 25 m distance and not inside buildings	Mode unit definition, transfers
Trip	Activity > 30 minutes	Purpose
Subtour	Location that is origin and destination of a chain of trips	Vehicle availability, purpose
Tour	Home	Vehicle availability, purpose
Dayplan	Midnight or end of tour started before midnight	Important behavioural cycle of activity and recovery

An exemplary dayplan resolved in stage units is shown in Fig. 2, which allows to describe several critical points of the trajectory unit definition. The first tour starts at home and includes activities of work, meeting, lunch and shopping. Here, the shopping activity at the railway station is assumed to take less than the threshold time (e.g. 30 minutes), and therefore the walking section is counted as access stage. Because in this example, the grocery shop and the railway stop in the same building, the access section after shopping is omitted following the MZ2010 definitions, and a PT stage is directly following the activity. For the same reason, the short access and egress walks to the bike are omitted as well. The issue of omission of short walking stages is discussed later in Section 2.4.1.

The first tour can be split up in two work-based (and closed-loop) subtours, and the remaining two half-tours home-work and vice versa, which are also counted as subtour in this work.

Figure 2: Artificial example of a dayplan



2.3.2 Analytical units for mode

The definition of mode depends on one's perspective. In the common perception, transport modes are closely linked to motorized vehicles of either individual or public transport. At the same time, the individuals behaviour is eventually influenced by its own properties (e.g. due to long-term decisions about mobility tool ownership) and the properties of the actual connection. In fact, it is impossible to fully disentangle the characteristics of single movements, that are defined by coordinates and time-of-day, and what may be referred to by the somehow artificial notion of mode as an analytical unit. From the analysts perspective, the alternatives of the choice set can be arbitrarily defined, as long as they include the chosen alternative and they are mutually exclusive, while their number is finite (Train, 2009). At the same time, it is limited for reasons of the capacity and cost of information processing by the decision maker. From the transport system perspective, mode choice is limited to the number of different networks.

For statistical evaluation and for the choice modelling in this work, vehicle-related modes are grouped into categories with similar properties, in order to allow for high homogeneity regarding unobserved effects within these groups (Table 2). Walk and bike are treated separately and not summarized in a non-motorized mode group because the differences in requirements and unobserved attributes are suspected as relevant for further analysis. Individual motorized modes are grouped into one category denoted ’car’, as car being by far the most important mode regarding distance travelled. The public transportation group includes the standard modes which are the most important modes for daily travel that are also included in available timetables. All other modes are grouped in a miscellaneous category, even if some of them are important for some areas or purposes: Taxi (urban areas), cable cars and boats (tourism) or trucks (commercial). Airplane and coach are mostly important for long distance travel and for foreign destinations. Even if the a priori definition of those mode groups is somewhat deliberate, the four main groups (except ’Other’) should quantitatively respresent the short-term mode choice in agglomerations, and not lead to inacceptable distortions.

Table 2: Analytical units of mode, definitions used for this work, based on Swiss Microcensus 2010

Mode groups	**Stage modes**
Walk	Walk
Bike	Bike
Car	Motorbike
	Small motorbike
	Motorbike as passenger
	Small motorbike as passenger
	Car
	Car as passenger
PT	Train
	Postbus
	Bus
	Tram
Other	Taxi
	Coach
	Truck
	Boat
	Airplane
	Cablecar, rack railway, ski-lift
	Vehicle-like devices
	Other

2.3.3 Effect of aggregation rules

If reported travel behaviour on higher levels of aggregation should be derived from original data, observations as base units have to be aggregated. For continuous variables, the value of an attribute of a higher unit can be derived through summation or maximisation of the same variable of the related base units. For discrete variables like chosen mode rules have to be defined in order to allocate unique values of the aggregated variable. Otherwise, except the case of perfect homogeneity of variable values regarding the relation to a higher unit, the number of categories potentially grows to the number of all possible combinations. In the case of three mode groups on the original level, aggregation would result in a combination of modes and a maximum of 6 categories for the mode variable would be necessary. In the other case with the number of categories held constant, aggregation means a decrease in resolution, i.e. loss of information.

One possibility is to a priori define a hierarchy of applicable categories based on the expected relative importance. Alternatively, a criterion is evaluated for every individual aggregation, and the dominant category is identified in evaluating e.g. the sum of duration per mode category. On the example presented in Fig. 2, the principle aggregation of mode variable on stage level to higher levels of movement is visualised in Fig. 3, showing that modes with lower hierarchy Bundesamt für Statistik, Bundesamt für Raumentwicklung (2011) tend to be omitted at the aggregated level. For example, PT is the mode for the first tour, even if car and walking is also reported on trip level. Note that the first and the last subtour sections of the first tour in Fig. 3 are counted together as one subtour.

Figure 3: Example for aggregation of mode variable

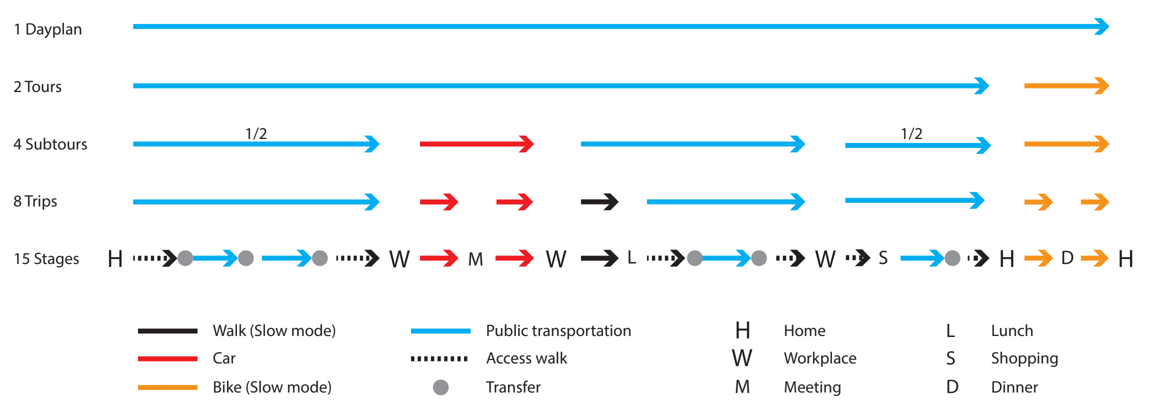
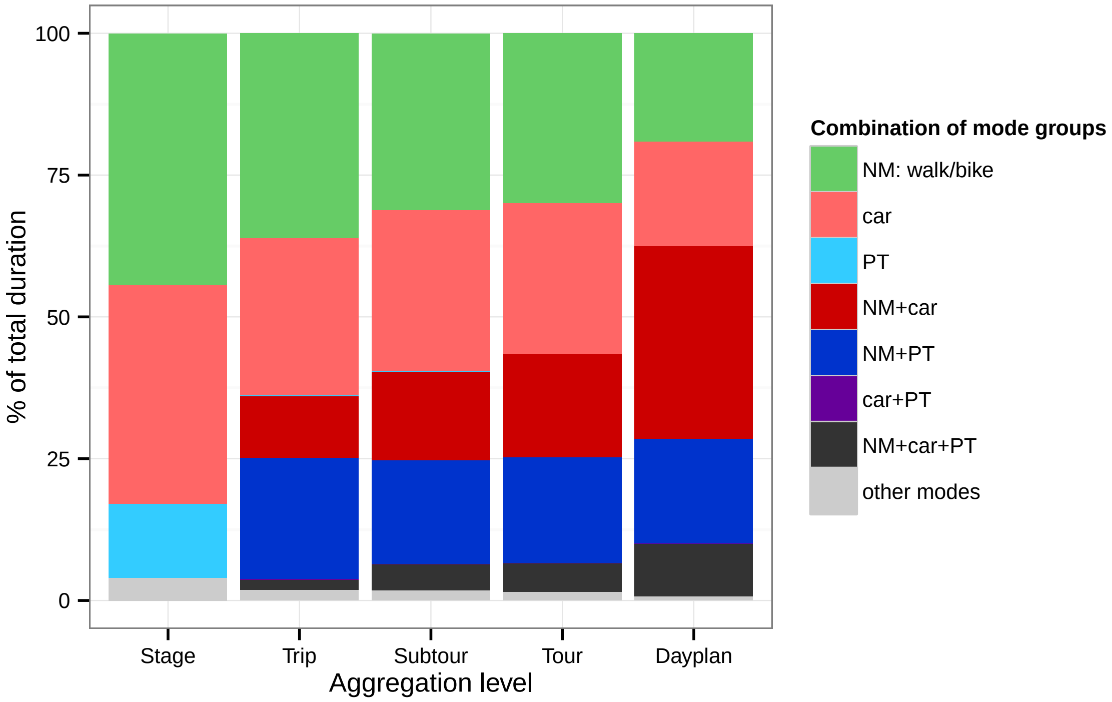


Fig. 4 illustrates this aspect based on Swiss Microcensus data. On the stage level, the observations are pure regarding the basic mode definition with 20 different modes, and consequently regarding the mode groups. With increasing aggregation, the fraction of mixed mode observations increases, while the share of individual non-motorized and car modes decreases. The number of PT-only observations quickly approximates zero with increasing number of stages, which reflects the fact that within trips, PT is combined with walking (or bike) in most cases.

Figure 4: Distance share of combinations of mode groups

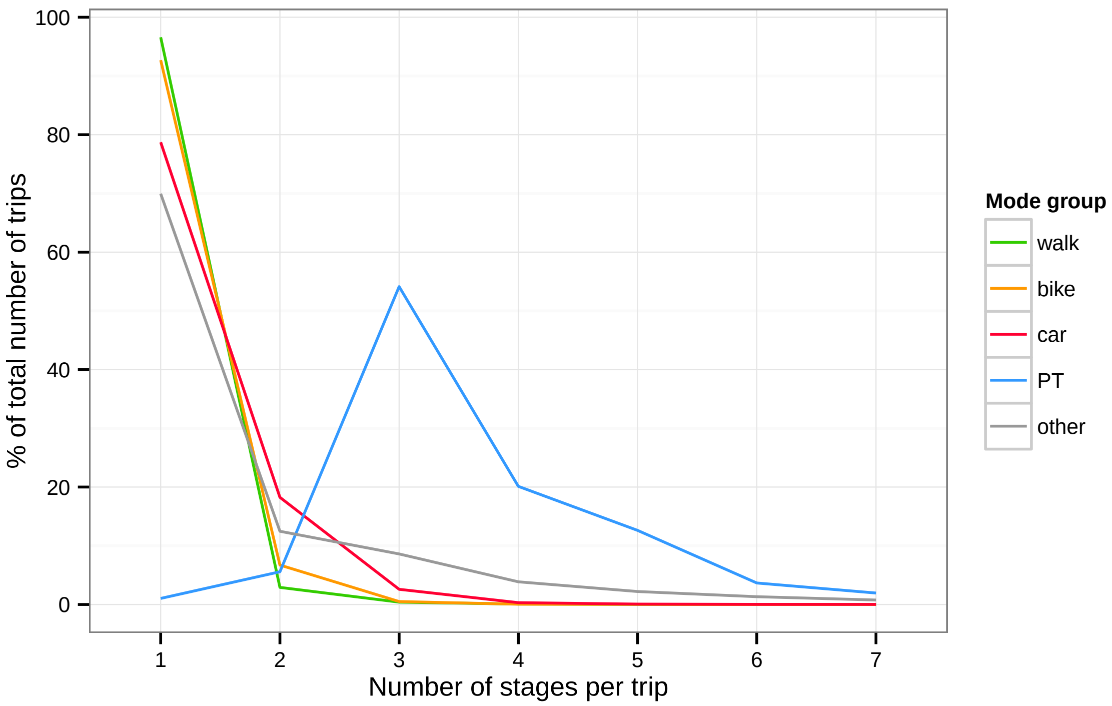


2.4 Implications of data aggregation

2.4.1 Mode chains in reported data

The aggregation units and rules discussed above are applied to Swiss Microcensus data. Trips are derived by aggregating stages. The trip mode represents the hierarchically highest level of mode among related stages, which is further simplified to one of 4 main transport mode categories that are used as alternatives (walking, bike, car and PT). This procedure results in the number of stages per trip distribution in Fig. 5. Trips of individual modes (walk, bike or car) mostly consist of one reported stage. Considering the stage concept discussed in Section 2.3 and assuming that most trips do not start or end less than 25 meters from the PT stop, three stages per PT trip would be expected for most movements. Evaluation shows that almost 10 percent of PT trips only include one or two stages, which means that either the start or end stage is a PT stage. This finding could be a hint that access and/or egress time as part of the actual PT movement is not reported in some cases, or that it is included in the respective PT stage. If the first holds, the PT trip travel time would be under-reported overall.

Figure 5: Number of stages per trip by trip main mode, in %



2.4.2 Capturing travel behaviour in an individualized and multi-modal society

Multi-modality is a loosely defined attribute, whose meaning is strongly dependent on the context. In a very general sense, it refers to transport policy strategies that aim at a social optimum of travel demand in offering viable mode options in order to reduce car-miles travelled. Because non-motorized modes like walking and cycling are limited in range, public transportation is the primary alternative to car. The degree of multi-modality in an individual's behaviour is dependent on the time period considered, or, more generally, on the analytical unit of the travel trajectory. Kuhnimhof et al. (2006) derive from German survey data that about one third of adult population uses both car and public transport in the long term, but only about 3% show habitual use of combined car and PT modes within a 1-week travel plan. As population groups prone to multi-modal usage are increasing in Germany, a similar trend can be expected for countries in Central Europe.

Analysis of the Swiss Microcensus shows that combined use of motorized modes (car or moto) and public transportation within dayplan accounts for more than 10% of the distance. This percentage drops towards lower levels of aggregation, and is only 1-2 % for trips (Figure Fig. 4). For the modelling of mode choice, this means that for example on the tour level, a substantial share of behaviour is neglected when not allowing multimodality in choice sets. However, an increase of multimodal behaviour in general is suggested to be part of efficient satisfaction of transport demand.

2.5 Theory of mode choice

2.5.1 Mode choice process

The observed choice of mode for a section of the trajectory like the stage is the outcome of an individual's choice process. Typically, the process itself is unobserved and knowledge has to be inferred from the performance of models to reproduce the observed behaviour.

The trade-off between generality and complexity in model structure is - to some extent - made informally in most cases of model development. Early models were based on simple multinomial logit form, mainly based on mode-specific and socio-economic variables. It can be argued that despite their simplicity, the performance of prediction accuracy was acceptable. On the other hand, it is obvious that such models fall short in representing the complexity and heterogeneity of the human decision process. For example, the individual might make mode choices for stages within a day with different time horizons: While the mode to work might be chosen years ahead, irregular activities like trips to social contacts might be chosen much more short-term. Thus, different model structures and the explanatory variables might be used to reproduce such observations. Ben-Akiva et al. (1998) mentions two aspects that are not represented in former models: Heterogeneity in taste across population and information acquisition. In fact, the dependence of the complexity of choice process on habit had also proven to be relevant (Verplanken et al. (1997), Schlich and Axhausen (2003), Kuhnimhof et al. (2006)) .

In former research, different choice set structures have been designed, depending on the purpose of analysis. Most disaggregate activity-based simulators mentioned above adapted some sort of tree logit form with a choice of primary mode on the tour-level, which then restricts the decisions on subtour or trip-level (Miller et al., 2005).

As an alternative to the separate model steps of mode and network assignment, Carlier et al. (2003) implemented a supernetwork, in which the mode and route choice is performed simultaneously.

2.5.2 Attributes and the aggregation level of movement

If the mode choice itself was partitioned into multiple sequential choices in order to approximate the actual unknown choice process, what is the relative relevance of the above mentioned effects on mode choice?

We propose that, because not only the choice set size, but also the number of attributes examined by the decision-maker is finite and a rather low, some attributes have to be either aggregated with others, or neglected by the decision-maker, which can change the relative perception or weight of the measurable attributes. This is exactly what should become visible in the relative values of estimated model parameters on different levels.

2.5.3 Determinants of mode choice

Observable behaviour at a certain point in time can be seen as a result of a sequence of decisions, starting long before the actual behaviour is executed. The amount of potential influences on mode choice is vast, and the potential interferences between the measurable effects is beyond the scope of this work. We review variables that are commonly used in models, but also discuss further variables that could explain behaviour. The variables can be grouped by object they belong to and can correspondingly be described as attributes of the person and/or its household (e.g. income), the principle means or service to overcome space (e.g. the safety-features of the car), and the actual plan to switch between two activity places (e.g. time-of-day).The mechanism of how those variables effect behaviour is then subject to the modelling procedure with hypothesis, estimation and testing. It is important that the mode choice decision is part of a sequence of decisions and can be effected by prior choices, and in turn predetermine successive choices effecting availability or attributes of alternatives. As mentioned above, this work is limited to mode choice, and variables as outcome of other decisions like location choice are taken as given.

In the beginnings of mode choice analysis in the United States, only attributes of the person or mobility tool ownership were included in models. Only later, attributes of the route like time or - more universal - generalised cost, were taken into account on the aggregated level with resistance formulations analogous to physics (Kirchhoff's law), and later with logit formulations. Due to the close relationship of travel purpose and mode choice, combined destination and mode choice models were developed (Ortúzar and Willumsen, 2011).

Attributes of the person Directly measurable socio-economic characteristics of a person are often available from household travel surveys and can be used as indirect measures for taste variation: Income as a measure of total personal or household budget, age as indices for walking speed, activities and social networks, and residential location as proxy for accessibility of transport services, travel budget (through real estate prices), and so on. Other measures that influence the persons choice process, reflecting for example satisfactory thresholds or social network characteristics are discussed in literature, but are so far mostly subject to specific experiments or surveys that are otherwise less comprehensive (Friman et al. (2001), Axhausen (2008)). Similarly, the identification of habitual mode choice (as a persons choice or attribute) would require survey periods to be longer than 1 day as in the Swiss Microcensus.

Mobility tool ownership Mobility tools are acquired by individuals or households in order to enable or optimise costs of their mobility needs. The respective decision is usually mid- to long-term, in contrast to short-term travel decisions. Thus a household predetermines the actual choice of short-term mode, when only variable "out of pocket" costs are included. Tool choice could be viewed as long term part of mode choice, and has strong relations to location choice.

The most important tools are car and drivers licence, and public transportation passes. Tools are either reported in household travel surveys like Swiss Microcensus (used in this work), or modelled directly from more basic characteristics of the population (e.g. Ciari et al. (2007)). Budget constraints lead to interactions between car and public transport pass ownership, which has been analysed by Scott and Axhausen (2006) on the household level.

The respective variables for this work are taken from survey data, as their modeling is beyond the scope of this work. It can be expected that with the direct use of mobility tool data, effects of variables like income and residential location are already included, and their direct effect should be lower.

Activity-dependent attributes The concept of activity is critical to most disaggregate travel demand simulations, as the activity is the primary source of utility and causes travel as a derived demand. It is known that taste coefficients for generalised cost components depend on the purpose of a particular travel action (König et al., 2004). For example, travel with luggage for leisure or shopping could favour the use of car, even if at the same time, the value of time is lower for such purposes. For the concept of subtour or tour it is further important that in the short term, primary activities are fixed and put restrictions on the choice of other activities. The primary activities are usually home, as the location of personal maintenance and rest ((Bowman and Ben-Akiva, 2001)), and work as the primary source of household budget. Apart from the effect of the particular purpose, the mode choice can also be influenced by the activity-schedule as the planned integration of activities and travel as a whole. Depending on the (preceding or successive) choice of location, a given activity schedule might only be feasible with a limited set of modes.

Activity-planning in the sense of related purpose of travel, and location choice are treated as preceding decisions in this work and are hence included as explanatory variables.

Attributes of the transport mode While the definition of the mode is arbitrary, the (reported or actual) plan determines the time- and space-dependent variables of the actual behaviour of a person. Besides travel time as a generic dimension, access time to vehicles of privat or public transportation might be distinguished. The plan also defines the origin and destination of each movement. This gives the possibility to include in the model spatial attributes like type of built environment, which can be perceived as a proxy for unknown deterministic or stochastic effects, like the probability of late arrival due to (unplanned) congestion or due to (unplanned) search for parking.

Attributes dependent on the trajectory Route-specific attributes are also summarized as generalised cost. This can include travel time and cost, physical environment along the route, safety, or weather conditions along the route. The latter depends on the season and on the exact time a route is undertaken.

Of course, allocation of attributes to the objects mentioned above is not always sharp, for example with safety, which is dependent on both the vehicle used and the part of road network used.

3 Methods and Data

In the first part of this chapter, the original data set used for this work is described, primarily regarding its structure. In the second part, the processing of the raw data to modelling input data is documented step by step. This process roughly consists of 1) the aggregation of data based on the originally reported stages and trips in the Microcensus 2010, 2) the generation of route attributes for stages and trips, 3) and the aggregation of the generated attributes from trip to higher levels like tours. Finally, based on certain variables it is decided whether an observation (e.g. a trip) is accepted and further used for modelling, or filtered and neglected for the further analyses.

The last part describes the methods and tools used for the model estimation.

3.1 The Swiss Microcensus 2010 Data

The Mobility and Transport Microcensus is a survey conducted every 5 years that provides a detailed picture of the mobility behaviour of the Swiss resident population. For this end, a sample of 63’000 persons were interviewed in the year 2010 about their travel behaviour. The data is stored as data base tables with linked information about travel behaviour as stages, trips and tours, persons, households, vehicles etc. The official data set includes about 300’000 stages, 210’000 trips and 65’000 tours starting and ending at home. For this work, only travel behaviour of the main survey part for travel on one appointed day per individual, and person/household characteristics have been used.

Start and end addresses of the stages, as well as residential and work addresses are geocoded. Distance estimates reported by the participants are validated and supplemented by routed distances during the computer-assisted telephone interview (CATI).

The official report with a general evaluation of the results contains a summary in English language (Bundesamt für Statistik, Bundesamt für Raumentwicklung, 2012). The data description report is only published in German language (Bundesamt für Statistik, Bundesamt für Raumentwicklung, 2011).

3.2 Choice set generation

In order to model mode choice on different levels, data of revealed or stated choices are required. Both approaches have been separately and jointly applied and discussed in the literature (see for example Hensher et al. (1998)). One advantage of revealed data for this application is that data on different levels is consistent, because it is based on the same smallest unit in reported data. Actually, it is rather a variation of perspective than a variation in behaviour, even if this change in perspective is imposed artificially.

The basis for the choice sets is the reported travel behaviour in Swiss Microcensus 2010, which is available as stages and also as assembled observations on trip and tour levels. Further, person and household data linked to the stage observations is used to describe socio-economic characteristics and mobility tool ownership. Route-specific attributes for the chosen mode and the non-chosen modes of stages and trips are generated using different approaches. Finally, for higher levels of aggregation (i.e. lower resolution) the trip choice sets are aggregated and invalid observations are excluded.

Data processing for choice set generation has been conducted with specifically coded scripts for the software R (R Core Team, 2014).

The procedure is described in higher detail in the following sections.

3.2.1 Attributes from reported data and aggregation

For the basic model specification, four possible alternatives (walking, bike, car and transit) are defined a priori. During the assembly procedure of stages, the reported mode like described in Section 2.3.2 is aggregated similar to the procedure documented in detail in Bundesamt für Statistik, Bundesamt für Raumentwicklung (2011). For example, different individual motorized modes are reported for stages, but now aggregated to one car mode. Although it would be possible to consider a more detailed set of alternatives, this would require more complex model formulations. Since the share of each motorized vehicle category other than car is very small, they are neglected as main modes for this study. This work only considers the mode 'car as driver'. While 'car as passenger' could in principle be represented in the model with differentiated travel cost, determination of the availability of the mode 'car as passenger' would require more information about social networks within and outside the household. Similarly, the car occupancy of the non-chosen mode cannot be identified, as this is beyond the range of choice of the regarded individual.

Availability of the alternatives is dependent on socio-economic characteristics of the person. The ability to walk is a prerequisite for all modes. In addition to that, bike mode is available for a person with at least one bike available, and car mode depends on availability of car and the ownership of a driver's license.

3.2.2 Generation of route-specific attributes for stage and trip level

The behaviour reported in the Microcensus data is taken as chosen alternative. In order to generate a choice set suited for the estimation of discrete choice models, route-specific attributes included as explanatory variables have to be generated. It is important to note that attributes are generated not only for non-chosen, but also for chosen alternatives. This ensures that potential distortions through differences of reported and generated variables are avoided.

Travel times for walk and bike modes For non-motorised modes like walk and bike, resolution of available network data for entire Switzerland is too low for meaningful routing results. Travel distances for those modes as mainly short, and missing network links could have distorting effects. Therefore, a similar approach as in Fröhlich et al. (2012) is applied, and travel times for those modes are roughly approximated using the reported crowfly distances between start and end coordinates of the reported observation, and applying detour factors and average speeds of 5 km/h for walking and 15 km/h for bike. Distance dependent detour factors are applied: For short distances up to 0.5 km, a value of 1.3. For longer distance the detour factor was decreased to 1.25 (<1 km), 1.2 (<2.5 km) and 1.1 (>2.5 km).

Route-specific attributes for individual motorized modes Route-specific attributes for individual motorized modes are generated using the routing algorithm in MATSim with a network from Teleatlas. The network scenario corresponds to an average weekday, where the load and hence the travel times are dependent on time of day. The derived attributes correspond to the time-shortest route between start and end coordinates of the reported observation at the specified time of day.

The total travel time consists of access and egress time from the address coordinates to the closest network link, for which a speed of 5 km/h was assumed, and the in-vehicle time on the links with link- and load-dependent speeds. Access and egress distances do not necessarily correspond to actual walks; with a low network resolution, the driven share would be increased. On the other hand, in the case of on-street parking, it would correspond to walked segments. Access and egress time was therefore not regarded as a reliable measure and not taken as a separate variable for individual motorized modes. In-vehicle travel time is not increased when nodes are passed, which could result in underestimated travel times, especially for routes with a high node-to-length ratio and a high network-load. No distinction between weekdays and weekends is made for the generation of attributes, as no weekend scenario was available.

Travel cost are derived from the generated in-vehicle travel distance, with a price per kilometre of 0.13 CHF as used in Fröhlich et al. (2012). This price does only include fuel cost, as only 'out-of-pocket' cost are considered for this analysis. Further, the price was held constant, which is an acceptable simplification with view of the fuel prices during the relevant period of 2010 (Bundesamt für Statistik, 2015).

Public transportation attributes The attribute data for the alternative of public transportation is derived using the routing algorithm of MATSim, with a network and timetable (Year 2012) compiled at IVT based on data provided by HAFAS. The generated connections are then post-processed in order to derive additional variables like service interval, and to choose the best connection per reported observation.

The routing algorithm at the time of the analysis returned the time-shortest connection from start to end coordinates, for a specified start time, with fixed penalties for access time and transfer. If a direct walk without the use of PT service between the two coordinates is faster despite the penalty for walking, this connection is returned.

In order to allow for a trade-off between different variables as part of the generalised cost, e.g. connection with a start or arrival time difference to the reported start or arrival time, start times were varied in steps of 10 minutes from -30 minutes to +30 minutes around the reported start time. As a consequence, the possible values for the interval were between 10 and 60 minutes, while for the case of only one detected connection within this interval, a value of 120 minutes was implemented. This limitation was accepted due to restricted time frame for this study. From the generated connections within the time interval, the dominated ones were excluded, and from the remaining set, the connection with the highest utility is chosen. For this, values for taste coefficients were taken from Vrtic and Fröhlich (2006). For early and late arrival, the time coefficients were taken as twice respectively three times as high as in-vehicle travel time.

In early runs, the generated connections show a quite high fraction of stages that are generated only with walking (see Section 4.5). Recent development of the MATSim application parallel to this work allows the variation of relative disutility factors for access time relative to in-vehicle travel time. For this end, the values in Bundesamt für Raumentwicklung ARE (2014) have been averaged across purpose, which resulted in a factor for access time of roughly 2 [-], which was higher than the values used in previous runs (where penalties of are used). In addition to that, alternative connections are searched for, even if the connection for the original start time did only use walking, which was not done in previous runs. Still, evaluation shows that the fraction of pure walking stages is quite high, and the choice set data is therefore not updated.

3.2.3 Exclusion of observations based on filter criteria

Part of the original observations are not used for further analyses because of issues with the reported or generated data. In some cases of excluded observations, origin or destination coordinates are either identical, or outside of Switzerland, which makes a meaningful estimation of mode attributes impossible. Another reason for exclusion is erroneous or problematic results of mode attribute generation. Note that those filter criteria are based on data on the respective level of stages and trips. In a second step, the effects of these filters are aggregated to higher units of movement, which is essential for the comparability of modelling results, in order to prevent an inconsistent bias due to applied exclusions. For example, if a tour contains a trip with erroneous attribute estimation results, the tour is excluded as well. As a consequence, all other trips in this tour are also excluded to ensure comparability. The quantitative description of the filter effects and the aggregation to higher levels is evaluated and discussed in the next chapter (Section 4.6 and Section 4.7). Due to the issue with PT routing and the missing availability information for 'car as passenger' mode, further observations had to be excluded. Their quantitative effect on the data set size is much greater, and the application of a subsequent downstream filter in order to ensure completeness of dayplans could not be applied.

3.2.4 Aggregation of generated mode attribute data

The choice sets with trip level resolution are aggregated to subtour, tour and dayplan level according to the same rule as for the generation of the reported observations (Section 3.2.1). Thereby, start and end destination per higher level of movement are conserved, because location choice is not allowed for in the models. Secondly, the generated alternatives are each composed of generated trips for the corresponding mode. This means that with the mode aggregation according to the priority rule (described in Bundesamt für Statistik, Bundesamt für Raumentwicklung (2011)), modes with higher priority tend to be increasingly represented with every level of aggregation, while reported movements with lower priority modes used, are not represented any more in choice set attributes with lower resolution. The route-specific attributes are aggregated using definitions in Table 3.

Table 3: General definitions of variables and aggregation rules

Variable	Definition	Aggregation rule
Total travel time	Address to address	Sum
(In-vehicle) travel time	Travel in vehicle	Sum
Travel cost	Cost with average prices per distance	Sum
Access time	Time from address to PT stop with average walking speed	Sum
Transfer time	Time used for PT transfers	Sum
Transfers	Number of transfers between PT vehicles	Sum
Interval	Average headway between two PT services	Maximum
Slope	Average slope from start to end address	Maximum
Distance	Network-based (Car, PT) or detour-factor based estimate	Sum

3.3 Estimation of discrete choice models

The prepared choice sets are used to estimate discrete choice models of the random utility type. Models of this type are widely used in the field of transportation planning, and they presume that compensatory decision rules are applied by decision makers. This means that the assumption is inherent that all attributes of the alternatives are regarded "at once", and that no thresholds of attribute values nor ranking of attributes are applied by the individuals.

In the following sections, a general introduction and overview of the model theory is given. Then, the model formulations applied are presented. Finally, estimation procedure and software tools are described.

3.3.1 Introduction in discrete choice

This is a brief introduction of discrete choice based on the work of Ben-Akiva and Lerman (1985) and Train (2009).

In contrast to continuous choice, discrete choice is about a choice among a discrete set of alternatives. A discrete choice model relates the observed choice of an individual to observed attributes of all alternatives in the choice set. Random utility theory assumes that an individual seeks to maximise utility and therefore always chooses the alternative with the highest utility, irrespective of the absolute utility value of the other alternatives. Part of the utility is deterministic and can be related to the attributes known to the analyst. In the probabilistic case, the utility is not entirely known to the analyst which is described by an uncertainty term. The probability of one alternative to be chosen equals the probability that the utility of this alternative is greater than of other alternatives:

$$U_{i,n} = V_{i,n} + \varepsilon_{i,n} \tag{1}$$

and

$$P_{n,i} = Prob(V_{i,n} + \varepsilon_{i,n} \geq V_{j,n} + \varepsilon_{j,n} \; \forall j \neq i) \tag{2}$$

$$P_{n,i} = Prob(\varepsilon_{j,n} - \varepsilon_{i,n} \leq V_{i,n} - V_{j,n} \; \forall j \neq i) \tag{3}$$

Different assumptions about distribution of and correlation between uncertainty terms across alternatives lead to the application of different model types. Multinomial logit has been widely used due to the closed form solution, which is very efficient in terms of computational requirements for estimation. The MNL is formulated as follows:

$$P_n(i) = \frac{e^{V_{i,n}}}{\sum_{j \in C_n} e^{V_{j,n}}} \tag{4}$$

with the deterministic component of the utility usually specified as linear-in-parameter function, with an alternative-specific constant that has to be fixed to zero for the so-called reference alternative:

$$V_{j,n} = \alpha + \beta' x_{j,n} \tag{5}$$

One of the most important limitations of MNL is the IIA property (Independence from irrelevant alternatives), which is basically a consequence of the assumption of independent distributions of the stochastic part of utility among alternatives. This is plausible from Eq. (5), as there is no other explanatory variable except the deterministic utility term (V). In the well-known example with a red and a blue bus, the composite choice probability is overestimated with MNL, because the joint systematic utility is higher than the individual utilities of the buses, despite that the two buses should be seen as one alternative. In application, MNL can produce good results if potential heterogeneities in preferences across population are reflected in the model with socio-economic variables.

In order to predict behaviour changes with a change in attribute values, taste coefficients can be inferred based on observed preference data. The parameter values that best explain the choices are searched for. In the case of maximum log-likelihood, the summed up estimated choice probabilities of the (observed) choices are maximized.

$$LL(\beta) = \sum_{n=1}^{N} \sum_{i} y_{n,i} \; ln \; P_{n,i} \tag{6}$$

When comparing different model specifications estimated with the same data set, the logarithm of the likelihood can be viewed as an absolute measure of the goodness of fit. Because this value is dependent on the number of observations, it does not allow to directly compare estimations for differently sized samples of choice sets. A more general measure denoted as ρ^2 is therefore calculated with the log-likelihood value of a given specification and choice set and a reference case estimation with the coefficients at zero.

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{7}$$

Train (2009) points out that this 'pseudo-fit' only measures the increase in log-likelihood with respect to the reference case, but that interpretation is not similar to R^2 in linear regression models. As a consequence, while an increase in this measure is preferable, it should not be used to make comparisons across different samples or alternative sets. Since for this work, choice set samples, although differently aggregated, reflect the same data, a comparison of ρ^2 is assumed to be valid.

Another advantage of MNL is that relative taste measures can easily be derived from the estimation results, like marginal rates of substitution or elasticities. One common measure of mode choice modelling is the value of travel time savings (VTTS), which is the marginal rate of substitution that can be calculated with an estimated coefficient of travel time (e.g. car travel time) and a coefficient of travel cost:

$$VTTS = \frac{\beta_{TT}}{\beta_{TC}} \tag{8}$$

3.3.2 Software tools used for choice model estimation

For the estimation of discrete choice models, various software tools are available. For this work, the R package mlogit (Croissant, 2013) and the software package biogeme (Bierlaire, 2013) have been used, which both are freely available. They are tested with simple MNL specifications for four modes estimating generic and alternative-specific parameters, based on a sample of choice set data. The tests show that the output parameter values are similar. While the two packages are found to produce similar results and comparable auxiliary information, they differ regarding data input requirements: While biogeme input data has to be in a table in the so-called 'wide format', i.e. with one row per choice situation and as many column for every alternative-specific attribute as there are alternatives, mlogit requires long format with 1 line per alternative. The latter is more efficient for many alternative-specific variables but not well-suited for observation-specific variables, because values are repeated on every line for a given observation. Another difference between mlogit and biogeme is the handling of alternative availabity. Biogeme supports an explicit variable for this, whereas mlogit expects lines with unavailable alternatives to be removed.

4 Generated Attribute Data

In the sections below, generated attribute data is evaluated and discussed on stage level. Further, results of excluding observations that do not comply with the filter criteria is presented.

4.1 Issues in generating choice set attributes

In order to estimate mode choice models, attribute values have to be available for the chosen and for all non-chosen alternatives. The route-specific attributes are therefore generated based on reported start- and end-coordinates and start time. For car and PT, the choice set data is generated using MATSim and the respective network and schedule data (see Section 3.2).

The generated attribute values correspond to approximated best-routes for non-motorized modes, time-shortest routes with loaded-network for car mode, and utility-maximal routes for PT mode, always from origin to destination coordinates. Therefore, under ideal conditions, those routes are expected to have the same or a better (a priori unknown) utility than the actually undertaken routes with the chosen mode. Potential deviations between the observation and the generated attributes could arise due to the following effects:

- Variability of preferences across individuals: The routing algorithm uses average a priori values for coefficients and hence is not identical from the preference of the individuals, i.e. the best route resulting from the routing algorithm and the unknown best route of the individual (under perfect information) are not identical.
- Incomplete information: The individual did not choose the best route
- Inaccurate network and/or schedule data: The exact connection used by the person is not available in the data used
- Surveyed data issues: Start and end coordinates and times, and/or mode do not correspond to the reported travel

Validation of the generated data is restricted to certain variables where comparable quantities are reported. This is because the attribute values of the chosen alternative are not completely reported, and the reproduction of the reported route was not part of this work. Alternatively, only general analysis of the results and indirect evidence for potential issues can be used for validation.

The following sections present results from comparison of generated travel times, reported durations and number of transfers. Later, cases of erroneous data and other criteria which are applied to improve quality of the final choice set data is presented. Note that these analyses are primarily done on the stage level in order to make sure that travel times are not increased by minor stops.

4.2 Generated travel time and reported duration

The generated and the reported travel times for the respective chosen mode can differ due to the reasons mentioned in the previous section. This analysis will give an overview and allow for potential corrections in the data used for model estimation. The descriptive statistics in Table 4 show, that the generated travel time values for the individual modes are lower than the reported duration for the median values, and the first and third quartiles for the ratio indicate that the compared variables differ by less than factor 2 for all modes. Observations with travel times of 1 day or more are excluded for this analysis. For public transportation stages the generated travel times are generally higher than the reported duration, meaning that reported durations are underestimated - or generated travel times are too large. This finding does not support the hypothesis that interviewed persons include access or egress stages into the main PT stages.

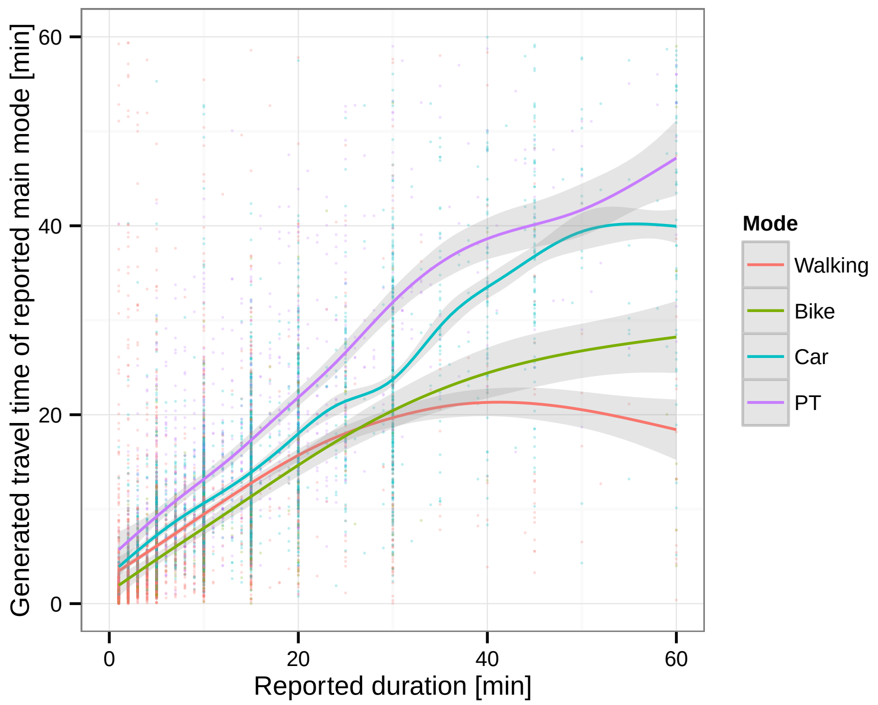
Table 4: Descriptive statistics for ratio of generated travel time of the chosen mode and the reported duration of the stage, by chosen mode

Main mode	Min	1. Q.	mean	median	3. Q.	max	sd
Walking	0.00	0.56	2.23	0.92	1.47	1411.66	13.89
Bike	0.00	0.49	1.11	0.77	1.15	274.55	4.12
Car	0.00	0.72	1.20	0.99	1.34	112.53	1.30
PT	0.01	0.83	1.40	1.07	1.54	255.89	1.99
All	0.00	0.66	1.66	0.97	1.40	1411.66	9.18

Fig. 6 shows a random sample of observations, comparing generated travel time for the chosen mode and the reported stage duration. The mode is indicated with different colours. For short movements below 10 minutes, the generated travel times tend to exceed the reported duration. This causes the mean values in the table above to be greater than one, and that the intercept of the lines in the figure is positive. With increasing durations, the reported duration is longer than the generated travel time, which reflects the median value for the individual modes being below 1. Hence, at least for longer movements, this would suggest that reported durations tend to be be overestimated by the participants of the survey. Murakami and Wagner (1999) found a similar trend in comparing machine-recorded trip times and travel times recalled by interview.

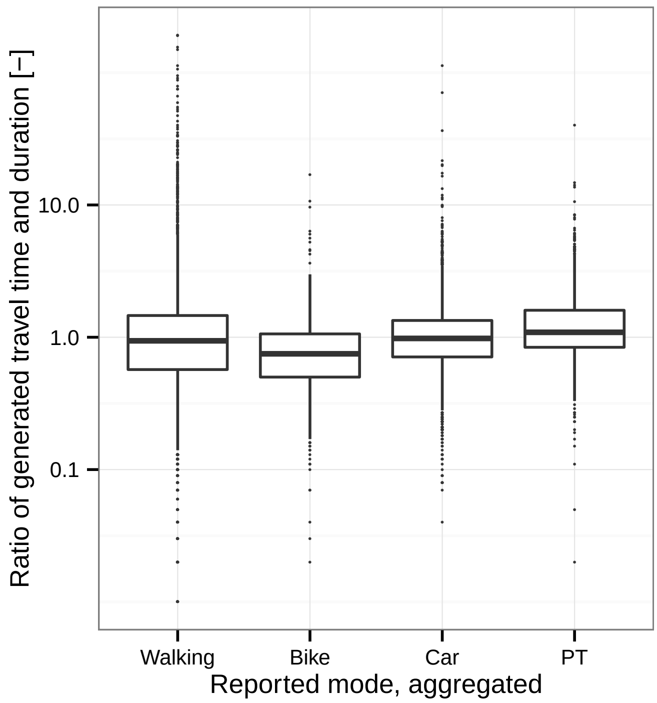
As the summary in the table before suggests, the smoother line for the PT observations is constantly above the line for car mode. The lines for bike and walking observations lie even lower, reflecting the tendency (of the median) of lower travel times compared to the reported duration. The variability is relatively large throughout the shown range up to 60 minutes (not all points shown in the figure). It is also apparent from the figure that the observations are not continuously distributed regarding reported duration, but are accumulated in vertical 'lines' in intervals of 1 minute or 5 minutes.

Figure 6: Generated travel time for reported mode to reported stage duration



This finding is summarized in Fig. 7, which also shows the distribution of the ratio of generated travel time and reported duration for each mode, together with the large variance for all modes. Although the reported duration is by no means free of systematic deviations relative to the true duration, it is a direct measure for how the durations are perceived when answering the survey. This can be taken as a proxy for how a person perceives an attribute like travel time in the choice process. In order to address a potential systematic effect between the modes, the travel time values could be corrected with respect to the reported durations. From the ratios in Table 4, the median corrections can be derived as the reciprocal value of the respective ratio: For walk and bike modes, the correction factor for the generated travel times would be 1.1 and 1.3, respectively. From this follows that either the applied detour factors are too low, or that travel speeds are too high. PT travel times would have to be corrected by 0.93. On the other hand, with the high variability in difference shown above, the reliability of the reported stage duration values can be questioned. Moreover, the main focus of the study is the relative evaluation of mode choice for different analytical units.

Figure 7: Boxplot of ratio of generated travel time and reported stage duration by reported mode



In Table 5 the differences are grouped by spatial structure type definitions according to the Swiss Federal Office for Spatial Development (Bundesamt für Raumentwicklung ARE, 2011). The first five rows represent spatial types ranging from the core city to its peripheral regions. The relative value of travel time and duration both for car and PT shows a clear increasing tendency with increasing distance from a core city, which is true for the respective mean and the median value. As at least the last two categories ('Alpine resorts' and 'peripheral rural') are not directly related to this agglomeration scheme, the respective values are more difficult to compare. The effect for car travel time could be explained be the fact that the routing algorithm is not sensitive to travel time consumption in nodes, and thus a tendency for an underestimation of travel times in urban areas (with a high node to link ratio) would be expected. At the same time, the tendency is visible for both car and PT stages, and with the assumption that both routing procedures are independent, the increasing differences might also be attributed to other effects which overestimate the reported duration with increasing urbanity of the area, or, vice versa, an underestimation with greater distance to an agglomeration core. For choice modelling, this finding can have two main consequences: As the revealed choice of the individuals is dependent on their perception and not on real (expected) times, the resulting taste parameters for travel time (which will be based on the generated travel times) are expected to be more negative for urban areas. Secondly, as the tendency is found for car and PT, the relative parameters within those modes are unaffected. With respect to overall mode choice, it could simply mean that in urban areas there is a relative preference for walking and biking.

Table 5: Comparative statistics for ratio of generated travel time to reported duration for different modes and spatial type

Main mode	Spatial type	median	mean	n
Walking	Not available	1.59	22.48	16
	Core	0.93	2.00	63598
	Extended core	0.95	2.06	14657
	Agglomeration	0.90	2.27	23559
	Isolated city	0.94	4.38	963
	Periurban rural	0.87	2.92	11237
	Alpine resorts	0.94	5.89	935
	Peripheral rural	0.91	3.25	2216
	All	0.92	2.23	117181
Bike	Not available	0.81	0.81	1
	Core	0.78	1.07	5816
	Extended core	0.77	1.03	2034
	Agglomeration	0.75	1.00	3725
	Isolated city	0.86	1.05	199
	Periurban rural	0.77	1.44	2090
	Alpine resorts	0.72	3.64	65
	Peripheral rural	0.72	0.90	237
	All	0.77	1.11	14167
Car	Not available	1.12	1.49	118
	Core	0.95	1.12	31739
	Extended core	0.97	1.14	17198
	Agglomeration	1.00	1.21	33380
	Isolated city	1.04	1.32	1074
	Periurban rural	1.04	1.27	20584
	Alpine resorts	1.12	2.38	657
	Peripheral rural	1.01	1.43	2856
	All	0.99	1.20	107606
PT	Not available	1.05	2.36	13
	Core	1.04	1.31	24404
	Extended core	1.12	1.50	4248
	Agglomeration	1.15	1.58	5201
	Isolated city	1.12	1.47	204
	Periurban rural	1.14	1.67	2213
	Alpine resorts	1.12	1.87	148
	Peripheral rural	1.20	1.68	357
	All	1.07	1.40	36788

While the aggregation of the ratios by spatial type seems to offer a clear tendency, the impression from Fig. 8 (only PT stages depicted) is of a more random nature: The map shows the relative differences which tend to be positive in sparsely populated areas while they tend to level out in denser areas. Still, the findings above with more positive values towards more rural areas are also visible here.

4.3 Generated and reported distances

An aggregated summary of the ratio between the generated distance and the reported distance for the chosen mode is shown in Table 6. While the median ratio for car stages is only slightly above 1, the inter-quartile range is less than +/- 0.1, the median value for PT stages is 0.92 and the first quartile ranging down by -0.1. This might be mostly due to access- and egress distance not included in the generated distance. The median for bike and walk trips is 1.22 and 1.1 respectively, with a much larger inter-quartile range compared to the faster modes. Note that reported walk and bike movements are, unlike car and PT movements, not compared and corrected as part of the data survey method described in Bundesamt für Statistik, Bundesamt für Raumentwicklung (2011).

In Fig. 9, the very good match of generated (best-route) distances and reported distance for car, and the relatively good match for PT becomes visible. On the other hand, the walk trips reveal a less clear picture.

Table 6: Ratio of generated and reported distance, by reported mode, [-]

Mode	Min	1. Q.	mean	median	3. Q.	max	sd
Walking	0.00	0.74	2.65	1.22	1.25	3720.98	28.41
Bike	0.00	0.78	1.37	1.10	1.15	457.58	7.66
Car	0.00	0.93	1.15	1.01	1.10	809.93	3.94
PT	0.00	0.82	0.97	0.92	0.97	618.93	3.97
All	0.00	0.84	1.83	1.00	1.25	3720.98	19.65

Figure 8: Map of relative difference ($\frac{x-y}{(x+y)/2}$) between generated travel time and reported stage duration

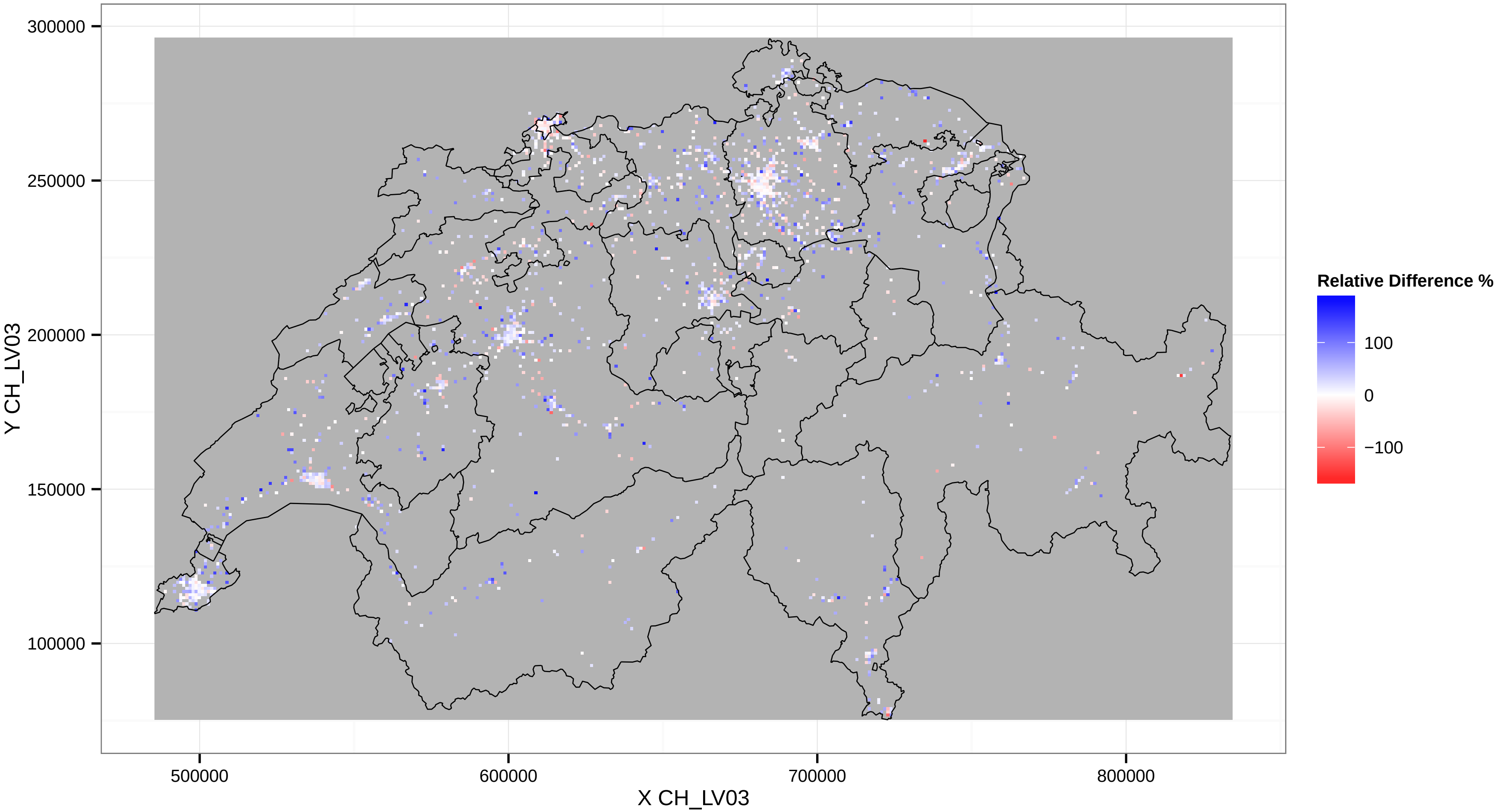
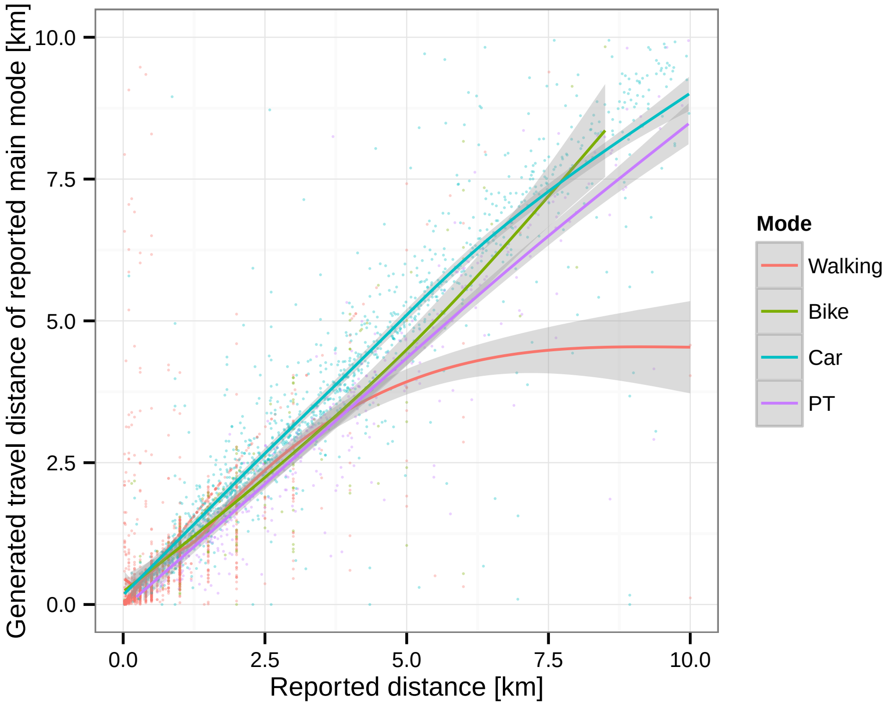


Figure 9: Comparison of generated and reported stage travel distance



4.4 Generated values for transfers

Table 7 shows that 83% of the reported PT stages are generated with zero transfers, and are thus consistent with stage definition. The rest of stages with reported mode PT are either done by walking only (7 %) or with more than one transfer (10%). For stages with a reported mode other than PT, more than 56 % of the generated PT stages are done by pure walking, which means that there were no time-fastest routes using PT vehicles or they were excluded because routes with walking only showed a higher utility (see Section 3.2.2).

Table 7: Generated stages by number of tranfers and reported mode

	Reported stage mode	
Evaluation of generated stage	PT	Other than PT
no PT used ('pure walk')	7%	56%
no transfers	83%	27%
1 or more transfers	10%	17%

4.5 Generated PT routes by walking only

Generated PT attributes are analysed in Table 8, that shows the ratio of occurrence of generated stages using at least one PT vehicle, and stages generated with walking only. This measure is evaluated with respect to crowfly distance bins and PT service class of the origin. The PT service class (German: 'OEV-Klasse') is a spatial attribute as a proxy for PT service quality dependent on 1) the quality of the closest PT stop (depending on service interval and transport modes) and 2) the distance to this PT stop. 'A' is the best possible value for coordinates with a first- or second-class PT stop within 500 m, and from there the value drops with longer access distance and/or lower-class PT stops (Bundesamt für Raumentwicklung ARE, 2011). A ratio of 1 means that both types have the same occurrence. The ratio shows a clear tendency to increase with a better 'PT-Class' and higher crowfly distance. For example, for a stage between 0.5 and 1 km of distance and with starting coordinates in class B, the ratio is one, which means that about the same number of observations are generated as pure walks and with the use of PT, i.e. each type accounts for about 50% of the cases. In the same distance bin but for class A, about 3 times more stages are generated with the use of PT vehicle compared to pure walks.

Table 8: Ratio of the number of stages with generated PT connections using PT service, to connections with walking only, aggregated by bins of crowfly distance and 'OEV-Class' ARE

	PT class				
Distance bin [km]	A	B	C	D	NA
(0,0.1]	0.00	0.00	0.00	0.00	0.00
(0.1,0.25]	0.03	0.01	0.00	0.00	0.00
(0.25,0.5]	0.50	0.15	0.05	0.03	0.00
(0.5,1]	3.25	1.03	0.50	0.23	0.05
(1,2.5]	27.90	8.24	3.37	1.50	0.41
(2.5,5]	84.38	29.08	14.50	6.22	2.14
(5,10]	110.55	43.68	37.51	18.22	5.82
(10,25]	186.97	96.40	88.98	30.39	10.73
(25,50]	956.67	548.00	124.20	86.87	33.75
(50,100]	1641.00	212.00	235.00	81.71	136.00

The observed effect indicates that the routing algorithm has a relative preference to walk over waiting and PT-riding for short distances. Longer distances are less affected, as the ratio of access/egress distance to in-vehicle distance is lower. The same is true for areas with a high level of service, because they are more likely to have a shorter access/egress egress distance. Still, there are relatively long routes generated with only walking. This can be due to PT service with very high interval or missing at all at the reported time of day.

This selective behaviour has to be accounted for when excluding those observations: Market shares and distance distribution will be affected in the remaining choice set.

4.6 Filtering of observations on stage and trip level

As a last step of alternative set preparation, observations are filtered in three steps, with the following criteria:

- Based on reported data: Identical coordinates, start and/or end outside Switzerland and/or irrelevant modes
- Based on generated attribute values: Removal of outliers, possibly from erroneous routing (before validation analysis)
- Based on excluded observations on higher and lower levels: Remove remaining elements of the identified dayplan

In the following, the filter criteria are evaluated in detail on the stage level and summarized for the trip level.

4.6.1 Initial filtering: Identical or abroad start/end coordinates and special modes

Observations with identical start and destination or start/destination outside Switzerland are excluded because they cannot be generated (ca. 8 % of all stages). Further, an additional 1 % of the observations are neglected because the reported mode cannot be assigned to one of the main modes. Table 9 shows that roughly 90 % of the observations are used for further analyses, and that the excluded categories are not entirely additive.

Overall, more than 70 % of the excluded stages are walking stages, while the other mode category each makes up around 10% of those excluded.

Table 9: Partition of data regarding initial filter criteria (stages)

	All		Partition by main mode (row percent)				
	n	Percent	Walking	Bike	Car	PT	Other
All	310193	100.0	45.2	4.8	36.1	12.6	1.3
Start/end coords							
Different	285112	91.9	41.3	5.0	38.9	13.5	1.2
Identical	25081	8.1	89.4	3.2	3.8	1.5	2.1
Start/end coords							
Domestic	305171	98.4	45.5	4.9	35.7	12.6	1.2
Abroad	5022	1.6	25.5	1.4	55.5	7.8	9.8
Mode type							
Accepted	306043	98.7	45.8	4.9	36.6	12.7	0.0
Other	4083	1.3	0.0	0.0	0.0	0.0	100.0
Total initial filter							
Passed	278440	89.8	42.1	5.1	39.0	13.8	0.0
Excluded	31688	10.2	72.0	2.7	10.6	1.8	12.9

4.6.2 Unrealistic or missing routing data

In addition to the observations excluded on original reported data, there are variable values from routing which are either missing or outside a meaningful range. The question whether to exclude the observation concerned as a whole, or to just set the alternative (mode) concerned to unavailable is not always straightforward. Table 10 summarizes the number of observations with a generated total travel time not available or non-positive including zero, that is obviously due to an error, as identical coordinates (German "Rundetappen") are already excluded. Other suspect routing results are treated next.

Of the total share of excluded observations (<1%), car stages are overrepresented, which represents cases where the next PT stop or destination is not found with a 1000 m radius search.

Table 10: Observations with missing or erroneous routing data (stages)

				Reported Mode			
		n	Percent	Walk	Bike	Car	PT
	All	278440	100.00	42.1	5.1	39.0	13.8
PT travel time	n/a	1208	0.43	6.7	1.5	72.5	19.3
	ok	277232	99.57	42.3	5.1	38.8	13.8
Car travel time	n/a	0	0.00	–	–	–	–
	ok	278440	100.00	42.1	5.1	39.0	13.8
Total missing data	passed	277232	99.57	42.3	5.1	38.8	13.8
	excluded	1208	0.43	6.7	1.5	72.5	19.3

4.6.3 Excluding outliers in generated data

Some results are treated as "outliers", e.g. the PT routes undertaken as pure walking (see section Section 4.5), or very long travel times for fast modes. For the latter, a thresholds is set to 24 hours, as longer durations are generally not within a dayplan anymore (Table 11).

Table 11: Outliers in generated travel time for fast modes (stages)

			Reported Mode			
	n	Percent	Walking	Bike	Car	PT
All	275884	100.000	42.5	5.1	39.0	13.3
Generated travel time of reported mode < 24h						
outlier	86	0.031	96.5	0.0	3.5	0.0
valid	275798	99.969	42.5	5.1	39.0	13.3
Reported duration < 24h						
outlier	0	0.000	–	–	–	–
valid	275884	100.000	42.5	5.1	39.0	13.3
Total missing data						
passed	275798	99.969	42.5	5.1	39.0	13.3
excluded	86	0.031	96.5	0.0	3.5	0.0

4.6.4 Summary of filters on trip level

Based on reported and estimated data on the trip level, filters are generated similarly to the stage level presented before. They are summarised in Table 12. Like for stages, the number of excluded observations in each filter step ist not entirely additional.

Table 12: Summary of filters on trip level

		n	Percent
	All	211445	100.00
Filter reported data	passed	190637	90.16
	excluded	20808	9.84
Filter no generated data	passed	187271	88.57
	excluded	24174	11.43
Filter outlier generated data	passed	206524	97.67
	excluded	1543	0.73
Filter total trips	passed	185386	87.68
	excluded	26059	12.32

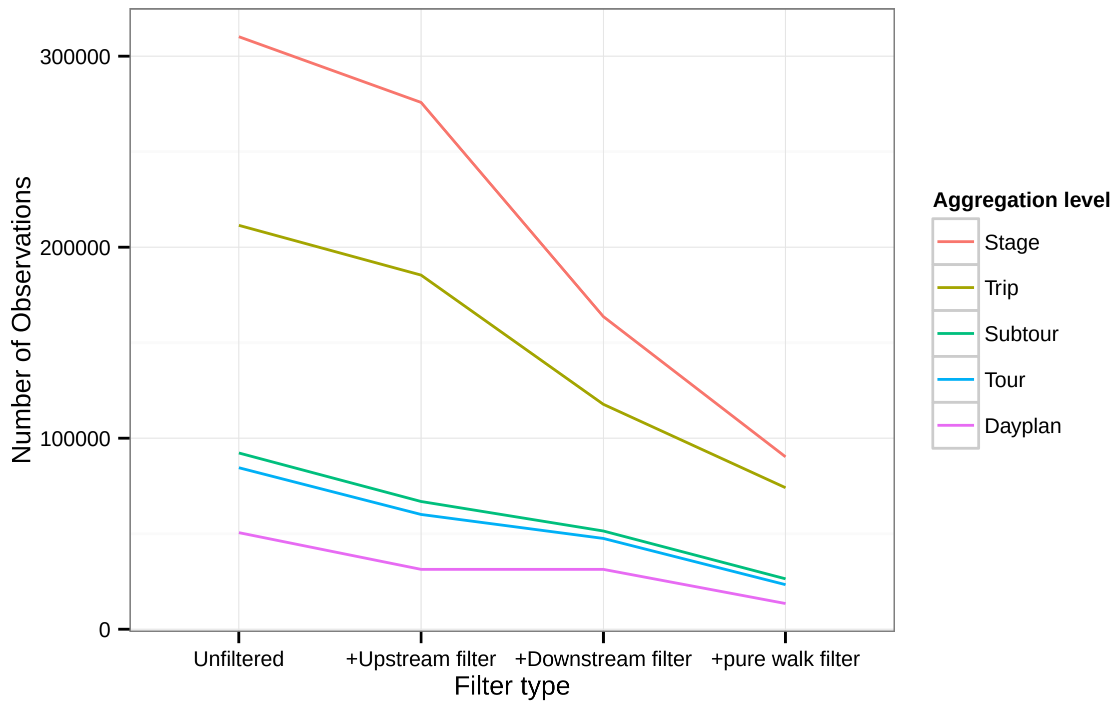
4.7 Application of filters to the choice set

In order to make aggregate evaluations of variables comparable across levels, the same observations have to be represented on every level. For example, if an observation on trip level has to be excluded due to missing routing data, a complete tour cannot be aggregated any more. This means that the remaining parts, e.g. trips, of this tour have to be excluded as well. If not, the sum of in-vehicle time would not be same on every level. This procedure results in a quite high filtering-out rate. Fig. 10 shows the effect of the application of the upstream and the downstream filter to the data: For lower levels, the upstream filter is leading to more exclusions than the downstream filter, and vice versa for higher levels. With both filter types combined, the choice set size is reduced between 50-70% depending on the level, compared to the unfiltered data.

Due to the issue with PT routing discussed in Section 4.5, for about half of the original number of observations, no meaningful attributes could be generated for the PT alternative. Those observations are removed from the choice set in addition to the already applied filters, because the number of remaining observations would have been too low with a regular procedure as with the other filters. Although this means that not all observations are part of complete dayplans any more, which reduces the degree of comparability. Moreover, original distributions of variables is further effected, e.g. of market shares of modes and of distances. This is shown in the next chapter.

After this procedure, between a fourth and a third of the original observations are remaining on each level, e.g. roughly 13'000 dayplans (see Section 5.2 below).

Figure 10: Effect of filter steps on choice set size by level



5 Descriptive Analysis of the Alternatives

In this chapter the choice set data used for the modelling work are presented. Initially, an overview of the persons characteristics and of aggregation levels of movement is presented. Then, different variables are evaluated with respect to aggregation level or mode or both.

5.1 Summary of the person characteristics

Socio-economic variables can directly serve as explanatory variables in the model, or affect the availability variable. Those variables are summarized from Bundesamt für Statistik, Bundesamt für Raumentwicklung (2012), and are based on the complete data.

The basic requirement for a person to participate in mobility that is adopted here, in line with the original microcensus definition, is the ability to walk without help. This criterium ensures access to walk and public transportation (PT) mode and includes about 97% of all interviewed persons.

The availability of the car mode further depends the driver's license ownership and the availability of a vehicle. Those criteria are met by about 74% of the interviewees (With a driver's license ownership of about 80% and a car availability of roughly 95%). The bike mode availability is determined in the same manner and identifies about 77% of all interviewees.

The public transportation pass ownership influences the travel cost of the PT mode. Roughly 50% of the persons own any pass. A half-price pass is owned by about 40%, and about 10% own a GA (full-price rebate).

In the used data, income is only reported on the household level. Observations are reported in income classes each covering a range of 2000 Swiss Francs (CHF), while one class is for an income above 16'000 CHF. Without reconstructing this "tail" with secondary data, only a rough average measure can be derived that is around 9'000 CHF pre-tax.

5.2 Sample size of alternative sets

Alternative sets are initially assembled on the stage and trip level, with generated mode-specific attributes for the chosen and the non-chosen alternatives. This means that reported attributes of the chosen alternative like travel times, are not used for the choice set (see Section 3.2.2).

The trip level variables for the mode-specific attributes are then aggregated to higher levels of movement for each mode with the aggregation rules discussed above. Other variables are the same for all mode alternatives on each level (e.g. attributes of the origin or destination), or even identical across all levels of movement (e.g. socio-economic or mobility tool ownership variables).

Table 13 shows the number of observations per mode with the percentage that passed through the filtering stage. The decrease in sample size from stages to trips is much higher for walk and PT modes compared to bike and car mode, which is due to PT trips' tendency to consist of several stages including access and egress walking stages (which are no more part of walk trip category).

Table 13: Accepted observations, number and percent of total observations by mode and aggregation level

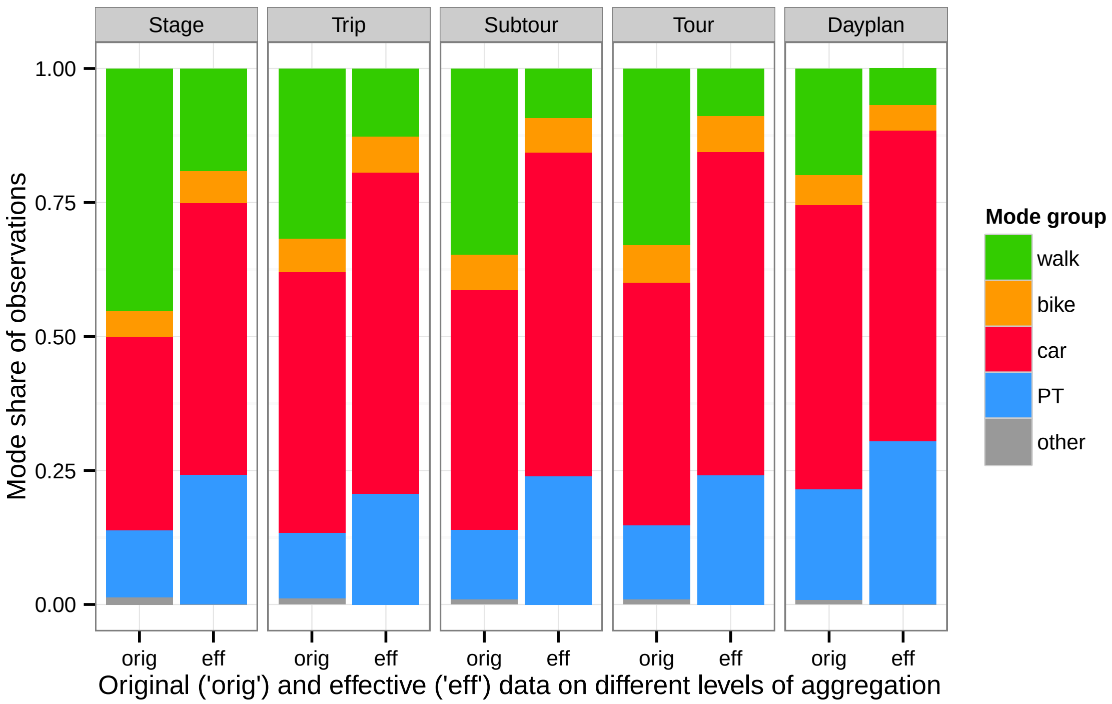
	Reported mode				
	Walking	Bike	Car	PT	Total
Number of stages	15828	4994	49343	20085	90250
% of original data	11	33	44	52	29
Number of trips	8514	4501	47224	13845	74084
% of original data	13	34	46	54	35
Numbers of subtours	2205	1556	16907	5714	26382
% of original data	7	25	41	48	29
Number of tours	1845	1430	14993	5057	23325
% of original data	7	24	39	43	28
Number dayplans	827	574	8356	3688	13445
% of original data	8	20	31	35	27

The filtering loss is mainly due to the exclusion of neglected modes, movements with identical start and end, and observations with unsuccessful routing. Further, it was ensured that only observations that are part of complete dayplans are used for the choice sets. For example, if a stage is excluded for some reason, observations on all aggregation levels were excluded, as well as the stages that are part of the same dayplan. The percentage of observations that passed the filter ranges from 61 to 96 Percent, and is increasing towards higher levels of aggregated movements. The generally lower fraction of valid observations for reported walk movement is mainly due to the higher fraction of relatively short and/or "Rundetappen" in this category, which are more likely to be excluded (due to the criteria mentioned in Section 4.6).

The potential bias caused by this sample exclusion is neglected, i.e. it has to be discussed together with modelling results.

PT attributes could up to date only be generated for around 60% of the stage or trip observations that otherwise would pass the filter. As discussed in Section 4.5), short observations in areas with high PT service level are more likely to be excluded. The mode shares in the filtered choice are therefore not conserved. Mode share of walk in the choice set is cut to almost one third of the original share. In the same time, car and PT shares increased by roughly 50% each (Fig. 11). Without further correction, the estimated model parameters do therefore not correspond to real market shares.

Figure 11: Market shares of mode groups by aggregation level, before and after filtering



Because of the high percentage of observations with missing PT attributes, the respective observations of stages and trips, and aggregated observations containing such an observation, were excluded. Unlike the filter stage before, this was done without upstreaming the filter, i.e. the subsequent elimination of lower-level dayplans that are not part of a complete dayplan anymore. This would have resulted in a very low choice set size. Apart from the selective filtering of walking and bike compared to PT, the distance distributions for observations within each reported mode are changed as well. This is discussed in the next section.

5.3 Availability of alternatives

Availabilities for modes are derived from the person's mobility tools. While walking mode is always available (excluding the fraction of population with a handicap), bike and car availability is dependent on vehicle and license ownership. An additional type of availability dependency had to be adapted for public transport alternatives: While in principle available always available, even if not preferred in a lot of cases due to very long access/egress distances, the PT routing algorithm produced pure walking connections. In Section 4.4 it is shown that this is the case for about 20 percent of reported PT routes, but almost 50% for observations where the PT is not the chosen mode. As pure walking is already a mode per se, PT connections not using PT are rather not associated with a PT alternative by the individuals. Therefore, those cases have to be treated specially; PT is either set unavailable, but this is unrealistic, as PT is generally available even in areas it is not really competitive. The second option is to exclude the observation as a whole, which substantially reduces the choice set size, and because short trips are overrepresented regarding this problem, distributions of different variables (e.g. market share of the modes) have to expected to change compared to the original data.

The resulting availabilities are 100% for walk mode, around 80% and 70% for bike and car mode, respectively. PT is only available in little more than 50% of the cases. Those numbers do not vary a lot with respect to levels of movement (see also Section 4.5).

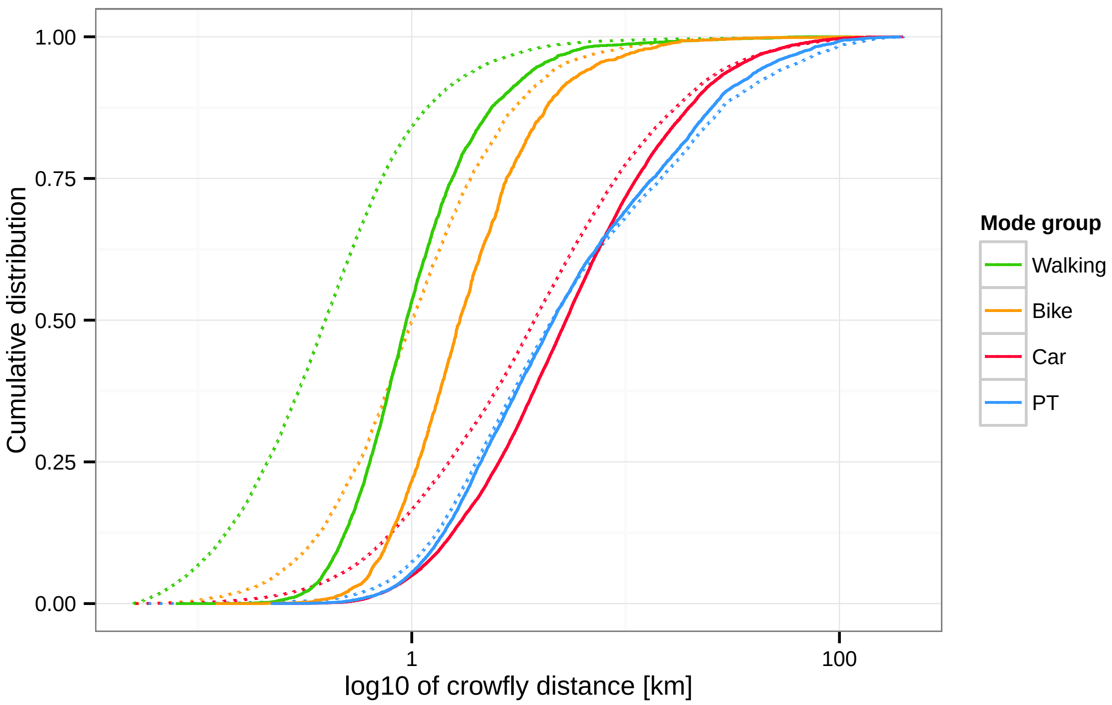
5.4 Distance distribution by reported mode group

The exclusion of observations due to filtering and especially because of the issue of missing PT attributes changes the distance distribution quite substantially. Cumulative distribution of direct distances by reported mode in Fig. 12 shows that the effect is strongest the walking mode, with a shift of the median from about 0.7 to 1 kilometre. This difference is lower for the bike and car modes, and only minor for the PT mode. Also, in the left section of each pair of graphs, the gap between original and filtered data is greater. In general, this confirms the discussion about short movements being more prone to this issue of PT routing. Also the difference in effect between car and PT mode is expected, as the percentage of successful PT routing is much higher for reported PT mode, and/or for movements in areas with good PT service (Section 4.5).

5.5 Total travel times by reported mode

In Table 14, the median of generated travel times of the different modes (rows of the table) is shown by the reported mode (columns). The row median varies because the average speed differs from mode to mode, and the column median is dependent on the average trip distance by reported mode. For example, the median walking travel time for walked stages is 5 minutes, but it takes 60 minutes on average to undertake a PT stage by walking. On the other hand, the PT

Figure 12: Effect of filter on cumulative distribution of direct distance by reported mode group, dotted lines for original data



travel time for a walked stage is 6 minutes, which is slightly more than by foot. For all stages, the travel time by car is lower or the same than by the chosen mode other than car. This means that on average, with travel time alone, only the choice of the car stages can be explained by travel time minimisation. It should be noted that for example for PT stages, median PT travel time is 6 minutes or about by a factor of 2 higher than car travel time. The same factor for car stages is more than 3. Obviously, PT has a comparative advantage for PT stages with respect to car stages.

5.6 Mode-specific attributes by level

The correlation coefficients shown in Table 16 have the expected signs and relative orders of magnitude. The travel times for individual modes (walk, bike, car) and the travel distance and cost for public transport have high correlations above 0.94, while the correlation of in-vehicle travel time for public transportation with those variables is around 0.8. As expected, the coefficients for interval of public transportation are negative, because on average, short journeys are often undertaken in urban areas where service interval is high. Further, access/egress time in public transportation alternatives is moderately correlated with other attributes.

Table 14: Median of generated travel times by mode, reported mode and level, in [min]

		Reported mode			
Level	**Mode**	**Walking**	**Bike**	**Car**	**PT**
Stage	Walk	5	18	67	60
	Bike	2	6	22	20
	Car	2	4	10	9
	PT	6	18	37	15
Trip	Walk	7	18	67	82
	Bike	2	6	22	27
	Car	4	6	12	15
	PT	9	18	36	33
Subtour	Walk	15	39	149	165
	Bike	5	13	50	55
	Car	8	14	26	33
	PT	19	40	82	70
Tour	Walk	16	40	160	172
	Bike	5	13	53	57
	Car	8	14	28	35
	PT	20	41	87	74
Dayplan	Walk	24	71	277	257
	Bike	8	24	92	86
	Car	12	24	46	49
	PT	29	66	136	103

Table 15: Median of mode-specific attributes by level, chosen and non-chosen

				Level		
Variable	Unit	Stage	Trip	Subtour	Tour	Dayplan
Travel time walk	[min]	64.6	77.6	197.2	207.1	340.5
Travel time bike	[min]	21.5	25.9	65.7	69.0	113.5
Travel time car	[min]	9.4	13.2	31.4	32.6	49.0
Travel cost car	[CHF]	0.7	0.8	2.1	2.2	3.6
Travel time PT	[min]	11.0	14.0	38.0	40.0	64.0
Access Time PT	[min]	14.4	17.3	39.5	41.3	51.6
Transfer Time PT	[min]	0.0	0.0	2.0	3.0	8.0
Transfers PT	[-]	0.0	0.0	1.0	1.0	2.0
Travel cost PT	[CHF]	1.7	2.2	5.8	6.1	10.1
Service interval PT	[min]	20.5	24.0	30.0	30.0	30.0

Table 16: Correlations of mode-specific attributes

	WALK TT	BIKE TT	CAR TT	CAR TC	PT TOT	PT TTI	PT ACC	PT TR	PT TRT	PT DIS	PT TCO	PT INT
WALK TT												
BIKE TT	1.00											
CAR TT	0.94	0.94										
CAR TC	0.98	0.98	0.96									
PT TOT	0.60	0.60	0.65	0.62								
PT TTI	0.82	0.82	0.85	0.84	0.63							
PT ACC	0.35	0.35	0.42	0.35	0.37	0.43						
PT TR	0.64	0.64	0.68	0.65	0.54	0.85	0.38					
PT TRT	0.47	0.47	0.49	0.48	0.51	0.80	0.29	0.70				
PT DIS	0.96	0.96	0.93	0.97	0.56	0.87	0.35	0.69	0.51			
PT TC	0.95	0.95	0.93	0.95	0.58	0.91	0.43	0.75	0.55	0.98		
PT INT	-0.33	-0.33	-0.36	-0.33	-0.31	-0.43	-0.51	-0.41	-0.33	-0.34	-0.40	

TT = Travel time, TC = Travel cost, TOT = Total travel time, TTI = In-vehicle travel time, ACC = Access time

TR = Transfers, TRT = Transfer time, DIS = Distance, INT = Interval

5.7 Summary of generated, mode-specific attributes on each level

The fallowing tables show descriptive statistics for the generated attributes on each level of aggregation. Travel time, travel cost and distance parameters are aggregated with addition and therefore show a tendency to increase from level to level. Note that the values in the tables are rounded, hence most values that indicate zero are not exactly zero. The slope, calculated as ratio of altitude change and direct distance on trip level, is aggregated with maximisation, e.g. the highest value of trip slope is taken for the related tour. This results in a distribution with a minimum substantially increasing with levels, while central tendency and maximum values only slightly increase.

Table 17: Descriptive statistics for generated attributes in stage level choice set

		min	1. Q.	median	mean	3. Q.	max	sd
TT Walk	[min]	2	27	65	147	160	4112	239
TT Bike	[min]	1	9	22	49	53	1371	80
Distance NM	[km]	0	2	5	12	13	343	20
Slope	[%]	– 59	– 1	0	0	1	61	3
TT Car	[min]	0	5	9	14	17	258	15
TC Car	[CHF]	0	0	1	2	2	49	2
Total time PT	[min]	0	15	28	38	51	548	34
Travel time PT	[min]	0	4	11	22	30	457	29
Access Time PT	[min]	0	7	14	16	24	176	12
Transfer Time PT	[min]	0	0	0	5	4	322	12
Transfers PT	[-]	0	0	0	1	1	8	1
Travel cost PT	[CHF]	0	1	2	4	5	77	5
Service interval PT	[min]	10	13	20	27	30	120	18

Table 18: Descriptive statistics for generated attributes in trip level choice set

		min	1. Q.	median	mean	3. Q.	max	sd
TT Walk	[min]	3	34	78	167	185	4112	258
TT Bike	[min]	1	11	26	56	62	1371	86
Distance NM	[km]	0	3	6	14	15	343	22
Slope	[%]	– 42	– 1	0	0	1	42	2
TT Car	[min]	1	8	13	18	22	261	17
TC Car	[CHF]	0	0	1	2	2	49	3
Total time PT	[min]	1	21	35	44	58	896	35
Travel time PT	[min]	0	5	14	25	35	858	30
Access Time PT	[min]	0	11	17	19	25	176	11
Transfer Time PT	[min]	0	0	0	6	7	816	13
Transfers PT	[-]	0	0	0	1	1	8	1
Travel cost PT	[CHF]	0	1	2	4	5	77	6
Service interval PT	[min]	10	14	24	28	30	120	18

Table 19: Descriptive statistics for generated attributes in subtour level choice set

		min	1. Q.	median	mean	3. Q.	max	sd
TT Walk	[min]	8	89	197	399	458	8224	580
TT Bike	[min]	3	30	66	133	153	2741	193
Distance NM	[km]	1	7	16	33	38	685	48
Slope	[%]	– 9	0	1	1	2	42	2
TT Car	[min]	3	19	31	43	52	449	38
TC Car	[CHF]	0	1	2	4	5	83	6
Total time PT	[min]	3	50	82	103	135	1075	77
Travel time PT	[min]	0	14	38	60	83	912	66
Access Time PT	[min]	0	27	40	43	55	330	24
Transfer Time PT	[min]	0	0	2	13	19	819	24
Transfers PT	[-]	0	0	1	2	3	22	2
Travel cost PT	[CHF]	0	2	6	10	13	135	13
Service interval PT	[min]	10	15	30	34	60	120	20

Table 20: Descriptive statistics for generated attributes in tour level choice set

		min	1. Q.	median	mean	3. Q.	max	sd
TT Walk	[min]	8	95	207	420	481	8224	608
TT Bike	[min]	3	32	69	140	160	2741	203
Distance NM	[km]	1	8	17	35	40	685	51
Slope	[%]	0	0	1	1	2	42	2
TT Car	[min]	3	20	33	45	55	449	41
TC Car	[CHF]	0	1	2	4	5	83	6
Total time PT	[min]	6	52	86	109	142	1229	84
Travel time PT	[min]	0	14	40	63	87	1033	71
Access Time PT	[min]	3	28	41	46	58	330	27
Transfer Time PT	[min]	0	0	3	14	20	819	26
Transfers PT	[-]	0	0	1	2	3	22	2
Travel cost PT	[CHF]	0	2	6	11	14	152	13
Service interval PT	[min]	10	17	30	35	60	120	20

Table 21: Descriptive statistics for generated attributes in dayplan choice set

		min	1. Q.	median	mean	3. Q.	max	sd
TT Walk	[min]	12	149	341	585	734	8224	719
TT Bike	[min]	4	50	114	195	245	2741	240
Distance NM	[km]	1	12	28	49	61	685	60
Slope	[%]	0	0	1	1	2	42	2
TT Car	[min]	3	29	49	62	79	449	49
TC Car	[CHF]	0	2	4	6	8	83	7
Total time PT	[min]	8	73	124	146	193	1229	102
Travel time PT	[min]	0	26	64	87	121	1033	84
Access Time PT	[min]	3	34	52	60	77	580	37
Transfer Time PT	[min]	0	0	8	19	28	419	29
Transfers PT	[-]	0	0	2	2	4	23	3
Travel cost PT	[CHF]	0	4	10	15	21	152	16
Service interval PT	[min]	10	20	30	37	60	120	20

6 Results from model estimation

This chapter presents the modelling results. First, different model specifications are evaluated on the trip level, which allows the comparison of parameter values and indicators to numbers in the literature.

In a further step, a comparison of the model fit and the relative values of parameters across movement levels is presented. For this, the model specification is developed from simple MNL models to more advanced formulations. In a second part, the aggregation rules for mode and movement are varied. Finally, the third part presents the results, which are proposed as most valuable in an empirical sense, in more detail.

6.1 MNL models for trip level

The stepwise development of specifications starts with generic variables for travel time and additional variables for PT transfers, interval and access time (MNL1). The specification is then extended to travel cost for car and PT (MNL2), mobility tool ownership (MNL3) and socio-economic variables (MNL4). Only linear effects are allowed in the models MNL1 to MNL4. The estimation is based on a sample of microcensus 2010 trips that includes only observations which are part of complete dayplans, and contain only complete stages. Further, PT trips for which only walking was estimated, are excluded as well.

The utility functions have generally linear-in-parameter terms, or non-linear terms for distance or income elasticities, or age. Table 22 shows the utility functions for MNL5 (results presented later) as an example.

The estimation statistics (Table 23) show a relatively good fit of the model with a ρ^2 of 0.44. The intercept (relative to the bike alternative) is highest for car. All coefficients have the expected negative sign, and are significantly different from zero. Remarkably, the in-vehicle travel time for PT (-0.013 min^{-1}) is lower in absolute term by at least a factor of two compared to other time coefficients with values ranging from -0.028 and -0.063 min^{-1}. Table 24 shows that one PT transfer has the same effect as 29 minutes of in-vehicle time, which is above the usual range of 10 to 20 minutes (e.g. Fröhlich et al. (2012) or König et al. (2004)).

The inclusion of travel costs in MNL2 does not substantially improve model fit. It seems that explanatory effects are shifted from PT in-vehicle time to the cost variable, since the in-vehicle time coefficient is decreased by more than a factor two compared to MNL1. It has to be noted

Table 22: Utility functions for MNL5

$$U_{walk} = \alpha_{walk} + \beta_{time,walk} * X_{time,walk}$$

$$U_{bike} = \alpha_{bike} + \beta_{time,bike} * X_{time,bike} + \beta_{always,bike} * X_{always,bike}$$

$$\begin{aligned} U_{car} = \alpha_{car} &+ \beta_{time,car} * X_{time,car} \\ &+ \beta_{cost,car} * X_{cost,car} * \left(\frac{X_{income}}{\overline{x}_{income}}\right)^{\varepsilon_{income}} * \left(\frac{X_{distance}}{\overline{x}_{distance}}\right)^{\varepsilon_{distance}} \\ &+ \beta_{always,car} * X_{always,car} \end{aligned}$$

$$\begin{aligned} U_{PT} = \alpha_{PT} &+ \beta_{time,PT} * X_{time,PT} \\ &+ \beta_{cost,PT} * X_{cost,PT} * \left(\frac{X_{income}}{\overline{x}_{income}}\right)^{\varepsilon_{income}} * \left(\frac{X_{distance}}{\overline{x}_{distance}}\right)^{\varepsilon_{distance}} \\ &+ \beta_{transfers,PT} * X_{transfers,PT} + \beta_{accesstime,PT} * X_{accesstime,PT} + \beta_{interval,PT} * X_{interval,PT} \\ &+ \beta_{routepass,PT} * X_{routepass,PT} + \beta_{halfpass,PT} * X_{halfpass,PT} + \beta_{fullpass,PT} * X_{fullpass,PT} \end{aligned}$$

here that RP data shows naturally a relatively high correlation between the alternative-specific variables. For example, PT transfers and in-vehicle time are correlated, and their marginal effect on choice can be similar. This would explain the very high value of 66 minutes of in-vehicle time per transfer. The very low value of time could be explained by a similar effect.

Due to the unrealistic effect, travel costs are left out for further specifications. In MNL3, mobility tool ownership variables are instead added and help to raise ρ^2 above 0.5. The added variables show coefficient estimates significantly different from zero and the expected positive signs. In the same time, time-related coefficients are decreased in absolute terms compared to MNL2.

In MNL4, a significant effect is found for sex and age regarding the choice of car and PT, the parameter estimates for income are not significant from 0. All three variables have negative signs regarding the choice of the PT alternative. Males are more likely to choose car than PT, while higher income has a positive (though not significant) effect on car choice.

Table 23: MNL models for trips

		MNL1	MNL2	MNL3	MNL4	MNL5
Model statistics						
n of parameters		10	11	15	24	18
N		57090	57090	57090	57090	57090
LL($\hat{\beta}$)		-39723	-39243	-34841	-34779	-34659
Likelihood ratio test		64531	65491	74295	74419	74659
ρ^2		0.448	0.455	0.516	0.517	0.518
Run time		00:46	00:49	01:05	01:38	05:51
Coefficients						
Walk(intercept)	-	**1.129**	**1.121**	**3.190**	**3.280**	**3.180**
Car (intercept)	-	**1.547**	**1.489**	**2.490**	**2.670**	**2.480**
PT (intercept)	-	**0.614**	**0.586**	**0.989**	**1.370**	**1.050**
Transfers PT	-	**-0.361**	**-0.332**	**-0.374**	**-0.362**	**-0.368**
Access PT time	min	**-0.031**	**-0.029**	**-0.022**	**-0.022**	**-0.022**
Interval PT	min	**-0.028**	**-0.027**	**-0.022**	**-0.022**	**-0.022**
Travel time walk	min	**-0.045**	**-0.047**	**-0.043**	**-0.043**	**-0.044**
Travel time bike	min	**-0.063**	**-0.068**	**-0.058**	**-0.058**	**-0.060**
Travel time car	min	**-0.052**	**-0.045**	**-0.042**	**-0.042**	**-0.044**
In-vehicle time PT	min	**-0.013**	**-0.005**	**-0.004**	**-0.004**	-0.003
Travel cost (TC)	CHF	-	**-0.169**	-	-	**-0.086**
Distance elasticity of TC	-					**0.556**
Income elasticity of TC	-					**-0.689**
Bike always available	y/n			**2.160**	**2.150**	**2.160**
Car always available	y/n			**1.260**	**1.270**	**1.270**
Transit pass route-specific	y/n			**2.170**	**2.150**	**2.180**
Transit pass "Halbtax"	y/n			**0.475**	**0.502**	**0.375**
Transit pass "GA"	y/n			**2.290**	**2.320**	**2.000**
Male (Walk)	y/n				**-0.206**	
Male (Car)	y/n				**-0.159**	
Male (PT)	y/n				**-0.362**	
Age (Walk)	yrs				0.000	
Age (Car)	yrs				**-0.004**	
Age (PT)	yrs				**-0.004**	
Income (Walk)	kCHF				-0.007	
Income (Car)	kCHF				0.024	
Income (PT)	kCHF				-0.029	

* In bold: Coefficients significant on 95%-level

Table 24: MNL models for trips: Indicators

		MNL1	MNL2	MNL3	MNL4	MNL5
Indices (Parameter ratios)						
Value of Time Walking	CHF/h	-	17	-	-	31
Value of Time Bike	CHF/h	-	24	-	-	42
Value of Time Car	CHF/h	-	16	-	-	31
Value of Time PT	CHF/h	-	2	-	-	2
Value of Time PT access	CHF/h	-	10	-	-	16
TT Car / TT PT	-	4.09	9.00	9.61	9.61	17.18
TT Walk / Access time PT	-	1.46	1.62	1.95	1.99	1.97
Transfer / TT PT	min	29	66	86	82	144
Interval / TT PT	-	2.24	5.40	5.07	5.07	8.63
Access time / TT PT	-	2.47	5.80	5.05	4.89	8.67

In MNL5, elasticities of travel cost regarding income and distance are estimated. Another non-linear interaction term is introduced in order reflect a squared relationship. The results show a positive elasticity of travel cost regarding distance, which would again suggest decreasing value of time. The opposite has been found in past research.

The cost elasticity regarding income has the expected negative sign: With increasing income, the influence of cost is reduced, and as a consequence, the derived value of time is increasing.

However, the model fit is only slightly increased relative to MNL4.

In MNL6, a model without travel cost, but with distance-dependent travel time coefficients has been estimated, with the same formulation as in MNL5. The interaction parameter is negative for walk, bike and car modes, which indicates an decreasing influence of travel time with increasing distance. This effect is strongest for walk, and decreased for bike and car. Note that the travel time coefficient values stated are for the median distance of approximately 9 km across all modes, and can therefore not be directly compared to coefficients in other models. Note that the constant for walk mode is incomparably higher than in other models. Nevertheless, the introduction of elasticity terms for travel time coefficients has improved ρ^2 to 0.55 compared to 0.52 in MNL3.

MNL7 in Table 25 is an extension of MNL3 and includes spatial and temporal attributes regarding the origin (Table 26). Despite the high number of additional dummy variables, it only slightly outperforms the more basic MNL3. The introduced variables seemingly decrease the influence of PT constant and travel time (regarding absolute values). For example, 144 minutes of PT travel time are estimated per transfer Table 27, which is substantially higher than in MNL3 (86 minutes/transfer).

Table 25: MNL models for trips, continued

		MNL6	MNL7
Model statistics			
n of parameters		19	35
N		57090	57090
LL($\hat{\beta}$)		-32261	-34067
Likelihood ratio test		79456	75844
ρ^2		0.552	0.527
Run time		30 min	03:34
Coefficients			
Walk(intercept)	-	**92.8**	**2.88**
Car (intercept)	-	**-1.52**	**3.17**
PT (intercept)	-	**-3.11**	**0.436**
Transfers PT	-	**-0.517**	**-0.337**
Access PT time	min	**-0.0369**	**-0.0182**
Interval PT	min	**-0.0236**	**-0.0167**
Travel time walk	min	**-0.616**	**-0.0397**
Travel time bike	min	**-0.146**	**-0.0536**
Travel time car	min	**-0.0666**	**-0.0372**
In-vehicle time PT	min	-0.00117	**-0.00239**
Bike always available	y/n	**2**	**2.14**
Car always available	y/n	**1**	**1.27**
Transit pass route-specific	y/n	**2.21**	**2.15**
Transit pass "Halbtax"	y/n	**0.476**	**0.459**
Transit pass "GA"	y/n	**2.33**	**2.24**
Slope max walk (quadratic)	$\%^2$		0.000255
Slope max bike (quadratic)	$\%^2$		**-0.012**
Distance elasticity of TT walk	-	**-0.975**	
Distance elasticity of TT bike	-	**-0.713**	
Distance elasticity of TT car	-	**-0.045**	
Distance elasticity of TT PT	-	**1.090**	

* In bold: Coefficients significant on 95%-level

Table 26: MNL models for trips, continued

		MNL6	MNL7
Attributes of origin			
In core city (walk)	y/n		0.0573
In core city (car)	y/n		**-0.777**
In core city (PT)	y/n		**0.369**
In extended core (walk)	y/n		-0.138
In extended core (car)	y/n		**-0.231**
In extended core (PT)	y/n		0.11
In agglomeration belt (walk)	y/n		**-0.188**
In agglomeration belt (car)	y/n		-0.0262
In agglomeration belt (PT)	y/n		**0.171**
Morning (walk)	y/n		0.0206
Morning (car)	y/n		**-0.546**
Morning (PT)	y/n		0.142
Noon (walk)	y/n		**0.42**
Noon (car)	y/n		**-0.214**
Noon (PT)	y/n		0.107
Evening (walk)	y/n		-0.118
Evening (car)	y/n		**-0.313**
Evening (PT)	y/n		0.00841

* In bold: Coefficients significant on 95%-level

Table 27: MNL models for trips, coefficient ratios

		MNL6	MNL7
Indices (Parameter ratios)			
TT Car / TT PT	-	57	16
TT Walk / Access time PT	-	17	2
Transfer / TT PT	min	442	141
Interval / TT PT	-	20	7
Access time / TT PT	-	32	8

6.2 Advanced models for trip level

An improvement in model fit can potentially be realized by relaxing the strong assumptions that are connected with multinomial logit, where the stochastic utility part is assumed to be independent across alternatives and across individuals (Section 3). In this case, the four aggregated mode alternatives have been defined to be relatively independent, with no obvious "duplicate" alternatives that could be expected to have correlated unobserved utility. Moreover, the effect of unobserved effects can be reduced in ideally including all relevant variables. Still, different nesting structures are tested: Distinction between slow and fast modes, or between individual and public modes.

While nesting structures can help to relax IIA assumption in incorporating differences in utility scale parameters, further developments of the model specification is possible:

- Representing taste heterogeneity in allowing random distribution of taste coefficients
- Making use of panel structure information in omitting assumption of independence between choices
- Allowing for non-identical distribution of unobserved utility across alternatives

6.3 MNL model for different data structure regarding PT availability

As mentioned before, a relatively large share of observations with reported mode other than public transportation is generated as pure walking. In order to evaluate the impact on the model, three different ways of treating those cases, are estimated separately with a relatively simple specification for trips: In the first set-up, the observations with a walked PT route are treated as unavailable, leaving only the alternatives other than PT available. In the second case, those observations are excluded as a whole, leaving only about 57'000 observations for the estimation. In the third model, the walking time of the respective observations are treated as access time, as the only mode-specific variable for such observations.

Table 28 shows, that excluding the noted observations results in the best model fit, and in significant parameters, even if the t-value of the travel time coefficient indicates only moderate probability for being different from zero. Moreover, this model also results in the highest value for value of time for PT, which is lower than expected anyway, as mentioned in the previous section.

Following this reasoning, the second case is adapted for modelling.

Table 28: MNL models for different treatment of PT trips as pure walking

		Unavailable	Excluded	Access time
Model statistics				
n of parameters		11	11	11
N		91435	57090	91435
LL($\hat{\beta}$)		-61105	-39243	-64036
Likelihood ratio test		79737	65491	99280
ρ^2		0.395	0.455	0.437
Run time		01:09	00:54	01:40
Variables		**coeff.**	**coeff.**	**coeff.**
Walk(intercept)	-	**1.8900**	**1.1200**	**2.0200**
Car (intercept)	-	**1.2800**	**1.4900**	**1.2000**
PT (intercept)	-	**0.6220**	**0.5860**	**-0.2800**
Transfers PT	-	**-0.3500**	**-0.3320**	**-0.3670**
Access PT time	min	**-0.0331**	**-0.0292**	**-0.0345**
Interval PT	min	**-0.0287**	**-0.0271**	**-0.0171**
Travel time walk	min	**-0.0712**	**-0.0469**	**-0.0817**
Travel time bike	min	**-0.0727**	**-0.0681**	**-0.0843**
Travel time car	min	**-0.0386**	**-0.0455**	**-0.0476**
In-vehicle time PT	min	**-0.0027**	**-0.0051**	-0.0003
Travel cost	CHF	**-0.1760**	**-0.1690**	**-0.1480**
Indices				
Value of Time Walking	CHF/h	24	17	33
Value of Time Bike	CHF/h	25	24	34
Value of Time Car	CHF/h	13	16	19
Value of Time PT	CHF/h	0.92	1.82	0.11
Value of Time PT access	CHF/h	11	10	14
PT Time per transfer	min	130	65	1385

* In bold: Coefficients significant on 95%-level

6.4 MNL model for each level

Initially, an MNL model is fitted only including route-specific variables like travel time. Travel cost are excluded because the comparison of different model specifications on trip level revealed that due to high correlation, cost parameters could not be reliably estimated.

Table 29 shows the (preliminary) parameter values for the basic model formulation, based on the entire choice set sample. Note that (mostly short) travel with pure walking as PT route are excluded, which is certainly influencing the result.

The goodness-of-fit measure ρ^2 shows very similar values for the respective levels. The model seems to explain the data best at the stage level, while the fit for the trip level is relatively worse, and again increasing towards higher levels. The decreased fit from stage to trip could be explained by the fact that short-term decisions are relatively stronger influenced by alternative-specific attributes, while the explanatory power is shifted towards individual attributes on the trip level. The slightly increasing fit from trip to higher levels might be either explained by a loss of heterogeneity in attributes through aggregation, or the decreased fraction of slower modes, for whose less of the choice might be explained with the available variables.

On the stage level, the PT interval and the PT travel time have (counter-intuitively) positive values, along with a relatively large constant for public transport. This is supposedly explainable by the characteristics of the stage concept, which makes partition of movement dependent on the chosen mode. This means that choice of PT stages in a trip is per definition often correlated, or from the choice point of view, context is missing. On the other hand, e.g. for reported car stages, the unchosen PT alternative exhibits a high number of transfers, compared to reported PT stages that are per definition without transfers. This would explain the large (negative) transfer parameter. The positive PT travel time and interval parameters are possibly due to the fact that chosen PR stages are relatively longer and less served compared to e.g. (shorter) chosen walking stages. Again, the underlying reason of missing context has to be taken into account here.

On the trip level, all parameters values are negative, while the constant of PT is lower relatively to the car alternative, compared to the stage level. The resulting substitution rates are roughly 30 min per transfer, a ratio of 2.5 between access time and travel time, and about the same magnitude for the ratio between headway and travel time. Comparing the travel times of different modes, the relatively large range of -0.005 for public transportation and -0.06 for bike (about factor of 10) becomes apparent.

Most parameters are generally decreasing with higher levels, which is expected as most variables aggregated additively (e.g. travel times or transfers), in opposite to interval and slope, where always the largest value is taken to the upper level. Noticeably, the substitution rate between PT travel time and transfers drops from more than 30 minutes on trip level to 7 minutes on dayplan level.

Table 29: Parameter values with significance level (against 0-hypothesis)

		Stage	Trip	Subtour	Tour	Dayplan
Model statistics						
n of parameters		10	10	10	10	10
N		70117	57090	20160	17624	10056
LL($\hat{\beta}$)		-43931	-39723	-13661	-11777	-6286
Likelihood ratio test		86998	64531	23541	20726	12426
ρ^2		0.498	0.448	0.463	0.468	0.497
Run time		01:26	01:04	00:29	00:31	00:16
Coefficients		coef.	coef.	coef.	coef.	coef.
Walk(intercept)	-	1.71	1.13	0.793	0.578	0.626
Car (intercept)	-	1.28	1.55	1.56	1.48	1.34
PT (intercept)	-	2.09	0.614	0.824	0.844	1.25
Transfers PT	-	-1.92	-0.361	-0.141	-0.135	-0.0814
Access PT time	min	-0.242	-0.0312	-0.0168	-0.0171	-0.0166
Interval PT	min	0.00322	-0.0283	-0.0214	-0.0345	-0.0397
Travel time walk	min	-0.0473	-0.0455	-0.0199	-0.0182	-0.0169
Travel time bike	min	-0.0606	-0.0631	-0.0305	-0.0300	-0.0296
Travel time car	min	-0.0456	-0.0517	-0.0286	-0.0266	-0.0242
In-vehicle time PT	min	0.0053	-0.0126	-0.0103	-0.00971	-0.0111
Indices (Parameter ratios)						
TT Car / TT PT	-	-8.60	4.10	2.78	2.74	2.18
TT Walk / Access time PT	-	0.20	1.46	1.18	1.06	1.02
Transfer / TT PT	min	-362.26	28.65	13.69	13.90	7.33
Interval / TT PT	-	0.61	2.25	2.08	3.55	3.58
Access time / TT PT	-	-45.66	2.48	1.63	1.76	1.50

* In bold: Coefficients significant on 95%-level

In order to estimate the effect of mobility tool ownership, a model specification only containing such variables was tested. The result is shown in Table 30. While the model fit is moderate at stage level, it steadily increases with each level to more than 0.5 for dayplans. While the relative coefficient values of vehicle availability is stable, with increasing level, the effect of public transport passes grows stronger.

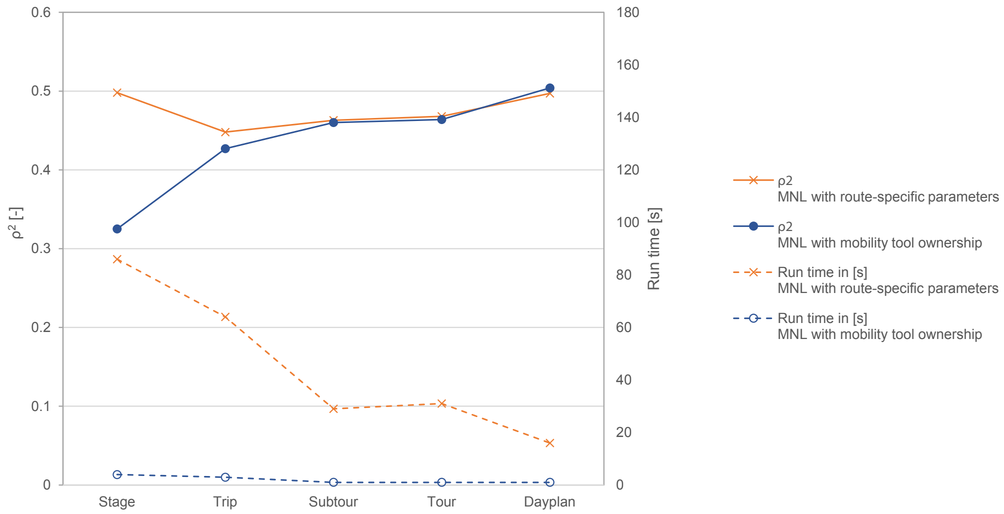
Table 30: MNL with mobility tool ownership on different levels

Model statistics		**Stage**	**Trip**	**Subtour**	**Tour**	**Dayplan**
n of parameters		8	8	8	8	8
N		70117	57090	20160	17624	10056
LL($\hat{\beta}$)		-59042.7	-41259.9	-13728.8	-11865.2	-6195.41
Likelihood ratio test		56775.69	61457.64	23404.6	20549.49	12606.63
ρ^2		0.325	0.427	0.46	0.464	0.504
Run time		00:04	00:03	00:01	00:01	00:01
Coefficients		coef.	coef.	coef.	coef.	coef.
Walk(intercept)	-	**2.76**	**2.29**	**2.05**	**1.89**	**1.76**
Car (intercept)	-	**3.19**	**3.36**	**3.5**	**3.44**	**3.4**
PT (intercept)	-	**1.61**	**1.28**	**1.51**	**1.47**	**1.75**
Bike always available	y/n	**2.01**	**2.07**	**2.12**	**2.07**	**1.90**
Car always available	y/n	**1.39**	**1.33**	**1.27**	**1.27**	**1.39**
Transit pass route-specific	y/n	**1.79**	**2.13**	**2.22**	**2.12**	**2.30**
Transit pass "Halbtax"	y/n	**0.539**	**0.607**	**0.641**	**0.663**	**0.786**
Transit pass "GA"	y/n	**2.25**	**2.53**	**2.63**	**2.54**	**2.77**

* In bold: Coefficients significant on 95%-level

Although the explanatory performance of the route-specific and the mobility-tool specific models is comparable on trip level and higher, the estimation procedure of the route-specific model takes much more computation time (Fig. 13). While this might not be relevant for simple models, it could be for more complex formulations where estimation requires simulation. For both models, with higher level, the run time decreases and the model fit increases at least from trip level.

Figure 13: Model fit (ρ^2) and computing time for two MNL models, by aggregation level



Another MNL model was estimated with dummy variables for spatial type of origin of the travel movement (Table 31, Table 32, Table 33). On both the choice of bike and walk mode, the slope has a negative effect, but in the case of bike alternative, it is not significant on trip level. For the car mode, the effect of an origin in the urban core or in the extended core area is significant on all levels of movement, and all related coefficients have a negative sign (with bike as reference mode). There is a notable difference between core area and extended core: While for the latter, the coefficient value is increasingly negative towards higher levels, the coefficient for urban core does not show a clear tendency. Although not significant, the coefficient for agglomeration area is higher on all levels compared to the other spatial types.

For walk mode, with only a part of the coefficients being significantly different from 0, there is an increasingly negative effect away from the core area, and towards higher levels.

Table 31: MNL model with dummy variables for spatial and temporal categories

		Stage	Trip	Subtour	Tour
Coefficients					
Walk(intercept)	-	**3.4062**	**3.0970**	**4.1062**	**3.9466**
Car (intercept)	-	**3.0173**	**3.1810**	**3.9831**	**3.9517**
PT (intercept)	-	**3.7370**	**2.0970**	**2.6704**	**2.8483**
Transfers PT	-	**-1.8550**	**-0.3210**	**-0.1568**	**-0.1515**
Access PT time	min	**-0.2281**	**-0.0230**	**-0.0151**	**-0.0154**
Interval PT	min	**0.0081**	**-0.0210**	**-0.0174**	**-0.0291**
Travel time walk	min	**-0.0422**	**-0.0420**	**-0.0180**	**-0.0168**
Travel time bike	min	**-0.0540**	**-0.0590**	**-0.0291**	**-0.0288**
Travel time car	min	**-0.0376**	**-0.0370**	**-0.0204**	**-0.0192**
In-vehicle time PT	min	**0.0084**	**-0.0030**	**-0.0050**	**-0.0046**
Travel cost (TC)	CHF	-0.0167	**-0.0900**	**-0.0409**	**-0.0428**
Bike always available	y/n	**2.1027**	**2.1990**	**2.2567**	**2.2112**
Car always available	y/n	**1.3306**	**1.4830**	**1.4552**	**1.4469**
Transit pass "GA"	y/n	**0.5160**	**0.8480**	**0.9664**	**0.9088**
Slope max (Walk)	[-]	**-2.5711**	**-2.1910**	-2.1957	-1.7626
Slope max (Bike)	[-]	**-1.2535**	-0.7690	**-16.6956**	**-17.6995**

* In bold: Coefficients significant on 95%-level

Table 32: MNL model with dummy variables for spatial and temporal categories, continued

	Stage	**Trip**	**Subtour**	**Tour**
Variables related to start coordinates				
Urban core (Walk)	**0.2282**	-0.0540	-0.0935	-0.1203
Urban core (Car)	**-0.8593**	**-0.8450**	**-0.8198**	**-0.9155**
Urban core (PT)	**0.3355**	**0.3800**	0.0288	-0.1196
Extended core (Walk)	-0.1257	**-0.2390**	-0.1780	-0.1161
Extended core (Car)	**-0.2636**	**-0.3170**	**-0.3798**	**-0.5080**
Extended core (PT)	**0.3038**	0.0740	0.1072	-0.0550
Agglomeration (Walk)	**-0.2519**	**-0.2610**	**-0.3160**	-0.1889
Agglomeration (Car)	-0.0590	-0.0870	-0.0465	-0.1045
Agglomeration (PT)	**0.2554**	**0.1670**	0.1885	0.0933
Morning (Walk)	0.0530	0.0330	**-1.5877**	**-1.5605**
Morning (Car)	**-0.4404**	**-0.4980**	**-1.5641**	**-1.5652**
Morning (PT)	-0.0896	0.0770	-0.1043	-0.1770
Noon (Walk)	**0.3140**	**0.4250**	-1.0660	**-1.3445**
Noon (Car)	-0.1136	-0.1610	-1.2178	**-1.2948**
Noon (PT)	-0.1794	0.0440	-0.2949	-0.4174
Evening (Walk)	-0.0211	-0.1070	**-1.4711**	**-1.4837**
Evening (Car)	**-0.2965**	**-0.2930**	-0.9496	-0.9414
Evening (PT)	**-0.2507**	-0.0550	-0.5739	-0.6366

* In bold: Coefficients significant on 95%-level

Table 33: MNL model with dummy variables for spatial and temporal categories, indices

		Stage	Trip	Subtour	Tour
Indices (Parameter ratios)					
Value of Time Walking	CHF/h	152	28	26	24
Value of Time Bike	CHF/h	194	39	43	40
Value of Time Car	CHF/h	135	25	30	27
Value of Time PT	CHF/h	-30	2	7	6
Value of Time PT access	CHF/h	819	15	22	22
TT Car / TT PT	-	-4.46	12.33	4.07	4.16
TT Walk / Access time PT	-	0.19	1.83	1.19	1.09
Transfer / TT PT	min	-220.43	107.00	31.28	32.92
Interval / TT PT	-	0.96	7.00	3.47	6.33
Access time / TT PT	-	-27.10	7.67	3.02	3.35

7 Conclusion

This work demonstrates the use of data from household travel survey as basis for mode choice models on different levels of aggregation. Data from Swiss Microcensus 2010 was enriched with generated attribute data for mode alternatives, resulting in large samples of related observations on stage, trip, subtour, tour and dayplan level. Besides the well-known advantages of RP data as a good quantitative basis for choice sets, this procedure made also use of the reported data in order to evaluate of the effect of resolution with respect to units of the individual travel trajectories.

Different model specifications were developed with a choice set on the trip level. A model with alternative-specific constants and variables for route-specific and mobility tool ownership variables offered a good explanation of the reported choice, taking into account the relatively low number of variables and simple model specification. Nevertheless, also coefficients for spatial and temporal attributes of the trajectories' origin coordinates were estimated. As expected, the start of travel in core agglomeration area goes along with a relatively lower probability of car choice, compared to observations that start further away from the core. Similarly, start of travel in the morning decreases the probability of choosing car, relative to start later in the day. The effect of topography was found to be significant on the choice of the bike mode, but not on the choice to walk. The more advanced models showed a slight improvement of goodness-of-fit.

A systematic estimation of models on stage, trip and higher levels showed that model performance regarding goodness-of-fit does not decrease with lower resolution of the choice set. This is somewhat counter-intuitive, as a descriptive evaluation of mode chains showed that the percentage of observations containing more than one used mode increased on higher level of aggregation, i.e. more 'multi-modality' with lower resolution. Hence, the difference between the reported travel behaviour and the generated attribute that data are pure regarding mode, is increasing with aggregation level. The consequence is a loss of information concerning choice variable and explanatory variables of the modes that are neglected with the aggregation rules deployed. Finally, this is expected to lead to a worsened model fit. As this is not the case, it must be explained with aggregation effects that are able to even offset this inaccuracy. This could be due to the observed shift of explanatory power from route-specific attributes to person-specific variables.

The findings seem to support the concept of approximating the natural choice process by a segmented mode choice prediction procedure, as it is implemented in the current version of MATSim: One mid/long-term decision dependent on socio-economic status, lifestyle, location choice, and mobility tool ownership which predetermines mode choice as a kind of 'modality lifestyle', and a short-term mode choice dependent on intra-household decisions and route attributes, which is basically a route choice decision.

However, two main challenges have to be faced with the implemented approach: The high correlation of variables and the computing of the non-chosen alternatives. A known issue with RP data is the high correlation of attributes in real and market-based choice-sets, especially for the Swiss road network, where "out-of-pocket" travel cost are mainly dependent on distance and mobility tool ownership, and with few tolled links. The correlation is not only high for attributes of the same alternative, but also across alternatives, because average travel speeds for each mode are generally within certain limits.

This work focused on the comparison of different resolutions of movement levels, and did therefore not evaluate systems of models linking two or more levels. Such systems are implemented in disaggregate demand simulators like MATSim and allow the prediction of different 'components' of mode choice on the appropriate level. For example, mobility tool ownership and location choice could be predicted based on characteristics of the household as a long-term decision, primary mode together with tour activity, and route choice based on primary mode on trip level.

In order to further exploit the opportunities of the data from present and future travel surveys, the complete dayplans in revealed preference data should be supplemented with stated choice experiments on different resolution levels, which would allow a joint RP/SP estimation and a more reliable comparison of relative indices of highly correlated variables. Furthermore, the PT routing algorithm should be continuously improved and tested.

Right now, travel behaviour seems to undergo substantial changes, which can affect the requirements for mode choice prediction: The 'multi-modal' behaviour is expected to increase and could lead to less inertia in behaviour, and shift the weight from long-term to short-term towards (super-network) route-choice, and from tour-based decisions towards shorter units like trips. Secondly, the promotion and the increasing modal share of non-motorized or motor-assisted modes like e-Bikes creates a substantial mode category with characteristics of different classic modes like bike and car.

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