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The temporal Effects of Life Events on Mobility Choices in The Netherlands

MASTER THESIS

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Abstract

The deliberation of the past and the future is an important factor in individual decision making but is generally overlooked in most behavioral models. Many studies have focused on anticipation or apprehension involved with the attributes of alternatives, but paid less attention to anticipation and lagged effects involving life events on car ownership and most frequent used mode. This thesis therefore made an attempt to narrow this research gap in terms of capturing the effects of anticipation and lagged effects of life events on car ownership and most used mode in the choice modelling framework, especially in the dynamic context. Car ownership and mode most used mode are selected in this study as dependents variables, because these two mobility choices are still underestimated in the analysis of life events. In addition, car ownership can be considered as mediating the relationship between the built environment and travel behavior and can affect trip frequency choice, and mode choice.

Four waves of data (2013 - 2016) from the world's largest ongoing mobility panel, 'The Netherlands Mobility Panel' (in Dutch: MobiliteitsPanel Nederland) (MPN) is used. The MPN is a state-of -the-art web based travel survey that contain panel data. Panel data was very important in this study, because it allowed the researcher to analyze the travel behavior over time of the same households/individuals and therefore measure the effects of life events. Additional built environment variables (e.g. destination accessibility and population density) were collected on postcode four level. Job accessibility by public transport, bicycle and car were also included. The MPN mobility panel contains approximately 6000 respondents in around 2500 complete households. 1273 stayer respondents (i.e. respondents who participated in all four years) with a total of 58035 trips are included in the analysis. In this thesis, joint mixed logit models of life events and car ownership, and life events and most used mode were developed and estimated to determine the temporal effects (i.e. anticipation and lagged effects of life events) on these two mobility choices.

The model results showed that work-related life events, spatial family-related life event (move house), non-spatial family related life event (child birth) and a combination of a work-related life event and having a baby or move house, have anticipation and or lagged effects on car ownership and most used mode. Overall, the anticipation effects are found to be stronger and more important than the lagged effects considering the model results and the elasticities of job accessibility in the analysis. Furthermore, the variables that were influential in determining the temporal effects of the life events in this study are: distance to daycare, urbanity, job accessibility by car and by public transport, employment, number of persons in the household, travel time and mode preferences for the purpose of work and leisure activities. Lastly, the results of the models and the estimated elasticities and probabilities were able to reveal the presence of the temporal effects of the life events and mobility choices. The use of the joint estimation of the life events and mobility choices have proven to be useful in this study, and the output of the research can provide insight to the field of analysing behavioural impacts of life events on mobility.

Keywords: *life events, anticipation-and lagged-effects, car ownership, most used mode, mixed logit, joint model*

Summary

Research on the association between characteristics of anticipated life events and their impact on present mobility is limited. Not only the time to consider the characteristics and impact of anticipative and lagged behavior in research, but also the time to collect comprehensive data, which is required for empirical and statistical analysis on the topic has been inadequate. As a result, the knowledge on the impact of anticipation and lagged effects of life events on the mobility system is limited and the need for additional insights is a prerequisite. Life events are major events that can change a person's circumstance, are rare events (do not occur frequently) and can have anticipated- as well as lagged effects on travel behaviour. Therefore, an appropriate description and analysis of dynamics in long-term mobility should focus at the effects of life events on mobility choices over multiple time periods. It is thus clear that there is a research gap in terms of capturing the effects of anticipation and lagged effects of life events on mobility choices (i.e. car ownership and most used mode) in the choice modelling framework, especially in the dynamic context.

This thesis used four waves of the MPN database in order to contribute to the literature by analysing the association between life events and the above-mentioned mobility choices. First of all, a main research question was formulated: To what degree do anticipation and lagged effects of the life events affect car ownership and most used mode? Further, also three (3) sub-research question were formulated: i) Which life events can be expected to have anticipation and lagged effects on car ownership and most used mode? (ii) Which factors are influential in determining the anticipation and lagged effects of life events on car ownership and most used mode? (iii) To what extent can the model output be implemented? (i.e. what policy implications can be recommended by using the model output for the estimation of elasticities for biographical or spatial variables?) Secondly, a literature study was conducted in order to determine the methodology to use and to select influential explanatory variables that can be used to analyse life events, car ownership as well as most used mode. From the literature study, a set of socioeconomic characteristics(SE) (e.g. income, employment, age etc.), built environment variables (BE) (e.g. destination- and job accessibility) and travel related variables (T), such as travel distance and travel time were selected. The life events available in the MPN dataset are grouped into 8 categories: 1. Work related-, 2. Education, 3. Family related non-spatial (child birth), 4. Family related spatial (move house), 5. Work and family related non-spatial (e.g. new job and child birth), 6. Work and family related spatial (e.g. new job and move house), 7. None (the respondents with zero (0) life events and 8. Others, which includes random combinations of life events (e.g. new job and change work location and move house). A distinction was made between spatial and non -spatial life events by exploring the variation in accessibility in terms of job accessibility, when people move their residential location or work location or change school or education. This distinction is important, because people can for example have a family related life event (child birth or move house or both) and when people move house, it can happen that they move to a neighborhood that is better accessible by for example public transport or less accessible by public transport. The life event move house can then be expected to have an impact on the most used mode or car ownership. However, this can only be measured clearly when there is a distinction between spatial and non-spatial events. The MPN data contains the residential location of the respondents on postcode four level and these were used in order to explore the moves of the respondents (it is clear to see when a respondent moved from postcode "A" to postcode "B") and if there was a change in accessibility level in terms of numbers of jobs reachable by car, public transport and bicycle. In contrast to the family related- and a combination of family and work-related life events, the education and work-related life events were not separated into spatial and non-spatial events, because there was no variation in terms of accessibility level for the respondents who reported these life events.

Car ownership and most used mode are interconnected and very important in the analysis of travel behaviour. However, to the best knowledge of the researcher and according the literature, these two mobility choices have not been used as dependent variables in a joint estimation/analysis of life events. Therefore, these two phenomena are used in the analysis of the temporal effects of the life events. For the car ownership models, binary alternatives where considered (i.e. "car acquisition", means the respondent has a car and "no car acquisition", means the respondent does not have a car). For the most used mode models, the alternatives included the most frequent used mode: car (as passenger or driver), bicycle, public transport and walk. There are 3 days per wave in the MNP survey where the respondents had to fill in a travel diary. From this travel diary it was possible to determine which mode was used the most by a particular respondent. For instance, if a

respondent used the car 5 times, the bicycle 3 times and public transport 2 times in these three days in a wave, then the car is selected as most used mode for this respondent in that wave.

This study considered the following steps: first of all, a literature study was done, then the available data had to be prepared for the analysis. Here the deltas (i.e. the difference between the explanatory variables between two waves, one year previous and one year after) were calculated. A set of statistical analyses were executed, such as correlation analyses and variance inflation factor test (VIF) in order to check for multicollinearity between the explanatory variables. Because variables that are highly correlated (correlation coefficient higher than 0.6) can cause problems during the model estimations. In addition, the mean and standard deviation of the delta parameters were also calculated in order to see what the level of variation in the deltas was. If the standard deviation is zero, then such a delta parameter has no variation and if it is close to zero, then the variation in such a delta parameter is very small, and therefore will not be estimated or will not be significant in the model.

Mixed logit as well as joint mixed logit models were used in this particular thesis. A mixed logit model is a highly flexible model that can approximate any random utility model and allows for random taste variation and does not exhibit independence from irrelevant alternatives(IIA). Furthermore, joint choice models are useful to determine the correlation between choices and have been implemented in different travel demand analysis. In order to understand the dynamics over time of the life events and to compare the models of the three (3) time intervals (wave 2013-2014, wave 2014-2015 and wave 2015-2016), only respondents who participated in all the four waves of the MPN survey were included. For this purpose, the deltas were determined and estimated in the models. Looking at anticipation effects, then the deltas between the explanatory variables of the present wave (denoted as "year t"), and the previous wave (denoted as "year t-1"), had to be considered. On the other hand, when analyzing the lagged effects, then the deltas between the explanatory variables of the present year (denoted as "year t"), and the next year (denoted as "year t+1"), are taken into account. The MPN data contains 4 waves and therefore, nine (9) mixed logit models were estimated because of two possibilities/situations. The first situation is where wave 2014 is considered as the present wave ("year-t"). Wave 2013 is then, "year t-1" and wave 2015 is "year t+1". The other situation applies when year 2015 is seen as the present wave ("year t"), and wave 2014 is then "year t-1", and wave 2016 functions as "year t+1". So, there are 3 sets of 3 models: considering the deltas of time interval 2013-2014 (set 1), then we have 3 models, namely the life event model, the car ownership model and the most used mode model. For time interval 2014-2015 (set 2) the same as well as for time interval 2015-2016(set 3).

From the model output, it was found that work-related life events, spatial family-related life events (move house), non-spatial family related life events (child birth) and a combination of a work-related life event and having a baby or move house, have anticipation and or lagged effects on car ownership and most used mode. However, one person having a life event and due to that life event, acquire a car or use a particular mode very frequent, can also be influenced by socio-economic characteristics or trip related variables, but more particularly, aspects of the build environment. The results showed that the built environment variables: distance to daycare, urbanity and job accessibility by car and by public transport affect the life event decisions of the people and as a consequence also affect car ownership or mode choice. In addition, the output of the models showed that, socio-economic characteristics, such as employment and number of persons in the household are also influential. The influential travel related variables are: travel time, mode preferences for the purpose of work and leisure activities. Furthermore, it can be concluded from the model results that the people who anticipated to have a baby, are also likely to acquire a car. This finding makes sense, because when a couple plan to get a baby, having a car can be seen as a comfortable and safe way of travel, like going to the doctor, doing grocery etc. and there is also more space available to carry the members of the house hold, including the baby. A combination of a work-related life event and a baby was also found to trigger car ownership in anticipation to the life event. Another finding was that people who anticipated to have a work-related life event were also likely to have the bicycle as most used mode. This can be explained by the fact that people who had a work-related life event (for example), change in work location, had moved their work location within the same municipality or moved to an area with the same accessibility level, and therefore, if they had the bicycle as most used mode, then they did not have to change it with another transport mode. However, it is still difficult to say what the exact effect is, since the alternative "Work" represent a work-related life event, which can be: a new job, stop working, work less, work more, change in work hours/days or change in work location. The analysis of the lagged effects revealed that the respondents who had a baby in 2014 were more likely to have walking as their most used

mode after having the baby. Another finding of the lagged effects is that the life event move house, has car acquisition as lagged effect. It was found that people who moved their house, acquired also a car after moving their house. A plausible explanation for this finding is that the people who moved their house, had moved to an area with less accessibility by public transport. Overall it can be concluded that the anticipation effects are stronger and more important than the lagged effects considering the model results and the elasticities of job accessibility in the anticipation analysis (wave 2013-2014). The anticipation effects should be further analysed in future research, because the best timing for policy makers to intervene is before the life event happens, because in the period before the life event people are already thinking of what kind of mobility choices to make, and policy makers/transport planner can really use this as a 'window of opportunity' to provide the people with information and solutions how to travel is a safe and sustainable way. Furthermore, the results of the models and the estimated elasticities and probabilities were able to reveal the presence of the association between the temporal effects of the life event and the mobility choices. The use of the joint estimation of the life events and mobility choices have proven to be useful in this study, and the output of the research can provide insight to the field of analysing behavioural impacts of life events on mobility.
Nevertheless, is further research on this topic a prerequisite. It is a good recommendation to use more advanced modelling technique for the specific purpose of studying the temporal impact of life events on mobility choices, since in this particular study the deltas were use, which are not able to analyze the effects of the life events beyond 12 months, because maybe there is still some effects of the life events more than 12 months backwards or forward in time.

1 Introduction

The aspiration and necessity to understand, explain and forecast travel behavior dates back many years and is broadly shared throughout society. However, people's travel behavior does not follow a fixed pattern but can be very dynamic, Choudhury et al. (2010). Reasons for these changes can be found in various directions. Often, they are the result of a certain change in one's personal life (for example relocation, having a baby, getting divorced etc.) or the built environment he or she is living in (for example a change in office location or going to a different school/university) or a combination of all these aspects. In life people make choices every day. These choices are most of the time about planning ahead of activities that are based on apprehension and anticipation and may have some impact on the present transportation system. For example, travelers may choose their route or mode based on anticipated travel times and one may decide to move his/her house or buy a new/extra/bigger car because of an anticipated life event. A life event is a major event in a personal life that will trigger a process of reconsidering current behavior, van der Waerden et al. (2003). A life event can be: giving birth, marriage, divorce, death of spouse, loss of job etc. A life event can also be described as a major event that changes a person's status or circumstances, and is often discussed in terms of stressors. According to Habib et al. (2006), a stressor can be defined as a discrepancy between a household's aspiration level and its current circumstances. However, an anticipated decision, is more about the planning ahead of an event or group of events. For instance, the planning of getting married, getting a child or to relocate. Due to this planning, people may change their travel behavior by for example changing their mode of travel or by buying a new or an extra car. Furthermore, there can be also lagged effects of life events present. For instance, relocation and car acquisition may occur simultaneously as well as at different times, depending on different household characteristics. People can make life decisions based on their current state but also considering past events and anticipated changes. According to Oakil (2013) life events (e.g. residential relocation and changing jobs) and changing car ownership do not occur frequently and instantaneously. The relationships between decisions on different dimensions may stretch across several years, which implies that lagged responses and anticipation of events have a vital role in the timing of such decisions. Oakil (2013) argued that neglecting these issues may lead to biased results in understanding interrelationship between life events, and therefore to biased predictions of their impact on travel demand. According to Oakil (2013), an anticipation effect is an action taken due to an event that is about to happen in the future, while a lagged effect is path-dependence or a reaction to an event that has occurred in the past. Many researchers have been able to analyze people's travel behavior and to some extent capture it in dynamic discrete choice models where one chooses the alternative that is expected to maximize his/her utility. According to Train (2009), a decision maker chooses the alternative in the current period that maximizes his/her expected utility over the current and future period.
However, many of these studies focused on anticipation or apprehension involved with the attributes of the alternatives, whereas these studies less focused on anticipation and lagged effects involving personal

circumstances or life events, such as having a child, getting divorced, changing employer, moving house, etc. Furthermore, research on the current relation between characteristics of anticipated life events and their impact on present mobility is limited. Not only the time to consider the characteristics and impact of anticipative and lagged behavior in research, but also the time to collect comprehensive data, which is required for empirical and statistical analysis on the topic has been limited. As a result, the knowledge on the impact of anticipation and lagged effects of life events on the mobility system is inadequate and the need for additional insights is a prerequisite. In this study, the focus is therefore on both the anticipation- and lagged effects of life events on mobility over multiple time periods. Data from four waves of the MPN database is used. A statistical analysis is conducted using the stayer respondents (i.e. the respondents who participated in all four waves) and a variety of logit models (i.e. Multinomial (MNL), Mixed logit (ML) and Joint mixed logit models) is developed and estimated. In this regard a set of built environment variables, trip related- demographic- and socio-economic - characteristics is used as explanatory variables that can capture the link or correlation between the life events and the mobility choices (i.e. car ownership and most used mode). The majority of the data (90%) is collected from the MPN database, some additional built environment variables (such as destination accessibility) from the CBS database and job accessibility by car, public transport (WnR) and by bicycle (BnR), were collected from the ASTRID project. ASTRID stands for Accessibility, Social justice and Transport emission Impacts of TOD strategies. This project is a joint collaboration between the University of Twente, the University of Surrey and the University of São Paulo and seeks to investigate the causal mechanisms underlying disparity and social injustice in job accessibility and air quality in metropolitan areas, and the potential of transit-oriented development to promote social justice.

1.1 **Research questions**

In order to achieve the research objective, a main research question and several sub-research questions have been formulated. These research questions are described and explained in this paragraph. The main research question is formulated as follows:

- To what degree do anticipation and lagged effects of the life events affect car ownership and most used mode? (considering aspects of the built environment, socio-economic-, personal- and travel related characteristics).

In order to find a satisfying answer in the available time and with the available resources, the main research question had to be operationalized, by formulating more specific sub-research questions:

i. Which life events can be expected to have anticipation and lagged effects on car ownership and most used mode?

Life events are rare events and do no happen often. It was therefore important to determine in advance which life events may have impact on the mobility choices. This research question was answered by following some steps. First, the dataset was explored by using the software: IBM SPSS Statistics, Excel and Tableau (a data preparation and visualization tool) to conduct a statistical analysis on all the individuals of the households that reported a life event. By doing so, it was possible to observe the occurrence of the life events over the waves. The alternatives of the life events were determined based on their spatial variation regarding job accessibility. Then, the prepared data sets were used to estimate MNL- and ML models (described in section 4). With the use of the software PythonBIOGEME Bierlaire (2016), the models were estimated and from these models it became clear which life events affect the mobility choices.

ii. Which factors are influential in determining the anticipation and lagged effects of life events on car ownership and most used mode?

A set of influential explanatory variables (i.e. built environment-, socio-economic- and travel related variables) were selected according the literature review, and are collected from the CBS database and the Astrid project at postcode four level. The residential postcodes available in the MPN data set were used in this regard. The correlation between the variables was also a point of attention. The built environment variables having a higher correlation (e.g. correlation coefficient higher than 0.6) can cause problems during the estimation process. Therefore, the selection of variables was based on literature, the availability of variables, the correlations between the variables and their statistical significance derived from the mixed logit models.

Furthermore, 9 mixed logit models and 6 joint mixed logit models were developed and estimated. The delta (i.e. the difference between the explanatory variables in each time interval) were very important in this regard to be able to find a causal effect between the life events and the mobility choices. The effect of 3-time intervals (i.e. 2013-2014; 2014-2015 and 2015-2016) are analyzed, as described in section 4. Time interval: 2013 – 2014 and 2014-2015, where year 2014 is considered as the reference wave (year "t"), 2013 as year "t-1"and 2015 as year "t+1", provides the information whether there is anticipated behavior of the life events and the mobility choices or not, while time Interval: 2014-2015, presents the lagged effect. On the other hand, considering time interval 2014-2015 and 2015-2016, where wave 2015 is the reference wave (year "t"), 2014 is year "t-1" and 2016 year "t+1", then time interval 2014-2015 can also present an anticipation effect, while interval 2015-2016 presents only the lagged effects.

iii. To what extent can the model output be implemented? (i.e. what policy implications can be recommended by using the model output for the estimation of elasticities for some built environment variables?)

This question was answered by estimating the probabilities for the different models and comparing them with each other. Elasticities were also calculated using job accessibility variables to forecast the travel demand of the respondents and derive policy implications from the findings.

The remainder of this thesis starts with the study background where the literature on the temporal effects of life events on travel behavior is described and discussed. Section 3 provides a brief description about the dataset that is used for conducting the analysis. In section 4 the research setup and used methods for the analysis are described, this section includes the data preparation and analytical framework. The descriptive statistics, model estimation and model results, forecasting and elasticities are discussed in section 5. Section 6 provides a conclusion about the results and gives some recommendations for future research on this topic. The paper ends with an overview of the used references and the appendices.

2 Study Background

2.1 Life Events

According to the literature the effects of the built environment, demographic-, socio-economic- and travel related characteristics on car ownership and mode choice have been studied by many researchers, and it is noticed that these variables are of great importance. However, the studies did not focus on the panel-, anticipation- and lagged - effects of life events, considering both car ownership and most used mode. A life event can be defined as a major event that changes a person's status or circumstances, such as giving birth, marriage, divorce, death of spouse, loss of job etc., and are often discussed in terms of stressors. Stressors can arise from different events and can be addressed by different longer-term decisions. For instance, a change in job location may increase commute distance and lead to a need to decrease travel time. According to Van Ham and Hooimeijer (2009) this can be achieved by different actions such as changing residential location close to work or owning a car or a combination of both. It is further very important to keep in mind that life events are rare events, and do not occur very often. Cao and Mokhtarian (2005) argued that if a household recently changed its residential location, it is likely to prefer a solution through a change in travel resources instead of changing residence again. Furthermore, changes in aspirations, leading to stressors, can also arise from various sources. For example, changes in the household composition, such as childbirth or home leaving of children, may trigger a change in the need for transportation options. For instance, childbirth might generate an extra demand for car because one has to drop off and pick up the children from a day care center, while home leaving of a child may imply a lower need for an additional car in the household.

voor Mobiliteitsbeleid–jaco et al. and Berveling et al. (2016) analyzed the mobility impact of three life events (child birth, move house and new job) using 3 waves of the MPN data (2013-2015). They found that 50% of the young adults (between 18 and 39 years) agreed that their mobility changed because of child birth, while almost 40% stated that their mobility changed because of the fact that they moved house and 80% of the young adults experienced a change in their mobility due to a new job. Furthermore, they concluded that child birth increases car ownership as well as walking, while decreasing the use of public transport and bicycle. They found that child birth has a lagged effect on car use, young women who got a child in 2014 were more likely to use the car in 2015. Moving house as well as getting a new job lead to a significant increase in car ownership. They further argue that life events provide a 'window of opportunity' for policymakers to intervene and provide information about safe and sustainable mobility to young mothers, because life events lead to a discontinuity of habitual behavior, and people are in this phase willing to think about and search for other transport options.

Child birth and home leaving of children can both be described as family related life events, but as described above, they can have different impact on mobility choices. Therefore, it is very important to take this issue into account when defining the alternatives for the life events. In this regard the life events can be divided into spatial and non-spatial life events. For example, child birth can be defined as a non-spatial life event, and home leaving of children as a spatial life event. Furthermore, a changed physical condition or a change in household's resources, such as income may lead to an increased aspiration for car ownership. For instance, an income increase will reduce budget limitations, but it might also create additional demand, for example a bigger car or an additional luxury car for more comfort. Chatterjee et al. (2013) used interview data in their analysis and they found that life events also led to changes in bicycle use. (Clark et al., 2016) studied how the likelihood of changing commute mode is influenced by life events and they found that changes in commuting behavior are strongly influenced by life events, spatial context and environmental attitude. However, much remains to be learned about the extent to which different life events trigger behavioral change and the conditions under which life events are more likely to trigger change.

Dargay and Hanly (2007) conducted a descriptive analysis of the British Household Panel Survey and found that commuters that moved home were more likely to change their mode between years than those who didn't moved their home. They also find a significant change in mode for commuters that changed employer as well as for those that changed both home and employer. Oakil et al. (2011) used data from a retrospective survey capturing 21-year life histories of nearly 200 respondents in the Utrecht region in The Netherlands and executed a multiple regression analysis of the relationship between a range of life events and commute mode changes. They found that switches from commuting by car were associated with changing to part time work, changing employer, and separation from a partner one year before the commute mode change. In addition, Switches to commuting by car were associated with birth of the first child, changing employer, and separation from a partner one year before the commute mode change. However, residential relocations were found to be insignificant. In addition, the effect of residential relocations on the commuting mode of 433 university employees was studied by Verplanken et al. (2008) and they concluded that employees who had moved within the last year used the car less frequently than commuters who had not moved within the last year. Oakil (2013) analyzed the anticipation and lagged effects of life events on car ownership level regarding mobility issues and other household events. He used Mixed Logit models to illustrate the relationship between changes in car ownership, other events and state variables.

However, the studies mentioned above analyzed the temporal effects of life events on travel behavior, but they did not consider both mobility choices (most used mode and car ownership) simultaneously, as dependent variables in joint models. In this thesis, these two aspects will be included both as dependent variables and will be estimated simultaneously in joint mixed logit models with the life events. In this regard, aspects of the built environment, socio-economic characteristics and travel related variables, such as travel time and travel distance will also be considered. Section 2.3 of this paper describes the literature background of the joint mixed logit estimation.

2.2 Car ownership and most used mode

Car ownership and mode choice are generally considered as important variables in travel behavior research. Some empirical studies consider car ownership as the dependent variable explained by the built environment, while other studies include it as the independent variables explaining car travel behavior (Van Acker & Witlox, 2010). However, most of these studies do not consider the temporal effects of life events (i.e. anticipation- and lagged effects) on car ownership and most used mode. According to Van Acker and Witlox (2010) car ownership can be considered as mediating the relationship between the built environment (BE) and travel behavior (TB). Modeling car ownership is very important in travel demand analysis because it is a key determinant of the travel behavior of individuals and households (Bhat & Pulugurta, 1998). In addition, car ownership can affect trip frequency choice, destination choice for non-work activity participation and mode choice to work and to non-work activity destinations.

The effects of life events on various aspects of travel behavior and mobility have recently been studied by some researchers. Oakil et al. (2014) conducted a panel analysis using data from a retrospective survey and they found a strong and simultaneous relationship between car ownership changes and household formation and dissolution processes. Furthermore, childbirth and residential relocation invoke car ownership changes. Changes are also made in anticipation of future events such as employer change and childbirth. Childbirth is associated with increasing the number of cars, while the effect of employer change decreases the number of cars. They also found that job change increases the probability of car ownership change in the following year. Verhoeven et al. (2005) analyzed the effect of life events on travel mode choice by using Bayesian Belief network in order to model the effects of life trajectories on mode choice decisions. Based on retrospective event history data, they found that housing status, car availability, public transport season ticket holder ship and income, as well as changes in these states are related to mode choice. Their findings also indicated the influence of time on the utility of mode choice. Prillwitz et al. (2006) studied ownership of mobility resources (such as car and public transport pass) and vehicle miles travelled. They analyzed ownership of mobility resources and found that birth of the first child and residential relocation are related to an increase in car ownership. Beige and Axhausen (2008), used hazard models, analyzing mobility resource ownership, residential, employment and education durations. They found that changes in residence, education and employment decrease the probability of variations in the ownership of mobility resources. In another analysis by Beige and Axhausen (2012), it was analyzed whether changes in mobility resource ownership are significantly related to changes in employment, education and residential location as well as in household demography. They concluded that there are significant associations between these events. For instance, an increase in the travel distance between residential location and education decreases the probability of changes in car availability.

Considering the above described aspects, in this thesis car ownership and most used mode are used as the dependent variables, with a set of explanatory variables (SE, BE and TR-variables) that can explain the link between the temporal effect of the selected life events in the MPN dataset.

2.3 Mixed logit and Joint Choice model

As described and discussed in section 2.1, is that research on the temporal effect of life events on mobility choices has been limited so far. However, Oakil (2013) conducted a study on households' decision to change their car ownership level in response to actions or decisions regarding mobility issues. In this regard, mixed logit models were used and have been able to analyze the anticipation effect of life events on car ownership level successfully. According to McFadden and Train (2000), the mixed logit (ML) is very flexible model that can estimate any random utility model and since the ratio of mixed logit probabilities (P_{ni}/P_{nj}) depends on the whole data set, including also attributes of alternatives other than *j* or *i,* ML does not exhibit independence from irrelevant alternatives (IIA). Furthermore, Bhat and Guo (2007) used joint model estimation in order to analyze residential location choice and car ownership, where the mixed logit framework is used to derive the joint model for the particular case of the simultaneous decisions of residential location choice and car ownership. Another good example is the work done by La Paix Puello (2012), where research was done on the impact of the built environment on travel behavior by using a joint mixed ordered model for simultaneously estimating residential location choice and the number of trips. The model included both socio-economic and built environment attributes and was able to successfully test residential self-selection. Like La Paix Puello (2012), and Bhat and Guo (2007), other researchers (see, Lerman (1976); Adler and Ben-Akiva (1976); Timmermans et al. (1992); Bhat et al. (2014)), have used joint estimation in the analysis of travel behavior as well, and have shown the benefits of the joint estimation. Lerman (1976), found in his study that estimation of joint-choice model proved to be feasible and resulted in behaviorally and statistically acceptable parameter values. All variables produced coefficients of the expected signs and magnitudes consistent with the behavioral notions on which the model specification was based. In general, the estimation of joint-choice models for travel demand was shown to be a computationally tractable alternative to less acceptable conditional approaches.

Since the objective in this thesis is to estimate whether the same set of explanatory variables, can explain both the life events model as well as the mobility choices and determine the association between the temporal effects of the life events on these mobility choices, both mixed logit and joint mixed logit models are used. In this regard the differences (deltas) of explanatory variables between the waves are determined and estimated in the models.

2.4 Influential Explanatory Variables

According to Schwanen et al. (2004), travel behavior that people actually have or that they want to have is not always matched, because of the built environment. Further, when considering the built environment, then it is important to describe the "5D" variables that can be used as measures of the built environment. These 5Ds, are density, diversity and design by (Cervero & Kockelman, 1997), and destination accessibility and distance to transit by (Ewing & Cervero, 2001). According to Stevens (2017), Density measures population, households, or jobs per unit area. Higher densities might reduce driving by placing destinations closer together, thus possibly reducing trip lengths and making alternative transportation options more feasible. Diversity measures the mixture of different land uses in a given area. Design measures street network characteristics within an area, helping to differentiate pedestrian-oriented from auto-oriented areas. Destination accessibility measures how easy it is to access trip destinations. It is sometimes measured as the distance from a household to downtown, or the number of jobs reachable within a given travel time by car (or by transit). Distance to transit is measured as the distance from a household to the nearest transit stop, following the shortest street route. Ewing and Cervero (2010) conducted a meta-analysis (an analysis that uses summary statistics from individual primary studies as the data points in a new analysis) in order to summarize empirical results on associations between the built environment and travel. They found that walking is most strongly related to measures of land use diversity, intersection density, and the number of destinations within walking distance. Bus and train use are equally related to proximity to transit and street network design variables, with land use diversity a secondary factor. However, population and job densities were found to be only weakly associated with travel behavior.

Like this study of Ewing and Cervero (2010), many other studies have analyzed the associations between the built environment and travel, but did not considered the temporal effects of life events. Therefore, adding the spatial dimension to the life events and analyzing their effect on travel (i.e. most used mode and car ownership) is an important point in this thesis. Determining the association between life events, the built environment (BE) and travel behavior (TB) can be very complex. The relationship between TB and BE is multidimensional in nature, La Paix Puello (2012). There are many aspects to the BE, including accessibility aspects, such as distance to transit stops, distance to employment location, presence and connectivity of walk and cycle paths, land-use mix, block sizes etc. Likewise, there are many dimensions of life events such as changing employer, getting a child, getting divorced and residential relocation that in turn might have some influence on the travel demand or behavior of people. Furthermore, commuting requirements are considered in home or job moves. According to Van Ommeren et al. (1997), every extra ten (10) kilometers of commuting distance decreased the expected duration of the current job and current residence by more than two years. Further, Clark et al. (2003) used Puget Sound Transportation Panel data over the years 1989–1997 and found a critical value of eight (8) kilometers as the commute distance beyond which the likelihood of decreasing commute distance (by moving home or changing job) increases strongly. Table 1 provides an overview of some influential variables that are used in order to analyze the life events, car ownership and most used mode of the respondents in the used MPN dataset over the four waves.

Table 1: Influential explanatory variables

Variable type	**Explanatory variables**	**Literature reference**
Demographic – and socio-economic - characteristics	Gender and Age	Bhat and Guo (2007); Boarnet and Sarmiento, 1988
	Employment and Education	Dieleman et al, 2002
	Personal net monthly income	Shay and Khattak (2004)
	Car driving license	Van Acker and Witlox, 2010; Shay and Khattak (2004)
	Parking availability for cars	
	Number of persons per household	
Trip-related characteristics	Travel distance and Travel distance	Van Ommeren et al. (1997); Clark et al. (2003); Yasmin et al., 2015)
	Preferred. mode for work, school. Grocery, shopping, Leisure	Van Acker and Witlox, 2010
Built environment variables	Urbanity level	Shay and Khattak (2004)
	Population density	Stevens (2017)
	Distance to baby day care	Ewing & Cervero, 2001; Ewing and Cervero (2010)
	Distance to train station	
	Job accessibility by Bicycle (**BnR**)	ASTRID project: Accessibility, Social justice and Transport emission Impacts of TOD strategies) project
	Job accessibility by public transport (**WnR**)	
	Job accessibility by car (**Car**)	

Furthermore, it has to be noticed that analyzing the effects of life events on travel behavior can be done on an individual level as well as household level, depending on the available data. Some life events can be individual life events and others, household life events. For instance, if an adult in the family gets a new job, then this does not automatically mean that it is a household life event. However, this could be a household life event if the whole household would have to move. There can be a household interaction, but that strongly depends on the individuals in the household. Demographic – and socio-economic - characteristics on the individual level as well as the household level are expected to affect both trip characteristics and activity characteristics (e.g. Clifton et al. (2016) and Bhat et al. (2004)). Furthermore, according to Van Acker and Witlox (2010) people may choose their residential location according to their personal attitudes and preferences. Bhat and Guo (2007) argue that one of the elements of the complex relationship between the built environment measures and travel is the moderating influence of the characteristics of decision makers on travel behavior (individuals and households).

These characteristics may include socio-demographic factors such as age, gender, income, and household structure, travel-related and environmental attitudes. These environmental attitudes can be preference for non-motorized or motorized modes of transportation and concerns about mobile source emissions, and perceptions concerning the built environment attributes. However, according to Kitamura et al. (1997), attitudes are more strongly associated with travel than land use characteristics. Further, the household structure is also an important aspect to consider, because it does not necessarily mean that if for example a household gets a baby, that they will automatically buy a car. It can also be that the mother/father or other member of the household stays at home to take care of the baby and therefore does not need a transport mode to take the baby to a day care.
Moreover, Shay and Khattak (2004) conclude that characteristics of a decision maker may have a direct influence on travel behavior. For example, higher income households are more likely to own cars compare to lower income households. However, there might also be an indirect influence on travel behavior by modifying the sensitivity to the built environment characteristics. For instance, it may be that high-income households, regardless of the residential location, own several cars and use them more often than low income households. In addition, travel distance can also be of great importance for individual mode choice (Yasmin et al., 2015). For a predefined origin destination, the distance is the same every time an individual travel. Therefore, trip distance does not depend on traffic. On the other hand, the travel time depends on the traffic (rush hour or off-peak, road works, accidents, incidents), mode etc. Thus, it can be argued that travel distance is more objective. However, travel time is very often considered as a very important attribute in transport modeling. As a result, in this thesis panel data is used to analyze life events, incorporating a variety of explanatory variables to describe the association between the temporal effects of life events and mobility choices (car ownership and most used mode), including travel-related, socio-economic characteristics and built environment variables.

3 The Netherlands Mobility Panel (MPN)

This study was conducted using data from 'The Netherlands Mobility Panel' (in Dutch: MobiliteitsPanel Nederland MPN). This mobility panel is the world's largest ongoing mobility panel and was initiated by the Netherlands institute for Transport Policy Analysis (KiM), in order to be able to identify and explain day-to-day variations in mobility and the role of habits in travel behavior, Hoogendoorn-Lanser et al. (2015). This mobility panel consists of a state-of -the-art web based three-day mobility diary, a household – and a personal survey. It contains approximately 6000 respondents in around 2500 complete households from whom data has been collected since 2013. The first data set was collected in the period from August to November 2013. 3,572 households have participated in this wave in the autumn and 6,126 persons completed a questionnaire. Nearly 4,000 people have filled out a three-day travel diary, which makes it possible to know various personal characteristics such as age, gender, education and employment status, life events as well as the mobility of these people. The life events that are present in the MPN dataset are presented below in the table 2. From table 2 it can be seen that the life events: new job, change work hours/days and change work location occur the most over the four waves, while the events: death of someone in the house hold, cohabitation and getting divorced have the lowest respondent year observations. As a consequence, these life events are not included in the analysis.

Table 2 : overview of the life event in the MPN database

		Wave 2013	**% of column total (N=847)**	Wave 2014	**% of column total (N=566)**	Wave 2015	**% of column total (N=576)**	Wave 2016	**% of column total (N=555)**	Wave 2013-2016-row total	**% of column total (N=2 544)**
1	New job	114	**13**	72	**13**	88	**15**	84	**15**	358	**14**
2	Start working	42	**5**	12	**2**	11	**2**	17	**3**	82	**3**
3	Stop working	90	**11**	44	**8**	41	**7**	32	**6**	207	**8**
4	Work less	63	**7**	54	**10**	56	**10**	47	**8**	220	**9**
5	Work more	42	**5**	51	**9**	55	**10**	43	**8**	191	**8**
6	Change work hours/days	131	**15**	106	**19**	110	**19**	91	**16**	438	**17**
7	Change in work location	96	**11**	77	**14**	63	**11**	74	**13**	310	**12**
8	Change in school/education	63	**7**	29	**5**	39	**7**	44	**8**	175	**7**
9	Birth of a child in household	46	**5**	34	**6**	37	**6**	34	**6**	151	**6**
10	Death of someone in household	9	**1**	5	**1**	2	**0**	4	**1**	20	**1**
11	Getting divorced or brake up	29	**3**	9	**2**	15	**3**	9	**2**	62	**2**
12	Cohabitation	21	**2**	10	**2**	11	**2**	22	**4**	64	**2**
13	Move house, one parent or one of the children leaves the house	71	**8**	43	**8**	29	**5**	40	**7**	183	**7**
14	One member of the household leaves the house	30	**4**	20	**4**	19	**3**	14	**3**	83	**3**
	Total	847		566		576		555		2544	

Furthermore, the MPN includes 1,978 households where all members filled out completely both individual questionnaires as well as the travel diary. This makes it possible to analyze travel behavior on an individual level as well as at the household level. The MPN survey provides travel data of four waves (2013 – 2016) for work and non-work activities. In non-work activities, MPN considers trips, such as picking up people or goods, shopping (grocery and non-grocery) trips, tours (including walking), hobbies (e.g. sports), leisure activities, personal care services etc. For each trip, the desired mode, time of the trip generation, distance covered from the trip generation point, trip generation and attraction area in the Netherlands, travel time from trip generation, parking costs, delays are collected by MPN survey. The four waves of the MPN database are used to conduct this study. However, only the stayer respondents of these waves are considered in the analysis. The stayer respondents are the respondents who participated in all four waves. There are 1273 stayers divided over 937 households. From these households, about 70% are single households, 25% of the households consist of 2 persons. 3% have 3 persons in the household, 1% with 4 persons and only 1 household consist of 6 persons. Since most of the households are single person households, it is likely that conducting the analysis on the individual level will provide better model output. Furthermore, a big advantage of the MPN survey, is the fact that it contains panel data. Panel data, also called longitudinal data or cross-sectional time series data, is data where multiple cases, such as people are observed at two or more-time periods. The MPN data therefore has the ability to overcome the limitation of the cross-sectional travel surveys where only one day is surveyed for each respondent. Hence, in order to understand the dynamics and changes in travel behavior the MPN survey examines the implication of the long-run dynamics, including short-run and temporal variation in individual travel behavior and accessibility for transport policy making (Geurs et al., 2012). Lastly, it is a great opportunity to use this dataset for conducting a joint mixed logit estimation on the temporal effects of life events on mobility choices, since this data set has not been used previously for this purpose of research.

4 Research Methodology

4.1 Available Data

About 95% of the data that is used is provided by the MPN survey, which contains panel data collected by a personal-, household survey and mobility diary from 2013 till 2016. Additional built environment data was collected from the CBS data base. Job accessibility by car, public transport (WnR) and bicycle (BnR) was also used in the analysis in this thesis. Those were collected on postcode four level from the ASTRID (Accessibility, Social justice and Transport emission Impacts of TOD strategies) project, conducted at the University of Twente. In this project an analysis was conducted on spatiotemporal variations in job accessibility by the above-mentioned transport modes in the Netherlands. Job accessibility by public transport (WnR), is the number of jobs reachable from a certain origin to a certain destination by public transport. Job accessibility by car, is the number of jobs reachable by car. On the other hand, the bike-and-ride option holds when it is faster than the walk-and-ride option and if the cycling component of the multi-modal trip is less than 30 minutes and further than 200 meters away from the network lengths (See also Appendix B: Data availability and variable selection). Further, demographic and socio-economic characteristics as well as trip related characteristics were selected and used in this thesis. An overview of all selected explanatory variables is presented in table 1.

4.2 Defining the dependent variables

Life events

As can be seen from table 2 is that there are 14 life events available in the MPN dataset. These life events occurred in the four waves and the time of occurrence was 0 to 24 months ago. For example, a life event reported by a respondent in wave 2016, could occur in the same year or in 2015 or in 2014. It is further very important to keep in mind that life events are rare events, and do not occur very often. Therefore, not all the life events mentioned in the table above could be included in the analysis, but only the events that had more than 2% of the total respondent observations and that could be segmented according the possible combinations of their occurrence over the four waves, see also Appendix C. As a consequence, three life events were excluded from the analysis, namely: *death of someone in the household*, *getting divorced* and *cohabitation*. The life events are grouped into

8 categories as shown in table 3, along with the alternatives of the mobility choices (car ownership and most used mode). However, a distinction was made between spatial and non -spatial life events by exploring the variation of accessibility in terms of job accessibility, when people move their residential- or work location or when they change school or education. This distinction is important, because people can for example have a family related life event (i.e. child birth or move house or both) and when they move house, it can happen that they move to a neighborhood with the same accessibility level, or that is better accessible by for example public transport or less accessible by public transport. If they move to a location with the same accessibility level, then there is no variation in the build environment variable, which means that these variables will also not be significant in the model estimation. Therefore, the variation or difference between waves (deltas: wave-13-14; wave-14-15 and wave-15-16) of the explanatory variables is important. The life event, move house (referred to as a spatial life event in this study) can then be expected to have an impact on the most used mode or car ownership if people move to a location with a different accessibility level compared to where they lived before. However, the impact on the mobility choices can only be measured clearly when there is a distinction between spatial and non-spatial events. The residential location of the respondents (on postcode four level) in the MPN data was used in order to explore the moves of the respondents. It was clear to see when a respondent moved from postcode "A" to postcode "B" and if there was a change in accessibility level in terms of numbers of jobs reachable by car, public transport and bicycle. In contrast to the family related- and a combination of family and work-related life events, the education and work-related life events were not divided into spatial and non-spatial events, because there was no variation in the spatial moves in terms of accessibility level for the respondents who reported these life events (see figure 4, Appendix C).

Table 3: Overview alternatives for life events, car ownership and most used mode (% of column total)

				WAVE_13-14			**WAVE_14-15**			**WAVE_15-16**		
		ALTERNATIVES	Description	LE	CO	MUM	LE	CO	MUM	LE	CO	MUM
Life events	1	Work related LE	LE: 1,3,4,5,6 or 7	23			23			22		
	2	Education related LE	LE: 8	2			2			2		
	3	Family related LE -Non-spatial	LE: 9	3			3			2		
	4	Family related LE -Spatial	LE: 13/14	4			4			4		
	5	Work-Family LE- Non-spatial	LE: (1,3,4,5,6 or 7) and (9)	2			1			2		
	6	Work-Family LE- Spatial	LE: (1,3,4,5,6,7) and (13 or 14)	3			2			1		
	7	None	LE: 0	56			60			61		
	8	Others	Random mix of LE	7			5			6		
Car ownership	1	Car acquisition			72			72			72	
	2	No car acquisition			28			28			28	
Most used mode	1	Car				47			46			48
	2	Public transport (pt)				11			12			12
	3	Bicycle (bike)				31			30			28
	4	Walk				11			12			12

LE: Life event; CO: Car ownership; MUM: Most used mode

As can be seen from table 3, is that the alternative "None", has the highest respondent observations (more than 50%). This alternative represents the group of respondents who did not have a life event. Again, the portion of this group underlines the fact that life events are rare events. As a consequence, alternative 7 was used as the reference alternative in the model estimations. An issue with the sample size of the life event model is that some alternatives have quite a low portion of observations (less than 5%). This can be a problem in the model estimation, since it will be difficult to add many parameters in the utility of those alternatives and will also not be able to show a lot of significance in the model output. For a better understanding of how the alternatives of the life event model are created and determined, see also Appendix C.

Car ownership and most used mode

As presented in table 3, the car ownership models include binary alternatives. These alternatives are "car acquisition" and "no car acquisition". "car acquisition" represents the group of people who had a car, while "no car acquisition" applies to the group of people who did not have a car. Table 3 shows that the alternative "car acquisition" has a lot more observations (72%), compared to "no car acquisition" (28%), nevertheless, "no car

acquisition" was considered as reference alternative in the modelling part. This was done because it was important for the analysis to measure the utility for the the group of people who own a car in order to analyze the association with the life events.
The most used mode models on the other hand, contain four alternatives: car (car as driver and passenger), public transport (Pt: train and BTM), bicycle and walk. For example, if a respondent used the car 5 times, the bicycle 3 times and public transport 2 times in a particular wave, then the car was selected as most used mode for this respondent in that wave. Furthermore, the alternative car was used as the reference in the model estimation, because this alternative has the largest observations. It was chosen to use the most used mode in the analysis, because when exploring the dataset, it was clear that people really had a dominant mode (most frequent used mode) in each wave over all the different travel purposes (during the three days- in their travel diary-). However, in a few cases it happened that there was no dominant mode (i.e. some modes were equally used). For example, it happened that the car and the bicycle, or the car and public transport, or the bicycle and public transport were equally used. In those situations, the car was chosen above the bicycle and above public transport. When the bicycle and public transport were equally used, then the bicycle was chosen above public transport. This was done because it was found from the statistics that for all trip purposes the car was the first dominant mode, or most used mode, followed by the bicycle, and public transport in the third place. From figure 8 in appendix C it is also clear that the car is the first dominant mode, followed by the bicycle and public transport in the third place. From the 14 trip purposes, in 12 cases the car is the dominant mode, while the bicycle is the second dominant mode in 10 trip purposes, and public transport takes the third place. Public transport appears to be the most dominant mode for education related trips, however with only 0.4% difference with the bicycle, and the second dominant mode in work- and business-related trips.

4.3 Model development and model framework

Discrete choice modeling is widely used in transport modeling in order to test the priori-assumptions formulated from the descriptive statistics and to provide more and clear information on the association between variables. Therefore, discrete choice modeling technique is applied in this study to identify the temporal effects (i.e. anticipation-and lagged effects) of the life events on mobility choices (i.e. car ownership change and most used mode). In this regard, several discrete choice models have been developed and estimated. These models are built based on the random utility maximization theory, which are well known and widely used in the estimation of such discrete choice behavior (Scarpa & Thiene, 2005; Wu et al., 2011). According to Train (2009), the mixed logit probability can be derived from utility-maximizing behavior in several ways that are formally equivalent but provide different interpretations. These derivations can be based on random coefficients or error components. Random coefficients are widely used and proved to be very useful. Nevertheless, first, only error components are applied in the mixed logit models to explore the anticipation and lagged effects of the life events. Next, for the joint models, both error components as well as random coefficients are included, since error components create correlations among the utilities for different alternatives and are very useful when using panel data, and random coefficient are also proved to be powerful in the analysis of segments of population. Furthermore, the statistical significance of the parameters is tested at 90% confidence level in order to select variables, but only variables with a significance level of 95% where kept in the final models. For two tailed tests, the critical value of t-statistics is 1.645 at 90% confidence level and 1.960 at 95% confidence level. The alternative specific constant (ASC) of the alternatives are also estimated, however, the alternative with the highest observations or with the least importance was considered as the base- or reference alternative. The variables were added one by one in the models based on the priori-assumptions of the descriptive statistics, and the parameters that were not significant were removed from the model according the specification test. Different model specifications are tested and the final models are chosen based on the informal tests (signs and magnitudes), t-test, p-value and overall goodness-of-fit measure. In this regard, Python BIOGEME (Bierlaire,2016) is used.

4.3.1 Model Framework

In order to have an idea of which parameters are influential in the modeling process, the modeler needs to conduct some descriptive statistics on the preliminary selected variables. Even though, the descriptive statistics are providing some information about the link between the life events and the mobility choices, it is still important to have a verification through discrete choice modeling. The conceptual model framework of the mixed logit models and that of the joint models are described in this section of the thesis and depicted in figure 1 and 2, respectively. Figure 1 provides a visualization of how the anticipation and lagged effects of the life events on car ownership or most used mode can be analyzed. For this purpose, the deltas (i.e. the differences between the explanatory variables in consecutive waves) were determined and estimated in the models. Looking at anticipation effects, then the deltas between the explanatory variables of the present wave (denoted as "year t"), and the previous wave (denoted as "year t-1"), had to be considered. On the other hand, when analyzing the lagged effects, then the deltas between the explanatory variables of the present year (denoted as year "year t"), and the next year (denoted as "year t+1"), are taken into account. The MPN data contains 4 waves and therefore, nine (9) mixed logit models were estimated because of two possibilities/situations. The first situation is where wave 2014 is considered as the present wave ("year-t"). Wave 2013 is then, "year t-1" and wave 2015 is "year t+1". The other situation applies when year 2015 is seen as the present wave ("year t"), and wave 2014 is then "year t-1", and wave 2016 functions as "year t+1". So, there are 3 sets of 3 models: considering the deltas of time interval 2013-2014 (set 1), then we have 3 models, namely the life event model (LE), the car ownership model (CO) and the most used mode model (MUM). For time interval 2014-2015 (set 2) the same as well as for time interval 2015-2016(set 3) (see figure 2 below).

The decision to use the deltas of the explanatory variables in the analysis of this thesis originated from the work done by Oakil (2013). Oakil analysed in his work whether child birth, residential relocation, job change or employer change and their time of occurrence, were associated with any kind of change (decrease or increase) in car ownership. Here the dependent variables were binary variables: changing car ownership level or not changing car ownership level, while the life events were used as explanatory variables. So, he used the explanatory variables as static variables and the dependent variables as the dynamic- or changing variables.

Since in the present thesis, the main objective was to analyse the temporal effects of life events on both car ownership and most used mode and to have these three aspects as dependent variables, where a set of explanatory variables is used to analyse the association between the life events and car ownership and between the life events and most used mode, it was decided to determine the change or difference (i.e. the delta) in the explanatory variables between two consecutive waves. Before using this approach, the explanatory variables were kept static, but it was noticed that it was not suitable for determining the anticipation and lagged effects of the life event. In order to really measure the effects, it was necessary to consider the changes (deltas) in the explanatory variables rather than keeping them static. A big advantage of using the approach of the deltas, is that it is a straightforward and simple to implement approach. A disadvantage is that with this approach it is only possible to measure the effects of the life events, maximum 12 months backwards or 12 months forward in time.

Further, the utility of the grouped life event models can be defined as a function of the change in socio-economic-characteristics (SE), built environment (BE)- and travel related (T)- variables. This is the same for the car ownership- and the most used mode models. The ε_{Mle} , ε_{Mco} and ε_{Mmfm}, represent error components of the life events-, the car ownership- and most used mode models, respectively. Furthermore, in order to provide a basis for comparison, MNL models were developed and estimated, where the parameters were put one by one in the model. To be able to find out which parameters may be statistical significant, basic statistics were conducted, which are presented in Appendix D: Elaborated statistics. MNL models are known as the simplest and most used logit models in discrete choice analysis and assume that the residuals are independent and Gumbel distributed (Train, 2009). However, the use of panel data can be an issue in the MNL model. Panel data represents a repeated

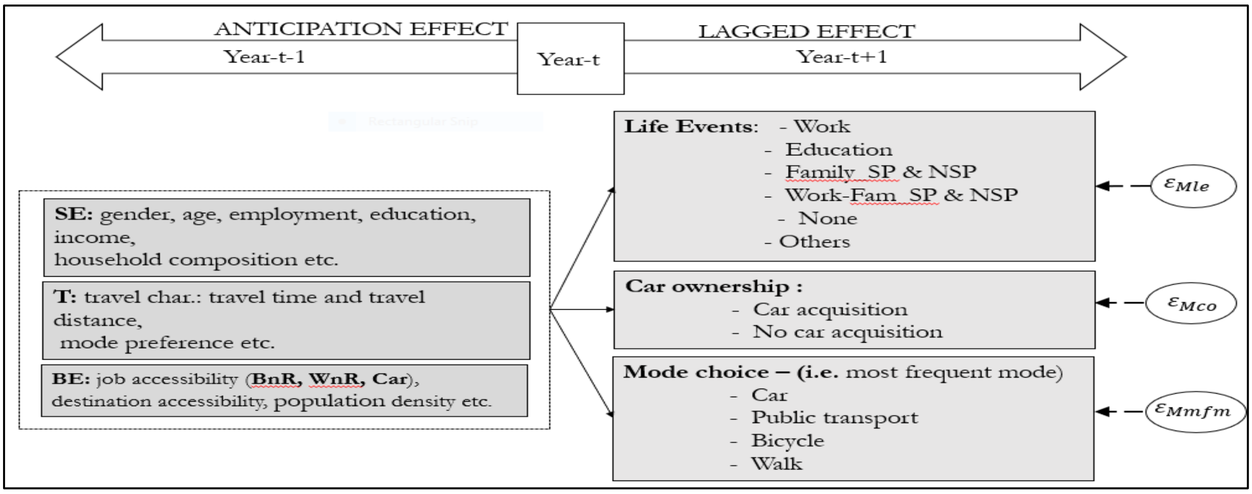

Figure 1: Conceptual Mixed Logit Models framework

choice. Dynamics associated with unobserved factors cannot be handled, since the unobserved factors are assumed to be unrelated over choices. In the situation where unobserved factors can affect each of the individual's choices, it is advised to use Mixed logit models. According to McFadden and Train (2000), the ML model is a highly flexible model that can approximate any random utility model. This model allows for random taste variation and does not exhibit IIA. Therefore, Mixed Logit (ML) models were also developed based on the final MNL models. According to Train (2009), a mixed logit model can be used simply representing error components that create correlations among the utilities for different alternatives. The utility of individual ***n*** relative to alternative ***j*** can be specified as:

$$U_{nj} = \beta \Delta X_{nj} + \mu z_{nj} + \varepsilon_{nj} = \beta \Delta X_{nj} + \omega_{nj} \qquad \text{Eq. (1)}$$

Where, ΔX_{nj} and Z_{nj} are vectors of observed variables that are related to the alternatives of the life events or of the mobility choices *j*. ΔX_{nj} represents the difference (delta) between explanatory variables in consecutive waves, β is a vector of fixed coefficient to be estimated and u is a vector of random terms with zero mean. ε_{nj} is distributed iid extreme value. The terms in Z_{nj} are error components that define the stochastic portion of utility, together with ε_{nj}. Thus, the unobserved (random) portion of utility, is: $\omega_{nj} = \mu z_{nj} + \varepsilon_{nj}$, which creates correlation with the individuals, depending on the specification of the error term Z_{nj}. Considering the model frameworks in figure 1 and 2, the utility equations for the different models can be written as follows:

$$\text{Anticipation}: \quad U_{nj(t-1)} = ASC_{j(t-1)} + \sum_{l=1}^{m} \beta \Delta X_{nj(t-1)l} + \omega_{nj} \qquad \text{Eq. (2)}$$

$$\text{Lagged:} \quad U_{nj(t+1)} = ASC_{j(t+1)} + \sum_{l=1}^{m} \beta \Delta X_{nj(t+1)l} + \omega_{nj} \qquad \text{Eq. (3)}$$

In above presented equations, the ASC's are the alternative specific constants, and the β*'s,* coefficients to be estimated. U_{nj} is the utility of individual ***n*** relative to alternative ***j*** over time interval *t-1 or t+1*. *J* is an alternative of the life events, or of car ownership or most frequent used mode. ΔX_{nj} is the delta (difference) between explanatory variables for individual *n* over alternative *j*, at time interval *t-1 or t+1*, *l* is an index of the explanatory variables and ω_{nj} is an alternative specific error component to be estimated. Furthermore, the unconditional probability can be written as the integral of the product across all values of *ω*, where *θ* is the vector of fixed parameters:

$$P_{nj} = \int \left(\frac{e^{u_{nj}}}{\sum_i e^{u_{ni}}} \right) f(\omega_{nj} | \theta) d\omega_{nj} \qquad \text{Eq. (4)}$$

Where, the first part, $\left(\frac{e^{u_{nj}}}{\sum_i e^{u_{ni}}}\right)$ represents the logit probability and the second part $f(\omega_{ni}|\theta)d\omega_{ni}$, the density function. Besides, simulation is used in order to estimate the mixed logit models. Which means that any given value for θ, it is possible to create ω_{nj}^{r}, where r =1,…..,R draws from $f\left(\omega_{nj}|\theta\right)$, which is consequently used in the estimation of the simulated probability (SP):

$$\breve{p}_{nj} = \frac{1}{R}\sum_{r=1}^{R}\left(\frac{e^{u_{ni}\left(\beta\,\Delta X_{nj}+\omega_{nj}^{r}\right)}}{\sum_{i=1}^{m} e^{u_{ni}\left(\beta\Delta X_{ni}+\omega_{ni}^{r}\right)}}\right) \quad \text{Eq. (5)}$$

Another important function is the simulated log-likelihood (SLL), which can maximize the estimated parameters and is defined as:

$$SLL(\beta) = \sum_n \ln(\breve{p}_{nj}) \quad \text{Eq. (6)}$$

Furthermore, the output of the ML models is used to perform a t-test. The objective was to use the t-test (using 95% confidence level) to see whether the effect of the used explanatory variables is significantly different or similar on both models: the life event model and the car ownership model, as well as the life events model compared to the most used mode models. Thus, the link/correlation between the life events and the mobility choices (i.e. car ownership and most used mode) can be determined. The t-test is calculated as follows:

$$T-test = \frac{(value\ of\ beta, life\ event) - (value\ of\ beta, mobility\ decision)}{\sqrt{\frac{variance\ life\ event}{n} + \frac{variance\ mobility\ decision\ model}{n}}} \quad \text{Eq. (7)}$$

Where, ''value of beta life event" is the value of the beta parameter of the mixed logit model where the grouped life events are used as dependent variables. "Value of beta mobility decision" is the value of the beta parameter of the mixed logit model where the car ownership alternatives and the most used mode are used as dependent variables. ''variance life event", is the square of the standard error of the parameters in the mixed logit model where the life events are used as dependent variables. "Variance mobility choices" is the square of the standard error of the parameters in the mixed logit model where the car ownership alternatives or most used mode are used as dependent variables**.** ***n*** is the number of parameters, however in this case, ***n*** is considered to be one (1), since the t-test is calculated for individual parameters. The decision rule here was then, if the t-test is less than or equal to 1.96, then the effect is not significant different, otherwise, significant different. When the t-test is less than or equal to 1.96, then it can be assumed that the life event to which these parameters belong can be expected to have a temporal effect on car ownership or the most used mode and therefore can be selected as common random parameters in analyzing anticipation and lagged effect of the life events on these mobility choices in the joint mixed logit estimation mentioned earlier. In addition, for the implementation of the model output, it was interesting to estimate the elasticities of a particular demand function regarding the dynamics in the values of a set of explanatory variables. In this regard the elasticity on the built environment variables (BE) (i.e. job accessibility) were analyzed. The elasticity function of an alternative or dependent variable (denoted as $\breve{p}_{nj}$), relative to the explanatory variable (BE_j) can be defined as:

$$E\left(\breve{p}_{nj}, BE_j\right) = \frac{d\breve{p}_{nj}}{dBE_j}\frac{BE_j}{\breve{p}_{nj}} \quad \text{Eq. (8)}$$

Furthermore, six joint models (JM1-JM6) were developed based on nine Mixed logit models mentioned earlier, considering both anticipation and lagged effects (see figure 2).

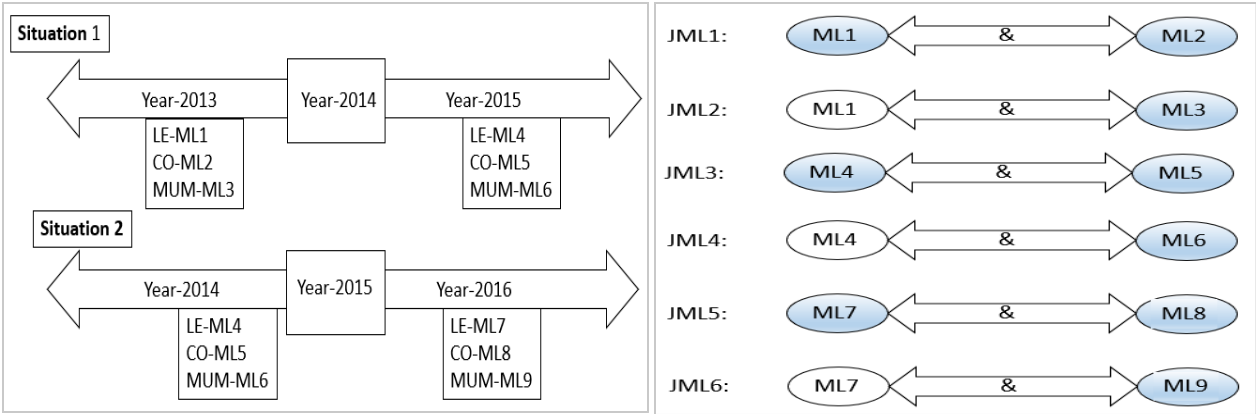

Figure 2: Visualization development of the joint models (JML) based on the mixed logit models (ML)

There are three (3) time intervals considered in the dataset: wave 2013-2014; wave 2014-2015 and wave 2015-2016. These time intervals provide in total nine (9) mixed logit models and in total six (6) joint models. Each time interval includes 2 joint models. One of the joint models is the joint estimation of the life event model (LE) with the car ownership model (CO) and the other one is the joint estimation of the life event model with the most used mode model (MUM). Figure 3 presents a conceptual framework for the joint estimation of the temporal association or correlation between the life events *(LE*)* and mobility choices *(MC*)* (i.e. car ownership and most used mode). As presented in figure 3, is that both error components as well as random coefficients are used in the joint models. It can be seen that three groups of explanatory variables are considered: – socio-economic characteristics (SE), trip-related variables (T) and built environment variables (BE)-. Furthermore, a part of each group of explanatory variables is included separately or as common parameter for *LE** or *MC**. The aim was then to estimate the probability (P_{nj}) of having a life event or group of life events and the probability of having a mobility choice, as product of the probability of the life event ($P_{nj}LE$) and the probability of the mobility choice ($P_{nj}MC$).

$$P_{nj} = P_{nj}LE * P_{nj}MC \qquad \text{Eq. (9)}$$

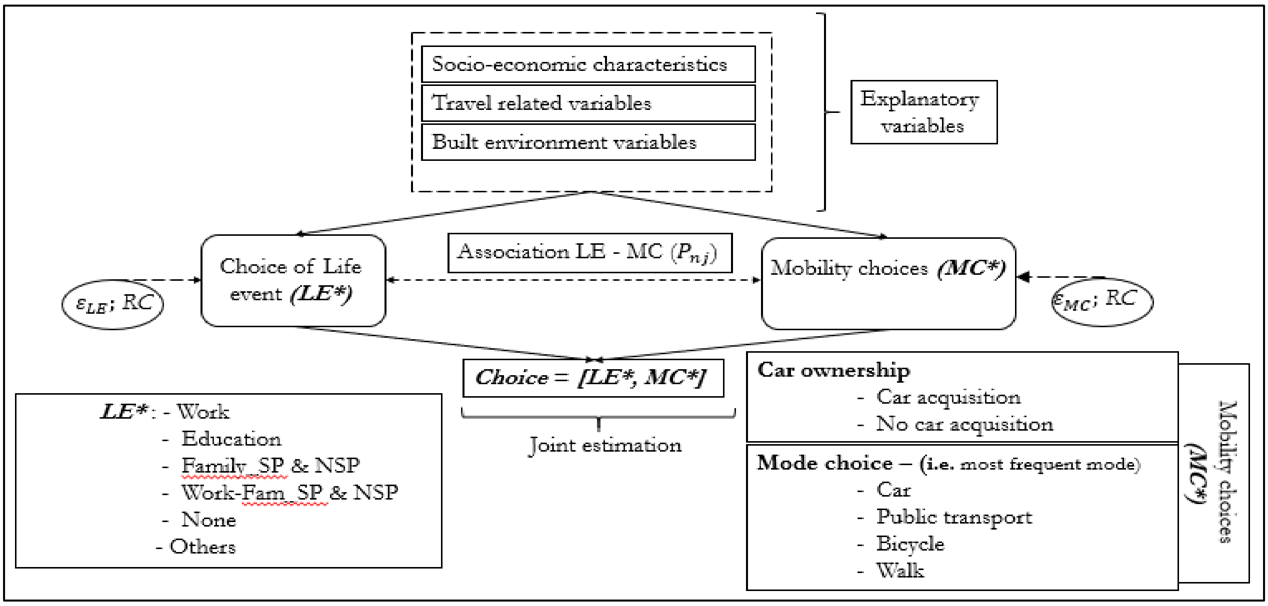

Figure 3: Model framework Joint Models

5 Data preparation and analysis

5.1 Descriptive Statistics

The data preparation process is a very important step in any research. The data set has to be inspected to check whether it satisfy the requirements given the research questions. Furthermore, the data can be specified by the following characteristics i.e., the quantity, how many data is available; the quality (is the data reliable); the resolution (what is the detail level of the data) and the completeness of the data (i.e. does the data set contains sufficient information?). Lastly, the data assembly takes place, where errors, outliers and missing data are dealt with. As stated before is that only the stayer respondents (1273 respondents) of the consecutive four waves are included in this research. These stayer respondents could be determined after mining and cleaning the dataset. The explanatory variables are briefly described in the next sections and an elaborated overview of these variables is presented in the appendix. In addition, other statistical tests, such as, variance inflation factor (VIF), which is a linear regression analysis, as well as a correlation test, in order to test the multicollinearity/correlation between variables are conducted. In this regard, the software SPSS was used, see Appendix D.

5.2 Explanatory Variables (SE, TR and BE)

This section of the paper describes and discusses the influential socio-economic characteristics (SE), travel related (TR)- and built environment variables (BE) that are used in the model estimation of the life events and mobility choices. In order to be able to determine the temporal effects of the life events on the mobility choices, it was necessary to look into the differences or deltas of the explanatory variables between the waves. When considering the deltas for anticipation effect then the difference between explanatory variables of the present wave (year "t") and the previous wave (year "t-1") are determined, while for the lagged effects, the deltas of explanatory variables between the present wave and the next wave (year "t+1") are estimated. When considering the deltas in the analysis, then it is very important to determine whether there is some variation in the variables, because if there is no change in a variable between the waves, then this parameter will not be calculated or will not be significant in the model output. With this in mind, the deltas of the used explanatory variables are described using their standard deviation (SD) and mean. The standard deviation provides information about the variation of the values among the mean and gives also insight about the variance. If the standard deviation is zero, then it is certain that there is no variation and the variance which is the square of the standard deviation, is then zero. If the standard deviation is close or very close to zero, then there might be some variation and the delta parameter needs to be estimated in the model to find out whether it is statistical significant or not. An overview of these parameters is given in table 4. Table 4 shows that the socio-economic parameters in time interval 2013-2014 have more or less the same standard deviation over the life event model (LE:M1), car ownership model (CO:M2) and most used mode model (MUM: M3). The same pattern can be noticed in the other two (2) time intervals: wave 2014-2015 and wave 2015-2016. Therefore, these parameters may have a similar influence on the dependent variables. However, as can be seen is that the standard deviations are close to zero and thereby still questionable whether they will be statistical significant in the model estimation.

Regarding the travel related parameters, travel distance and travel time show higher standard deviations, which also imply larger variations. These parameters can therefore be expected to show statistical significant values in the model estimation. It is also found from literature that travel distance and travel time can be of great importance for individual mode choice (Yasmin et al., 2015). For a predefined origin destination, the distance is the same every time an individual travel. Therefore, trip distance does not depend on traffic. On the other hand, the travel time depends on the traffic, mode etc. Furthermore, Bhat and Guo (2007), argue that personal preferences towards mode choice are also very important characteristics when one decides to travel.

Looking at the built environment parameters, then it can be seen that the job accessibility parameters have a larger variation compared to the urbanity, population density and destination accessibility (distance to daycare and distance to train station). The job accessibility parameters are therefore considered important in the analysis and are included in all the models. This is important for the explanation of the association between the life events and the mobility choices (i.e. car ownership and most used mode). According Mejía and St-Pierre (2008), providing access to jobs is very important task of the transport system, and mostly to opportunities, because inequality in access is associated with higher degrees of wage inequality and with lower human capital.

Table 4: Descriptive statistics of the deltas of the explanatory variables (Mean, SD)

		MODELS FOR WAVE13-14						MODELS FOR WAVE14-15						MODELS FOR WAVE15-16					
		LE: M1		**CO: M2**		**MUM: M3**		**LE: M4**		**CO: M5**		**MUM: M6**		**LE: M7**		**CO: M8**		**MUM: M9**	
	Delta parameters	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Socio-economic variables	Age	-0.2	0.4	-0.2	0.4	-0.2	0.4	-0.2	0.4	-0.22	0.41	-0.22	0.41	-0.2	0.4	-0.2	0.4	-0.2	0.4
	Education	-0.03	0.27	-0.03	0.27	-0.03	0.25	-0.07	0.45	-0.07	0.44	-0.07	0.45	-0.01	0.17	-0.01	0.17	-0.01	0.17
	Persons per household	-0.02	0.25	-0.02	0.24	-0.02	0.25	-0.03	0.27	-0.03	0.27	-0.03	0.27	-0.01	0.25	-0.02	0.25	-0.02	0.24
	Employment	0.15	1.75	0.15	1.75	0.15	1.76	0.01	1.15	0.01	1.15	-0.01	1.15	0.05	1.22	0.05	1.22	0.05	1.23
	Personal income	0.08	1.24	0.08	1.25	0.08	1.26	0.01	0.26	0.01	0.19	0.01	0.27	0.08	1.37	0.08	1.37	0.07	1.38
	Driving license	-0.01	0.12	-0.01	0.12	-0.01	0.12	-0.01	0.13	-0.01	1.20	-0.01	0.12	-0.01	0.15	-0.01	0.15	-0.01	0.15
	Free Parking at house	0.02	0.33	0.02	0.33	0.02	0.33	-0.02	0.30	-0.02	0.30	-0.02	0.30	0.03	0.29	0.03	0.30	0.03	0.29
Travel related variables	Preferred mode for work	-0.02	1.94	-0.02	1.95	0.01	1.96	0.15	1.82	0.15	1.82	0.14	1.84	-0.04	1.70	-0.04	1.71	-0.03	1.69
	Preferred mode for school	0.01	1.24	0.01	1.25	0.02	1.23	-0.01	1.06	0.01	1.07	-0.01	1.08	0.03	1.15	0.03	1.16	0.03	1.19
	Preferred mode for leisure	0.17	2.91	0.16	2.91	0.16	2.90	0.07	2.67	0.06	2.67	0.08	2.68	0.01	2.55	0.01	2.55	-0.01	2.51
	Travel distance	2.47	59.52	2.72	59.76	3.05	61.09	-1.45	69.69	-1.78	69.77	-1.37	70.25	2.27	69.81	2.35	70.31	1.38	70.01
	Travel time	8.82	96.56	9.21	97.10	9.25	96.36	2.42	74.82	2.26	75.19	2.88	76.43	-5.09	100.40	-5.20	101.10	-5.04	98.88
Built environment variables	Urbanity	0.02	0.35	0.02	0.35	0.03	0.36	-0.01	0.15	-0.01	0.15	-0.01	0.16	0.08	0.36	0.08	0.36	0.08	0.37
	Population density	107	975	108	983	108	978	130	1098	132	1108	131	1070	80	1289	79	1300	93	1336
	Distance to daycare	-0.02	0.29	-0.02	0.30	-0.02	0.30	-0.01	0.13	-0.01	0.13	-0.01	0.09	-0.01	0.17	-0.01	0.17	-0.01	0.17
	Job acc. by Bicycle (BnR)	2071	26846	2118	27081	2023	26892	820	25268	834	25496	1342	16654	502	23905	470	24113	612	24675
	Job acc. by public transport (WnR)	1321	15999	1355	16134	1260	15662	330	13427	336	13548	295	13725	186	12286	172	12396	247	12523
	Job acc. By car (Car)	2003	26144	2175	25848	1875	24831	1137	42855	1158	43242	1027	42982	-1184	43488	-1255	43909	-955	44469
	Distance to train station	-28.16	677.70	-29.35	683.20	-19.85	627.90	35.84	469.90	36.49	474.20	37.87	480.30	5.30	688.60	4.51	695.20	2.02	718.50

LE: Life event; CO: car ownership; MUM: most used mode; M, M2, M3, M4, M5, M6, M7, M8 and M9 represent the 9 mixed logit models

5.3 Model Estimation and Discussion Results

In order to analyse the temporal effects of the life events on car ownership and the most used mode, 9 mixed logit models and 6 joint models are estimated. The development of these models is described and explained earlier in section 4. For the mixed logit models, several model specifications have been tested and the final mixed logit models, used for estimating the joint models were selected based on the signs and magnitudes of the parameters, the t-test (95% confidence level). For the mixed logit models, error components were used in order to capture and understand the panel effects, while both error components as well as random coefficients were used in the estimation of the joint models. The delta parameters that are statistically significant and are not significantly different from each other in the model of the life event compared to the mobility choices models, are included as common random coefficients in the estimation of the joint models. A t-test calculation was conducted in order to test whether the delta parameters were significantly different or not (see equation 7, and the t-test calculations in appendix D). Further, the correlation among utilities for different alternatives was captured by the error components with the individuals. In this regard, the models were estimated with 250 draws, using the software, Python BIOGEME Bierlaire(2016). The results of the mixed logit (ML) models (M1-M9), as well as the joint models (JM1-JM6) for the time intervals: wave-2013-2014; wave-2014-2015 and wave-2015-2016 are shown in table 5, table 6 and table 7, respectively. The delta parameters of wave-2013-2014 were used to test for anticipated behaviour of the life events, car ownership and most used mode, while wave-2014-2015 functioned as time interval for analysing the lagged effects as well as anticipation. The delta parameters of wave-2015-2016, were then used to estimate the lagged behaviour of the life events, car ownership and most used mode. The delta parameters (SE-, Trip related- and BE-variables) are estimated as alternative specific parameters in the models of the life events (models: M1, M4 and M7), and the models of most frequent used mode (models: M3, M6 and M9), where the alternative "None" is the base in the life events model, and the alternative "Car" is the base in the most frequent used mode model. Models: M2, M5 and M8, represent the car ownership models. These models comprise binary alternatives (i.e. car acquisition and no car acquisition), where "no car acquisition" is the reference alternative.

Table 5 shows that the t-test of the alternative specific constants (ASC) of all the alternatives of M1 (the life events), M2 (car ownership) and M3 (most frequent used mode) are highly significant. This implies that the attributes included in the model specifications were not able to represent the average phenomenon very well and that a lot of noise is left unexplained. The t-test of the life event alternatives, are also negatively significant, underlining the fact that life events are rare events and not likely to happen often. This is in line with the literature, Cao and Mokhtarian (2005). However, when comparing the alternatives with each other, then the alternative "Work", has the highest value, which means that it is the least unlikely alternative, if the others stay constant. Looking at the t-test of the car ownership model (M2), then we see that the respondents are very likely to acquire a car, since the t-test is positively significant. The most used mode model shows that the bicycle is the least unlikely mode among the other modes, compared to the car, which is the reference alternative. This result is also in line with the descriptive statistics. The joint models, JM1, which is the joint estimation of the life events model with car ownership and JM2 (joint estimation of the life events and the most used mode), show almost the same pattern, but joint model 1 (JM1) shows that the alternative "Education" is in this model the least unlikely alternative, which is not according the descriptive statistics. This could happen due to some random effects of the delta parameters or the number of observations. Furthermore, all the error components of the mixed logit models (M1, M2 and M3) are significant. According to Train (2009), this means that the error components have been able to create correlations among the utilities for the different alternatives. Regarding the joint models, not all the error components are significant. The error component for the the alternatives: work related life events and spatial related life event (move house) are not significant in the joint estimation of the life events and car ownership. In joint model 2 (life events and most used mode model), the alternative: work and family related non-spatial (Work-Fam-NSP) is not significant. In this case, the error components have not been able to create correlations among the utilities for the different alternatives. This could be, due to the fact that, random coefficients were also applied in the joint model estimation or a lack of observations of this alternative (this alternative has only 2% observation, see table 3).

Socio-economic characteristics (wave-2013-2014)

Analysing the t-test of the deltas for the socio-economic parameters between wave 2013 and 2014, then it can be seen that the deltas for the variables: persons per house hold and employment are statistically significant for the non-spatial family related alternative (i.e. child birth) as well for car ownership (car acquisition) and mode use (public transport). Considering the signs of the t-tests, then it can be seen that the delta for persons per house hold has the same impact on child birth as well as on car ownership, and shows a different effect on most used mode (in this case public transport). This implies that the respondents who anticipated to have a baby, are also likely to acquire a car. The joint estimation of the life events and car ownership (JM1) shows the same result as well. This finding is in line with the study of Oakil (2013) and it makes sense, because when a couple plan to get a baby, having a car can be seen as a comfortable and safe way of travel, like going to the doctor, doing grocery etc. and there is also more space available to carry the members of the house hold, including the baby. The deltas for the variable income are also significant. This parameter is found to have the same impact on a combination of a work-related life event and move house (Work-Fam-SP) as well on car ownership (car acquisition) in the joint model (JM1). This result suggests that people who anticipated to have both, a work-related life event (such as new job, change work location, change working hours or days etc.) and move house, were also likely to acquire a car. This finding is a bit surprising, because you would expect that if a person anticipated to have a new job or change his/her work location for example and at the same time move house, then you would expect that they move their house closer to the new work location, or they try to find a job close to their new residential location, and therefore would not necessarily need to acquire a car, but use other modes such as cycling or public transport.

Travel related variables (wave-2013-2014)

The deltas for the travel related parameters were not found to be significant in the car ownership model and are therefore not presented in the model output. However, when considering the t-test of the deltas for the variable, mode preference for the purpose of leisure activities, then we see that the t-test is positively significant for the alternative: move house (i.e. Fam-SP), and negatively significant for most used mode (i.e. in this case public transport -Pt). The joint model (JM2) shows the same results, which implies that the impact of this delta parameter (mode preference for leisure) on moving house and having public transport as most used mode is significantly different. This result, suggest that people who anticipate to move their house, are not likely to have public transport as the dominant mode or most used mode. When considering the t-test of the deltas for the variable, mode preference for the purpose of work, then it can be seen that the t-tests are positively significant for the alternatives: public transport and a combination of work-related life event with child birth (Work-Fam-NSP). However, when looking at the output of the joint estimation (JM2), then we see that the t-test for the alternative "Work-Fam-NSP" is negatively significant, while the alternative "public transport" is not significant at all (and therefore not present in the model output). Due to this discrepancy, it cannot be argued that people who anticipate to have both a work-related life event and a baby, are also likely to have public transport as the dominant mode. Travel time was also considered as an important variable and the deltas of this variable were estimated in the model as well. The t-test of these deltas show that travel time has the same effect on work related life events, as well on the alternative, bicycle. This implies that, people who anticipated to have a work-related life event are also likely to have the bicycle as most used mode. This can be explained by the fact that people who had a work-related life event, for example, change in work location, had moved their work location within the same municipality or moved to an area with the same accessibility level, and therefore, if they had the bicycle as most used mode, then they did not have to change it with another transport mode. However, it is still difficult to say what the exact effect is, since the alternative "Work" represent a work-related life events, which can be, a new job, stop working, work less, work more, change in work hours/days or change in work location.

Built environment variables (wave-2013-2014)

When analysing the t-test of the deltas for the built environment parameters, then it becomes clear that the deltas for the variable, distance to day care is statistically significant for the non-spatial family related alternative (i.e. child birth) as well for public transport in the joint estimation, but in the mixed logit model this is only for the alternative "public transport" the case. This shows a discrepancy and therefore, it is difficult to argue whether respondents who anticipated to have a baby, are also likely to have public transport as their most used mode.

Furthermore, the analysis of the t-test of the deltas for the built environment parameter, Bike and Ride (BnR), shows that this parameter has a positive impact on a combination of work-related life event and child birth (i.e. Work-Fam-NSP) as well on the bicycle in the output of the mixed logit models, but the output of the joint estimation (JM2), shows there is a negative effect. This implies that the respondents were not likely to anticipate a combination of a work-related life event and a baby, and have the bicycle as their most used mode. This can also be clarified by the the fact that when people have a work-related life event in combination with a baby, the probability of frequently using a motorised mode (such as a car – the car is reference alternative in the most used mode model-), is higher compared to using the bicycle.

The deltas for the built environment variable, job accessibility by car were also determined and estimated. Table 5 shows that the deltas for job accessibility by car, positively affects a combination of a work-related life event and move house (Work-Fam-SP), but has a negative impact on car ownership (i.e. car acquisition). These results are also consistent with the results from the join model estimation. These results suggest that people who anticipate a combination of a work-related life event and move house, do not need to acquire a car. A plausible explanation for these findings can be that, since job accessibility positively affects the decision of these group of people, to have a work- related life event and move house, they move their house to a place with at least the same job accessibility (by car), compared to where they used to live. Because of this, they probably also already had a car, and do not need to acquire an extra car. In addition, urbanity was also considered as an important built environment variable and the deltas of this variable were estimated in the model. The t-test of these deltas show that urbanity has the same effect on a combination of a work-related life event and child birth (Work-Fam-NSP), and also on car ownership (i.e. car acquisition). Furthermore, the calculated t-test with equation 7, showed that the delta for the variable "urbanity", has a similar effect (thus not significant different) on the alternatives: "Work-Fam-NSP" and "car acquisition". This parameter, could therefore be used as common random parameter in the joint model estimation. The results of the joint model (JM1) show that the sigma of this parameter is statistically significant. This, again implies that the respondents who anticipated to have a combination of a work-related life event and a baby, are also likely to acquire a car. According to Berveling et al. (2016), the car is seen as a comfortable and safe way of travel when having a baby. Which makes sense because there is more space needed to carry the baby.

Table 6 contains the model output for the delta parameters of wave-2014-2015, for testing the lagged effects on the life events and the mobility choices. The results regarding the alternative specific constants in the mixed logit models as well as the joint models for this time interval (wave-2014-2015) show that the t-test of the alternatives in the models are highly significant. This, again means that the attributes included in the model specification were not able to represent the average phenomenon completely, but still have some noise left unexplained. However, when comparing the alternatives with each other, then the alternative "Fam-NSP", has the highest t-test, which means that it is the least unlikely alternative, if the others stay constant. Looking at t-test of the car ownership model (M5), then we see that the respondents are likely to acquire a car, since the t-test is positively significant. The most used mode model (M6) shows that walking is the least unlikely mode among the other modes, compared to the car, which is the base. The joint models, JM3, which is the joint estimation of the life events model with car ownership, show that the respondents are very likely to acquire a car and JM4 (joint estimation of the life events and the most used mode), also show that the alternative walk is the least unlikely mode.

Socio-economic characteristics (wave-2014-2015)

Analysing the t-test of the deltas for the socio-economic parameters between wave 2014 and 2015, then it can be seen that the deltas for the explanatory variable: persons per house hold are statistically significant for the non-spatial family related alternative (i.e. child birth) and for the spatial related life event (i.e. move house) as well as for the alternative of car ownership (i.e. car acquisition) and of most used mode model (i.e. in this case, Walk). Considering the signs of the t-tests, then we see that the delta for the variable, persons per house hold has a positive impact on the alternative "Walk", on child birth(Fam-NSP) and move house (Fam-SP), but negatively affects car acquisition. These results imply that the respondents had walking as most used mode after moving their house or after getting a child and were not likely to acquire a car. However, these findings could not be validated by the joint model estimation. Therefore, it is hard to say whether this lagged effect of the life events move house or child birth on walking and car ownership are a causality or just a random correlation.

Travel related variables (wave-2014-2015)

The deltas for the travel related parameters were not found to be significant in the car ownership model and are therefore not presented in the model output. However, when considering the t-test of the deltas for the variable, mode preference for the purpose of work, then it is noticeable that the t-tests are negatively significant for the alternatives: work-related life event (Work), a combination of a work-related life event and child birth (Work-Fam-NSP), and for most used mode (i.e. in this case public transport -Pt). In order to validate these results, it is worth looking at the output of the joint models. The joint models show a discrepancy, which is that the t-test of the delta parameter in the alternative public transport is then negatively significant, while the alternatives of the life events are not significant at all (therefore not present in the model output). Thus, no effect of the deltas of the travel related variables found.

Built environment variables (wave-2014-2015)

The deltas for the built environment variables: Walk and Ride (WnR), Bike and Ride (BnR) and job accessibility by car (Car) were considered very important explanatory variables and therefore estimated as well. However, only job accessibility by public transport: Walk and Ride (WnR) happen to provide some association between the life events and the alternative "Walk". Table 6 shows that the t-test of the deltas for the job accessibility by public transport, positively affects child birth (Fam-NSP) as well as walking. This means that the respondents were likely to walk after having a baby, which is in line with the study of Berveling et al. (2016). Furthermore, the calculated t-test with equation 7, showed that the delta for the built environment variable, job accessibility by car, has a similar effect (thus not significant different) on the alternatives: "Work" of the life events and on "car acquisition" of the car ownership model. This parameter, could therefore be used as common random parameter in the joint model estimation. However, the results show that the sigma of this parameter is not statistically significant, which means that there is no association, thus also no lagged effect of the work-related life event on car ownership in this case.

Table 7 includes the model output for the delta parameters of wave-2015-2016, for testing the lagged effects on the life events and the mobility choices. The results regarding the alternative specific constants in the mixed logit models as well as the joint models for this time interval (wave-2015-2016) show that the t-test of the alternatives in the models are also highly significant. Looking at the t-test of the car ownership model (M8), then we see that the respondents are very likely to acquire a car, since the t-test is positive and highly significant in the joint model (JM5). The most frequent used mode model (M9) shows that the bicycle is the most likely mode among the other modes, compared to the car, which is the reference alternative in this model.

Socio-economic characteristics (wave-2015-2016)

When we analyse the t-tests of the deltas for the socio-economic parameters between wave 2015 and 2016, then it can be seen that the deltas for the explanatory variable: persons per house hold are positively significant for the spatial family related alternative (i.e. move house), for the alternative of car ownership (i.e. car acquisition) and of the most used mode model (Bike). This implies that there is a link between move house and car acquisition and also between move house and the bicycle as most used mode. The association between the life event move house and car acquisition could be confirmed by the joint estimation of the life events and car ownership (JM5). Furthermore, the calculated t-test with equation 7, showed that the delta for the explanatory variable, persons per household, has a similar effect (thus not significant different) on the alternatives: child birth (Fam-NSP) of the life events and of the most used mode model (Bike). This parameter, could therefore be used as common random parameter in the joint model estimation and the results show that the sigma of this parameter is statistically significant, however, the mean is not significant. Therefore, it cannot be concluded whether there is indeed a causal effect. The explanatory variable, employment was included in the analysis as well and the deltas were determined. These delta parameters turned out to have a negative impact on life events (work-related life event and child birth), car ownership and public transport (Pt). Nevertheless, the temporal association between this life event and car ownership and mode choice could not be clarified by the joint model estimation, since the signs of the deltas are different in the joint model for the alternative of the life event. Income, is another influential variable that was included in the model estimation. The deltas of this variable were determined and estimated in the mixed logit models as well as the joint models. Even though, the fact that an association was found between the life event child birth (Fam-NSP) and car ownership, from the output of the mixed logit models, this was not confirmed in the joint model estimation, because the sigma of these delta parameter is not significant (the t-test is -1.49).

Travel related variables (wave-2015-2016)

The deltas for the travel related parameters were not found to be significant in the car ownership model and are therefore not presented in the model output. However, considering the t-test of the deltas for the variable, mode preference for the purpose of going to school, then it can be seen that the t-tests are significant for the alternatives: a combination of a work-related life event and child birth (Work-Fam-NSP), and for most used mode (i.e. in this case public transport). This indicates that people who got a baby, were also likely to have public transport as their most used mode after getting the baby, which is unlikely, since you would expect that when people get a baby, then they would be more likely to acquire a car. This finding is in contrast with the study done by Berveling et al. (2016).

Built environment variables (wave-2015-2016)

The deltas for the built environment variables: Walk and Ride (WnR), Bike and Ride (BnR) and job accessibility by car (Car) were also estimated in the models of the time interval: wave-2015-2016. Nevertheless, only the delta parameter of the variable, job accessibility by public transport (WnR) happen to provide a clear association between the life event, a combination of a work-related life event with move house (i.e. Work-Fam-SP) and public transport. Table 7 shows that the t-test of the deltas for the job accessibility by public transport positively affects the alternative "Work-Fam-SP", as well as the alternative public transport. This means that the respondents who had a combination of a work-related life event and move house were also likely to have public transport as their most used mode after the life event. However, these findings could not be confirmed by the joint estimation, therefore it is not clear if these effects are indeed lagged effects of the life event.

Table 5: Model results (Mixed logit models-Wave-13-14-Anticipation)

		Mixed logit models for WAVE-13-14						Joint models for WAVE-13-14			
		LE: M1		**CO: M2**		**MFM: M3**		**JM1: M1 and M2**		**JM2: M1 and M3**	
	Name	**value**	***t-test***	**value**	***t-test***	**value**	***t-test***	**value**	***t-test***	**value**	***t-test***
Alternative Specific Constants	ASC-Work	-2.58	***-14.12***					-1.19	***-60.8***	-1.58	***-4.52***
	ASC-Education	-20.7	***-17.76***					-5.14	***-14.8***	-4.91	***-10.16***
	ASC-Fam-NSP	-17.3	***-21***					-5.02	***-28.3***	-3.57	***-42.61***
	ASC-Fam-SP	-15.7	***-27.49***					-3.15	***-20.2***	-16.8	***-9.65***
	ASC-Work-Fam-NSP	-14.1	***-20.51***					-4.14	***-32.7***	-4.16	***-5.95***
	ASC-Work-Fam-SP	-14.5	***-26.51***					-3.52	***-69.2***	-3.68	***-20.81***
	ASC-Others	-11.1	***-27.44***					-2.4	***-34.4***	-2.39	***-26.31***
	ASC-None	Ref.						Ref.		Ref.	
	ASC-Car acq.			63.5	***8.93***			3.36	***5.06***		
	ASC-No Car acq.			Ref.				Ref.			
	ASC-Pt					-15.9	***-18.76***			-6.27	***-13.48***
	ASC-Bike					-2.62	***-9.09***			-0.599	***-11.52***
	ASC-Walk					-22.9	***-20.32***			-2.37	***-17.95***
	ASC-Car					Ref.				Ref.	
Socio-economic char.	Persons per household (Fam-NSP)	-10.5	***-19.91***					-3.71	***-25.7***		
	Persons per household (Car acq.)			-19.9	***-2.79***			-1.06	***-3.99***		
	Persons per household (Pt)					13.2	***2.97***			0.937	***2.48***
	Employment (Fam-NSP)	-0.68	***-9.66***					-0.0618	***-3.41***		
	Employment (Caracq.)			-18.3	***-8.22***						
	Employment (Bike)					0.968	***12.35***			-0.0304	***-2.16***
	Income (Work-Fam-SP)	-1.01	***-4.18***					-0.297	***-3.61***		
	Income (Car acq.)							-0.479	***-4.63***		
Travel related characteristics	Preferred mode for work (Work-Fam-NSP)	0.322	***7.4***							-0.0848	***-2.2***
	Preferred mode for work (Pt)					0.68	***12.76***				
	Preferred mode for leisure (Fam-SP)	0.54	***13.88***							0.651	***7.73***
	Preferred mode for leisure (Pt)					-3.48	***-19.89***			-0.0511	***-2.31***
	Travel time (Work-Fam-SP)	0.00116	***5.42***								
	Travel time (Work)	-0.00419	***-24.45***							-0.0002	***-2.3***
	Travel time (Bike)					-6E-04	***-3.44***				
Built environment variables	Urbanity (Walk)					22.5	***20.65***				
	Urbanity (Work-Fam-NSP)	5.09	***15.58***								
	Urbanity (Car acq.)			16.2	***2.46***						
	Distance to daycare (Fam-NSP)									1.34	***11.56***
	Distance to daycare (Pt)					84.3	***19.17***			0.432	***3.05***
	Bike and Ride (Work-Fam-NSP)	6.6E-05	***16.94***							-2E-06	***-2.63***
	Bike and Ride (Bike)					4E-05	***5.08***			-9E-06	***-8.19***
	Walk and Ride (Fam-SP)	-6.3E-05	***-17.58***								
	Job acc. Car (Fam-SP)										
	Job acc. Car (Work-Fam-SP)	8.8E-05	***27.16***					8E-06	***11.78***		
	Job acc. Car (Car acq.)			-2.2E-04	***-5.18***			-1E-05	***-5.18***		
Common random	Travel time (Work-Fam-SP and Bike)									-0.0001	***-9.13***
	Standard deviation									-0.0013	***-9.96***
	Urbanity (Work-Fam-NSP and Car acq.)							-0.169	-1.76		
	Standard deviation							0.819	***5.83***		
Error components	σ-Work	9.79	***34.21***					-0.113	-1.13	1.85	***2.89***
	σ-Education	12.2	***18.06***					-1.42	***-5.33***	-1.52	***-4.04***
	σ-Fam-NSP	10.1	***23.1***					1.22	***8.94***	0.394	***2.21***
	σ-Fam-SP	-11.9	***-29.13***					-0.437	-1.13	8.38	***9.21***
	σ-Work-Fam-NSP	7.07	***22.04***					-0.653	***-3.63***	0.911	1.09
	σ-Work-Fam-SP	-10.1	***-27.91***					0.454	***6.89***	0.778	***3.47***
	σ-Others	-9.82	***-32.38***					0.411	***2.23***	0.529	***2.72***
	σ-None	Ref.						Ref.		Ref.	
	σ-Car acq.			-82.8	***-8.9***			5.16	***4.5***		
	σ-No Car acq.			Ref.				Ref.			
	σ-Pt					21.6	***20.2***			5.15	***12.75***
	σ-Bike					-14	***-20.51***			-1.53	***-9.61***
	σ-Walk					**22.6**	***20.57***			1.38	***8.77***
	σ-Car					Ref.				Ref.	
	Number of estimated parameters	36		7		24		33		37	
	Sample size (Trips)	22894		22027		15248		28788		20586	
	Sample size (Respondents year observations)	964		933		710		1239		925	
	Initial log-likelihood	-47606.7		-15268		-21138.2		-79817.284		-71345.639	
	Final log-likelihood	-10348.7		-760.70		-4165.01		-49592.806		-48391.659	
	Rho-square for the initial model	0.783		0.95		0.803		0.379		0.322	

Note: LE: life event; M1: mixed logit model1; CO: car ownership; M2: mixed logit model 2; MFM: most frequent used mode; M3: mixed logit model 3; JM1: joint model 1; JM2: joint model 2.

Table 6: Model results (Mixed logit models-Wave-14-15-Anticipation/Lagged)

		Mixed logit models for WAVE-14-15						**Joint models for WAVE-14-15**			
		LE:M4		**CO:M5**		**MFM:M6**		**JM3: M4 vs M5**		**JM4: M4 vs M6**	
	Name	**value**	***t-test***	**value**	***t-test***	**value**	***t-test***	**Value**	***t-test***	**value**	***t-test***
Alternative Specific Constants	ASC-Work	-6.03	***-23.3***					-33.5	***-2.75***	-8.68	***-4.56***
	ASC-Education	-26.1	***-21.78***					-4.31	***-54.8***	-6.48	***-6.24***
	ASC-Fam-NSP	-19.3	***-14.13***					-33.1	***-4.82***	-9.85	***-7.33***
	ASC-Fam-SP	-13.7	***-25.4***					-3.34	***-34.16***	-6.15	***-8.26***
	ASC-Work-Fam-NSP	-24.2	***-21.54***					-13.6	***-4.84***	-7.98	***-7.5***
	ASC-Work-Fam-SP	-13.4	***-24.1***					-4.25	***-63.09***	-30.1	***-4.64***
	ASC-Others	-9.73	***-23.9***					-2.89	***-83.16***	-3.31	***-7.39***
	ASC-None	Ref.						Ref.		Ref.	
	ASC-Car acq.			64.5	***9.57***			0.981	***65.07***		
	ASC-No Car acq.			Ref.				Ref.			
	ASC-Pt					-15.1	***-15.71***			-1.52	***-56.15***
	ASC-Bike					-10.8	***-12.45***			-0.438	***-20.44***
	ASC-Walk					-9.64	***-9.51***			-2.06	***-12.85***
	ASC-Car					Ref.				Ref.	
Socio-economic characteristics	Persons per household (Fam-NSP)	0.397	***1.98***								
	Persons per household (Fam-SP)	1.91	***6.59***					2.51	***17.71***	3.48	***9.51***
	Persons per household (Car acq.)			-45	***-9.58***						
	Persons per household (Pt)										
	Persons per household (Walk)					11.6	***12.59***			-0.53	***-5.76***
	Employment (Work-Fam-NSP)	-1.55	***-13.6***								
Travel related characteristics	Preferred mode for work (Work-Fam-NSP)	-1.91	***-16.3***								
	Preferred mode for work (Pt)					-0.243	***-5.57***			0.0445	***4.5***
	Preferred mode for work (Work)	-0.13	***-3.09***								
	Preferred mode for school (Bike)					-2.9	***-15.2***			-7.54E-05	***-1.98***
	Preferred mode for school (Pt)					-3.91	***-16.3***				
	Preferred mode for school (Education)	3.91	***20.1***					-0.106	***-2.42***	-0.00045	***-2.03***
	Preferred mode for leisure (Work-Fam-NSP)	0.859	***14.08***								
Built environment variables	Bike and Ride (Bike)					7.20E-05	***5.38***			-6.18E-06	***-5.24***
	Walk and Ride (Fam-NSP)	6.22E-05	***3.8***								
	Walk and Ride (Walk)					0.000355	***9.08***			1.57E-05	***4.55***
	Job acc. Car (Fam-SP)	-1.34E-05	***-17.7***								
	Job acc. Car (Work-Fam-SP)	-5.76E-06	***-8.51***								
	Job acc. Car (Car acq.)			6.29E-05	***4.52***						
	Job acc. Car (Work)	-8.9E-06	***-10.3***								
Common random	Job acc. Car (Work and Car acq.)							-1.11E-06	***-3.11***		
	Standard deviation							8.54E-07	0.88		
Error components	σ-Work	-10.6	***-28.7***					-38.9	***-2.8***	10.6	***4.57***
	σ-Education	-20	***-21.9***					Fixed		2.46	***4.04***
	σ-Fam-NSP	11.9	***15.69***					15	***4.79***	-4.3	***-6.34***
	σ-Fam-SP	7.81	***25.84***					0.281	0.84	-2.57	***-5.59***
	σ-Work-Fam-NSP	16.1	***22.56***					5.44	***4.36***	3.05	***5.54***
	σ-Work-Fam-SP	8.38	***25.42***					Fixed		-13.1	***-4.61***
	σ-Others	8.78	***26.68***					Fixed		-1.06	***-2***
	σ-None	Ref.						Ref.		Ref.	
	σ-Car acq.			64.3	***9.6***			-0.0154	-0.14		
	σ-No Car acq.			Ref.				Ref.			
	σ-Pt					20.3	***16.65***			Fixed	
	σ-Bike					-14.1	***-15.07***				
	σ-Walk					-23.7	***-12***				
	σ-Car					Ref.				Ref.	
	Number of estimated parameters	29		5		16		19		28	
	Sample size (Trips)	18827		22400		16426		22599		22404	
	Sample size (Respondents year observations)	828		989		772		1005		1052	
	Initial log-likelihood	-39149.6		-15526.5		-22771.3		-62657.733		-77646.347	
	Final log-likelihood	-6906.21		-1013.21		-4829.72		-35462.263		-49661.151	
	Rho-square for the initial model	0.824		0.935		0.788		0.434		0.36	

Note: LE: life event; M4: mixed logit model 4; CO: car ownership; M5: mixed logit model 5; MFM: most frequent used mode; M6: mixed logit model 6; JM3: joint model 3; JM4: joint model 4.

Table 7: Model results (Mixed logit models-Wave-15-16- Lagged)

		Mixed logit models for WAVE-15-16						Joint models for WAVE-15-16			
		LE:M7		**CO:M8**		**MFM:M9**		**JM5: M7 vs M8**		**JM6: M7 vs M9**	
	Name	**value**	***t-test***	**value**	***t-test***	**value**	***t-test***	**Value**	***t-test***	**value**	***t-test***
Alternative Specific Constants	ASC-Work	-4.4	***-24.12***					-38.1	***-3.93***	-1.57	***-11.51***
	ASC-Education	-41.3	***-20.91***					-5.78	***-10.76***	-8.01	***-5.77***
	ASC-Fam-NSP	-25.7	***-20.87***					-4.09	***-59.3***	-4.93	***-11.96***
	ASC-Fam-SP	-19.9	***-24.36***					-8.41	***-5.52***	-3.4	***-22.78***
	ASC-Work-Fam-NSP	-29.8	***-18.37***					-47.8	***-5.02***	-8.97	***-7.62***
	ASC-Work-Fam-SP	-29.9	***-22.73***					-5.72	***-13.24***	-6.52	***-2.98***
	ASC-Others	-9.91	***-26.96***					-51.9	***-5.42***	-3.11	***-13.15***
	ASC-None	Ref.						Ref.		Ref.	
	ASC-Car acq.			30.6	***9.63***			1.09	***38.82***		
	ASC-No Car acq.			Ref.				Ref.			
	ASC-Pt					-13.8	***-19.81***			-1.38	***-9.62***
	ASC-Bike					0.311	***2.01***			-0.563	***-34.2***
	ASC-Walk					-20.3	***-21.98***			-12.1	***-3.03***
	ASC-Car					Ref.				Ref.	
Socio-economic characteristics	Persons per household (Fam-NSP)	-9.28	***-16.98***					-2.78	***-21.55***		
	Persons per household (Fam-SP)	1.66	***6.26***					1.89	***4.67***		
	Persons per household (Car acq.)			3.81	***8.91***			-0.282	***-4.61***		
	Persons per household (Bike)					4.62	***15.55***				
	Persons per household (Pt)					-4.82	***-12.3***				
	Employment (Car acq.)			5.87	***9.59***			-0.111	***-8.51***		
	Employment (Pt)					-0.856	***-10.14***				
	Employment (Work-Fam-NSP)	-3.12	***-19.91***					1.57	***4.51***		
	Income (Fam-NSP)	-3.55	***-11.1***								
	Income (Fam-SP)							-0.743	***-4.54***		
	Income (Car acq.)			-7.07	***-9.09***						
	Income (Pt)					1.77	***19.36***				
	Income (Bike)					-0.697	***-11.66***				
Travel rel. Char	Preferred mode for work (Pt)					2.74	***20.49***				
	Preferred mode for school (Work-Fam-NSP)	3.96	***22.15***							0.00114	***4.9***
	Preferred mode for school (Pt)					-0.49	***-7.12***			0.000442	***7.45***
	Preferred mode for leisure (Pt)					-1.11	***-14.57***				
	Preferred mode for leisure (Work-Fam-SP)	-2.95	***-24.84***								
Built environ.	Bike and Ride (Bike)					5.64E-05	***7.9***				
	Walk and Ride (Work-Fam-SP)	0.000226	***26.18***								
	Walk and Ride (Pt)					0.000182	***18.55***				
	Job acc. Car (Car acq.)			5.34E-06	***7.06***						
	Job acc. Car (Work)							-0.00012	***-3.89***		
Common random	Persons per household (Fam-NSP and Bike)									0.0838	1.25
	Standard deviation									-0.544	***-3.47***
	Income (Fam-NSP and Car acq.)							-0.132	***-10.06***		
	Standard deviation							-0.0806	-1.49		
Error components	σ-Work	-6.77	***-33.03***					-45.4	***-3.93***	1.09	***4.13***
	σ-Education	-31.8	***-22.32***					-2.01	***-5.74***	3.31	***4.62***
	σ-Fam-NSP	18.4	***21.41***					-0.11	-0.37	1.61	***5.37***
	σ-Fam-SP	20.6	***25.65***					-4.48	***-4.79***	0.738	***3.39***
	σ-Work-Fam-NSP	18.4	***19.26***					21.9	***5.22***	3.57	***6.17***
	σ-Work-Fam-SP	29.9	***24.85***					-2.04	***-7.23***	2.58	***1.99***
	σ-Others	-8.21	***-28.87***					-32.4	***-5.46***	-1.05	***-3.75***
	σ-None	Ref.						Ref.		Ref.	
	σ-Car acq.			-39.9	***-9.69***			0.567	***5.96***		
	σ-No Car acq.			Ref.				Ref.			
	σ-Pt					15.3	***22.02***			-0.936	***-3.36***
	σ-Bike					11.3	***24.45***			Fixed	
	σ-Walk					17.8	***22.58***			9.98	***3.13***
	σ-Car					Ref.				Ref.	
	Number of estimated parameters	26		6		19		26		27	
	Sample size (Trips)	17509		22576		16512		24071		22202	
	Sample size (Respondents year observations)	786		1006		783		1083		1062	
	Initial log-likelihood	-6709.66		-15648.5		-22890.5		-66738.983		-76946.269	
	Final log-likelihood	59398.57		-1774.15		-5144.89		-39211.539		-51247.407	
	Rho-square for the initial model	0.816		0.887		0.775		0.412		0.334	

Note: LE: life event; M7: mixed logit model 7; CO: car ownership; M8: mixed logit model 8; MFM: most frequent used mode; M9: mixed logit model 9; JM5: joint model 5; JM6: joint model 6.

5.4 Model Implication – Forecasting and Elasticity

The model output of the mixed logit models and the joint models was used to do a forecasting and to estimate elasticities. According to literature, the built environment plays a very important role in the analysis of travel behaviour, therefore built environment variables namely job accessibility by car and by public transport are used in the analysis of the temporal effects of life events on mobility choices. As a results job accessibility by car and by public transport (BnR and WnR) are used for estimating the elasticities. Elasticity can be used to determine how the different approaches (i.e. the single mixed logit models and the joint models) can measure accessibility by comparing the effect of job accessibility on the life events and the mobility choices and then derive policy recommendations from the findings. All the three pairs of waves are used in this regard. Figure 4 presents the calculated probabilities and elasticities (with job accessibility by car and BnR) for the single mixed logit model of the life events (LE), for the car ownership model (CO), the most used mode model (MUM), the joint model of the life event and car ownership (JM1), as well as the joint model of the life event and most used mode (JM2). As expected, the probability of the alternative "None" is the highest among the alternatives of the life events, which clearly confirms the fact that life events are rare events and do not occur frequently. The work-related life event shows the highest probability among the other life events and this is also consistent with the descriptive statistics. Furthermore, JM1 shows overall a higher probability for the alternatives compared to JM2. This implies that JM1 provides a better estimation for determining the association between the life events and the mobility choice. In the model output (table 5), it is also clear that JM1 is a better model, since it has a higher rho-square than JM2.

Looking at the elasticities, then it can be seen that, the demand for having a life event as well as a mobility choice, significantly increases, when there is an increase in accessibility in terms of number of job reachable by car, but a less significant increase, when there is an increase in accessibility of jobs by public transport. This again shows the strong demand of having a car as well as the dominant mode. JM1 shows on the other hand a decrease in the demand for the life events move house (Fam-SP) and a work-related life event with move house (Work-Fam-SP). This implies that people do not necessarily need to move house or have a new job or change in work location, due to an increase in accessibility. However, this effect is less strong compared to the fact that accessibility do influence life events and as a result triggers people to have a mobility choice (i.e. acquire a car or have a dominant mode) in anticipation to the life event.

Furthermore, when analysing the elasticities of time interval: wave 2014-2015 and wave 2015-2016, then it can be seen that the elasticities are less powerful compared to those of wave 2013-2014. However, the overall conclusion that can be derived from the elasticities is that there is an association between the life events and the mobility choices: car acquisition and dominant mode, especially in anticipation to future life events.

Since life events have the ability to interrupt habitual behaviour and make people think about mobility choices, this can be a good opportunity for policy makers to intervene and provide information and options/solutions to the people of how to travel in a safe and sustainable way.

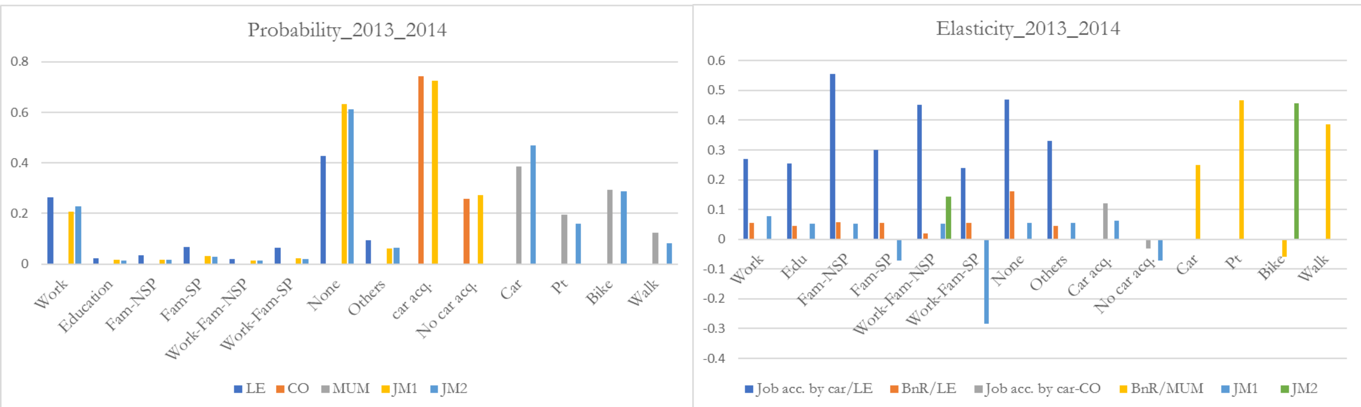

Figure 4: Probability and elasticity for wave-13-14

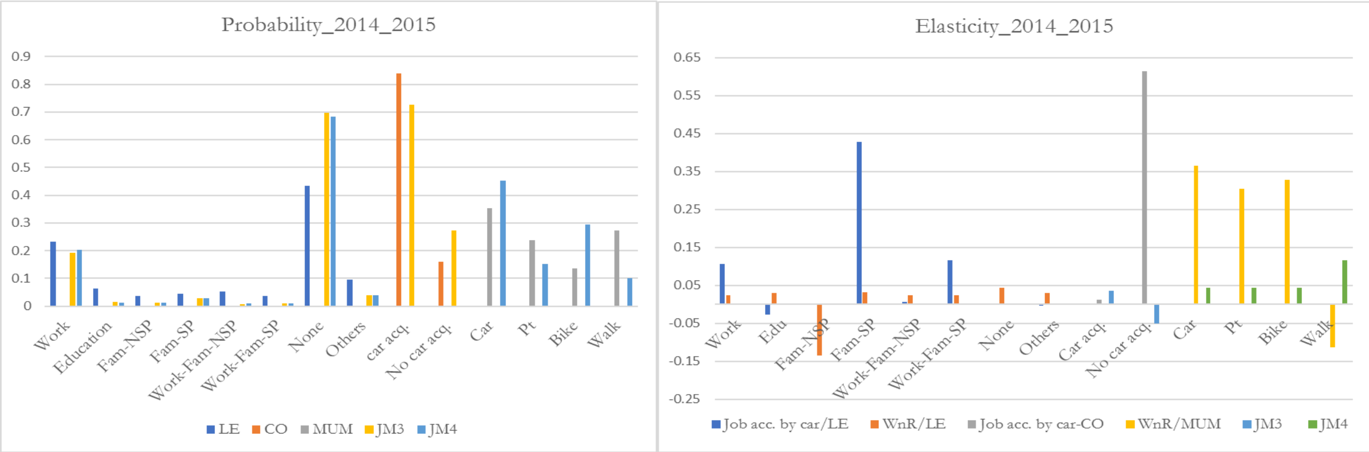

Figure 5: Probability and elasticity for wave-14-15

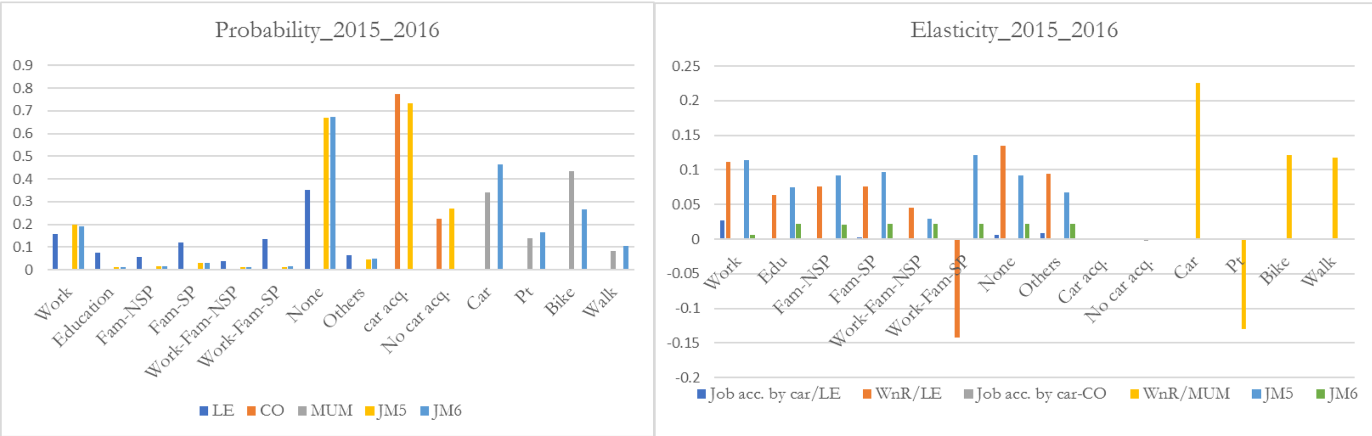

Figure 6: Probability and elasticity for wave-14-15

6 Conclusion

Discrete choice models are used to analyze the temporal effects of life events on mobility choices. This was done in order to narrow the research gap in the field of travel behavior analysis with respect to life events. In this regard, mixed logit models and joint models based on the mixed logit models were used to determine to what degree anticipation and lagged effects of the life events affect car ownership and most used mode, which is the main research question. In order to do this, the following sub-research questions were formulated: which life events can be expected to have anticipation and lagged effects on car ownership and most used mode? Which factors are influential in determining the anticipation and lagged effects of life events on car ownership and most used mode? And to what extent can the model output be implemented? (i.e. what policy implications can be recommended by using the model output for the estimation of elasticities for some built environment variables?) Life events are rare events and do not happen frequently, therefore one of the first steps in this research was to determine which life event or group of life events could be expected to have a temporal effect on car ownership or most used mode. From the mixed logit models, it was found that work-related life events, spatial family-related life events (move house), non-spatial family related life events (child birth) and a combination of a work-related life event and having a baby or move house have anticipation and or lagged effects on car ownership and most used mode. However, one person having a life event and due to that life event, acquire a car or use a particular mode very frequent, can also be influenced by socio-economic characteristics or trip related variables, but more particularly, aspects of the build environment. The results showed that the built environment variables: distance to daycare, urbanity and job accessibility by car and by public transport affect the life event decisions of the people and as a consequence also affect car ownership or mode choice. In addition, the output of the models showed that, socio-economic characteristics, such as employment and number of persons in the household are also influential. The influential travel related variables are: travel time and mode preferences for the purpose of work, education and leisure activities. Furthermore, it can be concluded from the model results that the people who anticipated to have a baby, are also likely to acquire a car. This finding is in line with the studies: Oakil (2013) and Berveling et al. (2016) and makes sense, because when a couple plan to get a baby, having a car can be seen as a comfortable and safe way of travel, like going to the doctor, doing grocery etc. and there is also more space available to carry the members of the house, including the baby. A combination of a work-related life event and a baby was also found to trigger car ownership in anticipation to the life event. Another finding was that people who anticipated to have a work-related life event were also likely to have the bicycle as most used mode. This can be explained by the fact that people who had a work-related life event (for example), change in work location, had moved their work location within the same municipality or moved to an area with the same accessibility level, and therefore, if they had the bicycle as most used mode, then they did not have to change it with another transport mode. However, it is still difficult to say what the exact effect is, since the alternative "Work" represent a work-related life event, which can be, a new job, stop working, work less, work more, change in work hours/days or change in work location. It can therefore be recommended as future research to analyse the temporal effects of the life events on a more disaggregated level, in order to know exactly which life event is causing the effect on the mobility choice.

The analysis of the lagged effects revealed that the respondents who had a baby in 2014 were more likely to have walking as their most used mode after having the baby. This finding is also in line with Berveling et al. (2016). Another finding of the lagged effects is that the life event, move house, has car acquisition as lagged effect. It was found that people who moved their house, acquired also a car after moving their house. A plausible explanation for this finding is that the people who moved their house, had moved to an area with less accessibility by public transport. Overall it can be concluded that the anticipation effects are stronger and more important than the lagged effects considering the model results and the elasticities of job accessibility in the anticipation analysis (wave 2013-2014). The anticipation effects should be further analysed in future research, because the best timing for policy makers to intervene is before the life event happens, because in this phase people are already thinking of what kind of mobility choices to make, and policy makers/transport planners can really use this as a 'window of opportunity' to provide the people with information and solutions how to travel in a safe and sustainable way. Furthermore, the results of the models and the estimated elasticities and probabilities were able to reveal the presence of the association between the temporal effects of the life events and mobility choices. The use of the joint estimation of the life events and mobility choices have proven to be useful in this study, and the output of the research can provide insight to the field of analysing behavioural impacts of life events on mobility.

Nevertheless, is further research on this topic a prerequisite. It is a good recommendation to use more advanced modelling technique for the specific purpose of studying the temporal impact of life events on mobility choices, since in this particular study the deltas were used, which are not able to analyze the effects of the life events beyond 12 months, because maybe there is still some effects of the life events more than 12 months backwards or forward in time.

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Appendices

Appendix A: Data cleaning and preparation

The data available for the execution of this study was the MPN dataset and some additional built environment data was also collected. According to Oakil (2013), to account for the fact that long-term mobility choices are dynamic, time dependent and interrelated, the data needs to fulfil seven requirements. First of all, it should cover a longer period (multiple years) to capture dynamics in household decisions. The MPN data includes data of 4 waves, which is also used in this study. Second, it should include households' demographic situation in terms of the number of persons in the household and their characteristics such as position in the household, age, gender, work situation and location. And in terms of a recording of important events such as cohabitation, separation, childbirth and child's home leaving. 3. It should have information of households' economic status over a longer period in terms of the income of the members of the household as well as the working status of the members of the household. 4. It should have information regarding households' long-term mobility status in terms of: - Residential location over a longer period as well as characteristics of the particular residence. The residential location of the respondents is represented in the MPN data set on postcode 4 level; - The work location over a longer period; - Car ownership level, driving license possession, availability of cars and public transportation over a longer period. 5. It should cover daily mobility aspects such as commuting time and mode over longer period. 6. It should incorporate households' intentions for the future with respect to the issues mentioned above. 7. It should facilitate analyses of external effects such as the effects of household's social network and perception of the housing and job market. The MPN data set is a very rich mobility panel, which contains data of four waves (2013 -2016) and the data set fulfils all of the above-mentioned requirements. However, in the data processing part, this had to be confirmed, before starting the analysis. Furthermore, the data sets of the four waves were provided separately and therefore had to be combined and sorted in a correct way. All empty cells were considered as missing data. There was 2 to 5% of missing data in selected data set. This was due to the fact that some respondents did not answers all questions in the survey.

Life events: for the analysis of the life events it was important to filter out the events that had very little person observations, that is life events with less than 2% of the total observations, were not considered. This was done by using the statistical software IBM SPSS, by exploring the frequencies of all the events in the data set. The same was done for the analysis of car ownership and mode choice. In order to be able to capture the panel effect, only the stayer respondents, that is those who participated in all the four waves, were considered. As mentioned earlier is that additional built environment variables were collected from the CBS data base (Centraal Bureau voor de Statistiek), a Dutch governmental institution that gathers statistical information about the Netherlands. This was done on postal code four level. The postal codes of the residential locations of the stayer respondents was used in this regard.

Appendix B: Data availability and variable selection

- Demographic- and socio-economic variables, from the MPN data base, see table 8 below.

Table 8: overview Socio-economic characteristics

Individual level		**Household level**	
Gender	Female	Annual gross household income	No own income
	Male		Less than €12.500
Age	15-17		€12.501- €26.200
	18-44		€26.201- €38.800
	45-64		€38.801- €65.000
	65 and older		€65.001- €77.500
Education	Uneducated		More than €77.500
	Basic education	Household structure	Single
	LBO\VBO\VMBO		Couple
	MAVO\1e 3 jaar HAVO-VWO\VMBO		Couple and children
	MBO		Couple with children and others

	HAVO en VWO \ WO en HBO propedeuse		Couple and others
	HBO\WO bachelor		Single parent and children
	WO-doctoraal of master		Single parent, children and others
	Unknown		Other structure
Personal netto monthly income	No own income	Number of cars in the household	0 cars
	€ 1.000,- or less		1 car
	€ 1.001 - € 1.500		2 cars
	€ 1.501 - € 3.000		3 cars
	€ 3.001 - € 5.000		4 cars
	More than € 5.000	Number of persons in the household	One person
	Unknown		Two persons
Car driving license	No driving license		Three persons
	Driving license		Four persons
Employment	Self-entrepreneur		Five persons
	Privatejob		Six persons
	Employed by the government		Seven persons
	Incapacitated		Eight persons
	Unemployed		Nine persons
	Retired		
	Student		
	Housewife/houseman		
	Volunteer		

Selected Spatial Variables:

- **Built environment variables**

The selected built environment, collected from the CBS data base are presented and described in table 11:

Source: https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische%20data/wijk-en-buurtkaart-2015

Table 9: overview additional built environment variables from CBS

Built environment variables	**Description**
Distance to train station	The average distance in kilometers (km) of all residents in an area to the nearest train station, calculated by road
Distance to daycare	The average distance in kilometers (km) of all residents in an area to the nearest daycare, calculated by road.
Population density	Number of residents per km^2
Urbanity	**Description**
Highly urban	More than 2500 addresses per km^2
Strong urbanized	1500-2500 addresses per km^2
Inadequate urban	1000-1500 addresses per km^2
Little town	500 – 1000 addresses per km^2
Not urban	Less than 500 addresses per km^2

Job accessibility

Three types of job accessibility, collected from the ASTRID project were added to the MPN data set. These are: Walk and Ride (WnR), Bike and Ride (BnR) and Car. Walk and Ride represents the number of jobs reachable from a certain origin to a certain destination by public transport. Job accessibility by car can be defined as the number of jobs reachable by car, where the door-to-door approach includes network geometry, speed limits and free flow speeds during uncongested times and the road speed profiles, provided by TomTom, in order to account for negative impacts of road congestion at different times of the day, as well as parking penalty to account for the time spent finding parking. The walk-and-ride and the bike-and-ride are two separate General Transit Feed Specification (GTFS) models for public transport. The walk-and ride model, models pedestrian access and egress and the bike-and-ride model incorporates the bicycle as a potential access mode to public transport. The bike-and-ride model was calculated by restricting bike access to the largest rail and metro stations as a result of the reality, where close to 40% of the national railways passengers report cycling to the stations, with the impact of the bike at the egress being much more reduced. The length of the bike segment was also considered very important in the analysis of the distance decay function for bicycle trips relying on the Dutch mobility survey (OVIN), which was aggregated over the years 2010-2014. Here it was found that individuals behaved different on the bike than on the rest of the transport modes, with 90% of the work trips by bike being less than 30 minutes and only 2.5% of the bike trips were took longer than 45 minutes. Therefore, a decision rule was made that the bike-and-ride option only holds if it is faster than the walk-and-ride option and if the cycling component of the multi-modal trip is less than 30 minutes long and further than 200 meters away from the network lengths, otherwise, the walk-and-ride option holds. It is further good to mention that all the travel times for the Netherlands were calculated using the network analyst tool and considering a log logistic distance decay function for all.

Appendix C: Defining the dependent variables

Life events

First of all, the frequencies of the 14 life events were calculated, and from this calculation it was noticed that 4 life events (life events 10, 11 and 12) had very low observations, less than 2% of the total number of observations in most of the waves.

Due to the low percentage of observations for these life events, they were excluded. Secondly, the remaining life events were segmented (grouped) into 8 categories according to their similarity as well as the possible combinations available in the dataset. A distinction was made between spatial and non -spatial life events based on the variation in accessibility in terms of job accessibility, when people move their residential location or work location or change school or education (see figure 7). This distinction is important, because people can for example have a family related life event (child birth or move house or both) and when people move house, it can happen that they move to a neighborhood that is better accessible by for example public transport or less accessible by public transport. The life event move house can then be expected affect the most used mode or car ownership. From the MPN dataset 220 possible combinations are found for the life events. These combinations are presented below. From the MPN data set it is found that some respondents had no life events during the 4 waves, or only one life event during the 4 waves, repeated live events during the 4 waves, multiple life events per wave or multiple life events in consecutive waves. As it would not be wise to have that many alternatives in a model, the possible 220 combinations of the life events were grouped in 8 types/categories.

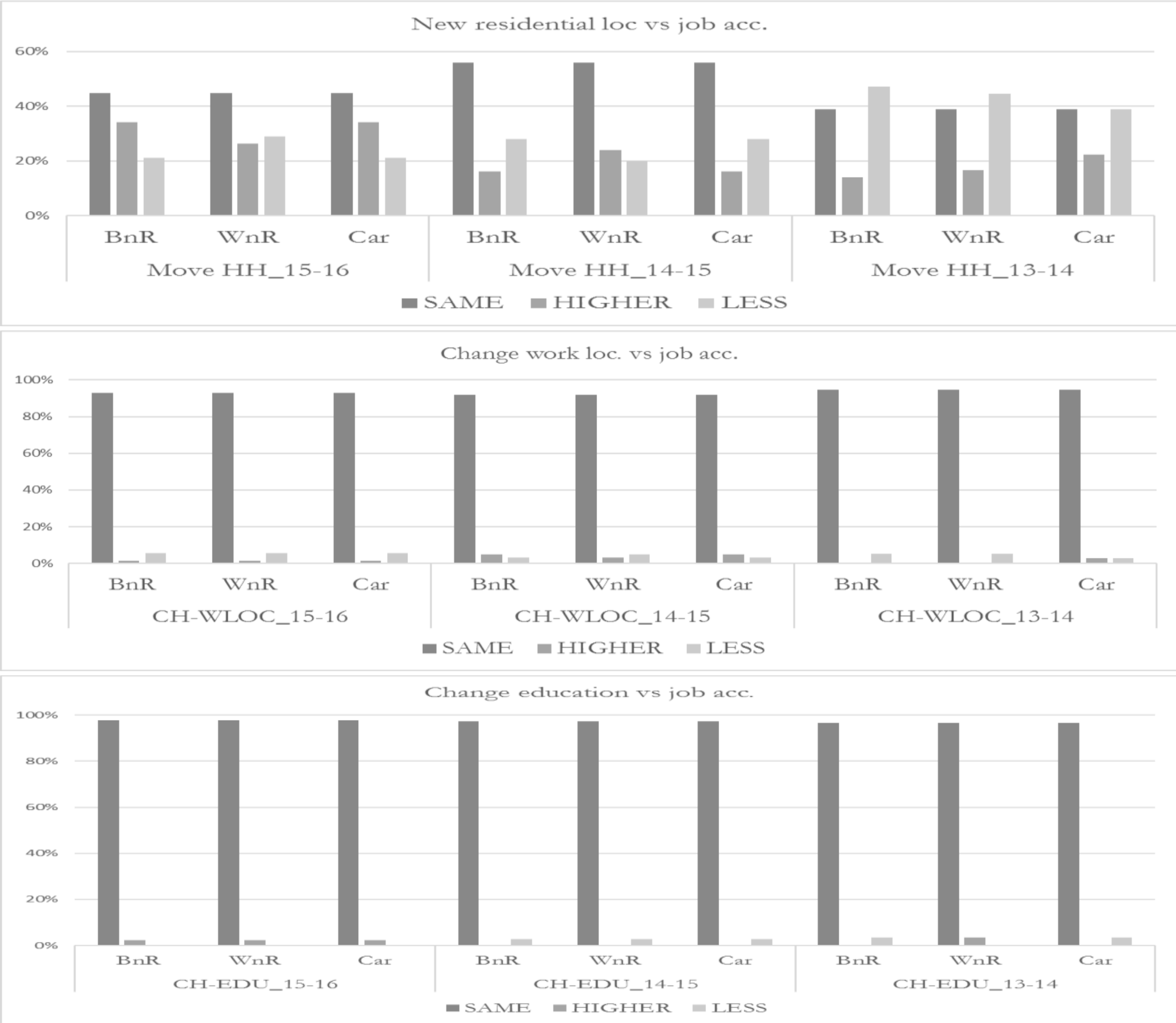

Figure 7: Overview variation in job accessibility level

Table 10: combinations of life events reported by the respondents

0	AE	DF	AEFGHM	EFG	GM	FGI	BK	DFM	DGJLM	AFG
A	ACEFGH	DM	CN	CIJ	DFHKL	EFKL	EFGM	AL	ABEFHM	DG
B	FG	ADGM	ABEF	IN	BG	AFGN	AGL	FGN	ILM	BH
C	AFGH	FGH	AGN	KLM	GH	ABCFGHK	ABG	CFG	DFGM	FMN
D	AEFH	AD	BC	EG	AKM	EHK	ADGI	DFHL	AEMN	FK
E	GHM	MN	CKM	ADFGH	IM	DGH	ABEFLM	ABGLM	ABF	BFI
F	ADG	DFI	ABCEFK	ABCDF	HL	ABLM	DIM	ACHM	EH	ABDEM
G	AF	DI	AN	ADFGL	AHI	ACEG	ADGIM	AFGLN	BM	DHJ
H	AK	CL	FN	GMN	CH	ABFGM	HKM	ABGH	ABFG	AGI
I	ALM	DEK	CJ	KM	AFI	ACFG	EFM	KL	CDF	AFGI
J	DFH	DFG	DK	AGLM	AI	FGK	ACEF	CHK	EGN	GK
K	FL	DH	ABFGH	DFIM	AEFGM	ABEFM	ACD	AEFM	ADKM	DE
L	CDI	ADFGI	AGM	AEFHI	ADF	BHM	FGM	AEFGLM	EFGH	EK
M	GN	FH	HI	EI	AFLM	FKM	BF	ABCEFGK	FM	AHN
N	HM	FI	GHK	EM	ADEFG	AFHJ	AHM	ABC	CHM	CI
ACDF	BN	AH	CDG	ADFI	AM	ACDFG	ABHM	AFHK	AEG	DFGLM

EF	KMN	ACF	BCN	AEFGH	AFGLM	AGMN	ABDKM	ADEFGKM	DFL	AFGM
DFHM	AEF	ADFG	ABH	ABCF	GI	AEGM	ADL	JM	EFH	AGH
DN	CF	DFN	AC	AB	EJ	ABM	ACG	AFGHM	ABGM	AHLM
AG	CM	AEFG	LM	ADH	AIM	BCH	FHJ	ADI	ABFGL	FGIM

Table 11: description of the letters used for the combinations of the life events in table A5

0	No life event
A	New job
B	Start working
C	Stop working
D	Work less
E	Work more
F	Change work hours/days
G	Change in work location
H	Change in school/education
I	Birth of a child in household
J	Death of someone in household
K	Getting divorced or brake up
L	Cohabitation
M	Move house, one parent leaves or one of the children leaves the house
N	One member of the household leaves the house

Most frequent used mode

In order to define the most frequent used mode of the respondents, the frequencies (i.e. the number of times a respondent used a particular mode) of the travel modes used by the respondents in each wave was an important aspect. By analysing the frequencies, it was possible to see which mode was used the most by a respondent in a particular year and that mode was then noted as the main mode or most frequent used mode of that respondent. See also table 12. For example, respondent with respondent ID, 3000462102, used during the three-days travel in year 2013: 1 time the car (as car driver), 4 times the bicycle and walked 3 times. Thus, this respondent his/her most used mode in wave 2013 is then the bicycle. The same was done for all the stayer respondents for the four waves. In the MPN data set, eight (8) modes are presented as main used travel mode, however, these 8 modes are aggregated into five (5) groups, see table 13.

Table 12: Example of definition most used mode by respondent per wave

	Respondent ID and mode	**Number of times that a mode is used in Wave 2013**	**Most used/ Main mode respondent wave 2013**	**Number of times that a mode is used in Wave 2014**	**Most used/ Main mode respondent wave 2014**	**Number of times that a mode is used in Wave 2015**	**Most used/ Main mode respondent wave 2015**	**Number of times that a mode is used in Wave 2016**	**Most used/ Main mode respondent wave 2016**
ID respondent	3000462102								
Mode choice respondent	1	1		3		3		3	
	2		6		6	2	7	2	6
	6	4		4				4	
	7	3		2		6		2	
ID respondent	3000540101								
Mode choice respondent	2	3						2	
	3	9	3		7		7		7
	4	3						2	
	6	4							
	7	2		4		6		3	

ID respondent	3000598602								
Mode choice respondent	1	9	1	13	1	3	6	7	6
	2	1		1					
	6	2		5		9		10	
	7							1	

Table 13: grouped main travel modes

Mode choice respondent	Segregated modes	Grouped modes
1	Car driver	Car
2	Car passenger	
3	Train	Public transport
4	Bus/tram/metro	
5	Moped/scooter	Bike
6	Bicycle	
7	Walk	Walk
8	Others	Others

In addition, it was also tested whether the most used mode was also the mode that included the most trips for all the different travel purposes, such as going home, go to work (commuting), business trips, transportation as job, pick up goods, pick up people etc. Table 14, 15, 16 and 17 present an overview of the fact that the most used mode always includes the most trips over for all the different travel purposes over the four waves in the MPN dataset. As became clear from table 12 is that, the respondent with respondent ID, 3000462102, used the bicycle the most in wave 2013. As a result, table 14 shows that this respondent also used the bicycle to carry out most of the trips (16 trips) for all the different travel purposes. Thus, the most used mode is also the mode that is used to carry out the most trips for the different travel purposes, see also table 15, 16 and 17 for the waves 2014, 2015 and 2016, respectively. In some cases, it happened that the car and the bicycle, or the car and public transport, or the bicycle and public transport were equally used. In those situations, the car was chosen above the bicycle and above public transport. When the bicycle and public transport were equally used, then the bicycle was chosen above public transport. This was done because it was found from the statistics that for all trip purposes the car was the first dominant mode, or most used mode, followed by the bicycle and public transport in the third place. From figure 8 it is also clear that the car is the first dominant mode, followed by the bicycle and public transport in the third place. From the 14 trip purposes, in 12 cases the car is the dominant mode, while the bicycle is the second dominant mode in 10 trip purposes, and public transport takes the third place. Public transport appears to be the most dominant mode for education related trips, however with only 0.4% difference with the bicycle, and the second dominant mode in work- and business-related trips.

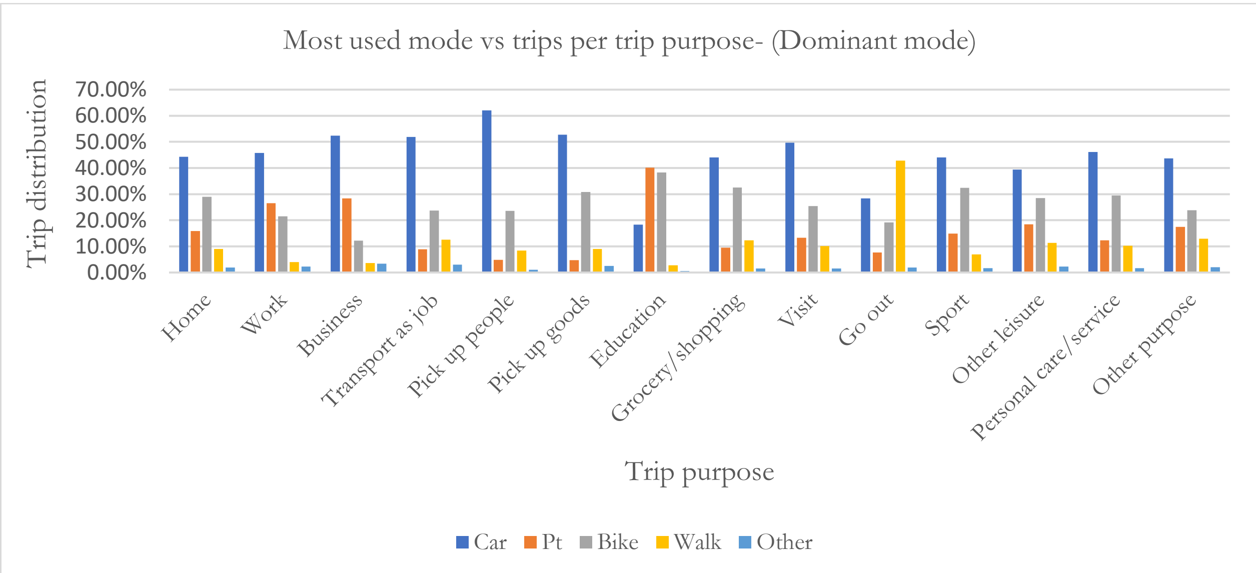

Figure 8: Most frequent used mode versus trip purpose

Table 14: Example of prove that the most frequent used mode is the mode with the most trips for all trip purposes (wave 2013)

Respondent ID	Most frequent used mode	Mode choice	Home trips	Work trips	Business trips	Transport as job trips	Pick up people trips	Pick up goods trips	Education trips	Grocery/shopping trips	Visit trips	Go out trips	Sport trips	Other leisure trips	Personal care/service trips	Other purpose trips	Unknown trips	Total trips for all travel purposes
3000462102		Car	3															3
	Bike	Bike	8						4	4								**16**
		Walk								3		1		3				7
3000540101		Car	4											8				12
	Pt	Pt	9							18	12							**39**
		Bike	4							8				4				16
		Walk	4										4					8
3000598602	Car	Car	6	3						9			9	3				**30**
		Bike	2											2				4
3001072801	Car	Car	10	4						5	10							**29**
3001072802	Car	Car	6	4							2							**12**
3001153801	Car	Car	4	2							2							**8**
3001156302		Car	4								4							8
	Bike	Bike	8	8														**16**
3001443002		Car	9				5				4							18
	Bike	Bike	9	5			5						4					**23**
3001592701		Car	13								6			7				26
	Walk	Walk	16						6	3				10				**35**
3001622402	Car	Car	10							18	3							**31**
		Bike	4							4								8
		Walk									3							3
3002228701	Car	Car	14	12						2								**28**
		Walk	4								4							8
3002244702		Car	15	5						3	10							33
	Bike	Bike	30	10						20				10				**70**
		Walk								10								10
3002482301	Car	Car	18	4				5		5			9					**41**
		Bike	2										2					4

Table 15: Example of prove that the most frequent used mode is the mode with the most trips for all trip purposes (wave 2014)

Respondent ID	Most frequent used mode	Mode choice	Home trips	Work trips	Business trips	Transport as job trips	Pick up people trips	Pick up goods trips	Education trips	Grocery/shopping trips	Visit trips	Go out trips	Sport trips	Other leisure trips	Personal care/service trips	Other purpose trips	Unknown trips	Total trips for all travel purposes
3000462102		Car	5									5		5				15
	Bike	Bike	8							4				4				**16**
		Walk	5											5				10
3000598602	Car	Car	6	3			6			36			18			3	3	**75**
		Bike	12				6						6	6				30
3000598604	Pt	Pt	20						28							15		**63**

		Bike	15	3					6	6								30
3001443001	Car	Car	4								2		2					8
		Other	2	2														4
3001707301		Car	8															8
	Bike	Bike	75		10	8				24	27				18			**162**
		Walk							10			9				10		29
3001878301	Car	Car	30				16			8			23		7		8	**92**
		Bike	15	15			8											38
		Walk										39					8	47
3002228701	Car	Car	19	10						21	3							**53**
		Bike	4	4														8
3002244702		Car	15	7						3	5							30
	Bike	Bike	12							24					7			**43**
		Walk										10						10
3002820501	Car	Car	10							5	5		10					**30**
		Bike	12							5			7					24
		Walk												5				5
3002820502		Car	20				8			7	7		10					52
	Bike	Bike	35	8						7	8		12					**70**
		Walk	8							8				5				21
3002938201	Car	Car	13	4							5			9				31
		Bike	5							5								10

Table 16: Example of prove that the most frequent used mode is the mode with the most trips for all trip purposes (wave 2015)

Respondent ID	Most frequent used mode	Mode choice	Home trips	Work trips	Business trips	Transport as job trips	Pick up people trips	Pick up goods trips	Education trips	Grocery/shopping trips	Visit trips	Go out trips	Sport trips	Other leisure trips	Personal care/service trips	Other purpose trips	Unknown trips	Total trips for all travel purposes
3000598602		Car	3	3						3								9
	Bike	Bike	11							3			11					25
3000598604	Pt	Pt							70					21				**91**
		Bike	21						9		14		16					60
		Walk	7								7							14
3001072802	Car	Car	23	5			21											**49**
3001153801	Car	Car	14	2						6					6			28
		Walk	2							2								4
3001156301	Bike	Bike	8	8														**16**
		Walk	4									4						8
3001156302	Car	Car	7	2						10								**19**
		Bike	7							2	5							14
3001296701	Car	Car	12				10				3			7				**32**
		Bike	9	9														18
3001443001		Car		2														2
	Bike	Bike	3										3					**6**
		Walk										4						4

		Other	2														2
3001443002	Car	Car	3	3			3										**9**
		Bike	3										3				6
		Walk										3					3
3001707301	Car	Car	6	6		6				6	6						**30**
		Bike	3		3										3		9
		Walk							6								6
3001801101	Car	Car	14	8							11			14		8	**55**
		Bike	24							13	6			7			50
		Walk	6									6		6			18

Table 17: Example of prove that the most frequent used mode is the mode with the most trips for all trip purposes (wave 2016)

Respondent ID	Most frequent used mode	Mode choice	Home trips	Work trips	Business trips	Transport as job trips	Pick up people trips	Pick up goods trips	Education trips	Grocery/shopping trips	Visit trips	Go out trips	Sport trips	Other leisure trips	Personal care/service trips	Other purpose trips	Unknown trips	Total trips for all travel purposes
3000462102	Car	Car	14								7	7		7				**35**
		Bike	8							4				4				16
		Walk	7							7								14
3000540101	Car	Car	4	8										4				**16**
		Pt									8							8
		Walk	2							4								6
3000598602		Car	9	2			14			7				7				39
	Bike	Bike	22							5			22			5		**54**
		Walk								5								5
3001072802		Bike	10							10								20
	Other	Other	46	6			44				4							**100**
3001130201	Car	Car	10	4									6					**20**
		Pt	8											8				16
		Walk	4	4														8
3001153801	Car	Car	3							3					3			**9**
		Walk	4	2						2								8
3001153803	Pt	Pt	12	12														24
3001336201		Car	5							10								15
	Bike	Bike	10								11			2				**23**
3001443001	Car	Car	6				4						2					12
		Other	4	4														8
3001707301	Car	Car	16	4				12										**32**
		Bike	12				4			8								24
		Walk	6					6										12
3080240202		Car	14	2						6			6					28
	Pt	Pt	18										18					**36**
		Bike	2	2														4

Appendix D: Elaborated statistics

Descriptive Statistics Socio-economic Characteristics

Before building the discrete choice models, it was important to understand the variation and nature of all the variables available in the dataset and suitable for the analysis in this thesis report. These are the socio-economic characteristics, trip related-, and built environment-variables. As mentioned earlier, is that only the respondents who participated in the four consecutive waves (2013, 2014, 2015 and 2016), are included in the analysis. There are 1273 stayer respondents with a total of 58035 trip observations. Furthermore, the deltas, that is the differences between the explanatory variables of two consecutive waves were considered in order to be able to analyze the temporal effects of the life events on the mobility choices (car ownership and most used mode). The figures below were used to build the models for wave 2013-2014. These figures gave an idea of which delta parameter could be expected to be statistical significant in the model estimation. Figure 9 for example represents the alternatives of the life event model versus the delta parameter of the variable "age" for the time interval: wave 2013-2014. Form this figure it could be assumed that the delta parameter "age" is the most significant or is the most influential for the alternative "Edu" (education), followed by "Others" and "Work", because the standard deviation is the largest for these alternatives, and the larger the standard deviation, the larger the variation, and the bigger the chance of having a statistical significant effect from such a parameter in the model estimation. The same statistics were carried out for all the selected delta parameters for the alternatives of the life events, the alternatives of the car ownership models and also for the alternatives of the models of the most frequent used mode, for the three (3) time intervals: wave 2013-2014, wave 2014-2015 and wave 2015-2016.

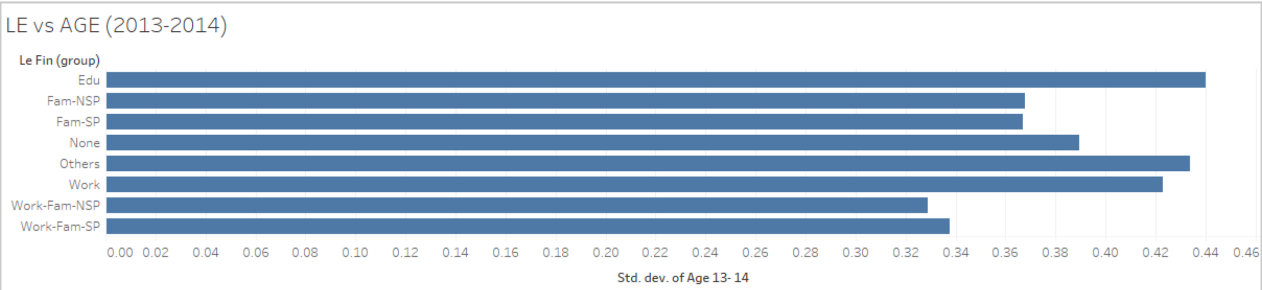

Figure 9: Life event alternatives vs Age (2013-2014)

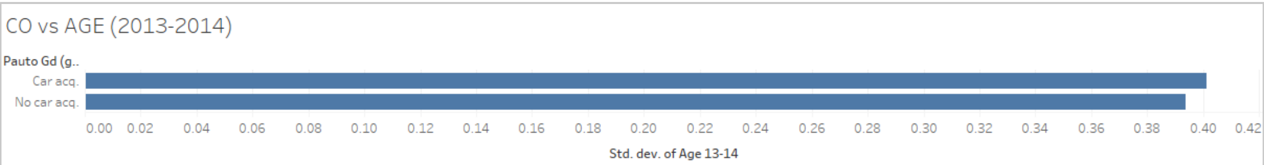

Figure 10: Car ownership alternatives vs Age (2013-2014)

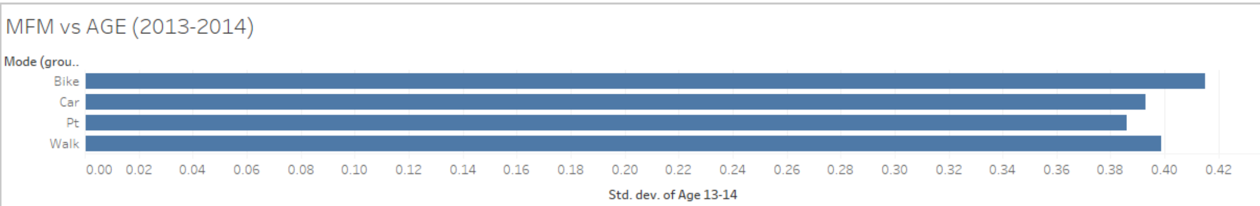

Figure 11: Most frequent used mode vs Age (2013-2014)

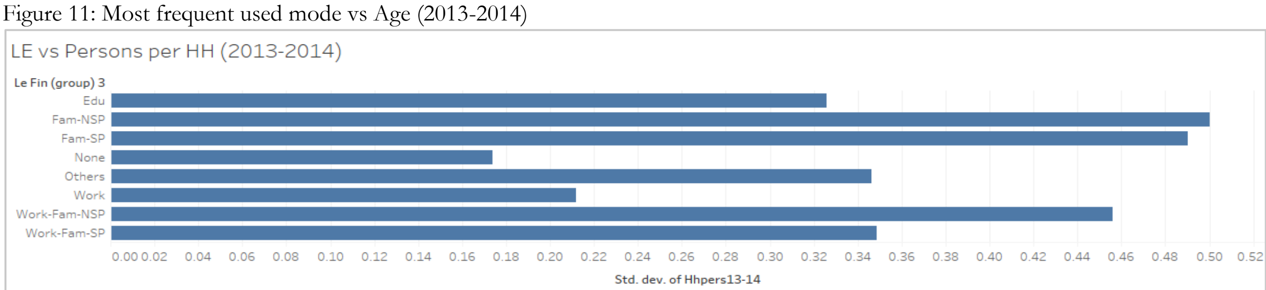

Figure 12: Life event alternatives vs persons per house hold (2013-2014)

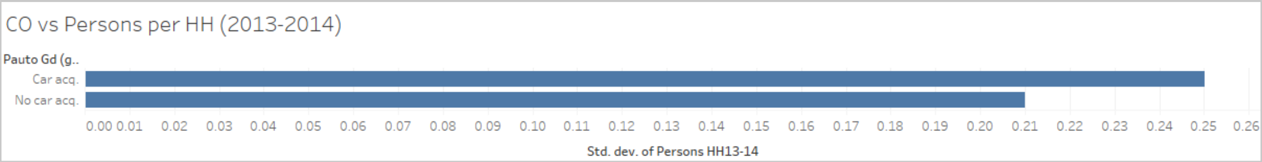

Figure 13: Car ownership alternatives vs persons per house hold (2013-2014)

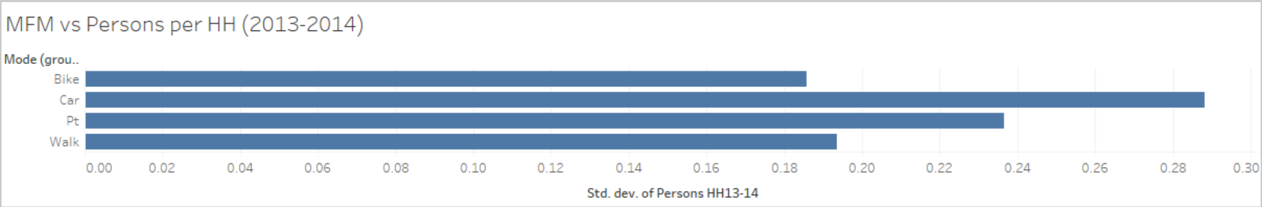

Figure 14: Most frequent used mode vs persons per house hold (2013-2014)

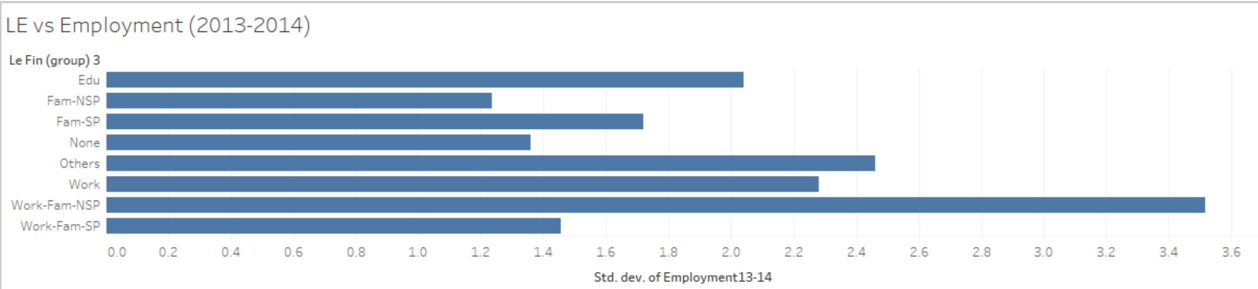

Figure 15: Life event alternatives vs Employment (2013-2014)

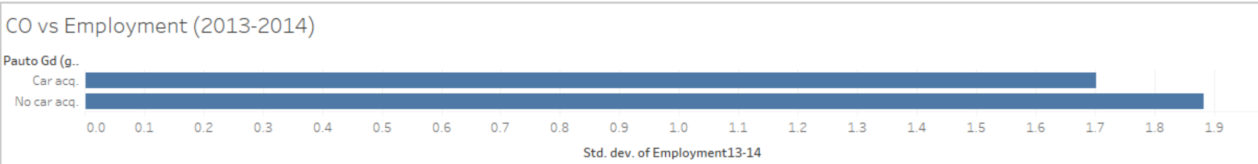

Figure 16: Car ownership alternatives vs Employment (2013-2014)

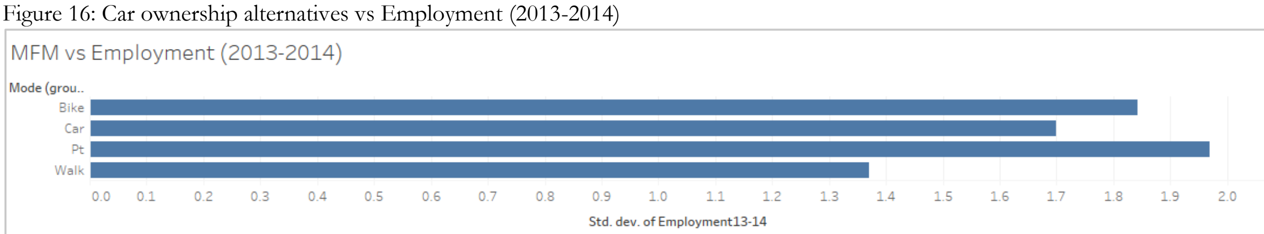

Figure 17: Most frequent used mode vs Employment (2013-2014)

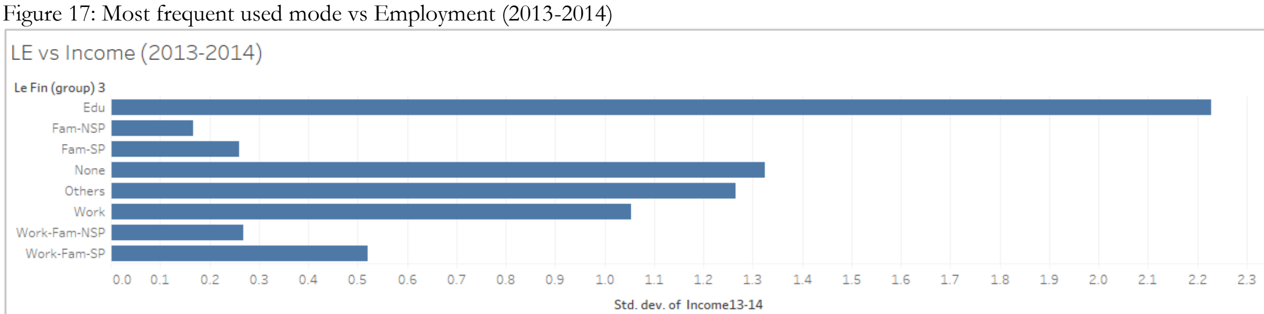

Figure 18: Life event alternatives vs Income (2013-2014)

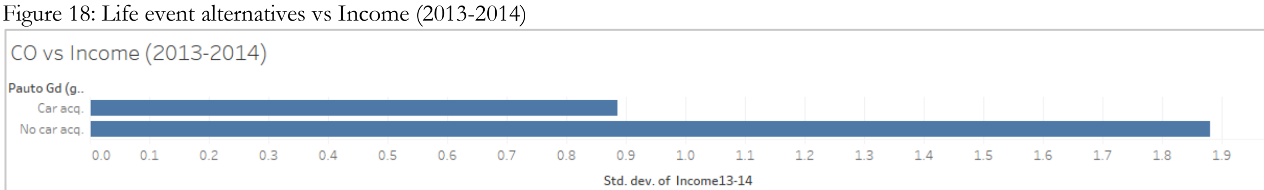

Figure 19: Car ownership alternatives vs Income (2013-2014)

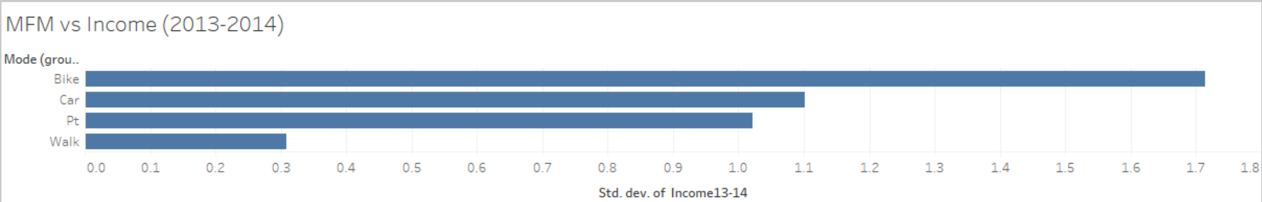

Figure 20: Most frequent used mode vs Income (2013-2014)

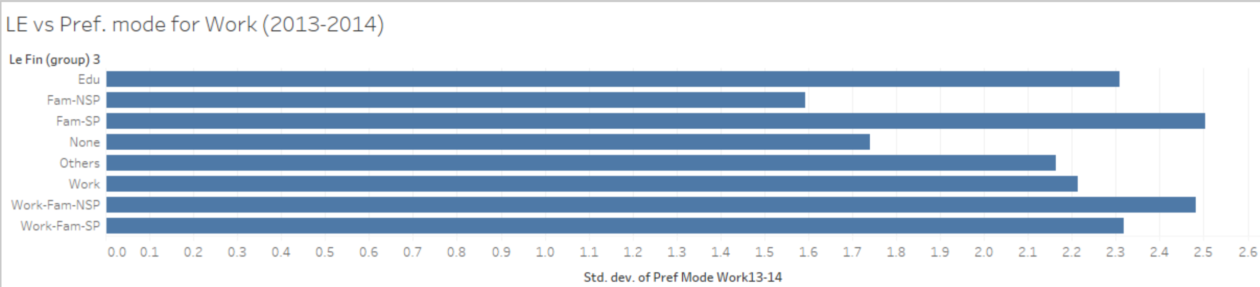

Figure 21: Life event alternatives vs preferred mode for work (2013-2014)

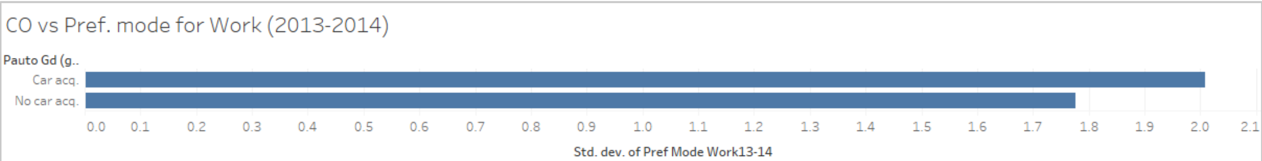

Figure 22: Car ownership alternatives vs preferred mode for work (2013-2014)

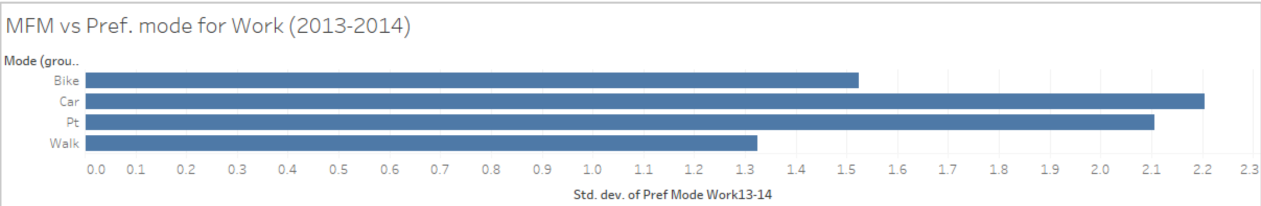

Figure 23: Most frequent used mode vs preferred mode for work (2013-2014)

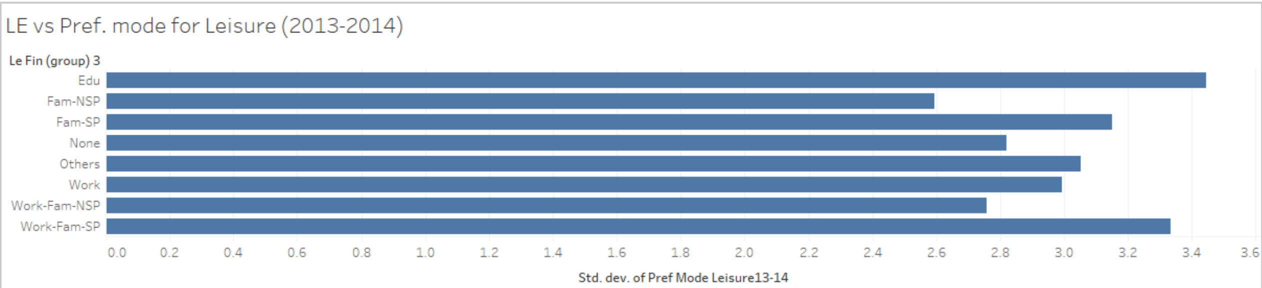

Figure 24: Life event alternatives vs Preferred mode for leisure (2013-2014)

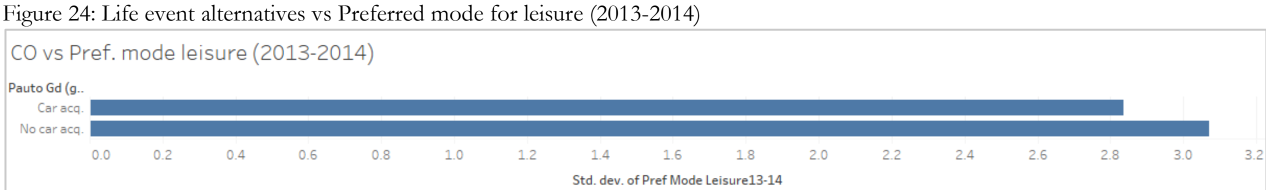

Figure 25: Car ownership alternatives vs preferred mode for leisure (2013-2014)

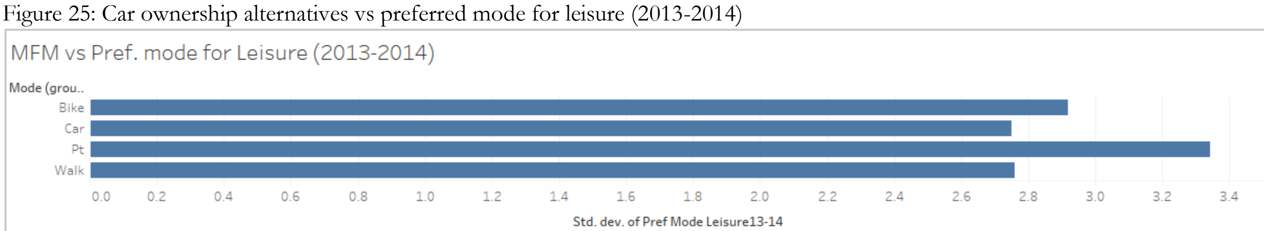

Figure 26: Most frequent used mode vs preferred mode for leisure (2013-2014)

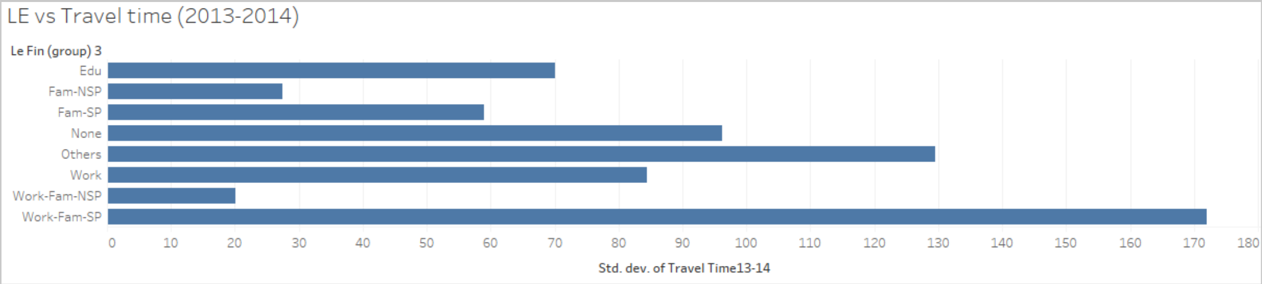

Figure 27: Life event alternatives vs travel time (2013-2014)

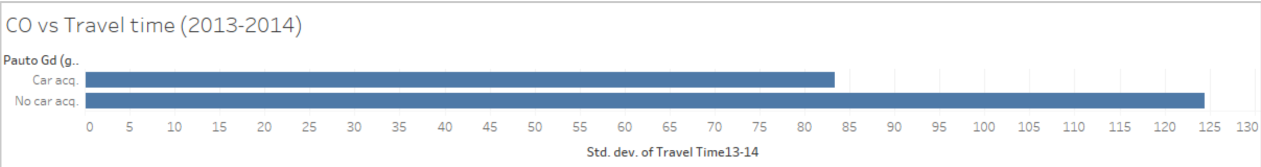

Figure 28: Car ownership alternatives vs travel time (2013-2014)

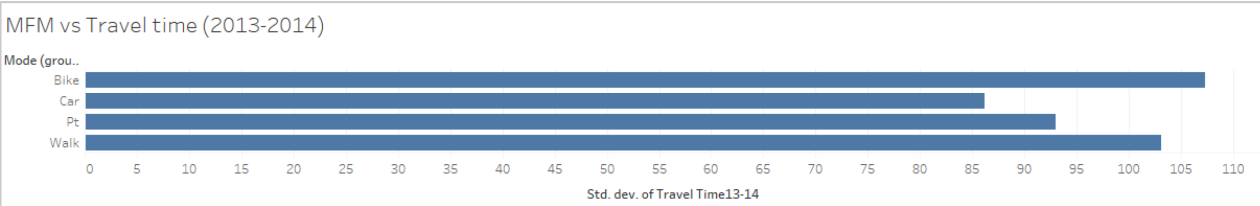

Figure 29: Most frequent used mode vs travel time (2013-2014)

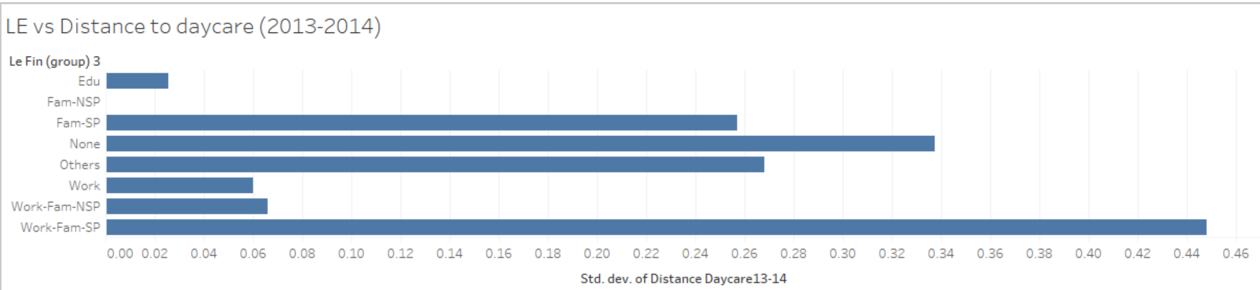

Figure 30: Life event alternatives vs Distance to daycare (2013-2014)

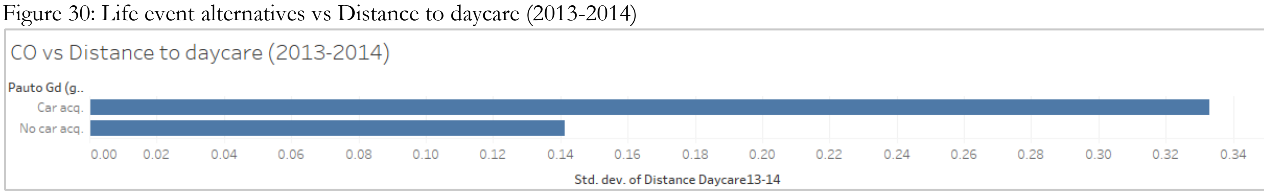

Figure 31: Car ownership alternatives vs Distance to daycare (2013-2014)

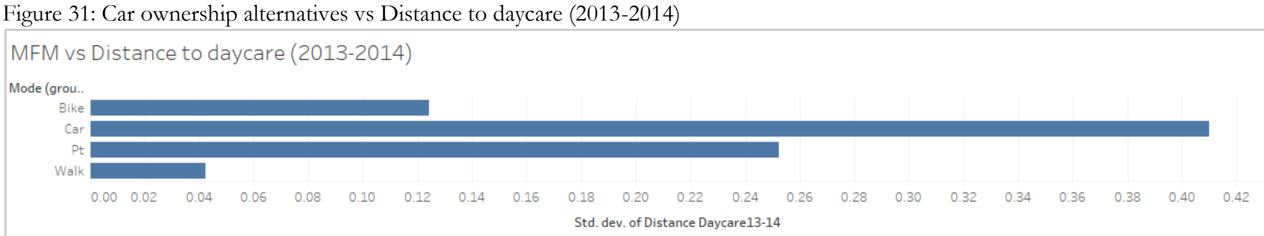

Figure 32: Most frequent used mode vs Distance to daycare (2013-2014)

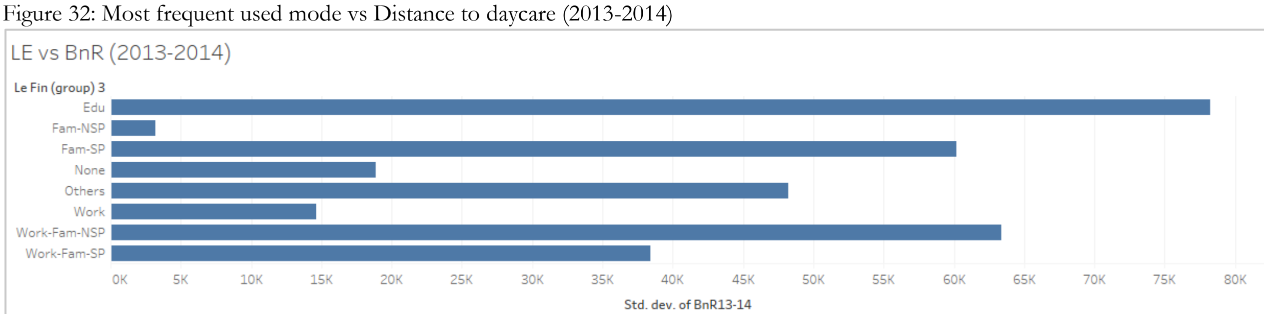

Figure 33: Life event alternatives vs BnR (2013-2014)

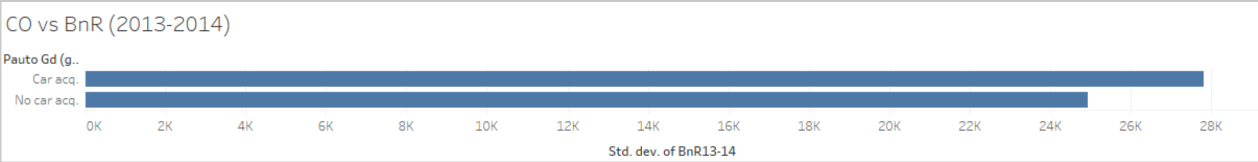

Figure 34: Car ownership alternatives vs BnR (2013-2014)

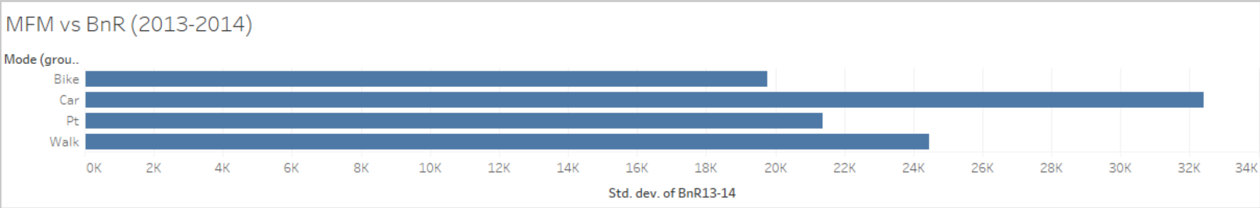

Figure 35: Most frequent used mode vs BnR (2013-2014)

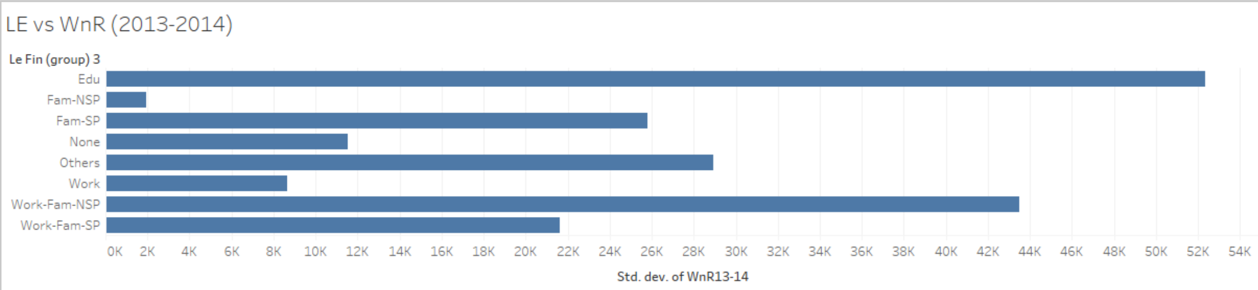

Figure 36: Life event alternatives vs WnR (2013-2014)

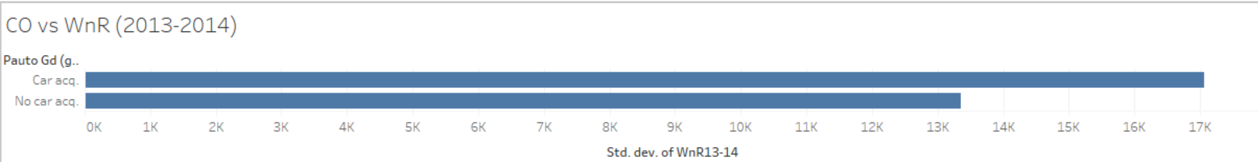

Figure 37: Car ownership alternatives vs WnR (2013-2014)

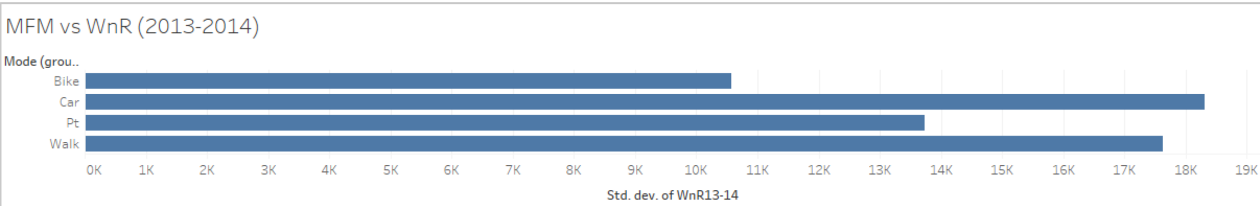

Figure 38: Most frequent used mode vs WnR (2013-2014)

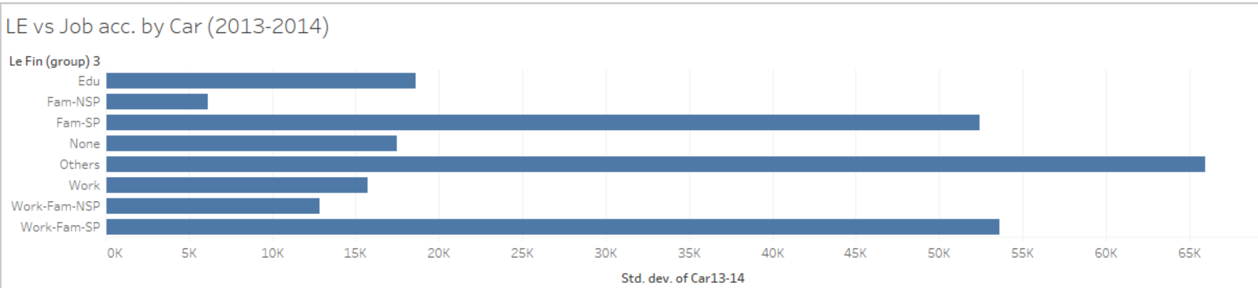

Figure 39: Life event alternatives vs Job accessibility by car (2013-2014)

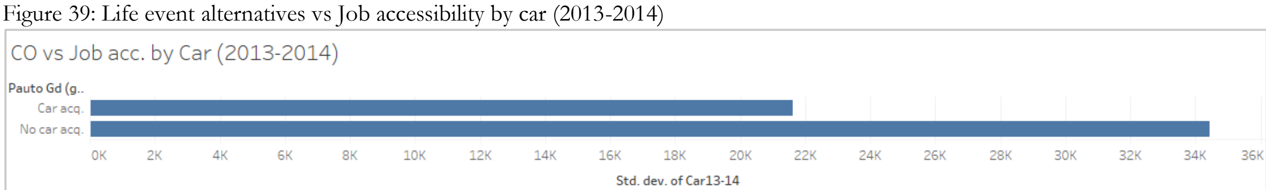

Figure 40: Car ownership alternatives vs Job accessibility by car (2013-2014)

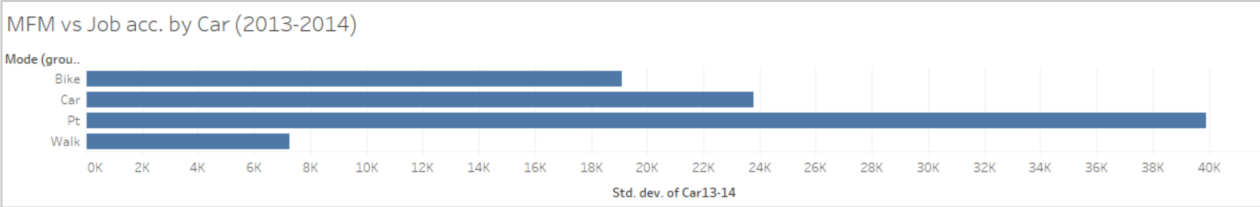

Figure 41: Most frequent used mode vs Job accessibility by car (2013-2014)

Statistical tests for the selection of variables

In order to be able to understand the correlation or multicollinearity between the explanatory variables, statistical tests are performed. This was important, because variables that are highly correlated can affect the model estimation and produce wrong results. Therefore, a correlation analysis is used for testing the correlation, as well as the variance inflation factor (VIF) test. This test is a linear regression analysis where the one variable is one time a dependent variable and another time an independent variable. The analysis is an iterative process, where the selected variables are being swapped around each other. The statistical software IBM SPSS was used for this task. It is important to mention that the results of these statistical analysis are only done in order to provide insight in the priori-assumptions that are needed for building the model, because these analyses are just simple regressions. The table with the VIF output of the explanatory variables is provided in table 19

Table 18: Threshold VIF correlation

Variance Inflation Factor (VIF)	**Multicollinearity**
VIF = 1	Not correlated
1 < VIF < 3	Slightly correlated
VIF > 3 to 5	High multicollinearity
VIF > 5	Very high multicollinearity

Table 19: Overview VIF test results

Parameter	**VIF**	**Parameter**	**VIF**	**Parameter**	**VIF**
Persons per household	1.402	Preferred mode school	1.232	Opinion parking	1.017448
Travel distance	2.595	Preferred mode visiting	1.407		
Travel time	2.620	Preferred mode leisure	1.287		
Population density	1.706	**Parking at house yard**	**4.140**		
Distance to baby day care	1.304	**Free parking at house**	**4.030**		
BnR	**6.917**	**Paid parking at hosue**	**9.841**		
WnR	**4.872**	Gender	1.032		
Car	**4.592**	Employment	1.155		
Distance to onramp	1.156	Preferred mode work	1.236		
Distance to train station	1.381				
Distance to metro/tram	**4.168**				
Distance to bus stop4xpu	1.634				
Dependent Variable: Age		**Dependent Variable: Parking permit at house**		**Dependent Variable: Education**	

Table 20: overview correlation between explanatory variables

		correlation coefficient
Urbanity	BnR	-0.72
	WnR	-0.73
	Distance to downtown	0.62
	Distance to transfer point	0.61
Persons per household	Household composition	0.68
Free parking at house	Parking permit at house	0.79
	Paid parking at house	0.83
Parking at house yard	Parking permit at house	0.79
	Paid parking at house	0.83
Parking permit at house	Paid parking at house	0.97
Job accessibility by Bicycle (BnR)	WnR	0.86
	Car	0.74
Job accessibility by public transport (WnR)	Car	0.62

Appendix E: Model output

Table 21: Model 1 (M1 – life events) versus Model 2 (M2 – Car ownership): WAVE-13-14 **- t-test calculation**

Life event model: M1 (WAVE-13-14)			Car ownership model: M2 (WAVE-13-14)			Calculated T-TEST			
Name	Value	***t-test***	Name	Value	***t-test***	Difference of the beta's	Sum of variance	Calculated t-test	Significant different or not
ASC-Work	-2.58	***-14.12***							
ASC-Education	-20.7	***-17.76***							
ASC-Fam-NSP	-17.3	***-21***							
ASC-Fam-SP	-15.7	***-27.49***							
ASC-Work-Fam-NSP	-14.1	***-20.51***							
ASC-Work-Fam-SP	-14.5	***-26.51***							
ASC-Others	-11.1	***-27.44***	ASC-Car acq.	63.5	***8.93***				
ASC-None	Ref.		ASC-No Car acq.	Ref.					
Employment (Fam-NSP)	-0.68	***-9.66***	Employment (Car acq.)	-18.3	***-8.22***	17.62	4.98	7.90	Yes
Person per HH (Fam-NSP)	-10.5	***-19.91***	Persons per HH (Car acq.)	-19.9	***-2.79***	9.40	51.12	**1.31**	**No**
Urbanity (Work-Fam-NSP)	5.09	***15.58***	Urbanity (Car acq.)	16.2	***2.46***	-11.11	43.67	**-1.68**	**No**
Job acc. Car (Work-fam-SP)	8.84E-05	***27.16***	Job acc. Car (Car acq.)	-0.00022	***-5.18***	3.06E-04	1.78E-09	7.26	Yes
σ-Work	9.79	***34.21***	σ-Car acq.	-82.8	***-8.9***				
σ-Education	12.2	***18.06***	σ-No Car acq.	Ref.					
σ-Fam-NSP	10.1	***23.1***							
σ-Fam-SP	-11.9	***-29.13***							
σ-Work-Fam-NSP	7.07	***22.04***							
σ-Work-Fam-SP	-10.1	***-27.91***							
σ-Others	-9.82	***-32.38***							
σ-None	Ref.								

Table 22: Model 1 (M1 – life events) versus Model 3 (M3 – most frequent mode): WAVE-13-14 **- t-test calculation**

Life event model: M1 (WAVE-13-14)			Most frequent mode model: M3 (WAVE-13-14)			Calculated T-TEST			
Name	Value	***t-test***	Name	Value	***t-test***	Difference of the beta's	Sum of variance	Calculated t-test	Significant different or not
ASC-Work	-2.58	***-14.12***							
ASC-Education	-20.7	***-17.76***							
ASC-Fam-NSP	-17.3	***-21***							
ASC-Fam-SP	-15.7	***-27.49***							
ASC-Work-Fam-NSP	-14.1	***-20.51***	ASC-Pt	-15.9	***-18.76***				
ASC-Work-Fam-SP	-14.5	***-26.51***	ASC-Bike	-2.62	***-9.09***				
ASC-Others	-11.1	***-27.44***	ASC-Walk	-22.9	***-20.32***				
ASC-None	Ref.		ASC-Car	Ref.					
Age (Education)	-5.79	***-13.29***	Age (Bike)	-6.86	***-15.57***	5.47	0.21	11.89	Yes
Age (Work)	-1.39	***-10.63***	Age (Pt)	-2.97	***-8.87***	-2.82	0.30	-5.13	Yes
Age (Education)	-5.79	***-13.29***	Age (Pt)	-2.97	***-8.87***	1.58	0.13	4.40	Yes
Persons per HH (Fam-NSP)	-10.5	***-19.91***	Persons per HH (Pt)	13.2	***2.97***	-23.70	20.17	-5.28	Yes
Employment (Fam-NSP)	-0.68	***-9.66***	Employment (Bike)	0.968	***12.35***	-1.65	0.01	-15.66	Yes
Employment (Fam-NSP)	-0.68	***-9.66***	Employment (Pt)	1.11	***13.51***	-1.79	0.01	-16.55	Yes
Income (Work)	-0.0843	***-2.26***	Income (Bike)	1.86	***17.7***	-1.27	0.02	-9.24	Yes
Income (Work-Fam-SP)	-1.01	***-4.18***	Income (Bike)	1.86	***17.7***	-1.94	0.01	-17.45	Yes
Pref. mode work (Work-Fam-NSP)	0.322	***7.4***	Pref. mode work (Pt)	0.68	***12.76***	-0.36	4.73E-03	-5.20	Yes
Pref. mode leisure (Fam-SP)	0.54	***13.88***	Pref. mode leisure (Pt)	-3.48	***-19.89***	4.02	0.03	22.42	Yes
Travel time (Work)	-0.00419	***-24.45***	Travel time (Bike)	-0.00065	***-3.44***	-3.54E-03	6.53E-08	-13.84	Yes
Travel time (Work-fam-SP)	0.00116	***5.42***	Travel time (Bike)	-0.00065	***-3.44***	1.81E-03	8.15E-08	6.35	Yes
Urbanity (Work-Fam-NSP)	5.09	***15.58***	Urbanity (Walk)	22.5	***20.65***	-17.41	1.30	-15.30	Yes
Distance to Train (Others)	-0.00192	***-28.26***	Distance to Train (Walk)	-0.00295	***-19.75***	1.03E-03	2.71E-08	6.26	Yes
Bike and Ride (Work-Fam-NSP)	6.59E-05	***16.94***	Bike and Ride (Bike)	4.80E-05	***5.08***	1.79E-05	1.04E-10	**1.75**	**No**
Walk and Ride (Fam-SP)	-6.26E-05	***-17.58***	Walk and Ride (Pt)	0.000257	***13.75***	-3.20E-04	3.62E-10	-16.79	Yes
σ-Work	9.79	***34.21***	σ-Pt	21.6	***20.2***				
σ-Education	12.2	***18.06***	σ-Bike	-14	***-20.51***				
σ-Fam-NSP	10.1	***23.1***	σ-Walk	22.6	20.57				
σ-Fam-SP	-11.9	***-29.13***	σ-Car	Ref.					
σ-Work-Fam-NSP	7.07	***22.04***							
σ-Work-Fam-SP	-10.1	***-27.91***							
σ-Others	-9.82	***-32.38***							
σ-None	Ref.								

Table 23: Model 4 (M4 – life events) versus Model 5 (M5 – car ownership): WAVE-14-15 **- t-test calculation**

Life event model: M4 (WAVE-14-15)			Car ownership model: M5 (WAVE-14-15)			Calculated T-TEST			
Name	Value	*t-test*	Name	Value	*t-test*	Difference of the beta's	Sum of variance	Calculated t-test	Significant different or not
ASC-Work	-6.03	***-23.27***							
ASC-Education	-26.1	***-21.78***							
ASC-Fam-NSP	-19.3	***-14.13***							
ASC-Fam-SP	-13.7	***-25.36***							
ASC-Work-Fam-NSP	-24.2	***-21.54***							
ASC-Work-Fam-SP	-13.4	***-24.06***							
ASC-Others	-9.73	***-23.87***	ASC-Car acq.	64.5	***9.57***				
ASC-None	Ref.		ASC-No Car acq.	Ref.					
Persons per HH (Work)	-0.721	***-3.07***	Persons per HH (Car acq.)	-45	***-9.58***	44.28	**22.05**	9.43	Yes
Persons per HH (Fam-NSP)	0.397	***1.98***	Persons per HH (Car acq.)	-45	***-9.58***	45.40	**22.04**	9.67	Yes
Person per HH (Fam-SP)	1.91	***6.59***	Persons per HH (Car acq.)	-45	***-9.58***	46.91	**22.08**	9.98	Yes
Job acc. Car (Fam-SP)	-1.34E-05	***-17.69***	Job acc. Car (Car acq.)	6.29E-05	***4.52***	-7.63E-05	1.94E-10	-5.48	Yes
Job acc. Car (Work-Fam-SP)	-5.76E-06	***-8.51***	Job acc. Car (Car acq.)	6.29E-05	***4.52***	-6.87E-05	**1.94E-10**	-4.93	Yes
Job acc. Car (Work)	-8.98E-06	***-10.32***	Job acc. Car (Car acq.)	6.29E-05	***4.52***	**-7.19E-05**	**1.94E-10**	-5.16	Yes
σ-Work	-10.6	***-28.67***	σ-Car acq.	64.3	***9.6***				
σ-Education	-20	***-21.99***	σ-No Car acq.	Ref.					
σ-Fam-NSP	11.9	***15.69***							
σ-Fam-SP	7.81	***25.84***							
σ-Work-Fam-NSP	16.1	***22.56***							
σ-Work-Fam-SP	8.38	***25.42***							
σ-Others	8.78	***26.68***							
σ-None	Ref.								

Table 24: Model 4 (M4 – life events) versus Model 6 (M6 – most frequent mode): WAVE-14-15 **- t-test calculation**

Life event model: M4 (WAVE-14-15)			Most frequent mode model: M6 (WAVE-14-15)			Calculated T-TEST			
Name	Value	*t-test*	Name	Value	*t-test*	Difference of the beta's	Sum of variance	Calculated t-test	Significant different or not
ASC-Work	-6.03	***-23.27***							
ASC-Education	-26.1	***-21.78***							
ASC-Fam-NSP	-19.3	***-14.13***							
ASC-Fam-SP	-13.7	***-25.36***							
ASC-Work-Fam-NSP	-24.2	***-21.54***	ASC-Pt	-15.1	***-15.71***				
ASC-Work-Fam-SP	-13.4	***-24.06***	ASC-Bike	-10.8	***-12.45***				
ASC-Others	-9.73	***-23.87***	ASC-Walk	-9.64	***-9.51***				
ASC-None	Ref.		ASC-Car	Ref.					
Age (Fam-SP)	5.49	***19.83***	Age (Pt)	16.4	***15.92***	-10.91	0.58	-14.32	yes
Persons per HH (Work)	-0.721	***-3.07***	Persons per HH (Walk)	11.6	***12.59***	-12.32	0.56	-16.54	yes
Persons per HH (Fam-NSP)	0.397	***1.98***	Persons per HH (Walk)	11.6	***12.59***	-11.20	0.54	-15.24	yes
Persons per HH (Fam-SP)	1.91	***6.59***	Persons per HH (Walk)	11.6	***12.59***	-9.69	0.58	-12.68	yes
Pref. mode work (Work)	-0.13	***-3.09***	Pref. mode work (Pt)	-0.243	***-5.57***	0.11	0.00	2.22	yes
Pref. mode work (Work-Fam-NSP)	-1.91	***-16.34***	Pref. mode work (Pt)	-0.243	***-5.57***	-1.67	0.01	-13.83	yes
Pref. mode school(Education)	3.91	***20.1***	Pref. mode school(Bike)	-2.9	***-15.19***	6.81	0.06	28.95	yes
Pref. mode school(Education)	3.91	***20.1***	Pref. mode school(Pt)	-3.91	***-16.3***	7.82	0.07	28.95	yes
Walk and Ride (Fam-NSP)	6.22E-05	***3.8***	Walk and Ride (Pt)	-5.04E-05	-1.94	0.00	0.00	2.50	yes
Walk and Ride (Fam-NSP)	6.22E-05	***3.8***	Walk and Ride (Walk)	0.000355	***9.08***	0.00	0.00	-4.13	yes
σ-Work	-10.6	***-28.67***	σ-Pt	20.3	***16.65***				
σ-Education	-20	***-21.99***	σ-Bike	-14.1	***-15.07***				
σ-Fam-NSP	11.9	***15.69***	σ-Walk	-23.7	***-12***				
σ-Fam-SP	7.81	***25.84***	σ-Car	Ref.					
σ-Work-Fam-NSP	16.1	***22.56***							
σ-Work-Fam-SP	8.38	***25.42***							
σ-Others	8.78	***26.68***							
σ-None	Ref.								

Table 25: Model 7 (M7 – life events) versus Model 8 (M8 – car ownership): WAVE-15-16 **- t-test calculation**

Life event model: M7 (WAVE-15-16)			Car ownership model: M8 (WAVE-15-16)			Calculated T-TEST			
Name	Value	*t-test*	Name	Value	*t-test*	Difference of the beta's	Sum of variance	Calculated t-test	Significant different or not
ASC-Work	-4.4	***-24.12***							
ASC-Education	-41.3	***-20.91***							
ASC-Fam-NSP	-25.7	***-20.87***							
ASC-Fam-SP	-19.9	***-24.36***							
ASC-Work-Fam-NSP	-29.8	***-18.37***							
ASC-Work-Fam-SP	-29.9	***-22.73***							
ASC-Others	-9.91	***-26.96***	ASC-Car acq.	30.6	***9.63***				
ASC-None	Ref.		ASC-No Car acq.	Ref.					
Persons per HH (Fam-NSP)	-9.28	***-16.98***	Persons per HH (Car acq.)	3.81	***8.91***	-13.09	0.48	-18.87	yes
Person per HH (Fam-SP)	1.66	***6.26***	Persons per HH (Car acq.)	3.81	***8.91***	-2.15	0.25	-4.27	yes
Employment (Work-Fam-NSP)	-3.12	***-19.91***	Employment (Car acq.)	5.87	***9.59***	-8.99	0.40	-14.23	yes
Income (Fam-NSP)	-3.55	***-11.1***	Income (Car acq.)	-7.07	***-9.09***	3.52	0.71	4.19	yes

σ-Work	-6.77	***-33.03***	σ-Car acq.	-39.9	***-9.69***				
σ-Education	-31.8	***-22.32***	σ-No Car acq.	Ref.					
σ-Fam-NSP	18.4	***21.41***							
σ-Fam-SP	20.6	***25.65***							
σ-Work-Fam-NSP	18.4	***19.26***							
σ-Work-Fam-SP	29.9	***24.85***							
σ-Others	-8.21	***-28.87***							
σ-None	Ref.								

Table 26: Model 7 (M7 – life events) versus Model 9 (M9 – most frequent mode): WAVE-15-16 **- t-test calculation**

Life event model: M7 (WAVE-15-16)			Most frequent mode model: M9 (WAVE-15-16)			Calculated T-TEST			
Name	Value	***t-test***	Name	Value	***t-test***	Difference of the beta's	Sum of variance	Calculated t-test	Significant different or not
ASC-Work	-4.4	***-24.12***							
ASC-Education	-41.3	***-20.91***							
ASC-Fam-NSP	-25.7	***-20.87***							
ASC-Fam-SP	-19.9	***-24.36***							
ASC-Work-Fam-NSP	-29.8	***-18.37***	ASC-Pt	-13.8	***-19.81***				
ASC-Work-Fam-SP	-29.9	***-22.73***	ASC-Bike	0.311	***2.01***				
ASC-Others	-9.91	***-26.96***	ASC-Walk	-20.3	***-21.98***				
ASC-None	Ref.		ASC-Car	Ref.					
Persons per HH (Fam-NSP)	-9.28	***-16.98***	Persons per HH (Bike)	4.62	***15.55***	-13.90	0.39	-22.36	Yes
Persons per HH (Fam-NSP)	-9.28	***-16.98***	Persons per HH (Pt)	-4.82	***-12.3***	-4.46	0.45	-6.64	Yes
Persons per HH (Fam-SP)	1.66	***6.26***	Persons per HH (Bike)	4.62	***15.55***	-2.96	0.16	-7.44	Yes
Persons per HH (Fam-SP)	1.66	***6.26***	Persons per HH (Pt)	-4.82	***-12.3***	6.48	0.22	13.69	Yes
Employment (Work-Fam-NSP)	-3.12	***-19.91***	Employment (Pt)	-0.856	***-10.14***	-2.26	0.03	-12.70	Yes
Income (Fam-NSP)	-3.55	***-11.1***	Income (Bike)	-0.697	***-11.66***	-2.85	0.11	-8.79	Yes
Income (Fam-NSP)	-3.55	***-11.1***	Income (Pt)	1.77	***19.36***	-5.32	0.11	-16.03	Yes
Pref. mode school (Work-Fam-NSP)	3.96	***22.15***	Pref. mode school (Pt)	-0.49	***-7.12***	4.45	0.04	23.21	Yes
Pref. mode leisure (Work-Fam-SP)	-2.95	***-24.84***	Pref. mode leisure (Pt)	-1.11	***-14.57***	-1.84	0.02	-13.04	Yes
Walk and Ride (Work-Fam-SP)	0.000226	***26.18***	Walk and Ride (Pt)	0.000182	***18.55***	0.00	0.00	3.36	Yes
σ-Work	-6.77	***-33.03***	σ-Pt	15.3	***22.02***				
σ-Education	-31.8	***-22.32***	σ-Bike	11.3	***24.45***				
σ-Fam-NSP	18.4	***21.41***	σ-Walk	17.8	***22.58***				
σ-Fam-SP	20.6	***25.65***	σ-Car	Ref.					
σ-Work-Fam-NSP	18.4	***19.26***							
σ-Work-Fam-SP	29.9	***24.85***							
σ-Others	-8.21	***-28.87***							
σ-None	Ref.								