Car-Sharing in Activity-Based Models

A case study in Rotterdam

By:

Dorenbos, G.T.J. (Gerben)

March 2018

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Final Report

In partial fulfillment of the requirements for the degree of
Master of Science
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Preface

This thesis report is the final result of a research conducted at the Netherlands Organisation for applied scientific research (TNO) and the Delft University of Technology (TUDelft) with additional support from the Transportation Research Institute of the University of Hasselt (IMOB).

This research provides a first step to implement new mobility concepts (such as car-sharing) in an activity-based model in regards with the low amount of data for a new mobility concept.

It was a challenge to complete this master thesis, regarding knowledge prior to this research, effort and perseverance. There are a couple of people I would like to thank, without them this thesis wouldn't have been possible.

First of all, I would like to thank Maaike Snelder, my daily supervisor from the TUDelft. Her meetings and feedback were extremely useful. She was always willing to make time to answer my questions or to give additional feedback.

Secondly, I would like to thank Erik de Romph, my daily supervisor at TNO. Even though he had a very busy schedule, he was able to provide me with helpful meetings and feedback on a weekly basis. His contacts helped me greatly in getting my research on track.

Thirdly, I would like to thank Bruno Kochan (and his colleagues) from IMOB for his support by mail and the meetings in Hasselt. Even though the link with Feathers in the final report is rather loose, his comments and feedback still helped me to gain a deeper understanding of activity-based modelling.

Fourthly, I would like to thank Sander van Cranenburgh, my external supervisor from the TUDelft. He gave very helpful feedback regarding discrete choice modelling and made noteworthy points from a different point-of-view.

Fifthly, I would like to thank prof. Bart van Arem, the chairman of my thesis committee, for hosting the meetings leading to my final presentation. He kept track of the main thread of my research and gave very inspirational feedback regarding my thesis report.

Besides my thesis committee I would like to thank all my colleagues and fellow interns at TNO for their interest in my work, their helpful support during lunch breaks and for offering a warm welcome from day one at the department by involving me in activities organized by the department and by JongTNO.

Finally I would like to give a special thanks to my parents and my brother for their limitless support during my master thesis. They have given me useful feedback regarding my writing skills and mathematical notations within my methodology.

Gerben Dorenbos

Delft, March 2018

Summary

A lot of space is devoted to cars, not just for transportation (i.e. roads), but also for the 'storage' of cars (i.e. parking). On the other hand, cars are idle for many hours during the day. They are used rarely more than 10% of the day. Car-sharing is an often provided solution for this phenomenom and a way to make cars more efficient. Car-sharing allows vehicles to be used by other people and thus decreases their time being idle. Forecasts for car-sharing predict a positive trend for car-sharing usage. If the potential for car-sharing is indeed as high as forecasts suggest, it is obvious that a tool is necessary to evaluate the effect of car-sharing as a new mode of transportation. The current transport demand models, based on the classic four step model, are insufficient for this task. This is because they are unable to capture consistency within the timeline of a person. Activity-based models are also better in incorporating personal characteristics. Activity-based modelling is thus often presented as a better alternative. However, activity-based models are less common in practice and are mainly used in a scientific context. Hence, the current existing activity-based models are not yet suitable to determine car-sharing demand.

The aim of this research is to develop a prototype mode-choice model to determine the potential car-sharing usage in a future scenario, for the urban area of Rotterdam, as a sub model within an activity-based framework.

Car-sharing comes in a lot of different forms. The following business models can be distinguished: round-trip, business-related, free-floating, peer-2-peer and private. One of the key differences between the business models is whether a car-sharing system is point-to-point or not. A point-to-point model means that the car can be dropped everywhere. A round trip model on the other hand, requires the user to drop the car off at the same point where the user has taken the car. Furthermore a difference can be made between car-sharing systems presented by a service provider and car-sharing systems where the cars are owned privately. It is important to keep the differences between the different car-sharing business models in mind, as they have different impact on the model and on the activity-based framework.

Furthermore, available market research has been analyzed. From the market research it is found that the following personal attributes lead to high car-sharing usage:

- Low vehicle ownership
- Age: between 25 and 44
- Small household size
- High level of education
- Higher than average income
- Certain extent of environmental concern.
- Some sensitivity towards innovation and/or sensitivity towards trying new things.
- Generally people attracted to car-sharing use car-alternative modes more often, like public transport, cycling and walking.

As well as the following spatial attributes:

- High household density.
- High amount of parking limitations or restrictions.
- Short distance to nearest car-sharing vehicle.

These attributes are thus important, and should be directly addressed in the mode choice model.

Besides understanding the concept of car-sharing, it is also important to understand the concept behind activity-based models. Unlike classic four-step models, activity-based models consider the schedules of agents. Based on the concept that each activity in a schedule has a certain location. A spatial difference between those locations then leads to a certain traffic demand. Generally, an activity-based model consists of a series of steps: the input of the model (land-use data, level-of-service data and observed schedules), generating a synthetic population, determining long-term strategic choices, determining mobility choices, generating the daily activity patterns, determining the tour & trip details, assigning those tours and trips to the network and finally the model outputs (see Figure 1) (Castiglione, Bradley, & Gliebe, 2015).

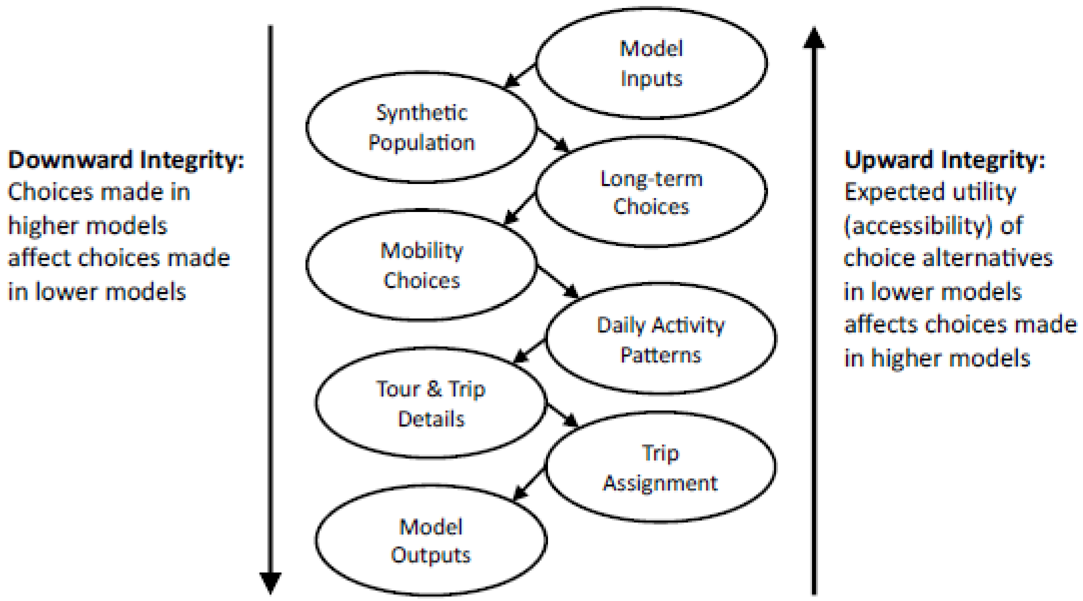


Figure 1 Steps in an Activity Based Model (Castiglione et al., 2015)

Based on the research on car-sharing, an overview has been given of the changes/implementations that have to be made within an activity-based model to fully implement car-sharing. These changes include:

- Additional data requirements within the model inputs.
  - Observed car-sharing data..
  - Level-of-service data for car-sharing.
  - Additional personal variables (environmental concern, sensitivity towards innovation).
- A Car-sharing subscription model within the mobility choices..
- Interaction/feedback loop between car-sharing and other mobility choices (i.e. car ownership), as part of the upward integrity.
- The mode choice itself within determining the tour & trip details.
- Multimodal trips & tours (car-sharing as access/egress for other modes and access/egress of car-sharing)
- Assignment step should include car-sharing

Since the mode choice is the most essential part for determining car-sharing, the mode choice will be the main focus in this research.

A stand-alone mode-choice model has been developed, including the car-sharing alternative. This model initially uses a multinomial logit and considers five conventional modes: car driver, car passenger, public transport, cycling and walking and then adds car-sharing as a sixth mode. It furthermore considers three distinct tour purposes: work, education and other. The mode choice model is then created in four steps.

First, the utility functions of the conventional modes are determined for each tour purpose (15 utility functions in total). Initially these utility functions contain personal attributes that lead to high car-share usage. These attributes are the attributes found from market research which are listed before.

Secondly, the utility function of car-sharing is determined by inheriting parameters from the utility functions of the conventional modes. The proposed utility function of car-sharing is given below:

$$U_{cs} = ASC_{cs} + \beta_{TT,cs} * TT_{cs} + \beta_{Cost,cs} * Cost_d * Dist_{cs} + \beta_{Cost,cs} * Cost_t * RT_{cs} + \beta_{AET,cs} * (AT_{cs} + ET_{cs}) + \beta_{car0,cs} * D_{car0} + \beta_{car1,cs} * D_{car1} + \beta_{age2544,cs} * D_{age2544} + \beta_{hh2l,cs} * D_{hh2l} + \beta_{educ34,cs} * D_{educ34} + \beta_{inc3h,cs} * D_{inc3h}$$

The alternative specific constant represents variables that influence the choice for car-sharing but that are not included in the other variables. The alternative specific constant in this utility-function has a range of possible values. It is assumed that the alternative specific constant for the car driver alternative is always higher than that of car-sharing due to the variables represented by the alternative specific constant being usually in favor of using a not shared vehicle (the ease of using an own car, and the comfort of an own car) The upper boundary of this range is thus given by the alternative specific constant of the car driver alternative. The lower boundary of this range is given by the lowest alternative specific constant among the conventional modes or zero. The beta's of the level-of-service components are set to the value of the conventional mode that is most similar to car-sharing. The beta's for the personal characteristics will also have a range of possible values. The upper boundary of this range is set to the most positive value among the conventional modes. Since it was established that these factors influence car-sharing positively, the lower boundary of this range is set to the lowest positive value among the conventional modes or to zero if there are no positive values.

Thirdly, the utility functions of the conventional modes are re-estimated with their own components, rather than components that lead to high car-share usage. This is done by analyzing the observed schedules and determining which attributes affect the choice for a certain mode. Besides the attributes already taken into account for the utility of car-sharing, the following attributes are considered: gender (for car driver and car passenger), age, roots (for public transport, cycling and walking), work occupation (for car driver), driver license (for car driver), urban density of the home municipality (for car passenger, public transport and walking) and the standardized household income (for walking). The re-estimation process is done by adding or removing an attribute from the initial utility function. Attributes where the beta-value is significant are kept. Attributes whose beta-value are insignificant or become insignificant due to adding other attributes, are removed from the utility function.

Finally, a nested logit model has been considered because of the possible similarities between the modes. Two different scenarios are considered, one scenario with a nest containing car driver together with car-sharing, and one scenario with a nest containing public transport together with car-sharing. The extreme cases of the nested logit are considered, assuming maximal correlation between the modes in a nest (a nest parameter of 0).

So, in total there are twelve different variations on the mode choice model which are considered, these variations are given in Table 1 below.

Table 1 Twelve different variations of the mode choice model

Nr	ASC_{cs}	β_{cs} for Pers. Cha.	Model
1	Lower boundary	Lower boundary	Multinomial Logit
2	Lower boundary	Upper boundary	Multinomial Logit
3	Upper boundary	Lower boundary	Multinomial Logit
4	Upper boundary	Upper boundary	Multinomial Logit
5	Lower boundary	Lower boundary	Nested Logit with Car Nest
6	Lower boundary	Upper boundary	Nested Logit with Car Nest
7	Upper boundary	Lower boundary	Nested Logit with Car Nest
8	Upper boundary	Upper boundary	Nested Logit with Car Nest
9	Lower boundary	Lower boundary	Nested Logit with PT Nest
10	Lower boundary	Upper boundary	Nested Logit with PT Nest
11	Upper boundary	Lower boundary	Nested Logit with PT Nest
12	Upper boundary	Upper boundary	Nested Logit with PT Nest

The methodology has been applied for a case study for the urban area of Rotterdam, consisting of the area within the boundaries of the SRR: ‘stadsregio Rotterdam’. Only internal trips are considered. Observed schedules from OViN are used as input data for the mode choice model. The choices from the observed schedules are extended with level-of-service data from the RVMK (the current traffic demand model of Rotterdam). The level-of-service data from the RVMK is translated to a zonal level of 4-digit zipcode areas, the smallest unit given by OViN.

The results on the modal split are given in Figure 2 below. Depending on which values are used and whether a multinomial or nested logit model is used, the modal share of car-sharing will be between 3.6% and 45.8%. It was also found that the beta’s of the level-of-service variables, except those of the travel time, were not significant and thus these were excluded from the utility functions. Three reasons could be given for the level-of-service variables not being significant. First of all, the level-of-service variables might be too simplified: not considering parking times, parking fees etc. which still affects the mode choice given by OViN. Secondly, the level-of-service variables might be inaccurate or on a too high level of scale: travel times and costs are calculated to/from the center points of the 4-digit zipcode areas, this might give a mismatch especially on shorter trips. Finally, there is a possibility that the level-of-service variables might actually be insignificant: because Rotterdam is an urban area, the quality of public transport is relatively high. If all modes are comparable in level-of-service, the choice might actually not be affected as much by the level-of-service variables, but more so by the personal characteristics.

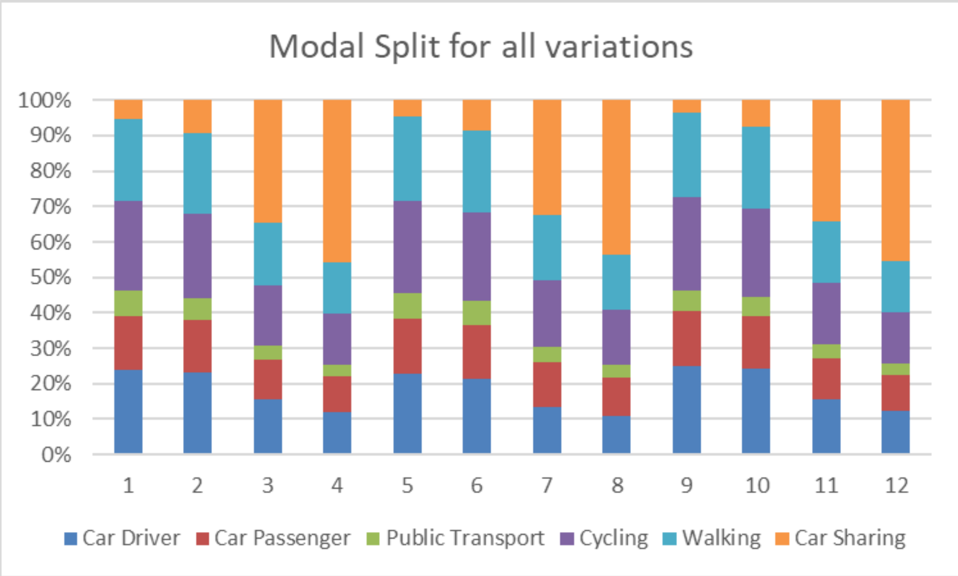


Figure 2 Modal Split of the twelve variations of the mode choice model, with car-sharing implemented

The large range of the modal share of car-sharing can be addressed due to the large range of the alternative specific constant in the utility function of car-sharing. Depending on whether the upper or lower boundary is used, the alternative specific constant of car-sharing varies with roughly 30%. The additional range of using the upper or lower boundary beta-values for the personal characteristics is about 4-10%. Whether a multinomial or nested logit is used doesn't affect the result that much. The modal share of car-sharing only increases or decreases by an additional 1 or 2%.

The large range of the alternative specific constant is rather bothersome. This implies that there are quite a lot of other variables that influence car-sharing usage that are not yet present in the model. It is recommended to do additional research regarding these variables. Future research should mainly be aimed at gathering more data sources. One could consider setting up a stated preference research to get more information about the attributes that influence car-sharing. Data of a stated preference research could also be used to estimate the parameters. Another recommendation is to improve the level of service data. This can be done by using smaller zones and by adding more detail to the level-of-service variables. If level-of-service data is more accurate and turns out to be significant in the utility functions, then the modelling approach for car-sharing can be used to model and compare different car-sharing business models.

Besides gathering additional data, future research could also be aimed at actually implementing the mode choice model within an activity-based model. Furthermore, future research could consider the level of a trip leg when considering mode choice. In this way, modelling combinations of modes becomes possible (for example using car-sharing as the access mode of public transport). Finally, future research could also aim at the other implementations of car-sharing into an activity-based framework: for example taking into account harder to quantify personal characteristics, car-sharing subscription modelling, the relation between car-sharing availability and car-ownership and including car-sharing in the assignment step.

Table of Contents

1 Introduction

1.1 Problem Definition

The amount of vehicles on the road is increasing drastically, leading to congestion and thus a reduction of travel times. The reason that so many people rely on cars as their daily transport mode is due to the fact that owning and driving a car is relatively easy and that it allows relatively fast point-to-point travelling or travelling in areas with a lack of proper public transport. A lot of infrastructure is devoted to cars, not just for transportation (i.e. roads), but also for the 'storage' of cars (i.e. parking). On the other hand, cars are idle for many hours during the day. They are mainly used during peak hours and rarely more than 10% of the day (OECD, 2015). On average, in the Netherlands, each car is active only one hour a day (Deloitte, 2017). An often provided solution for this phenomenom is car-sharing. Car-sharing is a short-term vehicle rental service, which ensures that cars can be used more efficiently, while still retaining the advantages of a car, i.e. point-to-point travelling or easy travelling in areas with a lack of proper public transport. Forecasts for car-sharing usage are mostly positive and the general concensus is that there is a growing trend in car-sharing usage (Deloitte, 2017; KiM, 2015a). That being said, car-sharing is currently only used for a very small portion of all trips. In 2014, car-sharing was used for only 0.02% of all car trips in the Netherlands (KiM, 2015b). In the total modal split the modal share of car-sharing would be even lower. Because of this, there currently isn't much data about car-sharing available.

If the potential for car-sharing is indeed as high as forecasts suggest, it is obvious that a tool is necessary to evaluate the effect of car-sharing as a new mode. The current transport demand models, based on the classic four step model, are insufficient for this task, because implementing new transport technologies such as car-sharing in the current transport models would lead to an exponential increase of the computation time of the model and/or the current transport models have too many limitations to correctly represent the car-sharing alternative. In these cases activity-based modelling is often presented as a better alternative to the classic four-step-model. The concept of activity-based modelling is fundamentally different: using daily activities as input and building forth on the idea that each activity corresponds to a certain location and thus requires a trip between locations/activities. Because of the disaggregated modelling approach these models should do better when modelling a trip chain consisting of different modes. However, unlike classic trip- and tour-based models, based on the four step model, activity-based models are a lot less common in practice and are, except for a few American-based models, mainly used in scientific contexts. Hence, the current existing activity-based models are not yet suitable to determine car-sharing demand.

1.2 Research Questions

The aim of this research is to develop a prototype mode-choice model to determine the potential car-sharing usage in a future scenario, for the urban area of Rotterdam, as a sub model within an activity-based framework.

The key challenge of this research is to provide a theoretical overview of the necessary implementations to fully implement car-sharing within an activity-based framework. One of these implementations is then worked out in more detail within this research. FInally a car-sharing demand model is developed while dealing with the lack of (observed) car-sharing data due to the low share in the modal split. This model is used to predict the potential effect of car-sharing on the modal split.

The main research question of this research is:

> *How can the potential of car-sharing demand be determined, considering the concept of an activity-based model?*

To answer this research question, the following sub questions have been defined:

- *What are the common attributes/motives of car-share users?*
- *How does car-sharing affect the structure of an activity based model?*
- *How can the mode choice model be specified?*
- *How can the parameters for car-sharing be estimated, regarding the lack of observed data?*
- *How does car-sharing affect the modal split?*

1.3 Scope

This paragraph defines the scope of the research.

First, car-sharing is defined as a system where people can rent a shared vehicle for a certain period of time. This research doesn't take into account ride-sharing/carpooling which is when multiple users use the same vehicle during (part of) the same trip. This definition is important as in some countries (like United Kingdom), this definition seems to be different and the term 'car clubs' is used to identify the system more commonly known as car-sharing, and the term car-sharing is used for the system more commonly known as ride-sharing or carpooling.

Secondly, this research will not take into account automated vehicles as automated vehicles induce a lot of uncertainties additional to those of car-sharing which would increase the complexity of the research. Besides that, it is expected that only a high level of automation (SAE level 5), would impact car-sharing demand. The methodology, however, is based on having a low amount of observed data available, and a similar methodology could thus also be applied for other new transport technologies such as automated vehicles (as a stand-alone concept).

This research will not go in-depth on the actual implementation within one of the existing activity-based models. The general activity-based framework as described in (Castiglione et al., 2015) will be used as a reference. Besides that, the mode choice model developed in this model, will act as an independent stand-alone model. Actually implementing the mode choice model in an activity-based model, could be part of future research.

This research is aimed at predicting the future potential of car-sharing, assuming car-sharing to be a fully available and realistic alternative. The goal of this research is not to explain and model current car-share usage as realistically as possible, this task would be difficult due to the lack of data/research in the Netherlands to validate the findings. Besides the current penetration rates are too low to model an accurate base year scenario. Only the modal split is taken into account as the final result, the actual assignment of traffic will not be done. If a municipality wants to estimate changes on the key performance indicators due to car-sharing, additional research has to be done.

1.4 Terminology

In later chapters some terms are used, regarding the schedule of a person and his/her movement through space and time. Because there is no unanimity in literature about these terms, the terms are defined below. One could refer to this paragraph for an explanation of certain terms.

Imagine a fictive person X. Person X goes to work at 08:00 in the morning. He arrives at work (W) at 09:00. He then works until 11:50 when he leaves work for a business lunch meeting (B), which lasts from 12:00 till 13:00. He is back at work at 13:10 and continues working until 16:30. On his way back home he goes to a shop (S), where he stays from 17:00 till 17:20, after that he continues his way home (H). He finally arrives home at 17:50. He leaves his home again in the evening at 19:40 for a leisure activity (L). The leisure activity lasts from 20:00 until 22:00 and after that he returns back home, arriving home at 22:20. He doesn't undertake any other activities for that day. The full description of all activities of person X during this day and all 'moves' between those activities is called a daily schedule, or simply a **schedule**, and always lasts from 0:00 till 0:00. In Figure 3 the schedule of person X is represented graphically.

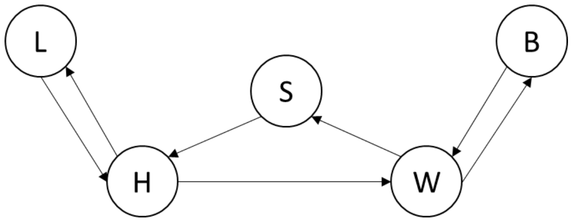


Figure 3 Graphic representation of schedule of person X

Each **activity** is continuous in time and occurs at a fixed location and with a certain purpose. Person X in this case has 8 activities. Both the work activities, and the three home activities are considered as separate activities. This is where definitions start varying. Some sources would consider both work activities to be a single activity with a break in the middle. In that case the two parts of the activity would be called two separate 'episodes'. However in this research that definition is not used and each episode is just considered as a fully self-contained activity. All activities in this example case are numbered and can be seen in Figure 4.

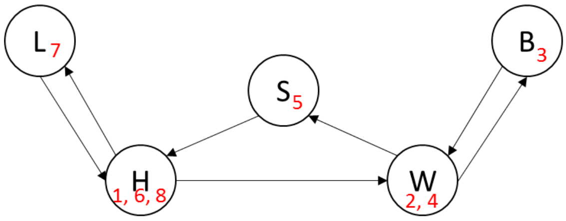


Figure 4 Definition of an 'activity'

Because activities are likely situated in different locations, the person has to move between two consecutive activities. This 'move' is called a **trip** and is defined as the movement of a person between two activities. In the example case, person X makes 7 trips. The definition of a trip is visualized in Figure 5. Each trip has a certain **goal**, which is usually the type of activity followed by the trip. The goal of the first trip in this case is 'working', the goal of the third trip is 'working', the goal of the fifth trip is 'going home' and so on. Note that the goal of a trip is not the same as the **purpose** of a trip which is the reason why a certain trip has been conducted. The purpose is never 'going home' as that is not a reason to travel (the person could have simply stayed home) and the purpose does not always say something about the destination. In this example the purpose of the first trip is 'working'. The purpose of the second and third trips is 'business'. The purpose of the fourth and fifth trips is 'shopping' and so on.

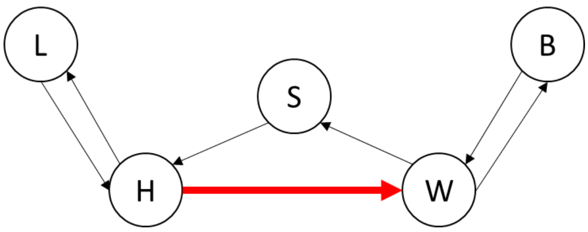


Figure 5 Definition of a 'trip'

A full chain of trips and activities from and finally back to home is called a **tour**. In this research tours are always home-bound, meaning that the origin and final destination of a tour is always the home address. If 'tours' are not home-bound, if the first trip of the day does not originate from a home and/or if the last trip of the day does not arrive at home, this is called a **one-sided tour**. This happens when a tour spans multiple days or in the rare case where a person moves his or her home to another place, or having a second home. In the example case person X makes two full tours, the trips to/and from the leisure activity and the leisure activity itself are considered to be a separate tour, because they are separated from the work/shopping tour by a home activity. In Figure 6 the first tour of person X is marked in red. Just like a trip, a tour can also have a purpose. This is called the **tour purpose**. The tour purpose is the most important activity in the chain. In case there is any work or business activity in the tour, the tour purpose is 'working'. If not, if there is any education activity in the tour, the tour purpose is 'education'. Else, the tour purpose is classified as 'other'. Only these three types of tour purposes are considered. In the example case the tour purposes of the first tour would be 'working'. The tour purpose of the second tour would be 'other'. For each trip in the tour, a different mode can be chosen. If two or more modes are used in the same tour, this is called a **multimodal tour**.

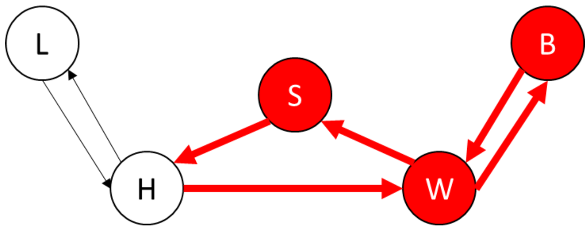


Figure 6 Definition of a 'tour'

Also within a trip, multiple modes can be used. This is often the case for public transport trips, where for example the bicycle is used as an access mode, followed by a train, then followed by a bus, and finally egress is done on foot. This is also the case for P+R (park-and-ride) or K+R (kiss-and-ride) concepts where one part of the trip is done as car driver or car passenger, followed by a part of the trip done by public transport. If multiple modes are used within the same trip, the trip is called a **multimodal trip**. Each 'part' of the trip, where a different mode is used (or the same mode twice separated with an interchange) is called a **trip leg**. Between trip legs, there is often a waiting time, this waiting time is part of the total trip, but not part of any of the trip legs. In case of a multimodal trip, the mode of the trip is the main mode used over all trip legs. In this research however, the lowest level of detail will be that of a trip and information about trip legs is later filtered (see paragraph 4.2).

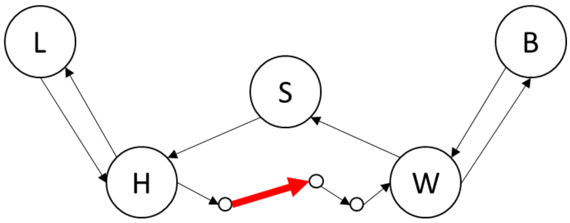


Figure 7 Definition of a 'trip leg'

1.5 Structure of the Report

The remainder of the report contains a literature study (chapter 2), both covering a more general overview about activity-based modelling and car-sharing as well as previous research considering the implementation of car-sharing into travel demand models. After that an overview is given of the proposed methodology for developing a mode choice model with car-sharing (chapter 3). The methodology is then applied to a case study for Rotterdam (chapter 4) including results. After that, a conclusion and recommendations for further research are followed (chapter 5). The report ends with a reflection (chapter **Fout! Verwijzingsbron niet gevonden.**)

2 Literature Study

In this paragraph the findings from literature study are summarized. The first 2 paragraphs are about car-sharing. In paragraph 2.1 car-sharing is described in general, as well as business models for car-sharing. In paragraph 2.2 the focus is on the car-share system users, conclusions of market research are summarized to get an overview of common personal and spatial attributes, as well as motives of car-share users that lead to car-share usage. Paragraph 2.3 then continues about activity based modelling in general. Paragraph 2.4 shows an overview of previous research and models about implementing car-sharing. Finally, paragraph 2.5 shows the most important conclusions that can be drawn from literature research and how these are used in the following chapters.

2.1 Car-Sharing

Car-sharing exists in many forms (business models). In literature there are various distinctions within car-sharing systems. One of these distinctions is between round-trip usage car-sharing models and point-to-point car-sharing models (Le Vine, Zolfaghari, & Polak, 2014). The first group of car-sharing systems could be seen as 'static' systems in the sense that the car has to be returned to the exact location as where it is picked up. The second group could be seen as 'dynamic' systems in the sense the car can be picked up at a certain location and can be dropped off at another, this allows for one-way trips. The round-tip car-sharing systems are further divided into 'round-trip' systems and 'peer-to-peer' systems. The point-to-point car-sharing systems are further divided into 'point-to-point free-floating' systems and 'point-to-point station-based' systems.

Another report considers five types of car-sharing systems in the Netherlands (CROW-KpVV, 2016). First a distinction is made between car-sharing systems where the provider is the owner of the vehicle fleet and car-sharing systems where the users themselves are owners of the individual vehicles. Then the car-sharing systems are further divided into: 'classic' car-sharing systems, 'business' car-sharing systems, 'one-way' car-sharing systems, 'peer-2-peer' car-sharing systems and 'private' car-sharing systems. These five business models are briefly described below, under more common frequently used names, as well as how they might differ in the way they are used.

Round-Trip

Previously labelled as 'classic' car-sharing systems, but more commonly known throughout literature as 'round-trip' car-sharing systems or 'two-way station-based' car-sharing systems is a static way of car-sharing where the vehicle fleet is owned by the car-sharing provider. Because they have to be returned to the place where they were picked up and because usually payment is per minute with the activity time counting towards the total in-use time of the vehicle, it is expected that these vehicles are mostly used for shorter trips (grocery shopping, dropping someone off at the railway station etc.). Examples of round-trip car-sharing systems are Greenwheels and Zipcar.

Business-Related

Similar to round-trip car-sharing systems, business-related car-sharing systems are static and thus the car has to be returned to the same parking spot. The vehicle fleet is either owned by a company or outsourced to a third company. The users are the employees of the company. The shared vehicles are used mainly for work-related travels (work-work, extern appointments etc.)

Free-Floating

Previously labelled as ‘one-way’ car-sharing systems, but more commonly known as (point-to-point) free-floating car-sharing systems throughout literature. The vehicles are owned by the service provider. Free-floating car-sharing systems are dynamic and in principle, shared vehicles can be dropped off at any legal parking spot. These car-sharing systems promise a much larger potential as they could be used for one-way trips and thus, unlike round-trip systems, users don’t have to pay for their activity-time. Because of this, free-floating vehicles could be used for home-work trips and for leisure trips. Relocation strategies and providing enough vehicles are crucial factors for free-floating systems to work as the lack of availability of a vehicle can lead to a great disutility for the system. An example of a free-floating car-sharing system is Car2Go.

In some literature a distinct category of shared vehicles are the ‘one-way station based’ car-sharing systems or ‘point-to-point station based’ car-sharing systems. These systems are basically the same as free floating systems, with an additional limitation that the cars will have to be dropped off at another station, so in contrast to round-trip models, they can be dropped off at any station, not just the one where it was picked up. CROW-KpVV confusingly uses the term ‘one-way’ for ‘free-floating’ car-sharing systems as a whole, and not just ‘one-way station based’ car-sharing systems. Specific examples of on-way station based car-sharing systems are Autolib’ (FR) and some pilots by Zipcar.

Peer-2-peer

Peer-2-peer car-sharing systems are static. They classify themselves by shared vehicles which are not owned by the service operator, but owned privately. The service operator mainly serves as a matchmaking device between a car-owner and a car-share user. The service operator typically gets paid a small fee for usage of the shared vehicle. On the other hand the service operator can also be responsible for the administrative side of the car-sharing system (insurance etc.) Because payment can be negotiated between parties and because payment is more often per distance travelled instead of a time-related payment, peer-2-peer shared vehicles can be more easily used for work-trips. An example of a peer-2-peer system is SnappCar.

Private

Private car-sharing systems are static. They are very similar to peer-2-peer systems, in the way that the vehicles are owned by individuals. However, unlike peer-2-peer car-sharing systems there is no service operator involved. There can still be a third party involved offering support however. Usually the car owner and car-share user know each other (friends, family, neighbors) and also payment is often per travelled distance rather than per travelled time-period.

2.2 Market Research

Ideally, when implementing car-sharing into a travel demand model, data is required that can estimate the group of car-share users based on given personal and spatial attributes. Unfortunately, literature regarding demand estimation for car-sharing is quite limited, because the penetration rate of car-sharing systems is still quite low. On the other hand, a lot of market research has been done among car-share users. While this doesn't directly help in estimating car-sharing demand in future scenarios, it will help profiling the type of person that is attracted to car-sharing.

Market research can be divided into three different themes. First of all the relationship between spatial attributes and car-share users, secondly the relationship between personal (or household) attributes and car-share users and finally the motives why people joined a particular car-sharing scheme.

In some reports (Jorge & Correia, 2013; Kortum, 2012) an extensive summary has been provided of previous market research where the relations between car-share users and various spatial and personal attributes have been examined. Below, their findings will be listed, as well as some additions and appropriate references underpinning the relations.

Personal/household attributes:

- Low vehicle ownership (Celsor & Millard-ball, 2007; Cervero, 2002; Millard-Ball, Murray, ter Schure, Fox, & Burkhardt, 2005; Steininger, Vogl, & Zettl, 1996; ter Schure, Napolitan, & Hutchinson, 2012; Zhou & Kockelman, 2011).
    - This relation can work both ways: car-sharing might also lead to a drop in vehicle ownership (Martin & Shaheen, 2011).
- Low age, most notably people between their late twenties and early forties (Brook, 2004; Cervero, 2002; Lane, 2005; Steininger et al., 1996).
- Small household size (Burkhardt & Millard-Ball, 2006; Millard-Ball et al., 2005)
- High level of education (Brook, 2004; Lane, 2005; Shaheen & Rodier, 2005; Steininger et al., 1996).
- Higher than average income (Millard-Ball et al., 2005; Shaheen & Rodier, 2005; Steininger et al., 1996).
    - However interest in car-sharing is also present among people with lower than average income (Abraham, 1999).
- Certain extent of environmental concern (Burkhardt & Millard-Ball, 2006; Costain, Ardon, & Nurul Habib, 2012; Millard-Ball et al., 2005; Shaheen & Rodier, 2005).
- Some sensitivity towards innovation and/or sensitivity towards trying new things (Burkhardt & Millard-Ball, 2006; Millard-Ball et al., 2005; Shaheen & Rodier, 2005).
- Generally people attracted to car-sharing use car-alternative modes more often, like public transport, cycling and walking (Cervero, 2002; Loose, Mohr, & Nobis, 2006).

Spatial attributes:

- High household density (Burkhardt & Millard-Ball, 2006; Cervero & Tsai, 2004).
- High amount of parking limitations or restrictions (Abraham, 1999).
- Short distance to nearest car-sharing vehicle (Abraham, 1999; Costain et al., 2012; Katzev, 2003).

Besides these attributes, a few other spatial attributes are mentioned (Stillwater, Mokhtarian, & Shaheen, 2009) like the street width, heavy rail availability (both negatively correlated to car-sharing demand) and average of the car-sharing stations and light rail availability (both positively correlated to car-sharing demand), but since there are no other sources backing-up these relations, it cannot be said if these relations are universally true.

In another report (Schaefers, 2013) qualitative research is performed to understand the motives why people choose to join a specific car-sharing program and they are linked to certain vehicle- and service-attributes of the car-sharing system. From this report four distinctive motives could be recognized: value-seeking, convenience, lifestyle and environmental. 'Value-seeking' in this case relates to the feeling of being able to save money by using shared vehicles. This can mostly be assigned to the fact that the car-share user can now go carless and that a lot of the fixed costs of driving can be replaced by cheaper variable costs. 'Convenience' as a motive is pretty self-explanatory, but it also relates to a time-saving component. Saving time is especially reached because the user is able to use designated parking spots which are empty and easy to find. The motive of convenience is furthermore largely related to service attributes. Different business-models (for example free-floating car-sharing) can have very different effects on the extent to which an increase of convenience is experienced and achieved. The motive 'Lifestyles' refers to the willingness to differentiate from other people by using shared vehicles. This motive relates strongly to the appearance of the shared vehicles and to values like 'belonging', 'status' and 'recognition'. Finally the 'Environmental' motive relates to the ability to use a more environmental alternative for the regular car. Note that overlap can be seen between certain personal attributes and the motives for joining a car-sharing scheme.

The only known market research done in the Netherlands, is a research in Utrecht (SmartAgent, 2011). It uses a cluster analysis to group people into five different lifestyles (market segments based on mobility). For each lifestyle an overview is given of common characteristics. Also the lifestyles are linked to the classes in the innovation theory of Rogers (innovators, early adopters, etc.). It does further research on the common characteristics of people who indicated that they were interested in car-sharing. The report ends with an overview of measures that can be taken or system specifics that can be implemented in order to increase car-share-usage. While this research seems relevant, the research data is inaccessible and it is unclear from the report if the research can be used directly for this research.

2.3 Activity-Based Modelling

Activity-based modelling is a relatively new modelling approach that is often presented as an alternative to the classic four-step model. The concept of an activity-based model is that they consider the activities of an individual and, because the activities are located at different locations, lead to a certain traffic demand. This is fundamentally different from the classic four-step model, which usually determines traffic demand on a more aggregated level and often determine traffic demand solely on zonal characteristics.

Activity-based models generally run through a series of steps to model the traffic demand and traffic flows (Figure 8).

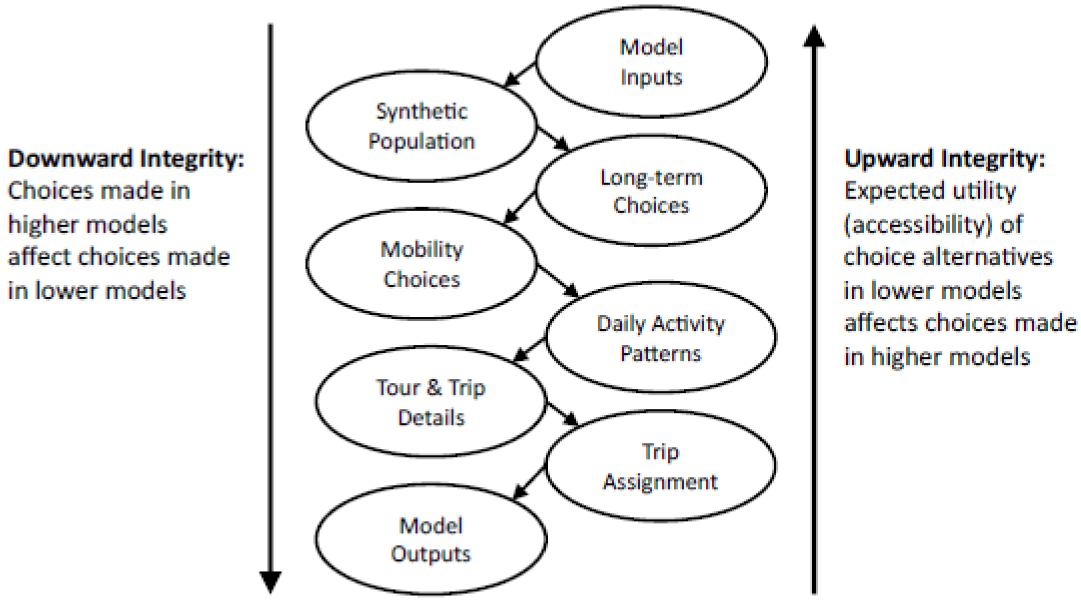


Figure 8 Steps in an Activity Based Model (Castiglione et al., 2015)

Activity-based modelling starts with the model inputs. The modal inputs might vary for each activity based model. Common model inputs include land use data, level-of-service data and observed schedules. The land use data is geographical information about the research area, where homes are located, where jobs are located and the urban density of certain areas. The land use data is often required on a certain zonal level. The level-of-service data is geographical information about the network (where the network links are located), as well as level-of-service data (free-floating travel times, frequency, time table of public transport etc.). The observed schedules are like a sample of the people and contain the person's characteristics as well as the person's schedule and activities, the trips made between those activities, the chosen mode and the duration of activities and trips.

The second step is the synthetic population. In this step a synthetic population is created. This synthetic population is a list of agents and their characteristics, as well as household characteristics on the level of an individual. The synthetic population is generated by totals derived from the land use data (total amount of inhabitants, total amount of persons in a certain age category) and a sample of individuals with disaggregated data, derived from the observed schedules. The reason for this step, is that there is often not a list available of all individuals and their characteristics, because of obvious privacy issues. The synthetic population represents the real population, but doesn't match the real population on the level of an individual, thus bypassing the privacy issue.

The third step is the long-term choices, choices that are not made on a daily base. Examples of these choices are the home location, the work location, but also household related choices such as the amount of children in the household. In some activity-based models this step is not present and data such as the home location, work location and amount of children is instead treated as input data and assumed fixed.

Mobility choices are similar to long-term choices but contain choices that directly affect mobility. Examples of these choices are the amount of vehicles in a household, owning a driver license, buying a public transport discount pass etc. Again, this step is not present in all activity-based models and is also treated like fixed input data in these models.

In the fifth step daily activity patterns are determined, usually this step contains a scheduling mechanism that adds activities to an agent's timeline, as well as their location and duration. This is usually done as a decision making process (i.e. for each agent questions are asked about his/her activities: is he/she going to work, how long is he/she going to work etc.). This can be done by a discrete choice model and/or by a decision tree. The scheduling mechanism uses the data from the observed schedules to estimate the parameters in the models.

In the sixth step the tour & trip details are determined, this step uses the spatial difference of locations in the schedule to determine mode choice and the length of tours and trips. The fifth and sixth step might be executed somewhat simultaneously. For example, the destination choice can be affected by the length of the trip and vice versa.

At this point a full daily schedule for each agent is created, including the trips between the activities and the modes chosen. Finally these trips are assigned to the network, using the level-of-service data, similar to the final step of the classic four step model. In a perfect case there is some upward integrity in the activity-based model, this means that choices in later steps of the activity-based model affect choices in earlier steps of the model. For example, the assignment step and the outcoming delays might influence the time choice when an agent is going to work, with the agent 'realizing' that by going to work earlier or later, he spends less time in traffic.

Examples of activity-based models are DaySim (Bowman, 1998), MATSim (Horni, Nagel, & Axhausen, 2016) and Feathers (Bellemans et al., 2010). In paragraph 2.4 MATSim is described in more detail and the car-sharing implementation that has been done in MATSim.

2.4 Previous Car-Sharing Implementations in Activity-Based Models

Previous attempts have been made to implement car-sharing into a model, or to estimate car-sharing demand. In literature (Jorge & Correia, 2013) an overview has been given of these implementations. However they also mention that all the studies presented except one are context specific and local and regional characteristics make standardization more complex.

An exception is the work of Ciari et al. (Balac, Ciari, & Axhausen, 2015; Ciari, Balac, & Balmer, 2015; Ciari, Bock, & Balmer, 2014a; Ciari, Schuessler, & Axhausen, 2013a). They have successfully implemented car-sharing into MATSim. Their papers show various stages of development considering car-sharing demand. In their first report (Ciari, Schuessler, & Axhausen, 2013b) they only take station-based car-sharing into account and assume that all people can use the car-sharing system (no membership required) and that all stations have an unlimited amount of cars available. In their second report (Ciari, Bock, & Balmer, 2014b) their model is extended for free-floating car-sharing systems. They also take membership into account, however they assumed a fixed amount of members, based on the current situation in their research area. Further research tries to capture the effect of varying pricing schemes on car-sharing demand (Ciari et al., 2015) and the effect of station locations for car-sharing (Ciari, Weis, & Balac, 2016).

MATSim (Figure 9), however, differs from the general concept of activity-based modelling as explained in paragraph 112.3. MATSim starts with an initial demand consisting of a memory with activity patterns of individual agents as well as an utility for each activity pattern. Next, MATSim will assign each agent to the network by a mobility simulator (MobSim). Agents choose a plan based on the scores attached to the plans in their memory: a plan with a higher score is more likely to be chosen than a plan with a lower score. New scores are given to the executed plans. Finally, a select percentage of agents is allowed to clone their selected plan and make modifications to their schedule in the 'replanning' module. These modifications include time choices (departure time, activity duration), route choice, mode choice and destination choice. By iterating the feedback-loop, eventually an equilibrium is reached (Horni et al., 2016). Compared to other activity-based models, the focus of MATSim is on the assignment step of the modelling process. The assignment step happens much later in the general activity flow-diagram (paragraph 2.3). In MATSim the activity scheduling process, time choices, destination choice and mode choice are all exogenously determined in the initial demand and/or changed through the feedback loop.

Car-sharing in their case is allowed as a mutation on the original schedule, made in their replanning module, within the feedback loop. That seems a bit unintuitively: it implies that car-sharing demand is indirectly dependent on the traffic state. Literature shows, however (paragraph 2.2), that car-sharing can be a more strategic choice, made beforehand, depending on personal and spatial attributes like parking restrictions and the ability to go car-less and thus save on fixed costs. Because of this, it seems more reasonable to implement car-sharing earlier into the activity-based model chain. Considering MATSim, car-sharing would have to be implemented in the 'initial demand' or implemented within an activity-based model that focusses more on the scheduling process.

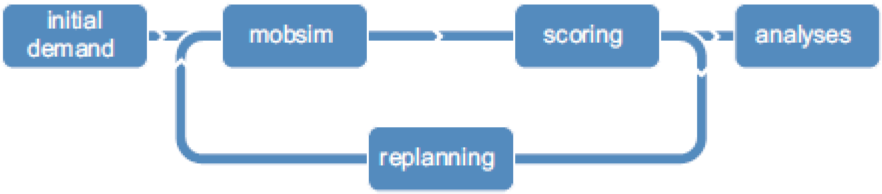


Figure 9 Flow-diagram of MATSim, also called 'MATSim Loop' (Horni et al., 2016)

2.5 Conclusions Literature Study

This paragraph gives a short summary of the most important conclusions that can be drawn from literature research. As well as how the conclusions from literature, relate to this research and the following paragraphs in the report.

Paragraph 2.1 gives an overview of the different car-sharing business models. One of the key differences is whether a car-sharing system is point-to-point or not. A point-to-point model means that the car can be dropped everywhere. A round trip model on the other hand, requires the user to drop the car off at the same point where the user has taken the car. Typically, in a round trip car-sharing system the user pays costs over time. This also includes time when the car is idle. This makes a round-trip model suitable for short tours only. A point-to-point model on the other hand can also be used for longer tours, but the user isn't guaranteed that there is a car available when the user wants to make the return trip. Some other business models have been mentioned in paragraph 2.1. The difference between car-sharing systems presented by a service provider and car-sharing systems where the cars are owned privately, is also addressed. It is important to keep the differences between the different car-sharing business models in mind, as they might have different impact on the model and on the activity-based framework.

Paragraph 2.2 gives an overview of previous market research that has be done regarding car-sharing. A list of personal and spatial attributes was given, these will be used directly in paragraph 3.2 and further as attributes of the utility-function of car-sharing.

Paragraph 2.3 explains activity-based modelling on the basis of the activity based framework. The findings from paragraph 2.3 are directly used in paragraph 3.1, where it is listed how car-sharing would affect the activity-based framework. It is assumed that the reader is familiar with the activity-based framework after reading paragraph 2.3.

Paragraph 2.4 gives an overview of the previous car-sharing implementations that have been done. The most important research is the research done in MATSim. While MATSim works differently than the activity-based framework, their work is still useful. The utility-function for car-sharing that is used in their research is taken as a base for the mode choice model used in this research (see paragraph 3.2), but is improved with the personal and spatial characteristics as found from paragraph 2.2.

3 Methodology

In this chapter a theoretical methodology is given to determine car-sharing demand. The activity-based framework is used as a starting point. In paragraph 3.1 an overview is given of how and where the concept of car-sharing would affect the activity-based framework. One of these implementations is worked out in detail, which is shown in paragraph 3.2.

3.1 Implementation of Car-Sharing into an activity-based framework

In this paragraph the steps in the conceptual activity-based framework (as introduced in paragraph 2.3) that are affected by car-sharing are discussed and an overview is given of additions to this framework in order to fully support car-sharing. These additions are then discussed in order of appearance in the flow diagram (see Figure 10 below).

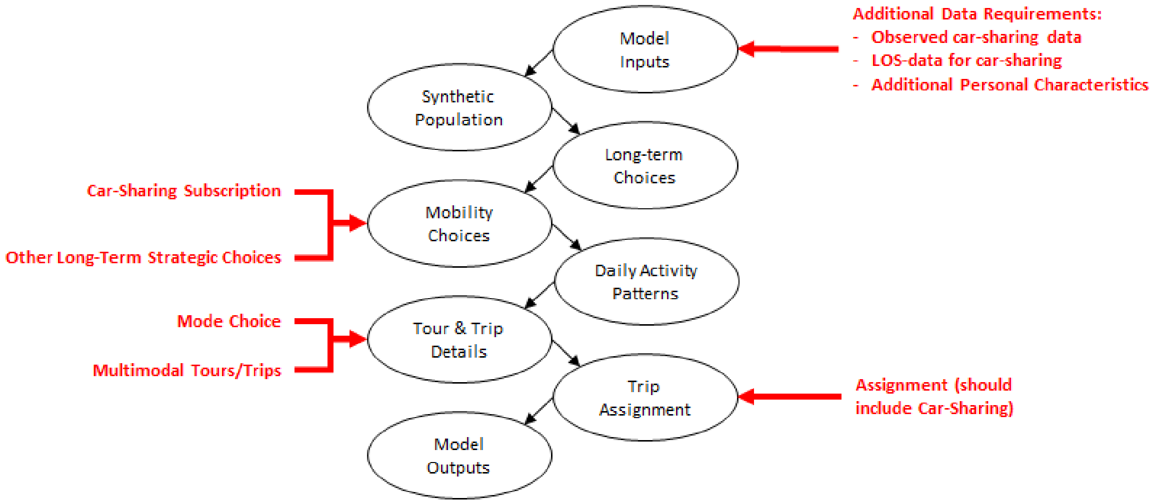


Figure 10 Overview of the necessary implementations to the conceptual flow-diagram of an activity-based model, in order to fully implement car-sharing

Observed Car-Sharing Data

Since the mode choice for each person is indirectly determined from the observed schedules, observed car-sharing data is required. However, observed data including the car-sharing alternative is currently not available, most likely because of the low share in the modal split (KiM, 2015b). Even if revealed preference car-sharing data would be available, the data would probably be very case specific. This is because mobility behavior and/or the car-sharing business model might be completely different in another region. Market research from car-sharing companies isn't sufficient either because it only contains trips where car-sharing was actually chosen and it doesn't consider any other modes.

An option is to use stated preference data as input for the car-sharing model instead. But again, no suitable data is already available. And if data would be available, the data would probably again be either case specific and/or specific for the type of car-sharing business model assumed. Besides, it is unlikely that all other necessary data requirements are also present in the same data source, which would imply that different data sources have to be combined to get a complete dataset. This is, however, a very time consuming process as the data from different data sources probably doesn't match. Therefore additional assumptions and translations have to be made to combine the data from different data sources. This has a strong negative implication on the accuracy of the constructed dataset. Because of these arguments, this seems no reliable solution for this research.

The only possibility is, setting up a completely new revealed or stated preference research. Because revealed preference research is quite cost expensive and because revealed preference research is less optimal for researching future modalities, a stated preference research would be advised. An even better recommendation however, is to include car-sharing in the already existing revealed preference surveys.

LOS-data for Car-Sharing

Similar as for the conventional modes, Level-of-service data (LOS-data) is necessary for the car-sharing alternative: travel time, cost and probably also some kind of access/egress component. Whereas the in-vehicle travel time of car-sharing is likely the same to the regular car alternative, the other LOS-data is dependent on the business model (see paragraph 2.1 for the various car-sharing business models). For example some business models require the user to pay a certain cost over time, whereas other business models require the user to pay a certain cost over distance, or a combination of both. Also, round-trip car-sharing systems might require the user to pay for the vehicle during his/her activity time, when the vehicles isn't actually in use, whereas this is not the case for point-to-point car-sharing systems, which in return might make more money per unit of distance, since the vehicles are more frequently in use. Finally the access/egress component is largely dependent on the vehicle density.

The best solution seems to get this data from a company that offers car-sharing services, or to vary the LOS-parameters to take into account the business models of multiple car-sharing companies.

Additional Personal Characteristics

In paragraph 2.2 an overview is given of common personal and spatial characteristics of car-share users based on literature. When modelling car-sharing usage, variables describing these characteristics ideally should be present, as these variables would affect car-sharing usage. Most of these variables are easy quantifiable and thus the data is relatively easy to obtain. This is especially true on the side of the spatial characteristics. On the side of the personal characteristics, however, a few characteristics are harder to quantify. These characteristics usually are not present in regular datasets. These characteristics are the extent of 'environmental concern' and the 'sensitivity towards innovation'.

An interesting option to grasp these harder-to-quantify variables, is to attach a certain lifestyle to each person as a dummy variable. This approach was used in the car-sharing market research done in Utrecht (SmartAgent, 2011) (also see paragraph 2.2). Required additional research in this topic would, however, be time-consuming. Furthermore, it's uncertain if these variables would actually really improve the model significantly.

Car-Sharing Subscription

In the long-term mobility choices step, next to car ownership and possession of a public transport discount pass, car-sharing subscription should also be modeled. The decision whether or not to buy car-sharing subscription should be dependent on the fixed cost of the subscription and the expected added utility of the car-sharing alternative. There should be some sort of interaction between the long-term choices and the mode choice later in the activity-based framework. If car-sharing proves to be an attractive alternative in enough trips made by the person, the person should be more likely to choose to buy a car-sharing subscription.

Other Long-Term Strategic Choices

As derived from literature, there is a strong correlation between car ownership and car-sharing usage. This correlation works in two ways: persons that do not own a car are more likely to use the car-sharing alternative, but having access to car-sharing as an alternative could also mean a reduction of car ownership. Ideally, there should be some sort of interaction ('upward integrity') between the mode choice and the long-term choices. This interaction is important. If car-sharing seems to be a more attractive alternative than the regular car, this should lead to a drop in car ownership.

There might also be a relation between car-sharing usage and possession of a public transport discount pass. In this case, people for whom car-sharing is more attractive, might be less interested in buying a public transport discount pass. This is the case, unless the car-sharing alternative is integrated as an additional option within the public transport travel subscription (for example Greenwheels).

Mode Choice

Within the scheduling process, a mode is selected for each trip made by the persons. Car-sharing as a new mode has to be introduced within the mode choice. This means that a new utility function is required for the car-sharing alternative, consisting of variables that are likely to explain car-sharing demand. The variables in the utility function are dependent on the business model of the car-sharing system. They should likely contain at least a travel time component, a cost component, an access/egress time component and personal characteristics that explain car-sharing demand. The cost component can either be the cost over distance (fuel costs), the cost over time (reservation time) or both. If the car-sharing business model is a round-trip model, the cost over time might also include costs over the time spend for activities. The access/egress component includes the walking time to the nearest available vehicle. If the car-sharing system is a point-to-point business model where the car has to be dropped off at a certain car-sharing station, egress time is involved as well. The access and egress time might be dependent on the 'vehicle density', the amount of available vehicles in a certain space, which is again dependent on the type of business model.

Multimodal Tours and Trips

Besides the mode choice itself, car-sharing also affects the multimodality of tours and trips. This is also dependent on the business model of the car-sharing system. In either case there should be a consistency: If the car driver alternative is selected for one of the trips in a tour, car diver should be selected for all trips in the tour. In case the car-sharing system is a round-trip model (see paragraph 2.1), this should also be the case for car-sharing. In a point-to-point business model car-sharing can be chosen as part of a multimodal tour. As an example, public transport could be used for the trip up and car-sharing could be used for the trip back. Besides the tour, the trips in the tour could also be multimodal. It has already been mentioned before that car-sharing requires an access/egress mode, but car-sharing itself can also be an access or egress mode for another mode, most notably for public transport. This is only the case for point-to-point car-sharing business models. It seems unlikely that car-sharing is chosen as part of a multimodal trip in case of a round-tip car-sharing business model, since the car will then be idle for a relatively long time, before it will be used again.

Assignment

A final change would be in the assignment module. The assignment should include the car-sharing alternative with car-sharers probably having the same behavior as regular car drivers. Besides that, the access and egress modes of car-sharing and car-sharing as an access/egress model itself, have to be assigned to the network as well.

3.2 Mode Choice

In paragraph 3.1 an overview is given of all necessary steps to fully implement car-sharing into an activity based model. Since the mode choice is the most essential part for the implementation of car-sharing, in this research the focus will be on the mode choice itself.

For this purpose a discrete choice model has been created. Initially a multinomial logit model is considered. The discrete choice model considers five conventional modes: car driver, car passenger, public transport, cycling and walking. Car-sharing is added as a sixth mode. Each mode has its own utility function. Furthermore, the utility function is different for three distinct trip purposes: work, education and other. This leads to a total of 15 utility functions for the conventional modes and three additional utility functions for the car-sharing mode.

Each utility function consists of three types of components:

- Variables that represent the level-of-service data of a certain alternative (such as travel time, cost etc.) and it's beta-value.
- An alternative specific constant, used to represent variables that are not present in the utility function but still affect the mode choice.
- Dummy variables that represent the personal characteristics of a person (age, gender, income etc.) and it's beta variable.

The discrete choice model is then created in three steps, by using Biogeme (Bierlaire, 2003):

- First, the utility functions of the conventional modes are estimated with components that should lead to high car-share usage according to literature.
- Secondly, the utility function for the car-sharing alternative is determined based on the beta-values in the utility functions of the conventional modes.
- Thirdly, the utility functions of the conventional modes are re-estimated, so that they contain components that relate to the mode itself instead of car-sharing.
- Finally, the effect of having a nested logit model, instead of a multinomial logit model, is tested.

In the first step the utility functions of the five conventional modes are determined. The level-of-service variables include the (in-vehicle) travel time, the cost over the distance (not for cycling and walking alternatives), the waiting time (only for the public transport alternative) and the access/egress time (only for the public transport alternative). Besides the walking alternative, all utility functions also contain an alternative specific constant. The alternative specific constant of the walking alternative is set to zero. The personal characteristics are represented through dummy variables (0 or 1). The personal characteristics are characteristics that would lead to high car-share demand according to literature. These are based on the personal characteristics of paragraph 2.2 and are, in order of appearance in the utility functions:

- Car ownership: 0 cars in household (D_{car0}) and 1 car in household (D_{car1})
- Age: between 25 and 44 years ($D_{age2544}$)
- Household size: 2 members or less (D_{hh2l})
- Education level: at least mbo or havo/atheneum/gymnasium (D_{educ34})
- Standardized household income: €40000 or more (D_{inc4h})

For the walk alternative the beta values for the personal characteristics are set to zero and thus not present in the utility functions. Note that these characteristics do not have to lead to more traffic demand for the five conventional modes, or at least not significantly. The purpose of this step is solely to determine to what extent personal characteristics affect the mode choice. The following utility-functions are proposed:

Car driver:

$$U_{cd} = ASC_{cd} + \beta_{Cost,cd} * Cost_{Dist,cd} * Dist_{cd} + \beta_{TT,cd} * TT_{cd} + \beta_{car0,cd} * D_{car0} + \beta_{car1,cd} * D_{car1} + \beta_{age2544,cd} * D_{age2544} + \beta_{hh2l,cd} * D_{hh2l} + \beta_{educ34,cd} * D_{educ34} + \beta_{inc3h,cd} * D_{inc3h}$$

Car passenger:

$$U_{cp} = ASC_{cp} + \beta_{Cost,cp} * Cost_{Dist,cp} * Dist_{cp} + \beta_{TT,cp} * TT_{cp} + \beta_{car0,cp} * D_{car0} + \beta_{car1,cp} * D_{car1} + \beta_{age2544,cp} * D_{age2544} + \beta_{hh2l,cp} * D_{hh2l} + \beta_{educ34,cp} * D_{educ34} + \beta_{inc3h,cp} * D_{inc3h}$$

Public transport:

$$U_{pt} = ASC_{pt} + \beta_{Cost,pt} * Cost_{Dist,pt} * Dist_{pt} + \beta_{TT,pt} * TT_{pt} + \beta_{WT,pt} * WT_{pt} + \beta_{AET,pt} * (AT_{pt} + ET_{pt}) + \beta_{car0,pt} * D_{car0} + \beta_{car1,pt} * D_{car1} + \beta_{age2544,pt} * D_{age2544} + \beta_{hh2l,pt} * D_{hh2l} + \beta_{educ34,pt} * D_{educ34} + \beta_{inc3h,pt} * D_{inc3h}$$

Cycling:

$$U_{cy} = ASC_{cy} + \beta_{TT,cy} * TT_{cy} + \beta_{car0,cy} * D_{car0} + \beta_{car1,cy} * D_{car1} + \beta_{age2544,cy} * D_{age2544} + \beta_{hh2l,cy} * D_{hh2l} + \beta_{educ34,cy} * D_{educ34} + \beta_{inc3h,cy} * D_{inc3h}$$

Walking:

$$U_{wk} = \beta_{TT,wk} * TT_{wk}$$

The beta-values of these utility functions are estimated with Biogeme (Bierlaire, 2003) by using the observed data, in which the chosen alternative is given. This is done for the three different motives: work, education and other. If one of the beta's for a certain variable is not significant for **all** of the conventional modes, it is left out of the utility function.

In the second step the utility-function for car-sharing is determined. Since there is no observed data available for the car-sharing alternative, the beta-values cannot be estimated by Biogeme. Instead beta-values from the other utility functions are used. The level-of-service variables contain a travel time component, the cost over the distance, an access/egress component (similar to that of public transport) and exclusively for car-sharing also a cost over the reservation time. The reservation time is the in-vehicle time plus a part of the activity times in the same tour. The cost over the distance and the cost over time have the same beta-value. This is, assuming that a customer has the same disutility for each euro he has to pay, independent of whether those are costs over the distance or costs over time. The level-of-service components of the utility function are based on the variables used in the implementation of car-sharing in MATSim (Ciari et al., 2013b). Like the utility functions of the five conventional modes, the utility function for car-sharing also contains an alternative specific constant. The dummy variables for the personal characteristics are the same as those introduced in the utility functions of the conventional modes. The utility function for car-sharing is thereby:

$$U_{cs} = ASC_{cs} + \beta_{TT,cs} * TT_{cs} + \beta_{Cost,cs} * Cost_{d} * Dist_{cs} + \beta_{Cost,cs} * Cost_{t} * RT_{cs} + \beta_{AET,cs} * (AT_{cs} + ET_{cs}) + \beta_{car0,cs} * D_{car0} + \beta_{car1,cs} * D_{car1} + \beta_{age2544,cs} * D_{age2544} + \beta_{hh2l,cs} * D_{hh2l} + \beta_{educ34,cs} * D_{educ34} + \beta_{inc3h,cs} * D_{inc3h}$$

The beta's for the level-of-service variables are set equal to the beta's of the level-of-service variables in the utility function of the mode with the most similarities to car-sharing. So the beta for the travel time of car-sharing is set equal to the beta for the travel time of car-driver, since in both cases the traveler would spend his/her time driving a car. The beta for the cost for car-sharing is set equal to the beta for the cost for car-driver, since in both cases the traveler would pay for a similar product. The beta for the access/egress-time for car-sharing is set to the beta for the access/egress-time of public transport since both and only these two modes have an access/egress-component.

The alternative specific constant in the utility function of car-sharing cannot be estimated in the regular way. Instead a range of potential values for the alternative specific constant is considered. The upper boundary for this range is set to the alternative specific constant of car driver. The reason for this is that it is expected that variables not presented in the utility function of car-sharing (such as comfort) should always be more positive towards the car driver alternative. For example: if the utility functions of the car driver and car-sharing alternative are equal (i.e. equal level-of-service characteristics, equally affected by personal characteristics), it is expected that a person still choses his/her own car. The own car feels more comfortable than a car used by anyone else. Also, it is relative easy to use your own car, in contrast to the process of reserving a shared vehicle. The upper boundary of the alternative specific constant of car-sharing can also be explained from a methodological point of view. Market research showed only personal characteristics affecting car-sharing usage positively. Thus, all beta's in the utility function of car-sharing regarding personal characteristics are positive. This is in contrast with the utility function for car driver. In the utility function of car driver there are components affecting usage of the mode in a negative way (for example a low age leads to car driver being chosen less often). The alternative specific constant of car-sharing should likely be negative to compensate for the lack of negative affecting components in the utility-function of car-sharing. The upper boundary of the alternative specific constant of car-sharing is thereby:

$$ASC_{cs} = ASC_{cd}$$

The lower boundary of the alternative specific constant of car-sharing is set to the lowest alternative specific constant among the conventional modes, or to zero (the alternative specific constant of walking) if all alternative specific constants are positive. This is because the scope considers a future scenario and it is assumed that car-sharing is just as much of a full-fledged alternative as the other modes. The lower boundary of the alternative specific constant of car-sharing is thereby:

$$ASC_{cs} = \min\left[ASC_{cd}, ASC_{cp}, ASC_{pt}, ASC_{wk}, 0\right]$$

Another option to determine the alternative specific constant is to assume a base year scenario and use the current modal share of car-sharing found in literature. One could then change the alternative specific constant, such that the resulting modal share matches the current modal share of car-sharing. A disadvantage of this approach is that the current penetration rates of car-sharing are low. Car-sharing is only used for 0.02% of all trips made by car (KiM, 2015b). This leads to a very low alternative specific constant. Since the low value of the alternative specific constant also accounts for car-sharing being a relatively new concept, it is not possible to determine the future potential of car-sharing with this alternative specific constant. It is expected that, once people get more familiar with car-sharing, the alternative specific constant will increase as well.

The beta-values of the personal characteristics in the utility function of car-sharing are determined in a similar way. Instead of considering a single value, again a range of values is considered. From literature research, it is known that these personal characteristics have a positive effect on car-sharing, thus the beta-values should be positive. The upper boundary is set to the highest beta-value of that personal characteristic in the utility functions of the conventional modes, or zero (the beta-value for the walking alternative). The lower boundary is set to the lowest positive value of that personal characteristic in the utility functions of the conventional modes, or zero if there are no positive values. So, for example for the beta-value considering car-ownership (having 0 cars in the household), the upper boundary of the beta value is given by:

$$\beta_{car0,cs} = \max[\beta_{car0,cd}, \beta_{car0,cp}, \beta_{car0,pt}, \beta_{car0,cy}, 0]$$

The lower boundary of the beta value is given by the following formula where B is the subset of all positive beta-values for the same personal characteristic:

$$\beta_{car0,cs} = \begin{cases} 0 & if\ B = \emptyset \\ \min[A] & else \end{cases}$$

In the third step the utility functions for the five conventional modes are changed, in such a way that they contain their own personal characteristics, instead of personal characteristics relating to car-sharing usage. This is done by analyzing the observed schedules data to see which personal characteristics have impact on a change of the modal share for a certain mode. The previously determined utility-functions are taken as a starting point. Then, the utility functions are changed by removing or adding one parameter each time, performing the following steps:

- First, it is checked whether any of the beta-values in the current utility function is not significant (p-value of 0.05 or higher).
    - If this is the case, the beta-value with the highest p-value is selected. The beta-value and the corresponding variable are then removed from the utility function, or joined together with the beta-value of another similar mode which shows a similar value.
- If all beta's in the utility function are significant, a new variable is added to the utility function, which is expected to have effect on the mode choice, by the results of the data analysis.

In the fourth step, the multinomial logit will be replaced with a nested logit. One could argue that a nested logit model might be better due to similarities between car-sharing and car driver and between car-sharing and public transport (as well as the similarities between car driver and car passenger). However, a nested logit model adds an additional uncertainty to the model. The nested logit has a so called nest parameter, which represents the correlation among the different alternatives within the same nest. Normally, the nest parameter can also be estimated, but due to a lack of data on the car-sharing side the nest parameter is unknown. Because of this, two extreme cases are considered: a nest parameter of 1, which leads to a multinomial logit model and a nest parameter of 0, which is the most extreme case of a nested logit (also see the red-blue bus paradox (Ben-Akiva & Lerman, 1985)). Two types of nested logit models are considered: a nested logit model with a 'car' nest which contains the car driver, car passenger and car-sharing alternatives and all of the other alternatives being in separate nests; and a nested logit model with a 'public transport' nest which contains the public transport and car-sharing alternatives, and all of the other modes being in separate nests.

So, in total twelve different variations on the mode choice model are considered. These twelve different variations have different parameters in the utility function of car-sharing and represent either the multinomial logit model or a nested logit model. The twelve different variations are summarized in Table 2. For all of these variations, the modal split will be determined separately.

Table 2 Twelve different variations of the mode choice model

Nr	ASC_{cs}	β_{cs} for Pers. Cha.	Model
1	Lower boundary	Lower boundary	Multinomial Logit
2	Lower boundary	Upper boundary	Multinomial Logit
3	Upper boundary	Lower boundary	Multinomial Logit
4	Upper boundary	Upper boundary	Multinomial Logit
5	Lower boundary	Lower boundary	Nested Logit with Car Nest
6	Lower boundary	Upper boundary	Nested Logit with Car Nest
7	Upper boundary	Lower boundary	Nested Logit with Car Nest
8	Upper boundary	Upper boundary	Nested Logit with Car Nest
9	Lower boundary	Lower boundary	Nested Logit with PT Nest
10	Lower boundary	Upper boundary	Nested Logit with PT Nest
11	Upper boundary	Lower boundary	Nested Logit with PT Nest
12	Upper boundary	Upper boundary	Nested Logit with PT Nest

4 Case

In this chapter the given methodology is applied for a case scenario in and around Rotterdam. In paragraph 4.1 the exact research area is defined. In paragraph 4.2 it is described how the input data for the mode choice model has been gathered and used. In paragraph 4.3 an analysis of the observed schedules is given. This analysis is also used to determine the parameters of the utility of the conventional modes. In paragraph 4.4 the methodology is applied on the research area using the input data. This paragraph describes the challenges that were faced during the execution of the methodology and how these challenges were handled. Finally, paragraph 4.5 shows the results. In this paragraph all values in the utility functions are listed, per tour purpose. This paragraph also shows the impact of car-sharing on the modal split, for each of the variations as listed in the methodology.

4.1 Research Area

The research area is defined as the area within the boundaries of the 'Stadsregio Rotterdam' (SRR). Stadsregio Rotterdam used to be one of the 'plusregio's' within the Netherlands, responsible for traffic and transport in a defined area of municipalities in the proximity of a city. At 1 January 2015 all plusregio's in the Netherlands are lifted (Rijksoverheid, 2013). Instead, 'Metropoolregio Rotterdam Den Haag' is now responsible for the traffic and transport in and around Rotterdam, as well as in and around The Hague.

There are two reasons that the old boundaries of the Stadsregio Rotterdam are used as the boundaries of the research area. First of all, the main focus is to research the impact of car-sharing for traffic within, to and from the city of Rotterdam. By using the boundaries of the SRR, we include Rotterdam itself as well as municipalities that are directly dependent on Rotterdam in terms of mobility, but eliminate interactions with other cities, mainly The Hague. The second reason is a more practical one: the current traffic demand model of Rotterdam is still limited to the boundaries of the Stadsregio Rotterdam. There are plans for a joint traffic demand model with The Hague, but because of an increase in computation times this is currently not yet done (MRDH, 2015). This means that it is easier to obtain level-of-service data of just the area of Rotterdam (single model).

The boundaries of the SRR are taken as a strict boundary of the research area. Tours/trips that pass this boundary are not considered in this research. This is done in line with the Activity-based concept. Because activity-based models use persons as a unit, instead of zones, computation time would increase drastically if one would consider external zones, because then for all persons in, to and from external zones a separate schedule has to be determined, even though the schedules of external persons might not even have a direct impact on Rotterdam. In the full activity-based framework, external trips have to be added in later, but since this research only focusses on the mode choice, external trips have been left out.

In Appendix A, an overview is given of all municipalities in the research area. In Appendix B, a list is given of all postal code areas within the research area.

4.2 Input Data

Normally the mode choice is part of one of the later steps within the activity-based modelling framework. In any case, after the schedule of a person has been generated. In this research we focus on the mode choice itself. As such, the observed schedules are treated as the schedules generated by the activity-based model. Instead of inserting the full (synthetic) population into the discrete choice model, only the sample from the observed schedules is used. It is then decided, based on the discrete choice model, who could have chosen for car-sharing for one or more of their trips based on the discrete choice model. By using the observed schedules as direct input for the discrete choice model, the possibility that a change in the modal split is affected by a different activity pattern is also eliminated. All changes in the modal split are exclusively due to the mode choice itself.

Besides the observed schedules, also level-of-service data is required for the mode choice. For the personal characteristics, the observed schedules are used as well. In the following sub-paragraphs it is described how these two data sources are obtained and in what way the input data is used.

Observed Schedules

For the observed schedules, data from OViN (Onderzoek Verplaatsingen in Nederland) is used. The advantage of using this data is that the data is already disaggregated. Each line in the dataset represents a single trip leg. The dataset includes personal characteristics, household characteristics, the trips (if any) made by a person, the characteristics of those trips (length, duration, mode etc.), the trip legs (if any) made by a person and the characteristics of the trip legs. OViN does not contain data about activities, but that could be derived from travel data: the activity duration is the start time of the trip after the activity minus the end time of the trip before the activity. The type of activity (work, shopping, leisure etc.) could be derived from the trip purpose of the trip before the activity and the location of the activity could be derived from the destination of the trip before the activity. Besides that, OViN does not contain data on a tour level. In activity-based models tours are more important and guarantee a certain level of consistency throughout the schedule of a person.

The locations in the OViN dataset are on a postal code 4 level, as the most aggregated zonal level. That means that the zones used in the OViN dataset consist of an area containing addresses in which the four numbers of the postal code are the same. Home locations and trip arrival and departure zones are all on this postal code 4 level.

OViN data from three years is used (2013-2015) as input for the discrete choice model. The reason three years are stacked, is to increase the significance of the parameters in the discrete choice model and thus improve the quality of the model.

The data from OViN has been filtered. There are three main reasons why the data has been filtered:

First of all, the edges of the research area are taken as a strict boundary. All persons living outside the research area, or all persons with one or more trips with an origin or destination outside the research area are filtered out. The reason for this is that by default an activity-based model would have more difficulty handling external areas: if one would create a schedule for every person, even those outside the research area, the computation time of the activity-based model would increase significantly. Besides that, a more practical reason for taking the edges of the research area as a strict boundary, is that it is harder to obtain level-of-service data for areas outside the research area.

Secondly, some data has been filtered due to being irrelevant for the mode choice or because it would make the mode choice more complex. This includes persons that didn't make a trip (mode choice would be irrelevant) but also trips that are made as a work-activity, where the mode choice is dependent on job characteristics and not on trip- or personal characteristics. It also includes trips that are made with the purpose of touring/walking, where the trip in itself is the activity, and not a way to get to the activity. Also the data about trip legs is filtered out. It would make the mode choice much more complex since a lot more possibilities (park-and-ride, kiss-and-ride, etc.) become available, especially in combination with car-sharing.

Finally, data has been filtered as a way to guarantee a certain level of consistency. Only persons that make full tours are taken into account, that means that each person's first trip should depart from their home location and each person's last trip should arrive at a home location. Also the arrival zone of any trip should be the same as the departure zone of the consecutive trip. Besides that there are also a couple of illogical schedules such as having two or more consecutive trips with a goal of going home.

Table 3 shows the exact criteria on which the dataset has been filtered, as well as the way the data is filtered and the amount of lines that are filtered out of the dataset with each step. Besides the filters, also information is added on a tour level, derived from the other data. A tour in this case is defined in the data as a series of trips with the first trip of the series being either the first trip made by that person, or being preceded by a trip with 'going home' as the trip goal. For each tour the arrival and departure zone are determined and the tour purpose, divided into three categories: work, education and 'other'.

Table 3 Criteria for filtering OViN-data

Instance	**Action**	**Issue**	**Lines Dataset**	
			Prior	After
Wogem ≠ {see list in Appendix A}	Deleted (persons)	Municipality is outside of research area.	387811	21007
Wogem = 568 or 612	Changed Wogem to 1930	Municipalities of Spijkenisse (612) and Bernisse (568) have been fused in 2015 into Nissewaard (1930).	21007	21007
Verpl = #NULL	Deleted (persons)	Person didn't made a trip.	21007	19697
Verpl = 0	Deleted (trips)	Some trips consist of multiple trips. However due to the complexity included when considering mutimodal trips, this will not be taken into account. This action assures that each line consists of an unique trip.	19697	16809
VertPC or AankPC ≠ {see list in Appendix B}	Deleted (persons)	One or more trips of a person goes outside the research area.	16809	11946
VertPC of first trip ≠ AankPC of last trip	Deleted (persons)	Person with one-way tours.	11946	11734
Verpl = 2	Deleted (trips)	Trip as work activity.	11734	11662
Verpl = 4	Deleted (trips)	Trip as work activity.	11662	11659
Verpl = 5	Deleted (persons)	Trip on holiday.	11659	11652
AankPC of trip ≠ VertPC of next trip	Deleted (persons)	Destination and origin of consecutive trips are not consequent.	11652	11590
Hvm = 24	Deleted (persons)	Mode choice is 'other', but it is not known what this mode is.	11590	11584
AantVpl = 1 en Doel ≠ 10	Deleted (persons)	Person has made only one trip, which is not an activity on itself.	11584	11531
Vertrekp = 2	Deleted (persons)	First departure point of person is not their home.	11531	11481
Doel of last trip ≠ 1	Deleted (persons)	Last trip was not a return trip back home.	11481	11279

Doel = 10 en VertPC = AankPC	Deleted (trips)	Trip was intrazonal and trip purpose is 'touring/walking'.	11279	10886

Besides the in Table 3 mentioned filters, some more data has been filtered by hand, considering illogical schedules or tours. An additional 794 lines are filtered this way, leaving a total of 10737 lines (trips) in the final dataset.

The remaining data is analyzed, on how certain characteristics affect the modal shares of the five conventional modes (car driver, car passenger, public transport, cycling and walking). The analysis is presented in paragraph 4.3.

Level-of-Service Data

Level-of-Service data is obtained from the current traffic demand model of Rotterdam, RVMK. The skim-matrices that are used consist of in-vehicle travel times, travel distances, waiting times, access times and egress times (the last three variables only for public transport). These skim matrices are generated for each pair of centroids, with the centroids representing the zones in the RVMK.

RVMK uses a different zoning system then OViN. The zones in RVMK are rather small and seem to be smaller than both postal code 4 areas and smaller than neighborhoods (the zoning system used by CBS). Because the schedules (OViN-data) is on a postal code 4 level, it is necessary to also translate the level-of-service data to a postal code 4 level. For this purpose each RVMK-zone is assigned to a single PC4-zone based on the largest area overlapping according to QGis. For example: a RVMK-zone that has 90% overlap with PC4-zone X and 10% overlap with PC4-zone Y, is assigned to PC4-zone X. Then, an average is calculated for each level-of-service characteristic for each pair of PC4 zones. This average is weighed over the population in the RVMK-zones to ensure that less-urbanized regions (where less people are coming from and traveling to, and which is generally less accessible) do not influence the level-of-service data too much.

Finally, the travel distance for the car is multiplied by €0,43 representing an average cost to drive a car per kilometer (fuel costs and depreciation costs) (Nibud, 2017). The travel distance for public transport is multiplied by €0,137 per kilometer plus a fixed amount of €0,89, which are the costs to travel in Rotterdam with the RET in 2017 (RET, 2017).

4.3 Analysis of the Observed Schedules

This paragraph gives an analysis of the observed schedules, which will be used to estimate the parameters in the utility functions. The aim of the analysis is to find which factors influence mode choice behavior for the five conventional modes. The findings will be used to decide which parameters to add to the utility functions of the conventional modes, in the third step of the methodology (see paragraph 3.2).

Figure 11 shows the modal split for all trips made by inhabitants of a certain municipality. The modal split for car driver fluctuates a lot and varies between 20 and 45%. The modal split for car driver is relatively high for the municipalities Westvoorne and Albrandswaard and relatively low for the municipalities Schiedam and Rotterdam. There seems to be a relationship between the urban density of the municipality and the percentage for car driver, municipalities with a higher urban density have a lower car-share usage, whereas municipalities with a lower urban density have a higher car-share usage.

The modal split for car passenger seems to be quite stable and is around 15%. The modal split for car passenger is relatively high for the municipalities Barendrecht and Albrandswaard and relatively low for the municipalities Krimpen aan den IJssel and Ridderkerk. The cause might be the highway accessibility: both Barendrecht and Albrandswaard have excellent highway accessibility. For Ridderkerk, although in the proximity of the highway, the highway doesn't seem to be a very logical option for trips to and from Rotterdam. Krimpen aan den IJssel doesn't have highway access.

The modal split for public transport seems to be quite stable and is about 5%. The modal split for public transport is relatively high for the municipalities Rotterdam and Capelle aan den IJssel and relatively low for the municipality Albrandswaard. The cause seems to be the public transport supply. Besides Rotterdam which obviously has a good public transport system, Capelle aan den IJssel is also served by 3 metro lines, a train station and a good underlying bus network, whereas Albrandswaard is only served by a single metro line and doesn't have great bus links either.

The modal split for cycling fluctuates a lot and varies between 15% and 42%. The modal split for cycling is relatively high for the municipalities Krimpen aan den IJssel and Lansingerland and relatively low for the municipalities Maassluis and Albrandswaard. The cause might again be in the highway accessibility, combined with the distance to Rotterdam. Krimpen aan den IJssel and Lansingerland are at a cyclable distance from Rotterdam and have no highway connection to Rotterdam. Maassluis and Albrandswaard on the other hand are a bit further away from Rotterdam and have excellent highway connections with Rotterdam.

The modal split for walking varies slightly between 15 and 30%. There are not really any municipalities that have an extreme modal split either in favor or against walking, but as a general trend municipalities with a higher urban density such as Rotterdam have a higher walking percentage and municipalities with a lower urban density such as Lansingerland have a lower walking percentage.

The municipality will not be taken into account as a variable in the utility functions of the conventional modes, as it is preferred to use spatial variables that are more quantifiable.

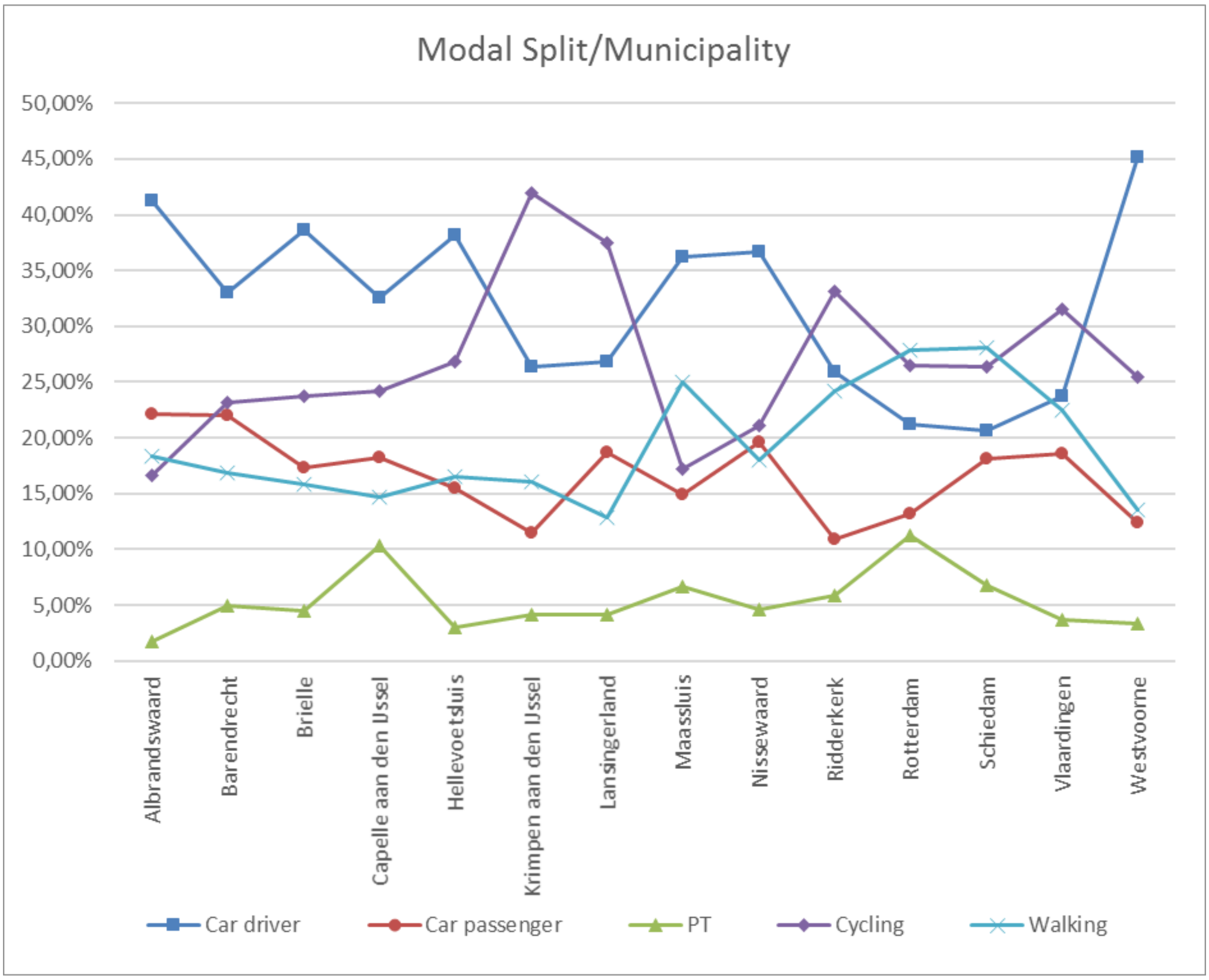


Figure 11 Modal split of observed data per municipality of the person

Figure 12 shows the modal split of all trips made by an inhabitant of a municipalities in a certain class of urban density, where the urban density of the home municipality is highest at 1 and lowest at 5.

In the figure, it can be clearly seen how the urban density of the home municipality affects the modal split. Trips made by a person from a home municipality with a high density choose relatively more for public transport and walking as transportation modes, whereas persons from a home municipality with a low urban density choose relatively more for car (both driver and passenger) as their form of transport. Cycling as a mode choice behaves rather strange, being used for more than 25% of the trips in areas with a high urban density, which is a relatively high share of the modal split. In areas with a lower urban density, the bike becomes a less attractive choice of mode, in favour of car driver. Then, in areas with an even lower urban density, the bike becomes an even more often chosen mode alternative, being used for more than 35% of all trips. The modal split might however be slightly biased by the fact that there are only a few municipalities in each urban density class.

Because the modal split might be biased due to each category of the urban density only containing one or a few municipalities, it is decided not to use the urban density as a variable in the utility functions of the conventional modes.

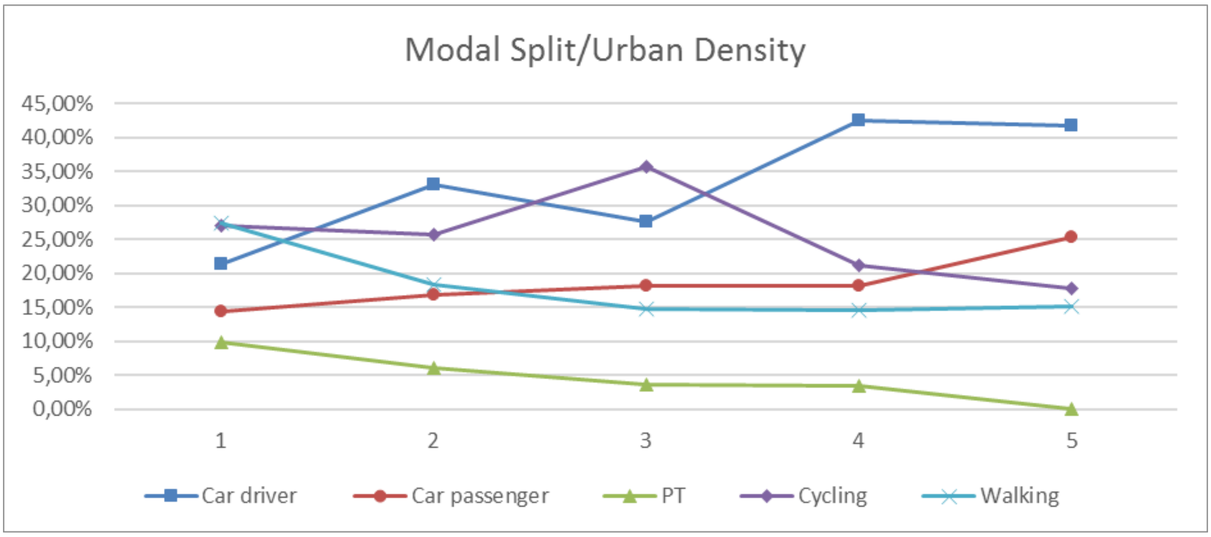


Figure 12 Modal split of observed data per urban density of the municipality of the person

Figure 13 shows the modal split over the gender of persons. It can be seen that the modal share of cycling is about equal for men and women (around 27,5%). The modal share of car driver is much lower for women, about 22%, than for men, about 32%. On the other hand the modal share of car passenger is much higher for women, about 18%, versus the modal share of 12,5% for men. Women also seem to use public transport and walking slightly more often.

Gender is therefore considered as a variable to be implemented in the utility functions of car driver and car passenger. The effect on public transport and walking seems to small to consider.

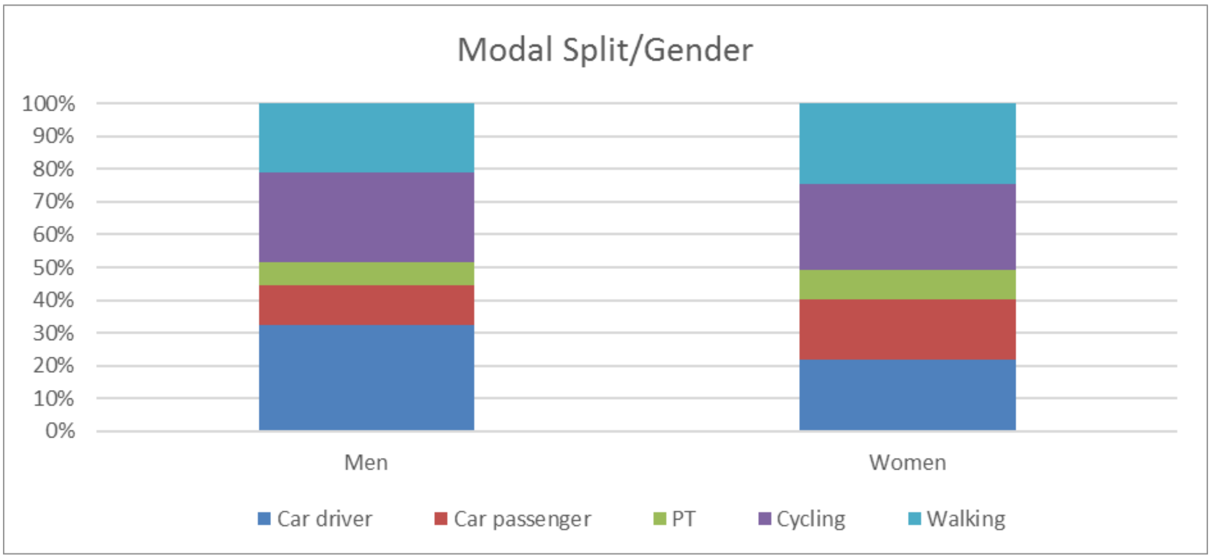


Figure 13 Modal split over the gender of persons

Figure 14 shows the modal split of all trips over the age of the person. The age is discretized and each number represents five years, except for age class 4 which only represents ages 16 to 18 and age class 5 which only represents ages 19 and 20.

It can be seen that trips made by children under the age of 10 are mostly made as a car passenger (about 40%) or by foot (about 30%). Cycling becomes a more used mode as the child growing older, peaking at an age between 16 and 18 with a modal split of 50%. Public transport becomes a more used mode as well during the final years of being a child, which continues through the early stages of adulthood. Public transport as a mode choices peaks at an age of 19/20, being used in about 32% of all trips, being used slight more than the cycling as the 2nd most used mode. This can be explained that persons in this age class (students), quite likely have a free public transport pass. After that the modal split changes in favour of car driver. The modal split is roughly the same during the ages of 30 to 70 where car driver is most used, for about 40% of all trips, followed by cycling in more than 25% of all trips, again followed by walking used for about 20% of all trips and finally followed by car passenger and public transport both used in less than 10% of all trips. After that age of 70, the modal split again changes significantly with car driver and cycling becoming less chosen modes and walking as well as car passenger becoming more often chosen. This last phenomena might be explained due to the fact that elder people might be scared to participate in traffic on their own, and will more likely chose a slower safer mode (walking) or travel together with someone else.

In the initial utility functions of the conventional modes there is already a dummy variable for people with an age between 25 and 44. But, it can de concluded from this analysis that being between the age of 25 and 44 has only a minor influence on the mode choice, if any. Most changes in mode choice behaviour seem to be in the ages below 25. Therefore, in the final utility functions of the conventional modes, different dummy variables for the age are considered. The following dummy variables are considered for the utility functions: an age between 0 and 11 for the walking alternative, an age between 0 and 14 for the car passenger alternative, an age between 0 and 17 for the car driver alternative, an age between 12 and 17 for the cycling alternative and an age between 18 and 29 for the public transport alternative.

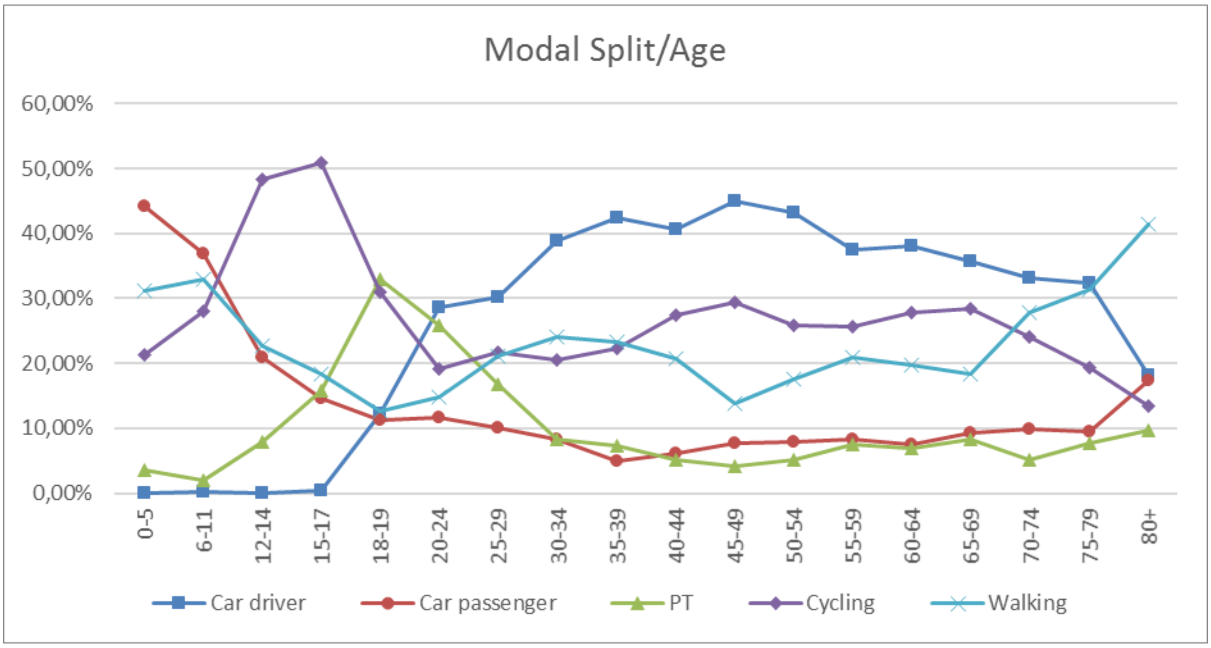


Figure 14 Modal split over the age of persons

Figure 15 shows the modal split over the roots of a person. The trend that can be seen is that foreigners tend to choose less for car driver and cycling as their modes of transport and more often use public transport and walking. This is even more apparent for foreigners from non-western countries. For trips of persons in this category, the modal share of walking is actually higher (over 30%) than car driver and cycling. A reason that the modal split for cycling is lower for foreigners, might be due to them not being familiar with the mode of transport. Similarly, foreigners might not be familiar enough with Dutch traffic to use the car or they might not have a Dutch license.

Roots are thus considered as a dummy variable, representing non-western foreigners in the utility functions of public transport, cycling and walking.

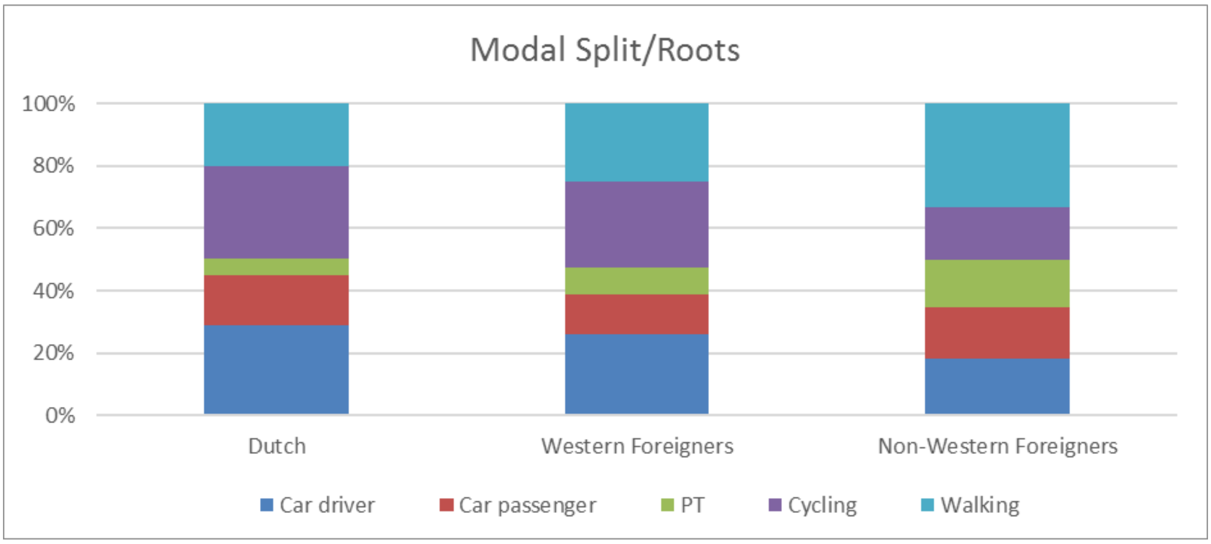


Figure 15 Modal spit over the roots of the person

Figure 16 shows the modal split over the work occupation of the person. The work occupation in this case is expressed in either 'no work' or an amount of working hours per week. A clear relation can be seen between the amount of working hours of the job and the person and the modal share of car driver. Car driver is much more chosen for people with a job of more than 12 hours, and especially for people with a job of more than 30 hours. In contrast, public transport, cycling and walking are less chosen as mode alternatives if the work occupation is higher.

A dummy variable for people with 12 work hours or more is considered for the utility function of car driver.

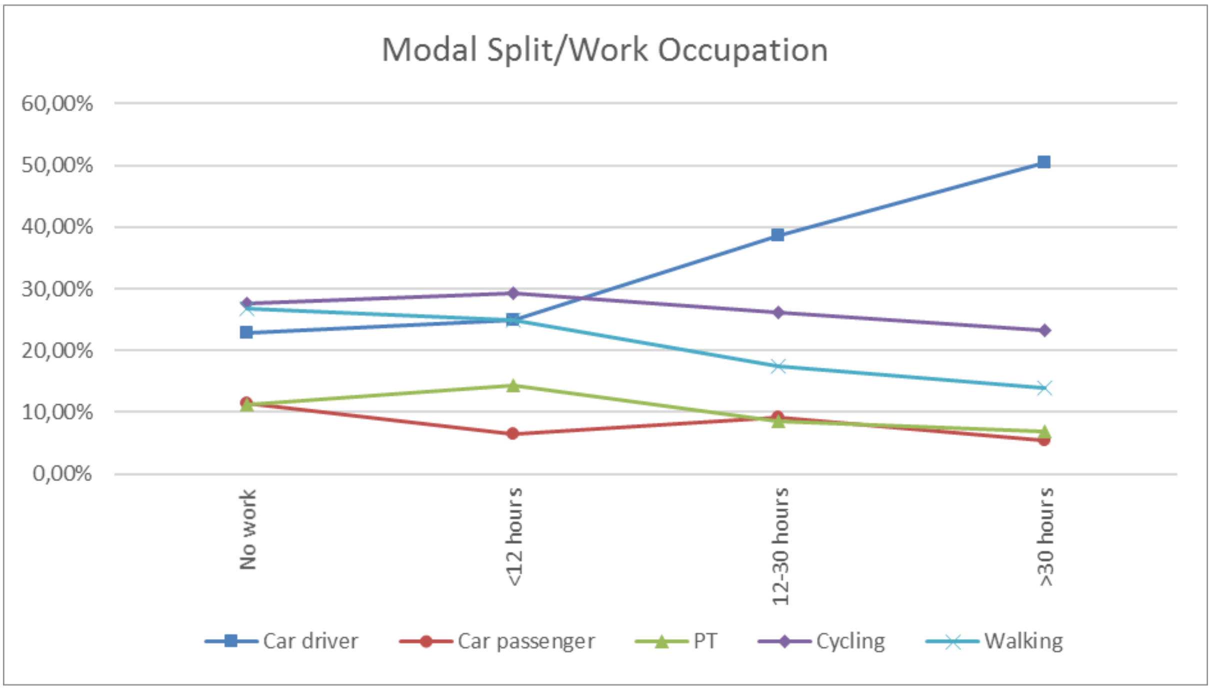


Figure 16 Modal split over the work occupation of the person

Figure 17 shows the modal split over the highest form of education of the person. All persons below the age of 15 are filtered out, as well as the one's where the education was classified as 'other' or unknown. The terms used are the Dutch types of education. The final three categories also include similar level of educations that are either less known or an old type of education, that used to exist, but does not exist anymore since the education system in the Netherlands has changed. Again a few clear trends can be seen. Notably the modal share of car driver increases if the person has a higher education level. On the other hand the modal share of walking decreases when the person has a higher education level. We also see a slight drop in the modal share of public transport and car passenger, especially for people that followed an education at an hbo or university.

There might be a correlation between the education level and the household income: people with higher educations might have jobs that earn them more money and thus those people might more easily be able to afford a car. Also there might be a correlation between the age and the education level. Even though people under the age of 15 are filtered out, people with a low education level (primary school) might just be at a low age (below 18), which explains why they didn't chose for car driver.

A dummy variable for the education level is already present in the initial utility functions of the conventional modes, created in the first step of the mode choice model.

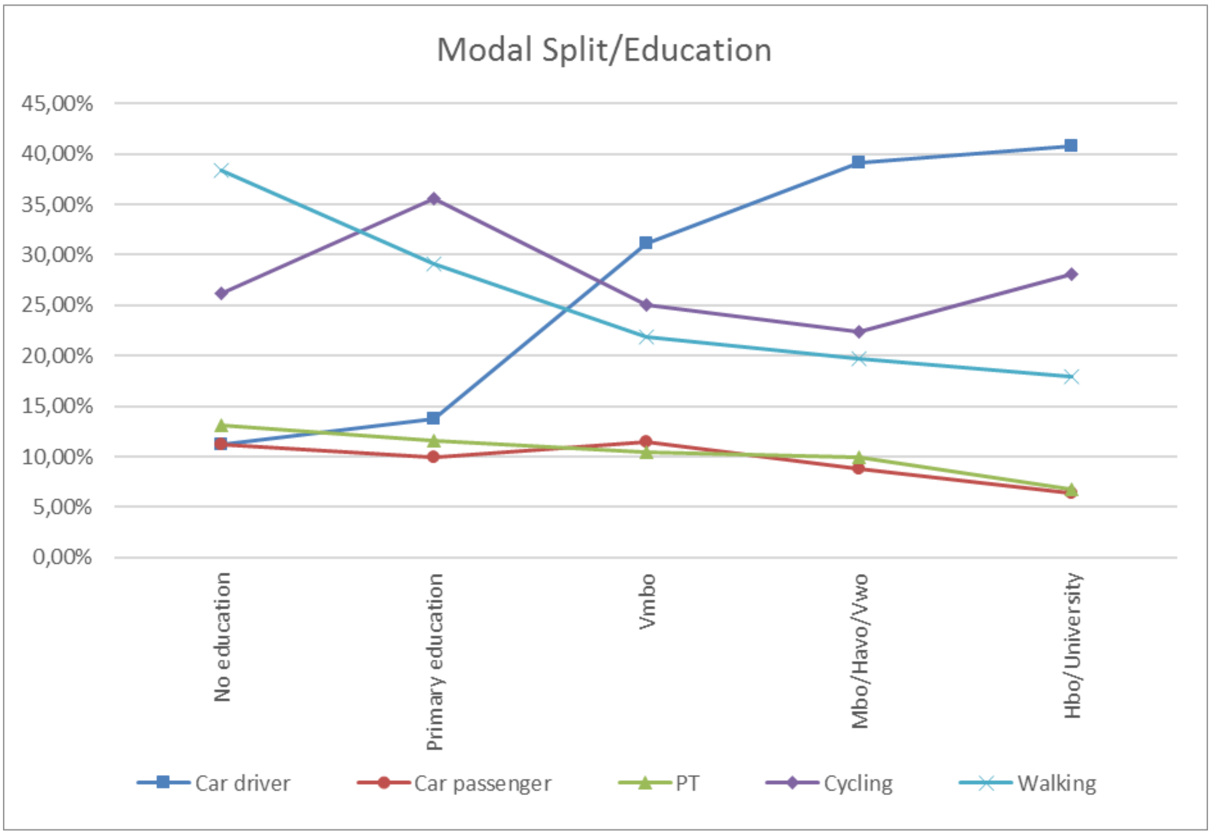


Figure 17 Modal split over the education level of the person

Figure 18 shows the modal split over the income of the household. The household income is standardised, which means that a correction has been applied for households with more members, such that households with a higher number of members (and a higher number of people earning an income) can be compared with households with a lower number of members. Furthermore the incomes are lowered with certain taxes. Households were the income was unknown are filtered out.

There seems to be a relation between the household income and the modal split. Persons from a household with a higher standardised income are more likely to choose car driver and less likely to walk or use public transport. This can easily be explained by the fact that people with higher incomes are more likely to be able to afford a car. There turn around point seems to be around a standardised income of €20000. Persons with a lower income than that are most likely to walk, persons with an income higher than that are most likely to choose car driver.

The modal share of cycling also seems to be lower for incomes that are lower than €10000. This might be explained due to the fact that these persons might not even be able to afford a bike or don't need a bike that much because all their trips are relatively short distances away from home. It's also possible that there is a correlation with the roots of the person, which means that the households with the lower incomes might consist of foreigners who don't use the bike because of their unfamiliarity with the mode of transport.

In the initial utility functions of the conventional modes, there is already a dummy variable representing the people with a household income of €40000 or more. Besides that, a clear relationship between household income and the choice for walking can also be seen. Because of that, a dummy variable representing people with a household income of €20000 and lower is considered for the utility function of walking.

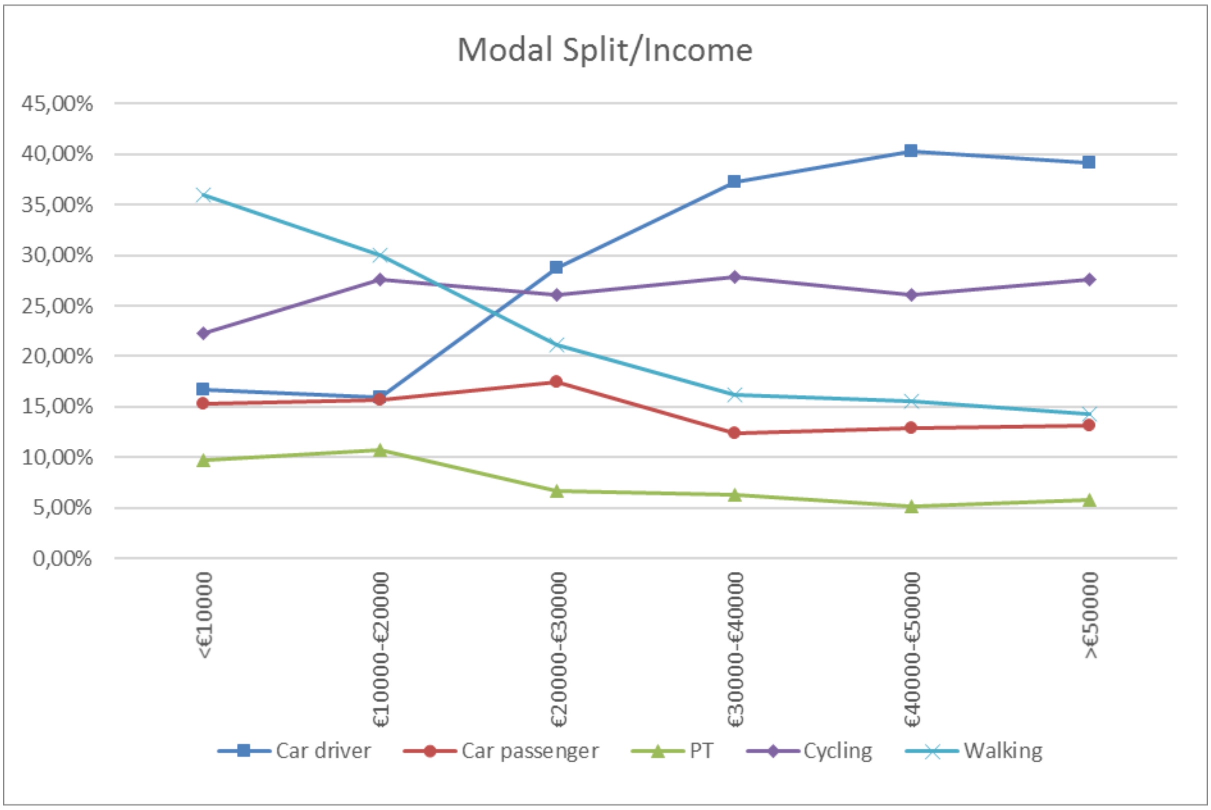


Figure 18 Modal spit over the household income

Figure 19 displays the modal split over the possession of a driver license of the person. The first column represents the modal split of all journeys of people without a driver license. The second column represents the modal split of all journeys of people with a driver license. People with an age below 17 are filtered out.

There is an obvious relationship between the possession of a driver license and the modal split. Persons with a driver license are much more likely to choose the car driver alternative which makes up for about 45% of all trips, compared to almost 0% for trips made by persons without a driver license. In contrast, the modal share of all other modes decreases for people with a driver license. It is however noteworthy that public transport and walking are most affected and the alternatives car passenger and cycling are less affected by driver license availability.

Because of the large impact of having a driver license, a dummy variable representing people with a driver license is considered for the utility function of car driver. The effects on the other modes are to small to take into consideration.

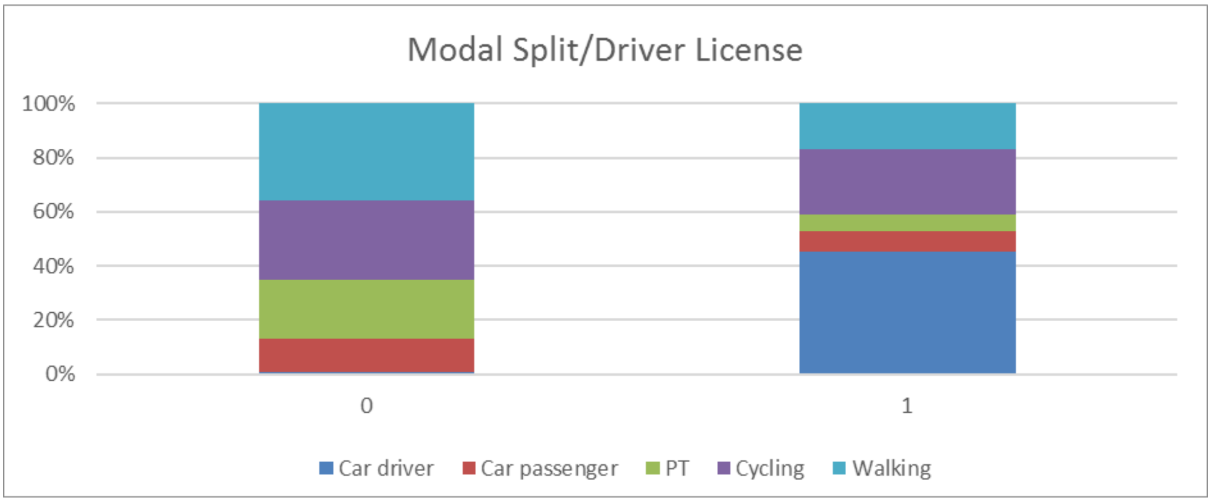


Figure 19 Modal split over the possession of a driver license

Figure 20 displays the modal split over the car ownership of the household. The first column represents the modal split of persons from households with 0 cars, all the way to the last column, which represents the modal split of persons from households with 3 or more cars.

A clear relationship can be seen between the modal share of car driver and the car ownership. Persons from households with more cars, tend to use the car driver alternative more often. The modal share of cycling and walking decrease for households with a higher car ownership. The modal shift of walking decreases a lot and goes back from a modal share of about 40% for households with 0 cars to a modal share of about 10% for households with 3 or more cars. The modal shift of cycling decreases to a lesser extent with a modal share of about 25% for households with 0 cars, but still a modal share of about 20% for households with 3 or more cars.

A less logical phenomenon is the modal share of car passenger which increases for households with more cars, up to households with 2 cars and then decreases again. The fact that the modal share of the car passenger alternative increases over the first three categories can be explained due to the fact that the household members have more cars available to be a car passenger. For example: in a household with only 1 car, the car might be used by just a single car driver, with the furthest destination, whereas in a household with 2 cars the first car might also be used by just a single car driver with their furthest destination, but the second car can still be used by two more household members with closer destinations where one of the household members is the car driver, and the other one the car passenger, which can be dropped off somewhere along the route. An explanation that the modal share drops again for households with 3 or more cars could be that everyone in the household owns a car, so no-one has to be car passenger.

Also, the modal share of public transport is less logical, decreasing for households with more cars (in favour of the car), but then increasing again for households with more than 3 cars. It is unknown what causes this increase in the modal share.

Car ownership is already represented with a dummy variable in the initial utility functions of the conventional modes, so it is not taken into account again when re-estimating the mode choice model for the conventional modes.

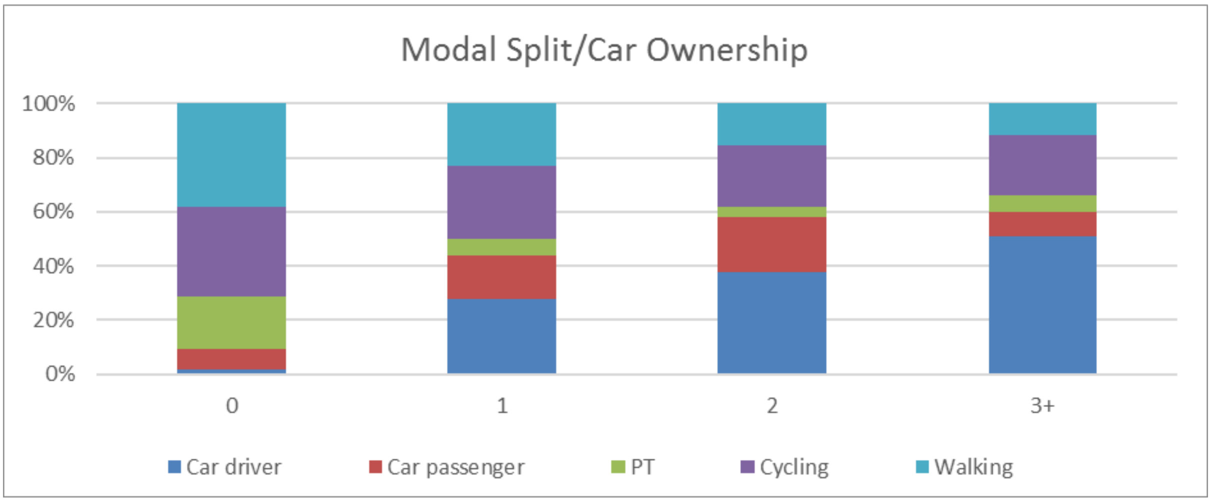


Figure 20 Modal split over the car ownership

Figure 21 shows the modal split over the days of the week. The modal split is quite stable during weekdays. Car passenger is chosen more often on Mondays, probably because working hours tend to be more fixed on Mondays and more flexible on other days of the week. The modal share of cycling is a bit lower on Thursdays compared to other weekdays, the cause of this phenomenon is unknown. In the weekend the modal share of car passenger increases, whereas the modal share of walking, public transport and most notably cycling, decrease.

Because the effects of the day on the mode choice behaviour are rather small, the day of the week is not considered for the utility functions.

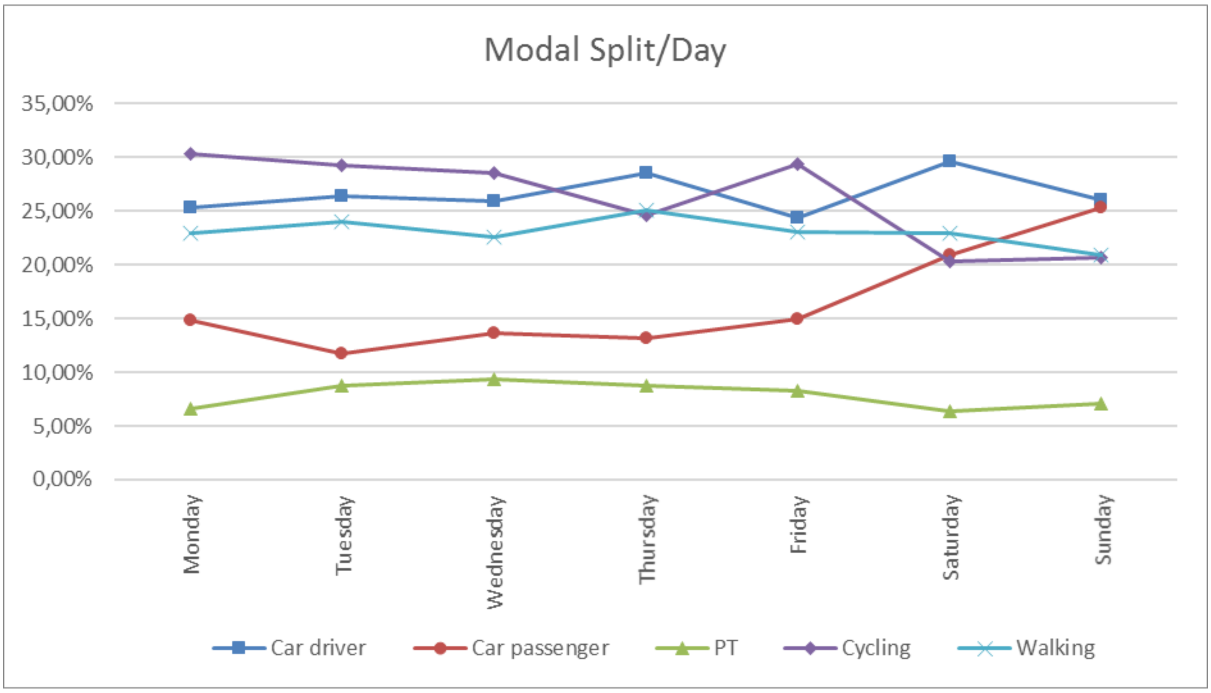


Figure 21 Modal split per day of the week

Figure 22 shows the modal split over the tour purposes. The modal split is very different for each tour purpose. For the purpose 'work', by far most people tend to choose 'car driver', having a modal share of approximately 50%. Walking (about 7%) and car passenger (less than 5%) have a very low modal share for the tour purpose walking. A reason that the modal share of walking is that low, is that work locations are often further away from the home location (compared to shopping for example). For the purpose 'education', the modal share of car driver is very low, being less than 3%. Having the tour purpose is likely correlated with age. A lot of people that have the tour purpose education are under the age of 18 and are thus not legally allowed to drive a car. Car passenger and cycling have relatively high modal shares compared to the other tour purposes, being used for respectively 22% and 38% of all trips. For the trip purpose 'other', the modes car driver, cycling and walking are chosen for an almost equal amount of trips. These three modes all have a modal share between 23% and 28%. With 17%, car passenger has a slightly lower modal share. Public transport is used for only 6% of all trips.

Tour purpose is already represented in the utility functions, by having a separate discrete choice model for each tour purpose, so it doesn't have to be taken into account anymore within the utility functions itself.

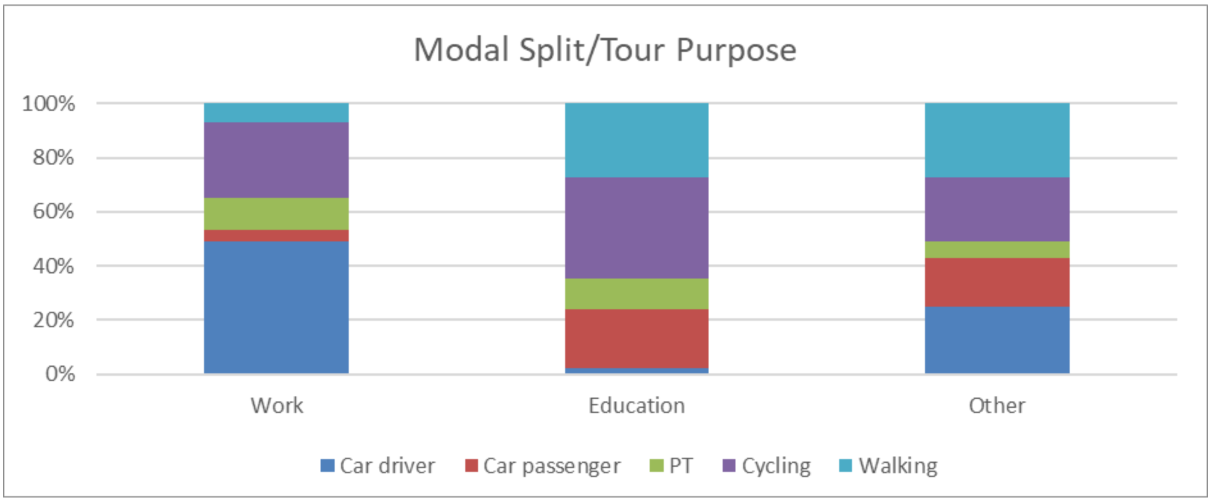


Figure 22 Modal split per trip purpose

Based on the analysis of the observed schedules data, the following variables are considered for implementation in the utility functions of the conventional modes in the third step of the methodology: gender (for car driver and car passenger), age, roots (for public transport, cycling and walking), work occupation (for car driver), driver license (for car driver), urban density of the home municipality (for car passenger, public transport and walking) and the standardized household income (for walking).

4.4 Utility Functions

In the utility functions for Rotterdam, the travel time is taken into account as the only level-of-service variable. Adding more level-of-service variables (like the cost) to the utility functions, leads to one of the level-of-service variables gaining a positive value, implying that a higher cost or travel time leads to a higher utility which is nonsense, or it leads to one of the level-of-service variables being insignificant.

There could be multiple causes (or a combination of these causes) leading to this problem:

First of all, it is possible that the level-of-service data is incorrect, or too simplified to represent the reality. The cost has been determined as a function of solely the distance. In reality however, the cost is a more complex variable. This is especially the case when the trip or tour purpose is work, in which case the person might get a travel allowance from his/her company, leading to the travel costs being either zero, or the person perceiving the travel costs as zero. Similarly, people could have a public transport discount pass, leading to a lower fee for the same unit of distance compared to other potential public transport users. Unfortunately there is no data available about whether or not a person has a public transport discount pass or whether or not a person gets a travel allowance from his/her company. The only cost-related information in the dataset is if someone has a 'studentenreisproduct', a government subsidized transport pass for students that gives them the ability to travel for free in either the weekend or on weekdays. However students are still a rather small part of the population who use the car less frequently anyway because of other characteristics (car ownership). Taking into account the fact whether someone has a studentenreisproduct or not when determining the travel costs, might be able to better represent the travel costs for students, but is still insufficient in explaining the real travel costs for other people. Also, the travel costs do not include additional costs for parking, which is especially the case for car drivers. A final thing that could be said about the cost is that the cost per distance could be different for the train than for bus/tram/metro, even though a single fee for public transport in general has been determined, since public transport is represented as a single mode.

Similar things could be said of the other level-of-service variables. The obtained travel times from the RVMK are free-floating times. More ideal of course would be to use actual travel times, to incorporate the effect of rush hours into the mode choice. This effect however is indirectly also captured within the alternative specific constants. Also, the travel time is point-to-point. For the mode car potential additional travel times associated with parking (searching a parking spot, and then walking to/from the parking spot to the destination), additional time required for parking could be a relatively large part of the travel time, especially for trips to and from the city center of Rotterdam. A final example of how the level-of-service data is too simplified to represent the reality is in the access/egress times. The access/egress times that are obtained from the RVMK model, assume that a person will always choose to walk as access/egress mode, this might of course not always be true as bicycles and even cars can also be used as an access/egress mode, thus the access/egress times might be lower in reality than in the data.

Secondly, the level of scale of the level-of-service data might be too high. Because the OViN-dataset, the observed schedules, had only data on a postal code 4 level, the level-of-service data from the RVMK had to be translated to this scale level as well (instead of the much smaller areas used in the RVMK). Even the smaller postal code 4 areas are around 500 by 700 meters at minimum. It seems counterintuitive to give these areas a single averaged value for each level-of-service variable. As an example: the average access time for public transport of an area might be 7,5 minutes, but in reality the access time might be between 0 and 15 minutes depending on the actual origin point of a trip, leading to much more variance in the utility of public transport. Similar problems arise for the waiting time of public transport and for trips between adjacent or close to adjacent to each other. In the latter case, the actual origin and destination of a trip might be much closer together or much further apart than the average trip travel time between the two zonal centers would suggest. Unfortunately, it is impossible to use the level-of-service data on a lower scale level since there are no observed schedules with a lower level of scale.

Thirdly, the level-of-service data might actually indeed be not significant. Since only trips within the urban area of Rotterdam are included and the quality of public transport is relatively high in urban areas, one could assume that public transport is always a comparable alternative for the car, in contrary to less dense areas where public transport might be either non-existent or are not a realistic alternative for the car. Because of this reason, one could argue that the level-of-service data does not influence the utility that much (since the level-of-service data is comparable for both car driver and public transport) but instead, the chosen alternative is much more dependent on personal characteristics. It is however not possible to test this hypothesis with the current dataset.

Since the other level-of-service variables are insignificant, it is inevitably impossible to compare different car-sharing business models (see paragraph 2.1) with each other.

For the third step of determining the utility functions (see paragraph 3.2), additional personal characteristics have been taken into account, and these are added to the utility functions if they were significant enough. The personal characteristics that are taken into account are chosen based on the analysis of the observed schedules (see paragraph 4.3). Besides the personal characteristics that are already present in the initial utility functions with car-sharing components, Table 4 shows the additional personal characteristics that are taken into account and for which mode.

Table 4 Additional personal characteristics taken into account for determining the utility functions of the conventional modes

Personal Characteristic	**Mode**
Gender (D_{fem})	Car driver, Car passenger
Age: between 0 and 11 years ($D_{age0011}$)	Walking
Age: between 0 and 14 years ($D_{age0014}$)	Car passenger
Age: between 0 and 17 years ($D_{age0017}$)	Car driver
Age: between 12 and 17 years ($D_{age1217}$)	Cycling
Age: between 18 and 29 years ($D_{age1829}$)	Public transport
Age: 70 years and older (D_{age70+})	Cycling, Walking
Roots: non-western foreigners (D_{roots3})	Public transport, Cycling, Walking
Work occupation: 12 hours and more (D_{occ12+})	Car driver
Driver license ($D_{license}$)	Car driver
Urban density of the home municipality: very low (1) (D_{urb1})	Walking
Urban density of the home municipality: very high (5) (D_{urb5})	Car passenger, Public transport
Standardized household income: €20000 or less (D_{inc2l})	Walking

4.5 Results

The values of the parameters in the final utility functions and the statistics of these utility functions are displayed below, per tour purpose.

Work

For the tour purpose work the statistics of the utility functions are displayed below. The values of the parameters of the utility functions of the conventional modes are shown in Table 5. The values of the parameters in the utility function of car-sharing are shown in Table 6, this table shows both the upper boundary as well as the lower boundary.

- Number of estimated parameters: 22
- Number of observations: 2251
- Number of individuals: 2251
- Null log-likelihood: -3622.845
- Cte log-likelihood: -2870.132
- Init log-likelihood: -3622.845
- Final log-likelihood: -2208.918
- Likelihood ratio test: 2827.853
- Rho-square: 0.390
- Adjusted rho-square: 0.384

Table 5 Values of the parameters in the utility-functions of the conventional modes with tour purpose work

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_{cd}	1.31	0.184	7.15	0	0.282	4.67	0
ASC_{cp}	-2.11	0.321	-6.58	0	0.359	-5.87	0
ASC_{pt}	-2.29	0.209	-11	0	0.302	-7.59	0
ASC_{cy}	0.755	0.152	4.97	0	0.256	2.95	0
ASC_{wk}	0	fixed					
$\beta_{TT,cd}$	-0.0967	0.0193	-5.02	0	0.0212	-4.56	0
$\beta_{TT,cp}$	-0.111	0.0232	-4.76	0	0.024	-4.6	0
$\beta_{TT,pt}$	-0.0479	0.0119	-4.03	0	0.0127	-3.76	0
$\beta_{TT,cy}$	-0.0701	0.0065	-10.8	0	0.00758	-9.25	0
$\beta_{TT,wk}$	-0.0545	0.0049	-11	0	0.0105	-5.16	0
$\beta_{car0,cd}$	-5.31	0.593	-8.95	0	0.582	-9.13	0
$\beta_{car0,pt}$	0.443	0.18	2.46	0.01	0.184	2.41	0.02
$\beta_{car1,cd}$	-1.05	0.11	-9.55	0	0.111	-9.49	0
$\beta_{educ34,cp}$	-0.56	0.226	-2.48	0.01	0.228	-2.46	0.01
$\beta_{inc4h,cd}$	-0.749	0.184	-4.06	0	0.181	-4.14	0
$\beta_{inc4h,cp}$	-1.41	0.488	-2.89	0	0.49	-2.87	0
$\beta_{inc4h,cy}$	-0.701	0.197	-3.56	0	0.196	-3.57	0
$\beta_{age0017,cd}$	-3.45	0.745	-4.63	0	0.651	-5.3	0
$\beta_{age1829,pt}$	1.06	0.16	6.65	0	0.159	6.69	0
$\beta_{fem,cd}$	-0.311	0.105	-2.97	0	0.104	-2.98	0
$\beta_{fem,cp}$	0.765	0.238	3.21	0	0.231	3.31	0
$\beta_{roots3,pt}$	0.843	0.167	5.06	0	0.169	5	0
$\beta_{roots3,cy}$	-1.34	0.173	-7.76	0	0.169	-7.92	0

Table 6 Values of the parameters in the utility-function of car-sharing with tour purpose work

	Upper boundary	**Lower boundary**
ASC_{cs}	1.09	-1.49
$\beta_{TT,cs}$	-0.08	-0.08
$\beta_{hh2l,cs}$	0	0
$\beta_{age2544,cs}$	0.665	0.272
$\beta_{car0,cs}$	0.788	0.167
$\beta_{car1,cs}$	0	0
$\beta_{educ34,cs}$	0	0
$\beta_{inc4h,cs}$	0	0

The parameters in the utility functions of the conventional modes are not very surprising. The values for the alternative specific constant seem to be relatively low, indicating that a large part of the mode choice behavior is explained by the other variables. There is a strong relationship between car ownership and car-usage. The beta-value for having zero cars in the utility function of car driver is negative and the value is quite low compared to other variables. This is logical: people who don't own a car, are less likely to choose car driver as their mode of transportation. The beta-value for owning a single car in the utility function of car driver also still has a negative value: this implies that people are less likely to choose car driver if there is only a single car available in the household, probably because another member of the household has already taken the car. On the other side, the beta for owning zero cars in the utility function of public transport shows a positive, albeit small value. Having a higher education level leads to being a car passenger less often, there might be a correlation between education level and income here, as someone with a higher education level, might also have a higher income, and is more easily able to afford and drive a car. The income itself is also present in the utility functions of car driver, car passenger and cycling, all with a negative value. In case of car driver this seems counterintuitive with the previous statement: if people have a higher income, they should technically be able to afford a car more easily. A reason that the beta value for having a high income in the utility function of car driver is negative, might be due to people with higher incomes living closer to the city center of Rotterdam (able to afford more expensive homes), and thus walking or using public transport to their work more often. Another reason might be, because the beta value tries to overcompensate for the other values. An age between 0 and 17 leads to less car driver usage, this is logical because people under the age of 17 do not have a driver license yet, and thus are legally not allowed to drive a car. It was however found that having a driver license (which was also a variable in the dataset), gave a less perfect fit of the utility function, and having both the age and driver license as explanatory variables in the utility function of car driver leaded to both of them being insignificant, probably due to the high correlation between the two. It is unknown why age is a better explanatory variables, as one could argue that people with an age of 18 and higher without a driver license should also not be able to choose car driver. Having an age between 18 and 29 leads to higher public transport usage, this can be explained due to students, which, in the Netherlands often have a public transport pass, allowing them to use public transport either free or with a discount. Finally there is some correlation between the roots of a person, with non-western foreigners using public transport more often and using cycling less often, the latter probably due to being unfamiliar with this mode of transport. Most of the results found in the utility functions of the conventional modes, line up with the analysis of the data beforehand, as shown in paragraph 4.3.

The parameters in the utility function of car-sharing show a less satisfying result, with many of the parameters set to zero, either because they were not significant in the utility functions of the conventional modes, or because the beta values in the utility functions of the conventional modes were all negative. The alternative specific constant is relatively high, compared to the other values, this would imply that a lot of car-sharing behavior cannot yet be explained with the current variables. There is also quite a lot of difference between the upper boundary and lower boundary of the alternative specific constant, with one of the alternative specific constants being positive. The same goes for the beta's of the personal characteristics. The difference in these values, might have a large effect on the range of the modal share of car-sharing.

Education

For the tour purpose education the statistics of the utility functions are displayed below. The values of the parameters of the utility functions of the conventional modes are shown Table 7. The values of the parameters in the utility function of car-sharing are shown in Table 8, this table shows both the upper boundary as well as the lower boundary. It seems strange to estimate mode choice for tour purpose education, as car-sharing should not really be a realistic alternative for the tour purpose education. Nonetheless, the research of the observed data in paragraph 4.3 shows that mode choice behavior is fundamentally different for the tour purpose education.

- Number of estimated parameters: 25
- Number of observations: 1731
- Number of individuals: 1731
- Null log-likelihood: -2785.937
- Cte log-likelihood: -2398.167
- Init log-likelihood: -2785.937
- Final log-likelihood: -1761.113
- Likelihood ratio test: 2049.648
- Rho-square: 0.368
- Adjusted rho-square: 0.359

Table 7 Values of the parameters in the utility-functions of the conventional modes with tour purpose education

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_{cd}	-3.83	0.617	-6.21	0	0.674	-5.69	0
ASC_{cp}	-2.91	0.276	-10.6	0	0.349	-8.33	0
ASC_{pt}	-3.89	0.241	-16.1	0	0.286	-13.57	0
ASC_{cy}	-0.707	0.151	-4.69	0	0.224	-3.16	0
ASC_{wk}	0	fixed					
$\beta_{TT,cd}$	0	fixed					
$\beta_{TT,cp}$	-0.0716	0.0173	-4.13	0	0.0181	-3.96	0
$\beta_{TT,pt}$	0	fixed					
$\beta_{TT,cy}$	-0.074	0.007	-10.6	0	0.0076	-9.74	0
$\beta_{TT,wk}$	-0.0888	0.0068	-13	0	0.0132	-6.75	0
$\beta_{hh2l,cd}$	1.24	0.519	2.38	0.02	0.466	2.66	0.01
$\beta_{car0,cd}$	-3.73	1.16	-3.21	0	1.49	-2.5	0.01
$\beta_{car0,cp}$	-1.42	0.243	-5.85	0	0.226	-6.29	0
$\beta_{educ34,pt}$	0.574	0.271	2.12	0.03	0.283	2.03	0.04
$\beta_{inc4h,cd}$	1.9	0.72	2.63	0.01	0.787	2.41	0.02
$\beta_{inc4h,cp}$	0.95	0.328	2.9	0	0.329	2.89	0
$\beta_{inc4h,pt}$	1.33	0.437	3.05	0	0.42	3.18	0
$\beta_{inc4h,cy}$	1.12	0.302	3.71	0	0.289	3.88	0

$\beta_{age0014,cp}$	1.73	0.222	7.77	0	0.236	7.31	0
$\beta_{age0017,cd}$	-2.94	0.913	-3.22	0	0.929	-3.16	0
$\beta_{age1217,cy}$	1.31	0.134	9.75	0	0.133	9.88	0
$\beta_{age1829,pt}$	1.77	0.275	6.43	0	0.291	6.08	0
$\beta_{occ12+,cd}$	1.17	0.464	2.52	0.01	0.495	2.37	0.02
$\beta_{fem,cd}$	-1.81	0.478	-3.78	0	0.612	-2.96	0
$\beta_{roots3,pt}$	0.45	0.212	2.13	0.03	0.218	2.06	0.04
$\beta_{roots3,cy}$	-1.04	0.139	-7.45	0	0.142	-7.31	0
$\beta_{license,cd}$	1.87	0.628	2.98	0	0.858	2.18	0.03
$\beta_{urb5,wk}$	0.35	0.13	2.7	0.01	0.128	2.74	0.01

Table 8 Values of the parameters in the utility-function of car-sharing with tour purpose education

	Upper boundary	**Lower boundary**
ASC_{cs}	-6.96	-6.96
$\beta_{TT,cs}$	-0.06	-0.06
$\beta_{hh2l,cs}$	1.63	0.147
$\beta_{age2544,cs}$	0.364	0.364
$\beta_{car0,cs}$	0.387	0.387
$\beta_{car1,cs}$	0	0
$\beta_{educ34,cs}$	3.96	0.164
$\beta_{inc4h,cs}$	1.26	1.01

The alternative specific constants in the utility functions of the conventional modes for the tour purpose education are relatively high compared to the other values, and also compared to those in the utility function of the tour purpose work. This indicates that the variables in the utility functions are to a lesser extent able to determine the mode choice behavior. It's also noteworthy that the beta values for the travel time for both car driver and public transport are set fixed to 0, as otherwise they would have been insignificant. This is very counterintuitive. Apparently the travel time is not important for the mode choice, at least not when choosing car driver or public transport. A potential reason for this is that there having the tour purpose education is probably highly correlated to someone's age. A lot of people that have the tour purpose education, are probably under the age of 18 and are thus legally not allowed to drive a car, hence leading to the travel time being insignificant for the mode choice. The fact that the beta values for having zero cars in the household, in the utility functions of car driver and car passenger, are negative should lead to no surprise. If the household owns no cars, then it's unlikely that the person will use a car to drive to his place of education by car, nor that he/she is brought to his place of education by car by another member of the household. Household income seems to be an important variable, with members of households with a higher income being more likely to choose any mode besides walking (all the other modes have positive beta values for household income). Age is also an important variable. People between the age of 0 and 14 are likely to choose to be a car passenger. People between the age of 0 and 17 are unlikely to be a car driver, again because they have no driver license. People between the age of 12 and 17 are more likely to cycle. People between the age of 18 and 29 are more likely to use public transport (students). Independent of age, the fact that a person has a driver license this time also influences mode choice and leads to the person choosing for the car driver alternative more often. Finally, roots again influence mode choice behavior. Non-western foreigners are slightly more likely to use public transport and less likely to cycle, probably because they are unfamiliar with that mode of transport.

All of the findings regarding the personal characteristics seem to be in line with the data analysis done beforehand, as shown in paragraph 4.3.

The alternative specific constant in the utility function of car-sharing is set to an absolute relatively high value. This would imply that the other variables in the utility function are only able to partially explain car-sharing usage. The upper boundary and lower boundary are the same, since the lowest alternative specific constant was that of car driver. Striking is also how the education level and the household size seem to influence car-sharing usage. The beta-values in this case are inherited from the utility function of car driver. Taking this into account, the result is rather interesting. Maybe people with a high education level, low household size (attributes positively influencing car-sharing behavior), who are now attracted to the car driver alternative, might be convinced to use car-sharing instead. The lower bound values for the household size and education level are much lower, these values are inherited from the utility function of cycling.

Other

For the tour purpose 'other' the statistics of the utility functions are displayed below. The values of the parameters of the utility functions of the conventional modes are shown Table 7. The values of the parameters in the utility function of car-sharing are shown in Table 8, this table shows both the upper boundary as well as the lower boundary. The tour purpose other includes all tours that didn't have any trips with a trip purpose work or education.

- Number of estimated parameters: 20
- Number of observations: 1309
- Number of individuals: 1309
- Null log-likelihood: -2106.754
- Cte log-likelihood: -1957.618
- Init log-likelihood: -2106.754
- Final log-likelihood: -1407.122
- Likelihood ratio test: 1399.265
- Rho-square: 0.332
- Adjusted rho-square: 0.323

Table 9 Values of the parameters in the utility-functions of the conventional modes with tour purpose 'other'

Name	Value	Std err	t-test	p-value	Robust Std err	Robust t-test	p-value
ASC_{cd}	-1.96	0.278	-7.04	0	0.331	-5.91	0
ASC_{cp}	-3.34	0.214	-15.6	0	0.303	-11.03	0
ASC_{pt}	-5.37	0.304	-17.6	0	0.369	-14.57	0
ASC_{cy}	-1.39	0.177	-7.85	0	0.252	-5.52	0
ASC_{wk}	0	fixed					
$\beta_{TT,cd}$	-0.0742	0.0155	-4.77	0	0.0138	-5.37	0
$\beta_{TT,cp}$	0	fixed					
$\beta_{TT,pt}$	0	fixed					
$\beta_{TT,cy}$	-0.0888	0.0098	-9.1	0	0.0114	-7.78	0
$\beta_{TT,wk}$	-0.114	0.0086	-13.2	0	0.0152	-7.51	0
$\beta_{hh2l,cd}$	0.891	0.184	4.83	0	0.178	5	0
$\beta_{age2544,cy}$	-0.4	0.175	-2.29	0.02	0.169	-2.37	0.02
$\beta_{car0,cd}$	-5.46	0.742	-7.36	0	0.711	-7.68	0
$\beta_{car0,cp}$	-2.09	0.296	-7.05	0	0.319	-6.55	0

$\beta_{car0,pt}$	1.29	0.322	4	0	0.326	3.96	0
$\beta_{car1,cd}$	-1.22	0.181	-6.71	0	0.171	-7.1	0
$\beta_{educ34,cd}$	0.761	0.184	4.14	0	0.189	4.04	0
$\beta_{age0011,wk}$	0.572	0.21	2.72	0.01	0.211	2.71	0.01
$\beta_{age0014,cp}$	1.92	0.206	9.31	0	0.207	9.28	0
$\beta_{occ12+,cd}$	1.04	0.176	5.94	0	0.178	5.87	0
$\beta_{fem,cd}$	-1.01	0.167	-6.07	0	0.159	-6.37	0
$\beta_{roots3,pt}$	-0.687	0.21	-3.27	0	0.214	-3.21	0
$\beta_{roots3,cy}$	-0.468	0.208	-2.25	0.02	0.214	-2.19	0.03

Table 10 Values of the parameters in the utility-function of car-sharing with tour purpose 'other'

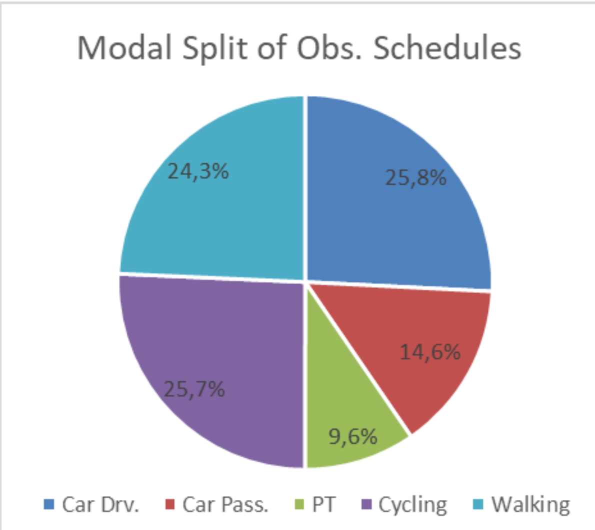
	Upper boundary	**Lower boundary**
ASC_{cs}	-2.15	-5.15
$\beta_{TT,cs}$	-0.05	-0.05
$\beta_{hh2l,cs}$	0.805	0.144
$\beta_{age2544,cs}$	0.266	0.148
$\beta_{car0,cs}$	0.966	0.966
$\beta_{car1,cs}$	0.169	0.169
$\beta_{educ34,cs}$	0.831	0.0828
$\beta_{inc4h,cs}$	0	0

The alternative specific constants in the utility functions of the conventional modes for the trip purpose 'other' are quite high. This is especially true for public transport. Apparently there is strong disutility towards public transport that cannot be explained by the other variables in the utility function. A reason for this could be due to the fact that tours with the purpose other tend to be very diverse and some of the destination within the tour might not be accessible by public transport (sport, visiting friends etc.), since public transport tends to focus more on a predictable demand (work- and education-related trips). Besides that, the beta value for the travel time was also set to zero for the car passenger and public transport alternatives, since the beta value was not significant. A reason for the beta value of car passenger not being significant, could be due to the fact that the beta value of travel time for car passenger is correlated with the beta value of travel time for car driver. A seemingly more important variable for choosing car passenger is whether or not more people (from the same household) decide to travel together (to the same destination), for example when a household is going to visit friends, or going out for dinner etc. Car ownership, again, plays a crucial role in the mode choice. Members of a household that doesn't own any car are less likely to use the car driver or car passenger alternative, and more likely to use public transport. Even if the household owns a single car, the person is still less likely to use the car driver alternative. Age also plays a crucial role: people between the age of 0 and 11 tend to walk more often and people between the age of 0 and 14 tend to be the car passenger more often. Finally, there is again a relationship between the roots of a person and the mode choice. Non-western foreigners are less likely to cycle for tours with the purpose 'other', again likely due to being unfamiliar with the mode of transport. Surprisingly, in contrast to the utility functions of tour purpose 'work' and 'education' there is also a negative sign in the utility function of public transport, this implies that non-western foreigners are also less likely to use public transport for tour purpose 'other'. Most of the results are in line with the data analysis done beforehand, as shown in paragraph 4.3.

The lower bound of the alternative specific constant in the utility function of car-sharing is inherited from the utility function of public transport and it's absolute value is relatively high. The upper bound is quite a lot higher, which could lead to a large range of the modal share of car-sharing. Also both of the absolute values of the alternative specific constant are quite high compared to the other beta values in the utility function of car-sharing. For tour purpose other the variables car ownership, household size and education level seem to explain car-sharing usage the most. However, besides for car ownership, the lower bound beta-values are a lot lower, thus leading to a rather broad range of utilities and thus probably leading to a rather broad range in the modal share of car-sharing.

Modal Split

In this section the modal split is presented for all internal trips within the research area: the urban area of Rotterdam and surrounding municipalities. The modal split considers all trips registered in OViN weighed by the weigh factors given in OViN so that they account for all trips made in the research area. Figure 23 shows the initial modal split, as derived from the input data. Car driver and cycling are both used for more than 25% of the trips, walking comes in at the third place being used in slightly less than 25% of the trips. Car passenger is used for 14.6% of the trips. Public transport is used for the least amount of trips, being used only for 9.6% of the trips.



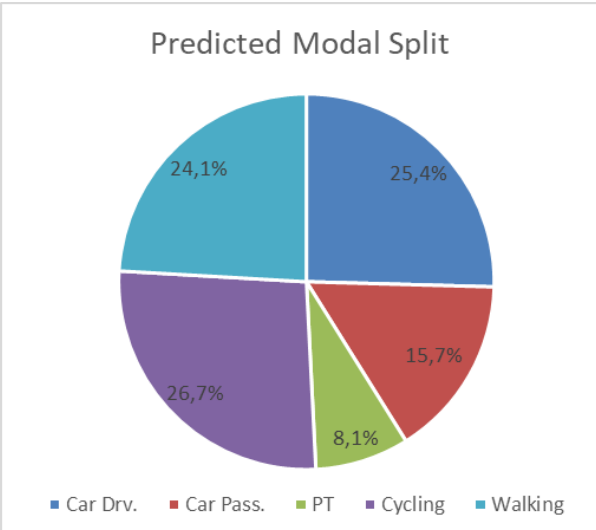


Figure 23 (left) Modal split of initial observed schedules
Figure 24 (right) Predicted modal split without car-sharing implemented

Figure 24 shows the predicted modal split by the mode choice model, without car-sharing implemented, using a simple discrete choice model. It gives an indication of how good the model is. It can be seen that the discrete choice model is not able to perfectly represent the observed data. Car-passenger is overrepresented by the mode choice model, being used in 15.7% of the trips, while in reality only used for 14.6% of the trips. On the other hand, public transport is underrepresented by the mode choice model, being used in 8.1% of all trips, while in reality used for 9.6% of the trips.

Table 11 shows the predicted modal split for each variation of the mode choice model with car-sharing implemented. The same is also shown in the form of a graph, in Figure 25. The differences in these variations are given in the second, third and fourth column of the table. Depending on which parameters are used, the modal share of car-sharing varies between 3.6% and 45.8%, which is quite a large range. The modal share of car driver varies between 10.8% and 24.9%. The model share of car passenger varies between 9.9% and 15.6%. The modal share of public transport varies between 3.3% and 7.4%. The modal share of cycling varies between 14.3% and 25.9%. The modal share of walking varies between 14.8% and 23.2%.

The large range of the resulting modal shares can largely be explained due to the alternative specific constant. It can be seen that the alternative specific constant of car-sharing influences the modal spit heavily. The scenarios where the upper bound alternative specific constant is chosen, result in a much larger modal share for car-sharing (around 30-40%). This is also in line with the results earlier in this chapter, where it was pointed out that the alternative specific constants have quite a high absolute value compared to the beta's for the personal characteristics and the beta for travel time. And thus, the alternative specific constants have a lot of influence on the utility of that mode. It was also pointed out that the alternative specific constant of car-sharing had a rather large range, which result in a large range in the total modal share of car-sharing.

The beta's for the personal variables have a much smaller effect on the modal share of car-sharing. Nonetheless the importance of these beta's shouldn't be ignored. In the scenarios were the lower bound for the alternative specific constant is considered, the beta values can make a difference of about 3-4% of the modal share. This seems a small percentage, but it almost doubles the modal share of car-sharing. In the multinomial logit, as well as in both nested logits, the increase of the modal share of car-sharing is enough to overtake the modal share of public transport. In the variations where the upper bound of the alternative specific constant is chosen, the beta values are able to increase the modal share of car-sharing by 10%. This might seem a lot, but doesn't change the order in which modes are chosen. Both with the upper bound beta-values as well as with the lower bound beta-values, car-sharing is the most chosen mode.

Finally, the difference between the multinomial logit and the two nested logits can be seen. In both of the nested logit models, the modal share of car-sharing is lower than in case of the multinomial logit. The impact on the modal split is rather small however. The difference in the modal share of car-sharing is 2.5% at max, which is less than the difference between using the upper bound or lower bound beta values for the personal characteristics. The modal share of car driver and public transport also do not change that much. The nested logit models can also be compared with each other. If, using the lower bound alternative specific constant, the modal share of car-sharing is lower when it is in a nest with public transport. If using the upper bound alternative specific constant, the modal share of car-sharing is higher when it is in a nest with public transport. When the car-sharing alternative is in a nest with car driver and the utility of car-driver is quite high, people might be less likely to choose the similar car-sharing alternative. The difference is smaller when car-sharing is nested with public transport, since the utilities of the modes are more similar. But, when the utility of car-sharing is high (due to the high alternative specific constant), the differences become bigger. Car-sharing is then a very attractive mode, compared to the public transport alternative, grouped in the same nest. While, in the car-nest, the utilities of car-sharing and car driver are more similar. A result that can be seen overall, is that the modal share of public transport drops significantly compared to the predicted modal share of public transport in the model without car-sharing and in some variations of the model, the modal share of car-sharing has overtaken the modal share of public transport.

Table 11 Modal Share for each mode for each variation of the mode choice model

	Alt. Spec. Constant	Beta for Pers. Char.	Type of Model	Car Driver	Car Passenger	Public Transport	Cycling	Walking	Car Sharing
1	Lower	Lower	Multinomial	24.0%	15.1%	7.2%	25.2%	22.8%	5.2%
2	Lower	Upper	Multinomial	23.1%	14.6%	6.3%	24.0%	22.1%	9.3%
3	Upper	Lower	Multinomial	15.4%	11.2%	4.2%	17.1%	17.4%	34.8%
4	Upper	Upper	Multinomial	12.0%	9.9%	3.4%	14.3%	14.8%	45.8%
5	Lower	Lower	Nested, Car Nest	22.8%	15.4%	7.4%	25.9%	23.0%	4.8%
6	Lower	Upper	Nested, Car Nest	21.4%	15.3%	6.7%	24.9%	22.6%	8.6%
7	Upper	Lower	Nested, Car Nest	13.5%	12.4%	4.5%	18.7%	18.7%	32.3%
8	Upper	Upper	Nested, Car Nest	10.8%	10.8%	3.7%	15.6%	15.9%	43.6%
9	Lower	Lower	Nested, PT Nest	24.9%	15.6%	5.7%	23.9%	23.2%	3.6%
10	Lower	Upper	Nested, PT Nest	24.1%	15.1%	5.2%	23.0%	22.5%	7.6%
11	Upper	Lower	Nested, PT Nest	15.7%	11.4%	4.1%	17.5%	17.6%	34.1%
12	Upper	Upper	Nested, PT Nest	12.2%	10.0%	3.3%	14.6%	14.9%	45.3%

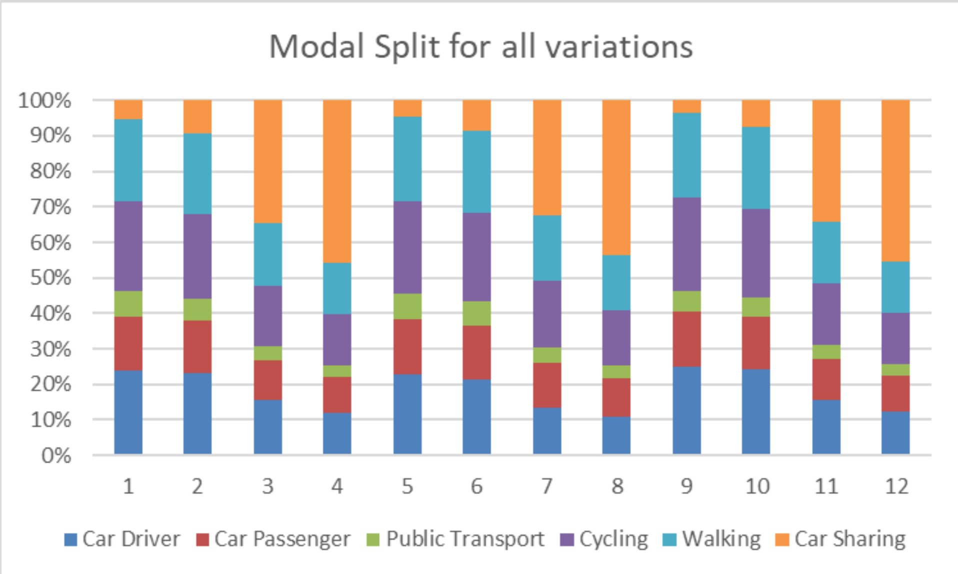


Figure 25 Modal Split of the twelve variations of the mode choice model, with car-sharing implemented

In Appendix C an overview is given of the modal split of all the twelve variations, for each tour purpose: work, education and other.

Car-Sharing especially has a lot of potential for the tour purpose work, where it is being used for 9.0% to 65.4% of all trips, depending on the used parameters. In the most optimistic cases for car-sharing, the modal shares of car-passenger, public transport and walking become almost non-existent, being used for respectively 1.2%, 3% and 2.7% of all trips.

For the purpose education the modal shares of car-sharing are very low. Car-Sharing for education is only used for about 0.1% to 2.0% of all trips, depending on the parameters used. This is similar to the modal shares of car driver which are also very low. It is expected that the tour purpose education is highly correlated with age. People where the tour purpose is education are likely to have a low age, and thus they will not possess a driver license or car. This leads to the low modal share of car driver, as well as the low modal share of car-sharing. It was also found that for the tour purpose education, the alternative specific constant doesn't affect the modal share of car-sharing that much. This can be explained by the fact that the upper boundary of the alternative specific constant in the utility function of car-sharing is set to the alternative specific constant of car driver. Since the alternative specific constant of car driver is already quite low out of all the alternatives, the range between the upper and the lower boundary of the alternative specific constant of car-sharing is rather small as well.

For the tour purpose other, the modal share of car-sharing varies between 2.2% and 46.5%. This is similar to the modal split over all tour purposes. The modal share of the other modes are also similar to the modal shares found in the modal split over all tour purposes. An exception is that the modal share of public transport is relatively small, with public transport being used in only 1.0% to 3.4% of all trips with tour purpose other.

5 Conclusion & Recommendations

5.1 Conclusion

The main goal of this research was to find a way to model car-sharing demand, considering an activity-based modelling approach. First a literature research has been done to search for the attributes that are relevant for car-sharing usage. A mode choice model has been estimated for the conventional modes for the research area of Rotterdam. Car-sharing has been implemented into this mode choice model as an additional mode. A methodology was developed to determine the modal share of car-sharing. Because there is no observed car-sharing data, it is impossible to estimate the parameters within the utility function for car-sharing. Because of this, a range has been determined based on the parameters of the utility functions of the conventional modes. Considering the upper and lower boundaries of the range and varying between a multinomial logit model and a nested logit model, a range of possible outcomes for the modal share of car-sharing was calculated. The range of the modal share is rather large. Inevitably due to the lack of observed data there is no way to validate these outcomes. Another challenge that arose was on the side of the level-of-service data. Some level-of-service variables like the cost, couldn't be determined accurately enough due to different zonal scales used in the OViN dataset and the RVMK model. Due to this, beta-values like the cost and access/egress time were found to be either insignificant or positive (even though a negative value would be expected). Without these variables, it is impossible to compare different car-sharing business models as listed in paragraph 2.1.

Dependent on which values are used and on whether a multinomial or nested logit is used for the discrete choice model, the results are different. It was found, as shown in paragraph 4.5 that the modal share of car-sharing will be between 4% and 46%. This range is rather large. The biggest reason that such a large range has been found is due to the alternative specific constant. Depending on whether the upper or lower bound of the alternative specific constant is used, the modal share of car-sharing varies with roughly 30%. The effect of the beta-values for the personal characteristics was found to increase/decrease the modal share of car-sharing with another 4 to 10%. Finally, it was found that under the given assumptions, it doesn't differ much whether a multinomial or nested logit is used, the type of model only increases/decreases the modal share of car-sharing by another 1-2% at maximum. Especially the large range caused by the alternative specific constant, is troublesome. This means that there are variables, currently not in the mode choice model, that are able to explain car-sharing demand. Part of this might be due to the travel time being the only level-of-service variable. More research has to be done to improve the mode choice model and decrease the effect of the alternative specific constant on the outcome.

If one would presume that the results are correct and the modal share of car-sharing would indeed be somewhere between 4% and 46%, given that car-sharing is a full alternative in a future scenario, the modal shares of the other modes would decrease. The modal shares of car driver and public transport would decrease the most. The fact that the car is used less, is not a problem, however the amount of cars on the road would still be the same (whether it be a personal owned car, or a shared vehicle). If people start using car-sharing instead of public transport, this might actually lead to some issues, as the amount of vehicles on the road would increase and thus would lead to more congestion and higher travel times. Car-sharing was initially introduced as a way to save space, most notably parking space. But if car-sharing proves to be a more attractive alternative to public transport, the amount of space required for traffic might actually increase.

Car-sharing has especially a lot potential for the purpose work. It is interesting to note that the business model of the car-sharing company can have a lot of influence on the modal split. Costs were not taken into account during this research. In a round-trip business model, people typically have to pay for their reservation time: travel time plus activity time. If people also have to pay, while their car is being idle, the potential of car-sharing might be much lower than the results of this research. If car-sharing has indeed high potential for the purpose work, it seems that a point-to-point car-sharing system would have a higher potential than a round-trip car-sharing system. This is because in a point-to-point model the user can leave the car when the user starts working, and thus, the user doesn't have to pay for the time when the car is idle.

5.2 Recommendations

While the mode choice model introduced in this research is capable to reproduce the findings from literature, there are still a lot improvements that could be made, before this model would be able to assist municipalities and other transport related agencies in determining traffic demand and accurately predict car-sharing usage.

One of the biggest issues in this research is the lack of data. The OViN-data used for this research does not include data about car-sharing. Nor is there any other revealed preference data available that includes car-sharing. This is likely due to the low penetration rates of car-sharing. Because of this, the beta-values in the utility function of car-sharing had to be estimated by inheriting beta-values from the utility functions of the conventional modes. Also, because there is no car-sharing data available, the results of this research cannot be validated. A way to fill the gap in data, is to use stated preference research. In a survey, people could be asked in which cases (under varying travel times, costs, trip/tour purpose) they would consider car-sharing. There is stated preference data already available (for example (SmartAgent, 2011)), but it's access is restricted, besides it is unknown if the data will actually be helpful in this research. Creating a new survey for stated preference research has a couple disadvantages as well. First of all it is very time consuming. A lot of data is required to estimate the mode choice model and gathering all of that data costs a lot of time and effort. Secondly, the obtained data due to stated preference research might be biased. In a survey people could give more socially desirable responses: they could say they would use car-sharing for a certain trip, while in reality they wouldn't. Finally, setting up a stated preference research especially for car-sharing does not give a solid research approach for future research. If another new modality has to be researched, another stated preference survey is required.

In paragraph 2.1 car-sharing was introduced by giving on overview of the various business models of car-sharing. Ideally, one would want to be able to compare different business models. To do so, one would need more level-of-service variables, at least including the cost over time, the cost over distance and some sort of car-sharing availability component (access/egress). It was found that the level-of-service variables, besides the travel time, were not significant. In paragraph 4.3 a broad overview has been given with possible explanations why these variables turned out to be not significant. The three main reasons were that the level-of-service data might be too simplified for reality (not taking into account parking time, travel allowances etc.), the scale of the level-of-service data is too high or the level-of-service variables should actually not be significant, due to all alternatives being almost equally attractive. It is advised to test at least the first two reasons given. The source of the level-of-service data, the RVMK, uses smaller zones. It would be beneficial if the observed data from OViN could also be translated to this scale level. An even better solution would be to abolish zones all together and calculate the level-of-service data on the address level (travel times, costs and access/egress times from one address to the other), this might however lead to a privacy issue. Currently, OViN also includes level-of-service data, but this is only for the chosen alternative. One could try to extend the OViN data with level-of-service variables and calculate travel times, distances, costs, waiting times and access/egress times for **all modes** from address to address, before aggregating the data to a higher scale level (for privacy reasons). By extending the OViN data, only a single data source would be necessary and this would lead to less compatibility issues. It could even be possible to ask the participants of the survey behind OViN to fill in perceived travel times and costs for each mode on the trips they've made. In this way it can be analyzed how perceived level-of-service data would affect mode choice behavior and in this way also time associated to parking, congestion and travel allowanced could be taken into account, as that would add to the perceived travel times. By solving these issues and adding other level-of-service variables into the utility function, different business models could be compared to each other and it could be tested which business model is the most effective for a certain case.

The model developed in this research currently functions as a stand-alone model. The next step in the research, would be to actually implement the mode choice model in a traffic demand model. Even though the activity-based framework was taken into account when developing this model, the model is currently quite simple and can (in current form) also easily be implemented and adapted for other disaggregated models (agent-based), not necessarily only for activity-based models. One of the examples that comes to mind is the current traffic demand models for the Netherlands, the LMS. By implementing this mode choice model in a traffic demand model, whether it be an activity-based model or a classic four-step model, one could analyze the effects of car-sharing on a much smaller scale. The results would not only include an overall modal split, but one could visualize for each link in the network the increase or decrease of the amount of vehicles. In this way the impact of car-sharing on the city can be determined much more accurately.

To decrease complexity, in this research car-sharing was determined on a trip level. For future research it is advised to take into account car-sharing on the level of a 'trip leg', (see paragraph 1.4). It is advised that the mode choice will be determined in three stages. First a mode is chosen for the full tour. Then a mode is selected for each trip, which is likely to be the mode used for the full tour, but can also be another mode (in case of a sub-tour, or a combination of different modes for the way up and way back). Finally a mode will be selected for each trip leg, in that case access/egress modes are taken into account. By doing this, the access/egress to/from car-sharing can be taken into account, as well as car-sharing as an access/egress mode on itself. This might have a positive effect on the modal split as car-sharing could be used as an access/egress mode in combination with public transport, while public transport was never an alternative for the full trip.

In paragraph 3.1 an overview is given of all necessary implementations to fully implement car-sharing into an activity-based framework. In this research, the focus was on the mode choice itself. If one wants to fully implement car-sharing into a traffic demand model, one has to take into account the other implementations as well. These implementations could all be subject of future's research. Besides the lack of observed data and level-of-service data and besides modelling car-sharing on the level of a trip-leg (modelling multimodal trips/tours), as already mentioned before, one could research and implement the following things within future research:

- The effect of personal characteristics that are harder to quantify on car-sharing behavior, such as environmental concern, sensitivity towards innovation and lifestyles.
- Owning a car-sharing subscription as a restriction to use car-sharing.
- The relation between car-sharing availability and other long term strategic choices, most notably car-ownership.
- The assignment-step including car-sharing.

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Appendix A List of Municipalities

Nr	Municipality
489	Barendrecht
501	Brielle
502	Capelle aan den IJssel
530	Hellevoetsluis
542	Krimpen aan den IJssel
556	Maassluis
568	Bernisse
597	Ridderkerk
599	Rotterdam
606	Schiedam
612	Spijkenisse
613	Albrandswaard
614	Westvoorne
622	Vlaardingen
1621	Lansingerland
1930	Nissewaard

Appendix B List of Zones by Postal Code

Postal Code	Town	Neighbourhood
2651	Berkel en Rodenrijs	
2652	Berkel en Rodenrijs	
2661	Bergschenhoek	
2662	Bergschenhoek	
2665	Bleiswijk	
2901	Capelle aan den IJssel	's-Gravenland
2902	Capelle aan den IJssel	Middelwatering-West
2903	Capelle aan den IJssel	Middelwatering-Oost
2904	Capelle aan den IJssel	Oostgaarde-Zuid
2905	Capelle aan den IJssel	Oostgaarde-Noord
2906	Capelle aan den IJssel	Schenkel
2907	Capelle aan den IJssel	Schollevaar-Zuid
2908	Capelle aan den IJssel	Schollevaar-Noord
2909	Capelle aan den IJssel	Fascinatio
2921	Krimpen aan den IJssel	
2922	Krimpen aan den IJssel	
2923	Krimpen aan den IJssel	
2924	Krimpen aan den IJssel	
2925	Krimpen aan den IJssel	
2926	Krimpen aan den IJssel	
2981	Ridderkerk	
2982	Ridderkerk	
2983	Ridderkerk	
2984	Ridderkerk	
2985	Ridderkerk	
2986	Ridderkerk	
2987	Ridderkerk	
2988	Ridderkerk	
2989	Ridderkerk	
2991	Barendrecht	
2992	Barendrecht	
2993	Barendrecht	
2994	Barendrecht	
3011	Rotterdam	Stadsdriehoek, Rotterdam Centrum
3012	Rotterdam	Cool, Rotterdam Centrum
3013	Rotterdam	Rotterdam Centraal, Weena
3014	Rotterdam	Oude Westen
3015	Rotterdam	Dijkzigt
3016	Rotterdam	Scheepvaartkwartier, Nieuwe Werk
3021	Rotterdam	Middelland

3022	Rotterdam	Middelland
3023	Rotterdam	Nieuwe Westen
3024	Rotterdam	Coolhaveneiland
3025	Rotterdam	Bospolder
3026	Rotterdam	Tussendijken
3027	Rotterdam	Spangen
3028	Rotterdam	Oud-Mathenesse
3029	Rotterdam	Schiemond, Nieuw-Mathenesse
3031	Rotterdam	Rubroek
3032	Rotterdam	Agniesebuurt
3033	Rotterdam	Provenierswijk
3034	Rotterdam	Crooswijk
3035	Rotterdam	Oude Noorden
3036	Rotterdam	Oude Noorden
3037	Rotterdam	Liskwartier
3038	Rotterdam	Bergpolder
3039	Rotterdam	Blijdorp
3041	Rotterdam	Diergaarde Blijdorp, Kleinpolder
3042	Rotterdam	Diergaarde Blijdorp, Kleinpolder
3043	Rotterdam	Overschie
3044	Rotterdam	Spaanse Polder
3045	Rotterdam	Zestienhoven
3046	Rotterdam	Schieveen
3047	Rotterdam	Bedrijventerrein Rotterdam Noord-West
3051	Rotterdam	Kleiwegkwartier
3052	Rotterdam	Schiebroek
3053	Rotterdam	Schiebroek
3054	Rotterdam	Hillegersberg Centrum
3055	Rotterdam	Molenlaankwartier
3056	Rotterdam	Terbregge
3059	Rotterdam	Nesselande
3061	Rotterdam	Kralingen-West
3062	Rotterdam	Kralingen-Oost
3063	Rotterdam	De Esch
3064	Rotterdam	Kralingseveer
3065	Rotterdam	's-Gravenland
3066	Rotterdam	Prinsenland
3067	Rotterdam	Het Lage Land, Oosterflank
3068	Rotterdam	Ommoord, Zevenkamp
3069	Rotterdam	Ommoord, Zevenkamp
3071	Rotterdam	Feijenoord, Noordereiland, Kop van Zuid
3072	Rotterdam	Afrikaanderwijk, Katendrecht
3073	Rotterdam	Bloemhof, Strevelswijk
3074	Rotterdam	Hillesluis

3075	Rotterdam	Vreewijk
3076	Rotterdam	Lombardijen
3077	Rotterdam	Oud-IJsselmonde, Stadion
3078	Rotterdam	Beverwaard, IJsselmonde
3079	Rotterdam	Groot-IJsselmonde
3081	Rotterdam	Tarwewijk, Maashaven
3082	Rotterdam	Oud-Charlois
3083	Rotterdam	Carnisse, Zuidplein
3084	Rotterdam	Zuiderpark, Wielewaal, Charlois
3085	Rotterdam	Zuidwijk
3086	Rotterdam	Pendrecht
3087	Rotterdam	Oud-Charlois, Waalhaven-Noord
3088	Rotterdam	Waalhaven-Zuid
3089	Rotterdam	Heijplaat
3111	Schiedam	Centrum
3112	Schiedam	Schiedam-Oost
3113	Schiedam	Nieuw-Mathenesse
3114	Schiedam	Schiedam-Zuid
3115	Schiedam	Schiedam Havens
3116	Schiedam	Schiedam-West
3117	Schiedam	Schiedam-West
3118	Schiedam	Nieuwland
3119	Schiedam	Nieuwland
3121	Schiedam	Groenoord
3122	Schiedam	Kethel
3123	Schiedam	Woudhoek
3124	Schiedam	Spaland
3125	Schiedam	's-Graveland
3131	Vlaardingen	Centrum
3132	Vlaardingen	Westwijk
3133	Vlaardingen	Havengebied
3134	Vlaardingen	Oostwijk, Babberspolder
3135	Vlaardingen	Ambacht
3136	Vlaardingen	Holy-Zuid
3137	Vlaardingen	Holy-Noord
3138	Vlaardingen	Broekpolder
3141	Maassluis	
3142	Maassluis	
3143	Maassluis	
3144	Maassluis	
3145	Maassluis	
3146	Maassluis	
3147	Maassluis	
3151	Hoek van Holland	

3161	Rhoon	
3162	Rhoon	
3165	Rotterdam Albrandswaard	
3171	Poortugaal	
3172	Poortugaal	
3176	Poortugaal	
3181	Rozenburg	
3191	Hoogvliet	Centrum: Middengebied, Boomgaardshoek
3192	Hoogvliet	Zuid: Meeuwenplaat, Zalmplaat
3193	Hoogvliet	West: Nieuw Engeland, Westpunt
3194	Hoogvliet	Noord: Oudeland, Gadering, Tussenwater
3195	Pernis	
3196	Vondelingeplaat	
3197	Botlek	
3198	Europoort	
3199	Maasvlakte	
3201	Spijkenisse	Centrum, Vierambachten, De Hoek, Gildenwijk, Haven, De Elementen
3202	Spijkenisse	Schiekamp, Hoogwerf
3203	Spijkenisse	Groenewoud
3204	Spijkenisse	Sterrenkwartier, De Akkers
3205	Spijkenisse	Waterland
3206	Spijkenisse	De Akkers
3207	Spijkenisse	Maaswijk, Schenkel
3208	Spijkenisse	Vogelenzang
3209	Hekelingen	
3211	Geervliet	
3212	Simonshaven	
3214	Zuidland	
3216	Abbenbroek	
3218	Heenvliet	
3221	Hellevoetsluis	
3222	Hellevoetsluis	
3223	Hellevoetsluis	
3224	Hellevoetsluis	
3225	Hellevoetsluis	
3227	Oudenhoorn	
3231	Brielle	
3232	Brielle	
3233	Oostvoorne	
3234	Tinte	
3235	Rockanje	
3237	Vierpolders	
3238	Zwartewaal	

Appendix C Modal Split over Tour Purpose

In this appendix the results for the twelve variations are shown, for each tour purpose: work, education, other. The results are displayed both in a table and in a graph.

Work

Table 12 Modal Share for each mode for each variation of the mode choice model for tour purpose work

	Alt. Spec. Constant	Beta for Pers. Char.	Type of Model	Car Driver	Car Passenger	Public Transport	Cycling	Walking	Car-Sharing
1	Lower	Lower	Multinomial	43,33%	3,44%	9,79%	24,72%	6,38%	12,34%
2	Lower	Upper	Multinomial	42,28%	3,23%	8,97%	23,51%	6,08%	15,92%
3	Upper	Lower	Multinomial	19,49%	1,39%	3,66%	11,50%	3,11%	60,85%
4	Upper	Upper	Multinomial	17,80%	1,20%	2,99%	9,93%	2,68%	65,41%
5	Lower	Lower	Nested, Car Nest	40,43%	3,82%	10,90%	26,70%	6,80%	11,36%
6	Lower	Upper	Nested, Car Nest	39,07%	3,67%	10,26%	25,82%	6,58%	14,60%
7	Upper	Lower	Nested, Car Nest	18,05%	1,71%	4,46%	14,03%	3,74%	58,01%
8	Upper	Upper	Nested, Car Nest	16,61%	1,46%	3,65%	12,10%	3,22%	62,95%
9	Lower	Lower	Nested, PT Nest	46,53%	3,84%	7,20%	26,59%	6,84%	9,00%
10	Lower	Upper	Nested, PT Nest	45,41%	3,60%	6,76%	25,25%	6,54%	12,44%
11	Upper	Lower	Nested, PT Nest	20,11%	1,45%	3,57%	11,86%	3,22%	59,79%
12	Upper	Upper	Nested, PT Nest	18,32%	1,23%	2,93%	10,18%	2,75%	64,59%

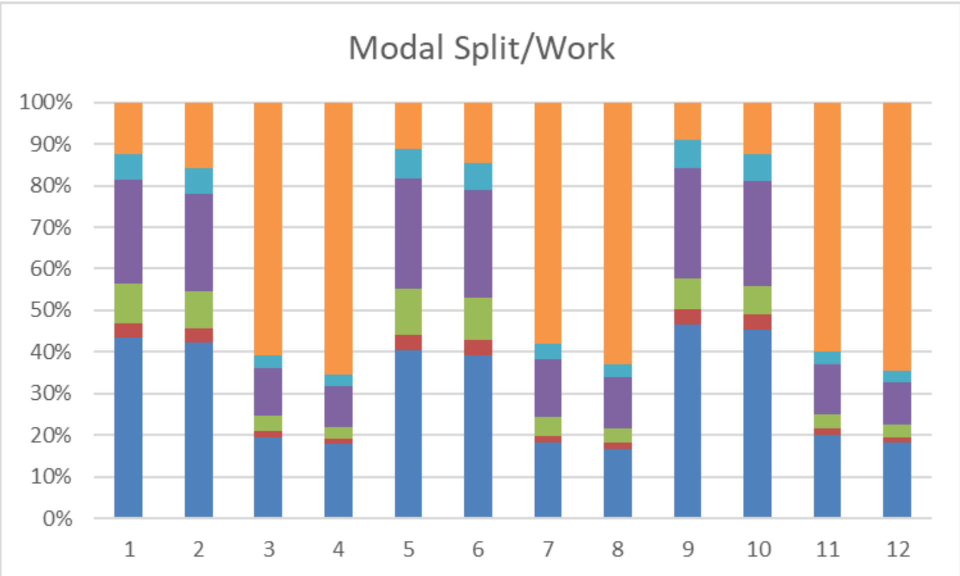

Figure 26 Modal Split of the twelve variations of the mode choice model, for tour purpose work

Education

Table 13 Modal Share for each mode for each variation of the mode choice model for tour purpose education

	Alt. Spec. Constant	Beta for Pers. Char.	Type of Model	Car Driver	Car Passenger	Public Transport	Cycling	Walking	Car-Sharing
1	Lower	Lower	Multinomial	2,24%	23,04%	11,62%	39,13%	23,82%	0,15%
2	Lower	Upper	Multinomial	2,04%	22,94%	10,85%	38,64%	23,62%	1,91%
3	Upper	Lower	Multinomial	2,24%	23,04%	11,62%	39,13%	23,82%	0,15%
4	Upper	Upper	Multinomial	2,04%	22,94%	10,85%	38,64%	23,62%	1,91%
5	Lower	Lower	Nested, Car Nest	2,19%	23,07%	11,64%	39,16%	23,83%	0,12%
6	Lower	Upper	Nested, Car Nest	1,71%	23,02%	11,08%	38,84%	23,71%	1,64%
7	Upper	Lower	Nested, Car Nest	2,19%	23,07%	11,64%	39,16%	23,83%	0,12%
8	Upper	Upper	Nested, Car Nest	1,71%	23,02%	11,08%	38,84%	23,71%	1,64%
9	Lower	Lower	Nested, PT Nest	2,25%	23,08%	11,50%	39,18%	23,85%	0,14%
10	Lower	Upper	Nested, PT Nest	2,19%	23,06%	10,32%	39,06%	23,78%	1,59%
11	Upper	Lower	Nested, PT Nest	2,25%	23,08%	11,50%	39,18%	23,85%	0,14%
12	Upper	Upper	Nested, PT Nest	2,19%	23,06%	10,32%	39,06%	23,78%	1,59%

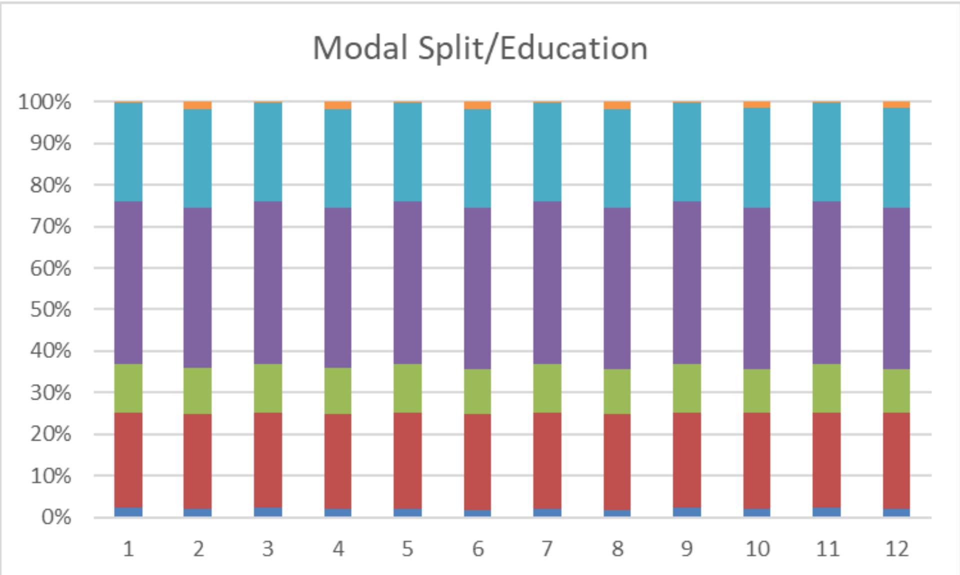

Figure 27 Modal Split of the twelve variations of the mode choice model, for tour purpose education

Other

Table 14 Modal Share for each mode for each variation of the mode choice model for tour purpose other

	Alt. Spec. Constant	Beta for Pers. Char.	Type of Model	Car Driver	Car Passenger	Public Transport	Cycling	Walking	Car-Sharing
1	Lower	Lower	Multinomial	23,75%	18,97%	3,39%	22,58%	27,95%	3,36%
2	Lower	Upper	Multinomial	22,97%	18,43%	2,94%	21,42%	27,06%	7,18%
3	Upper	Lower	Multinomial	17,87%	13,40%	1,49%	14,82%	20,52%	31,91%
4	Upper	Upper	Multinomial	13,18%	11,46%	1,01%	11,32%	16,52%	46,51%
5	Lower	Lower	Nested, Car Nest	22,87%	19,40%	3,45%	22,93%	28,24%	3,10%
6	Lower	Upper	Nested, Car Nest	21,35%	19,26%	3,04%	22,12%	27,63%	6,60%
7	Upper	Lower	Nested, Car Nest	15,24%	15,30%	1,67%	16,71%	22,38%	28,70%
8	Upper	Upper	Nested, Car Nest	11,56%	12,79%	1,13%	12,74%	18,09%	43,69%
9	Lower	Lower	Nested, PT Nest	24,14%	19,51%	2,28%	23,41%	28,45%	2,20%
10	Lower	Upper	Nested, PT Nest	23,36%	18,97%	2,23%	22,14%	27,51%	5,79%
11	Upper	Lower	Nested, PT Nest	18,07%	13,60%	1,45%	15,01%	20,70%	31,18%
12	Upper	Upper	Nested, PT Nest	13,28%	11,59%	0,99%	11,42%	16,63%	46,08%

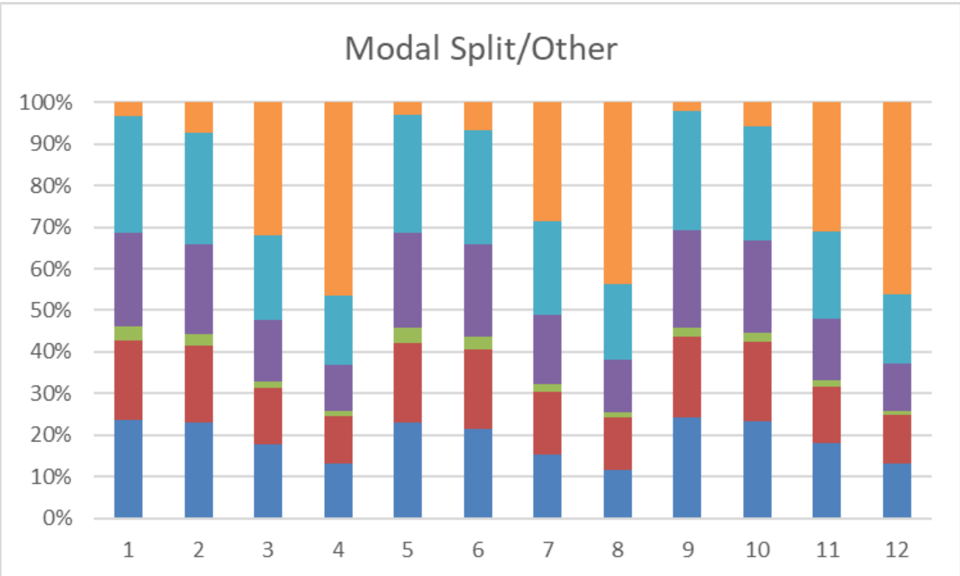

Figure 28 Modal Split of the twelve variations of the mode choice model, for tour purpose other