Do weather conditions and weather forecasts trigger changes in our daily travel behavior

Lieve Creemers

promotor :
Prof. dr. Gerhard WETS

co-promotor :
dr. Mario COOLS

Masterproef voorgedragen tot het bekomen van de graad van master in de verkeerskunde, afstudeerrichting mobiliteitsmanagement

Preface

As a first master student in Transportation Science, I got the assignment to investigate a mobility related issue as a 'case study'. My interest went out to investigate the effects of weather on travel behavior. There already was a lot of research done on the effects of weather on mobility, but until now the impact of weather on the actual underlying travel behavior was neglected. This thesis therefore includes the continuation of the 'case study' that was launched in the first master year.

This thesis represents the culmination of a 5-year study career. It is therefore the right time to express a word of thanks to everyone who has supported me in my studies. A special word of thanks goes to my parents, sisters and boyfriend who kept the fire burning and who gave me the freedom and support to do what I wanted to do.

In addition, the realization of this thesis could not have completed without the support of various people. First, I would like to express my gratitude to my promoter, Prof. Dr. Gerhard Wets, and co-promoter, Dr. Mario Cools. Mario, thank you for the excellent guidance and the intellectual support throughout the process! At last, a word of praise goes to my docents who have given me the necessary background to complete this thesis and to everyone who helped me directly or indirectly to data or other useful study materials.

Hoping to offer you some interesting reading material,

Lieve Creemers

May 11th, 2010.

Summary

In literature, a considerable amount of studies concerning the effects of adverse weather on traffic can be found. However, these effects are mainly assigned to three domains in traffic, namely traffic safety, network performance and traffic demand. The impact of adverse weather and forecasts on decisions that are related to travel behavior remains mainly neglected in literature.

Therefore, the main objective of this thesis is to investigate whether weather conditions and forecasts trigger changes in our daily travel behavior. This question will be investigated using both a stated adaptation and a revealed preference approach. In spite of the shortcomings in literature, it is important to acquire insight in the underlying travel behavior, both in terms of traffic safety and mobility management. First, behavioral adaptations in adverse weather influence traffic intensity, the first and primary determinant of traffic safety (Cools et al, 2007). Second, acquiring insights in travel behavior under adverse weather conditions is important in the context of developing weather sensitive dynamic traffic models and in the context of weather responsive traffic management.

The first part of this thesis consists of a stated adaptation approach of changes in travel behavior in response to adverse weather conditions and forecasts. The data for this approach is collected by means of a stated adaptation survey, which is both administered on the internet and via a traditional paper and pencil questionnaire. In total, 595 respondents completed this survey. In addition, weights are assigned to the dataset to obtain an optimal correspondence between the population and the sample.

A first subquestion in the stated adaptation part is to investigate the role of adverse weather on stated changes in travel behavior in Flanders, Belgium. In answering this question, it may be interesting to explore how and to what extent people change their travel behavior in response to adverse weather conditions. Therefore, the results from the stated adaptation survey will be analyzed and discussed. Moreover, the question can be asked whether the frequencies of changing travel behavior are influenced by trip purpose, as well as adverse weather condition and type of transport mode. This will be investigated using Pearson's chi-square independence tests.

A second subquestion in the stated adaptation part is to explore the role of various aspects of the weather forecast on stated changes in travel behavior in Flanders (Belgium). Following aspects of the weather forecast will be investigated: the degree of exposure to weather forecasts, the perceived reliability of the weather forecast and the media source of the weather forecast. For this purpose, again Pearson's chi-square independence tests will be performed.

The last objective of the stated adaptation part is to identify which determinants explain stated changes in travel behavior. Since these are discrete choices, generalized multinomial logit models will be estimated to meet this objective. Acquiring insights in the determinants of changes in travel behavior is especially important when developing weather sensitive dynamic traffic models.

The second part of this thesis consists of a revealed preference approach of changes in decisions that are related to travel behavior in response to adverse weather conditions. For this purpose, both data about the travel behavior of people and data about the weather are merged. This merge is based on the departure time of the trip. The weather data is on hourly level and is provided by the Royal Dutch Meteorological Institute (KNMI). The data on travel behavior is derived from the Mobility Research of the Netherlands (MON) and is mainly based on data coming from travel diaries in the Netherlands.

The main objective of the revealed preference part is to explore the role of extreme weather conditions on revealed travel behavior. More concrete, the effect of weather conditions on daily travel times is explored. Since the range of travel times can never be smaller than zero, the Tobit model is a suitable method to perform this analysis. Also the influence of weather on revealed modal choices is investigated. Since modal choice can be seen as a discrete choice, again generalized multinomial logit models will be estimated. This information is especially important when developing weather sensitive dynamic traffic models.

Index

List of Tables

List of Figures

Chapter 1: Introduction

As the title suggests, there are two central concepts in this thesis, namely 'travel behavior' and 'weather', which have both a huge impact on daily life.

Most people spend between 10 and 20 percent of their daytime travelling from one location to another (Immers and Stada, 2004). This travel behavior can be affected by different aspects. The most important aspects are person related (age, family situation, etc.), but the travel behavior can also be influenced by external circumstances such as weather conditions and spatial structure.

This thesis will focus on the impact of adverse weather conditions on various aspects of the travel behavior such as mode choice, departure time etc. Before elaborating on this matter, a brief background on the impact of weather on traffic is provided.

1.1 Background

In literature, a considerable amount of information concerning the effects of adverse weather conditions on traffic can be found.

Pisano and Goodwin (2003) made a distinction between the effects of adverse weather on roadway and environment and the effects on the transportation system. Examples of the effects of the first type are reduced visibility by rain or fog, reduced pavement friction by snow, reduced vehicle stability by high winds and infrastructure damage by frost. The latter effect became very clear last winter in Flanders, Belgium. The severe frost formed potholes that even led to the introduction of a speed limit of 90 km/h on the E313 between Antwerp and Herentals (Gazet van Antwerpen, 2010). Examples of the impact of adverse weather on the transportation system are reduced roadway capacity, reduced speeds, increased speed variability, increased delay and increased accident risk.

Maze et al (2006) described the impact of weather on traffic in three ways: in terms of traffic safety, network performance and traffic demand. The effects of weather on these domains will be shortly discussed in following subsections.

1.1.1 Impact of adverse weather on traffic safety

First, extreme weather conditions causes dramatic increases in crash rates, especially when they result in snowy and icy roads, since these kinds of road conditions reduces the skid-resistance of the road pavement. Khattak et al (2000) found that during a snowstorm crash rate increased by 13 times compared to normal weather conditions. Maze et al (2005) even found a crash rate that was 25 times higher on snow days than on normal days. Snow days were defined as days with more than 2.5 cm of snow fall.

Keay and Simmonds (2004) investigated the effect of rain on traffic accident count and found an increase of 5.0 accidents on wet days compared to dry days, an increase of 15.4%. Lin and Nixon (2008) and Sun et al (2009) found even more extreme values. Lin and Nixon indicated in their research that rain increased crash rate by 71%, while Sun et al found an increase in crash rate ranging from 70% to 161% (depending on the type of highway).

This increase in crash rate is also confirmed in other empirical studies (Khattak et al, 1998; Brodsky and Hakkert, 1988; Kilpelaïnen and Summala, 2007; Pisano and Goodwin 2003).

The above shows that literature is unanimous about the fact that adverse weather causes an increase in crash rate. However, when the focus is turned to the injury rate some contradictions could be noticed. Scharsching (1996) and Savenhad (1994) indicated in their Swedish research that on snowy and icy roads injuries are more severe than on roadways under normal conditions. This was also shown in a study by Perry and Symons (1991). They found that in the United Kingdom fatalities increased by 25% on snowy days. In contrast to these studies, Baass and Brow (1997) showed that accidents during inclement weather had a less severe outcome than under normal weather conditions, because of the lower speeds resulting from risk compensation. Yannis and Karlaftis (2009) came to similar conclusions for rain. They investigated the impact of rainfall intensity on injury rate in Athene and found that increases in rainfall reduced the number of fatalities. Just as Baass and Brow, they attributed this effect to the more cautious and less speedy driver behavior, better known as the safety offset hypothesis.

1.1.2 Impact of adverse weather on network performance

Second, a number of studies show that inclement weather influences traffic flow as well as capacity. The latter is defined as the maximum flow rate at which vehicles can travel on a roadway segment (Maze et al, 2005). Since traffic flow is a function of traffic speed (km per hour) and traffic density (vehicles per km per lane), it is also expected that weather has a significant influence on these aspects. This is also confirmed by a number of empirical studies.

Both Ibrahim and Hall (1994) and Pisano and Goodwin (2003) described that road capacity reduced 10% to 20% in to adverse weather. May (1998) investigated the effects of different weather conditions on capacity and concluded that especially rain, snow and fog had a reduced effect on freeway capacities. This was confirmed by Agarwal et al (2005) and Maze et al (2005). Agarwal et al found that heavy rain and heavy snow showed capacity reductions of respectively 10%-17% and 19%-27%. Maze et al (2005) reported very similar results. Moreover, they found following reductions in capacity: cold temperatures (1%-8%), wind speed (1%) and fog (10%-12%). In contrast to above results, Billot (2009) found a more extreme reduction in capacity due to rain, ranging from 18% to 40%.

Nowadays, many transportation networks are already operating near maximum capacity in normal weather conditions and when adverse weather reduces capacity, traffic congestion increase and affects the travel time. A recent example of this took place in Flanders, Belgium, in February 2010. Sudden snowfall during the morning rush resulted in a new congestion record of 948 km, twice the previous record. The economic costs of this congestion amounted to no less than 20 million Euros, a huge economic loss (Het Belang van Limburg, 2010). Pisano and Goodwin (2003) reported that 23% of total delay in traffic is due to adverse weather events. This is also confirmed by Tu et al (2007). They concluded from their research that fog, storm, snow but especially ice and rain increased the travel time and travel time variability on freeway corridors. On average, these weather conditions led to variability in travel times that was twice as large as in normal weather conditions. Consequently, travel time is less reliable during adverse weather.

Hanbali (1994) found an average speed reduction of 13%-22% on freeways due to adverse weather. A more substantiated result was reported by Ibrahim and Hall (1994).

They found in their research that light rain and light snow caused respectively a drop of 2km/h and 3 km/h in speed, while heavy rain and heavy snow caused respectively a 5 to 10 km/h and a 38km/h to 50 km/h drop in speed. Brilon and Ponzlet (1996) detected similar speed reductions due to rain. By estimating a multiple regression model, Kyte et al (2001) showed that a wet surface reduces the free flow-speed by 9.5 km/h, whereas a snow-covered surface reduces the speed by 16.4 km/h. They also found a significant decrease in speed through heavy wind (11.7km/h) and through low visibility (depending on degree of visibility). Billot (2009) came to the conclusion that both the individual speed as well as the free flow speed decrease during rainy conditions. Furthermore, he found that rain leads to a significant decrease of the time head-ways (the difference between the time when the front of a vehicle arrives at a point and the time the front of the next vehicle arrives at the same point in seconds).

1.1.3 Impact of adverse weather on traffic demand

At last, literature does not agree whether weather conditions have increasing or decreasing effects on intensities. Various empirical studies could be found in literature that confirm both statements.

First, it was found in literature that adverse weather can reduce intensities in both motorized and non-motorized transport modes. Concerning the non-motorized transport modes, various studies reported that cold temperatures, windy, and especially rainy days decrease travel demand from cyclists between 20% and 60% (depending on the weather type) (Wilde, 2000; Emmerson, 1998; Nankervis, 1998). Attaset et al (2009) investigated the impact of several weather variables on levels of pedestrian volume in Alameda County, California. Their results indicated that rain had the largest effect on pedestrian volumes. Though clouds, wind, and both warm and cold temperatures were also shown to decrease volumes. Aultman-Hall et al (2009) investigated the effects of precipitation on levels of pedestrian volume in Montpelier Vermont and found that precipitation reduced the hourly pedestrian volume with 13%. Moreover, they established that weather variables account for 30% of the variance measured in hourly volumes. Concerning the motorized transport modes, Cools et al (2007) indicated that precipitation (rain and snow), cloudiness and wind speed have diminishing effects on motorized traffic intensity. Al Hassan and Barker (1999) investigated the effect of extreme weather conditions on traffic intensities in Lothian, Scotland. They found that the impact of extreme weather conditions on intensities were less than 5%, except for snow wherefore they found a reduction of 10% to 15%. Also Keay and Simmonds (2004) found decreases in intensity on wet days in Melbourne, Australia. Intensities were between 1.35% and 2.11% lower on wet days compared to dry days. Associated with this effect was the fact that increased cloud amount also had a negative effect on traffic volumes. Finally, they indicated in their research that higher average wind speed is associated with traffic volume reductions.

Even though, there were also studies found indicating that adverse weather has an increasing effect on intensity. For example, Hagens (2005) found a significant increase in motorized intensities on wet days from around 4% compared to dry days. Khattak (1991) indicated that cold temperatures increased motorized traffic volumes and Cools et al (2007) found an increase in motorized traffic volumes for hail. Wilde (2000) indicated in his research that warm temperatures led to an increase in bicycle intensities. More concrete, Emmerson (1998) even found that a 1°C rise in temperature gives a 3% rise in daily cycle flows in the context of the United Kingdom.

Maze et al (2005) showed that reductions in traffic intensities due to extreme weather conditions were smaller in peak travel periods and on weekdays than on off-peak periods and weekends. Hagens (2005) came to similar conclusions concerning peak and off-peak periods. This suggests that travel demand reductions are dependent on trip purpose and that one is more likely to adapt their trip schedule in leisure trips than in commuting trips. This was also suggested by Nankervis (1998). When investigating the effects of weather on cycle commuting, he found that discretionary travel was more affected by weather than commuter trips. Al Hassan and Barker (1999) came to similar conclusions. The impact of extreme weather conditions on the intensities was higher during weekdays than during weekends, suggesting dependence on trip purpose. This dependency was also confirmed by Kilpelaïnen and Summala (2007) who found that leisure trips were clearly underrepresented during very poor driving conditions, suggesting that some trips are postponed or cancelled.

1.2 Research framework

As indicated in previous section, the effects of weather conditions on the three traffic domains (safety, performance and demand) are well documented and widely acknowledged. However, the domain which has the most potential for further research concerns travel demand. In this domain, literature mainly focuses on the effect of different weather conditions on traffic intensities and volumes. However it is interesting to study the underlying reasons that influence these changes in demand due to adverse weather conditions and even due to adverse weather forecasts. In other words, it is intriguing to better understand the travel behavior of individuals under adverse weather conditions and under adverse weather predictions. The main research question therefore investigates how people adapt their travel behavior when adverse weather occurs or when adverse weather is predicted.

In literature, little is known about the impact of weather on the underlying roots of travel behavior.

Despite this lack of information, acquiring insight in travel decisions under adverse weather and forecasts is important both in terms of traffic safety and mobility management.

First, as described in Section 1.1.3, behavioral adaptations in adverse weather influence traffic intensity, the first and primary determinant of traffic safety (Cools et al, 2007).
Second, acquiring insights in travel behavior under adverse weather conditions is important in the context of mobility management. Unfortunately, traffic analysis tools such as dynamic traffic models assume ideal conditions and do not take into account the uncertainties in demand and supply mainly caused by adverse weather conditions (Lam et al, 2008; Khattak and De Palma, 1997). Therefore, to fulfill the need of policy makers to make better long-term decisions, more accurate estimates of travel demand in traffic simulations are needed. Consequently, there is a trend to incorporate more realistic travel behavior in dynamic network models (Khattak and De Palma, 1997) and there arises a need to integrate the effects of weather conditions in traffic modeling. For this reason, it is interesting to study the behavioral adaptations and their determinants as a consequence of adverse weather conditions so that this information can be used in the future as input in dynamic models. This would lead to more accurate forecasts and consequently policy measures that are based on more accurate data.

Summarized, there arises a need for information that might provide us valuable insights that are important and useful in the context of future dynamic weather sensitive network modeling, but also for the recommending of policies in order to improve traffic safety and traffic performance during adverse weather.

1.3 Research goals

As the title of this thesis suggests, the main goal consists of investigating whether weather conditions and weather forecasts trigger changes in our daily travel behavior. This main goal can be subdivided in several subset questions, as described below.

I. What is the role of extreme weather conditions on (stated) changes in travel behavior?
   a) How and to what extent do people change their travel behavior in response to adverse weather?
   b) Does trip purpose influence the likelihood of changing travel behavior in response to adverse weather conditions?
   c) Does the type of adverse weather condition affect this chance?
   d) Does modal choice have a significant influence on these probabilities?

II. What is the role of weather forecasts on (stated) changes in travel behavior? Is there a need to boot a road weather information system in Flanders?
   a) Does the exposure to weather forecasts influence the likelihood of changing travel behavior in response to weather conditions?
   b) Does the perceived reliability of the weather forecast affect this chance?
   c) Does the media source of the weather forecast have a significant impact on these probabilities?

III. Which determinants explain these stated changes in travel behavior?

IV. What is the impact of extreme weather conditions on (revealed) travel behavior?
   a) Do weather conditions affect travel times?
   b) Do weather conditions influence modal choices?

1.4 Research delineation

There can be made a distinction between primary and secondary behavioral responses due to adverse weather conditions. Primary responses refer to the choice of a strategy reducing the negative impact of adverse weather. Examples of such primary responses are changing transport mode, changing departure time etc. Secondary responses involve adaptations that are required to make the broader activity pattern consistent with the change. For example, switching from car to public transport may limit the possibilities for trip chaining and induce extra separate trips as a secondary response. The scope of this thesis is confined to the primary behavioral responses due to adverse weather conditions.

1.5 Research methodology

1.5.1 A stated adaptation and revealed preference approach

In answering the research goals, as described in Section 1.3, two survey research methods that are common in the field of studying travel behavior will be used, namely a stated adaptation approach, which can be seen as an alternative of stated preference, and a revealed preference approach (De Palma, 1997). The difference between a stated adaptation and a stated preference approach is as follows: in a stated adaptation approach, respondents must indicate if and how they would change their travel behavior considering some scenarios while in a stated preference approach, respondents must indicate their preference towards different alternatives (Faivre D'Arcier et al, 1998). In this case a scenario can be defined as a particular weather condition in response with a particular trip purpose.

Stated preference data describes potential choices of individuals and only represent what an individual claims he would do in a given scenario. It does not show what behavior a person would actually exhibit in that scenario. For this reason, also revealed preference data is used which describes the actual choices based on market based behavior (Hensher, 1993). So this thesis captures both what people say they would do in adverse weather and what they actually do.

Research goals I, II and III will be investigated by using data coming from a stated adaptation experiment while research goal IV will be explored by use of data coming from a revealed preference experiment.

The data for the stated adaptation approach has already been collected in a previous case study, which can be considered as an introduction to this thesis (Creemers, 2009). This data applies to Flanders, the Dutch speaking part of Belgium. More information about the data collection and the survey building can be found in chapter 3. Regarding the data for the revealed preference approach, no suitable data sources were freely available for Flanders. Since this is the case in the Netherlands, it was preferred to use the Dutch data sources for the revealed preference approach. These data sources will be discussed in chapter 7.

1.5.2 Statistical analysis

1.5.2.1 Test for the difference between two population fractions

The z-test for the difference between two population fractions can be performed to draw conclusions about the difference in population fractions when only sample data is available. In this way, one can find out whether the differences that are noticed in the sampling are also true for the population. Following hypotheses could be drawn (Anderson et al, 1998).

H_0: $P_1 - P_2 = 0$
H_a: $P_1 - P_2 \neq 0$

These hypotheses can be tested using the following test statistic:

$$z = \frac{\bar{p}}{\sqrt{\bar{p}(1-\bar{p})(\frac{1}{n_1}+\frac{1}{n_2})}}, \qquad (eq.1)$$

Where:

n_1= sample size of population 1, n_2= sample size of population 2, $\bar{p}$ = pooled sample fraction. Latter is defined as:

$$\bar{p} = \frac{n_1\,\bar{p}_1 + n_2\,\bar{p}_2}{n_1 + n_2}, \qquad (eq.2)$$

Where $\bar{p}_1$ = fraction of population 1 and $\bar{p}_2$ = fraction of population 2.

The above test is only valid for a normal distribution, or in other words, if the sample size is large enough. A sample size is sufficiently large when n_1p_1, $n_1(1-p_1)$, n_2p_2, en $n_2(1-p_2)$ are all greater than or equal to 5.

The test for difference between two population fractions is used to get a first insight into the answers of research goals I (c) and II (a-b-c).

1.5.2.2 Pearson chi-square independence test

To test whether two multinomial variables are dependent, one could draw following hypotheses.

H_0: Independence between the two multinomial variables.

H_a: Dependence between the two multinomial variables.

These hypotheses can be tested using the Pearson's chi-square test statistic, which is defined by the following equation (Anderson et al, 1998):

$$\chi^2 = \sum_{i=1}^{k}\sum_{j=1}^{j}\frac{(n_{ij}-e_{ij})^2}{e_{ij}}, \qquad (eq.3)$$

Where n_{ij} is the observed frequency in cell (i,j) and e_{ij} the expected frequency in cell (i,j) based on the assumption of independence. With n rows and m columns in the χ^2-table, the test statistic has a χ^2-distribution with (n-1) (m-1) degrees of freedom, provided that the expected frequencies in all categories are five or more.
When the P-value (based on the χ^2-value and the degrees of freedom) is smaller than the level of significance, then this means that the null hypothesis can be rejected and the alternative hypothesis is true and vice versa (Anderson et al, 1998). In this thesis the level of significance always assumed equals 0.05, unless stated otherwise.

The requirement that the expected frequencies in all categories are five or more is particularly true in theory, but in practice there is a less stringent value used. At least 80% of the expected cells must be larger or equal to five. When this is not the case, the test may not be valid. Instead of using the large sample Pearson chi-square test statistic, one should use an alternative small sample test of independence, like the Fisher's Exact test (Agresti, 2002). Detrimental to the Fisher's exact test is the computationally unwieldiness. When the requirement that 80% of the cells must be larger or equal to five is not met in this thesis, alternative solutions will be searched because of the computationally unwieldy of the Fisher's exact test.

The Pearson chi-square test-statistic can also be used to test whether the sample composition follows the population distribution. Following hypothesis could then be drawn:

H_0: Sample composition follows the population distribution.

H_α: Sample composition does not follow the population distribution.

The Pearson chi-square independence test will be used to give an answer on the research goals I (b-c-d) and II (a-b-c).

1.5.2.3 Generalized multinomial logit model

According to Hensher and Button (2000), discrete choice analysis is an essential component of studying individual choice behavior in the field of transportation.

The general idea of discrete choice analysis is that the decision maker (the respondent) chooses that alternative from the choice set C (with k alternatives) with the highest utility to him/her (the utility maximization rule). In other words, the chance that individual i chooses for alternative j is equal to the chance that the utility of alternative j is bigger than the utility of all the other alternatives in the choice set, which can be displayed by the following equation:

$$P_i(j) = P(U_{ij} \geq U_{ik} \text{ for all k} \in C, \qquad (eq.4)$$

The utility function U_{ij} in the above equation can now be separated into two parts, as shown in following equation:

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \qquad (eq.5)$$

Where U_{ij} is the utility that person i gives to alternative j, V_{ij} the non-stochastic part that depends on the covariates and ε_{ij} the stochastic part (Bartels et al, 2000). The non-stochastic part is typically specified by a linear function and can be defined as follow:

$$V_{ij} = \hat{\beta}_j^T X_{ij} \qquad (eq.6)$$

Where β_j is a vector of parameters to be estimated and X_{ij} the vector of explanatory variables.

Based on above equations and assuming that $\varepsilon_{ik} - \varepsilon_{ij}$ has a logistic distribution, the probability from equation 4 can now be rewritten to:

$$\hat{P}_i(j) = \frac{\exp(\hat{\beta}_j^T X_{ij})}{\sum_{k \in ci} \exp(\hat{\beta}_j^T X_{ij})} \qquad (eq.7)$$

When this probability is calculated for each alternative, the alternative with the highest probability is selected as the alternative that is the most likely to be chosen by the individual. When the sign of the parameter estimate is positive, an increase in the explanatory variable results in an increase in the likelihood of the response variable and vice versa. The underlying reason for this will be explained in Section 6.3.2. The absolute values of the parameter estimates give information about the strength of the connection between the explanatory and the response variable (Bartels et al, 2000).

Equation 7 is called the multinomial logit model (MNL-model) and is used to model relationships between a polytomous response variable and a set of regression variables. There exist various types of MNL models. This study uses the generalized MNL model, which models the discrete choices of individuals (Kuhfeld and So, 2005). Other discrete choice models, like multinomial probit models, HEV-models and the mixed logit models could also be used. However, the focus in this thesis will lay on the multinomial logit model since this model is easier to display visually in contrast to other models for which the visualization can be quite complex.

Using the generalized MNL models, determinants will be detected that explain the adaptations in travel behavior in response to adverse weather. Parameter estimates trace to what extent these determinants explain these adjustments. MNL-models will therefore help to find a response to research goal III and research goal IV (a).

1.5.2.4 General estimation equations

In both data sets that will be analyzed in this thesis (data concerning both stated- and revealed preferences), we have to deal with correlated response data which we must take into account in our statistical analysis. In general, there are two large families of statistical models that may be used to account for the correlated structure, which are called the marginal and the conditional effect model. In marginal models, the mean function is modeled directly and the correlation structure is regarded as a nuisance parameter. In conditional effect models, correlation is introduced through shared random effects in the linear predictor (Kuss and McLerran, 2007). In this thesis, correlation will be taken into account by estimating the marginal effect model. This kind of model can be estimated using generalized estimating equations (GEE), a technique which is available in SAS via the genmod procedure. However, the current version of proc genmod in SAS only allows GEE-estimation for ordinal response models, but does not offer GEE estimation for models with multinomial response. Little research is conducted on this latter issue. Fortunately, Kuss and McLerran (2007) developed some really useful methods to perform the estimation of MNL-models with correlated responses in the statistical software program SAS. They specified a multinomial logistic model for correlated responses as a marginal model by reorganizing the response vector. This reorganizing can be interpreted as transforming the multinomial model into a multivariate binary model. The model equation is then:

$$\log(\frac{\pi_{ir}^*}{1-\pi_{ir}^*}) = \theta_r^* + X_{ij}^{'}\beta_r^*, \qquad r = 2,...R \qquad (eq.8)$$

Where π_{ir}^* denotes the expectation of all elements of Y_i^* belonging to response category r, θ_r^* the intercept, β_r a vector of parameters to be estimated and X_{ij} the vector of explanatory variables. Equation 8 can then be rewritten to equation 7. The parameter estimates are therefore interpreted in a similar way.

1.5.2.5 The Tobit model

The Tobit model is proposed by James Tobin (1958) and describes the relationship between a non-negative dependent variable y_i and a vector of independent variables x_i. The structural equation in the Tobit model is as follow (Long, 1997):

$$y_i^* = \beta X_i + \varepsilon_i \qquad (eq.9)$$

Where $\varepsilon_i \sim N(0, \sigma^2)$ and y_i a latent variable that is observed for values greater than 0. The observed y is defined by the following measurement equation (Long, 1997).

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \qquad (eq.10)$$

The estimated parameters can be interpreted as measuring the change in the expected value of the response variable when the given predictor variable is increased by one unit while all other predictor variables are held constant.

The Tobit model is a suitable model for investigating whether weather conditions affect the travel times of the displacements, since it takes into account that travel times can never be smaller than zero. Tobit models will therefore help to find a response to research goal IV (a).

The Tobit model can be estimated in the statistical software program 'SAS' via the proc lifereg procedure or via the proc QLIM procedure.

1.5.2.6 Model selection criteria

Backward selection is a procedure which selects the least significant variable and excludes it from the model, after which the procedure repeats itself. The procedure ends when only significant variables remain in the model.

By using each time different combinations of explanatory variables, many models can be developed for the same scenario, from which only one has to be selected. For this purpose, the estimated models of the same scenario can be compared based on model selection criteria. One powerful and widely used model-selection criterion is called Akaike's Information Criterion (AIC), which can be defined as follow:

$$AIC = -2ll + 2k$$ with *k the number of parameters*

with ll de loglikelihood $(eq.11)$

The AIC-value has some important advantages. First, it takes into account how well the model describes the data (-2ll as small as possible) and secondly it punish for the number of parameters in the model (k as small as possible) (Kutner et al, 2005).

The AIC-value is based on the loglikelihood and asymptotic properties of the maximum likelihood estimator (MLE). Since GEE is nonlikelihood based, we do not have a likelihood function in this context. The GEE estimator has also different asymptotic properties than in the case of MLE. This makes it impossible to determine the AIC-value. Fortunately, Pan (2001) proposed an extension of the AIC-criterion that is applicable in the context of GEE. He replaced the loglikelihood value in the AIC-criterion with the quasi-likelihood and also modified the penalty term. This adapted AIC-criterion is called the "quasi-likelihood under independence criterion", abbreviated as the QIC-criterion. As with AIC, the model with the smallest QIC-value is preferred.

Since the Tobit model is based on MLE, the AIC-value is an appropriate model selection criterion. In view of the fact that the MNL-model in this thesis is based on GEE, the AIC-value cannot be applied here and one have to look at the QIC-criterion.

1.5.2.7 Pearson's correlation coefficient

One problem that can arise when estimating models is the problem of correlation between explanatory variables. Correlation between explanatory variables does not, in general, inhibit the ability to obtain a good fit of the data nor does it tend to affect inferences about mean responses or predictions of new observations, provided that these inferences are made within the region of observations. However, correlation between the predictor variables does affect the sampling variability of the parameter estimates, which are in the presence of correlation extremely large. As a result, only imprecise information may be available about the individual true coefficients. The common interpretation of a coefficient as measuring the change in the expected value of the response variable when the given predictor variable is increased by one unit while all other predictor variables are held constant is also not fully applicable when correlation arise. It is not possible in practice to do so for predictor variables that are highly correlated (Kutner et al, 2005). To prevent the negative effects of correlation, a correlation matrix can be composed to trace which predictor variables are correlated to each other. For each cell in the matrix, the correlation between two variables is measured. One way to measure this correlation is the Pearson's correlation coefficient, for which the equation is as follow (Kutner et al, 2005):

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (eq.12)$$

As a rule of thumb, (absolute) correlation coefficients between 0.00 and 0.30 are considered weak, those between 0.30 and 0.70 are moderate and coefficients between 0.70 and 1.00 are considered high (Cohen, 1988). It is generally accepted that when the correlation coefficients exceeds 0.7, only one of the two correlated variables must be selected for further analysis.

1.6 Outline of the thesis

This introductory chapter is followed by a study of literature (chapter 2) regarding the subject of the thesis. Hereafter, the thesis is divided in two main parts, as is visualized in Figure 1-1 on page 17.

The first part consists of a stated adaptation approach of changes in travel behavior in response to extreme weather. After discussing the stated adaptation methodology (chapter 3), the role of respectively extreme weather conditions (chapter 4) and extreme weather forecasts (chapter 5) on stated changes in travel behavior is examined. The first part concludes with exploring which determinants explain these changes in travel behavior (chapter 6).

In the second part, the focus lies on a revealed preference approach of the impact of weather on travel behavior. After elaborating on the revealed preference methodology (chapter 7), the influence of weather on travel times and modal choices is examined (chapter 8).

At last, chapter 9 discusses how the findings of this thesis can be used by policy makers in the context of weather responsive traffic management.

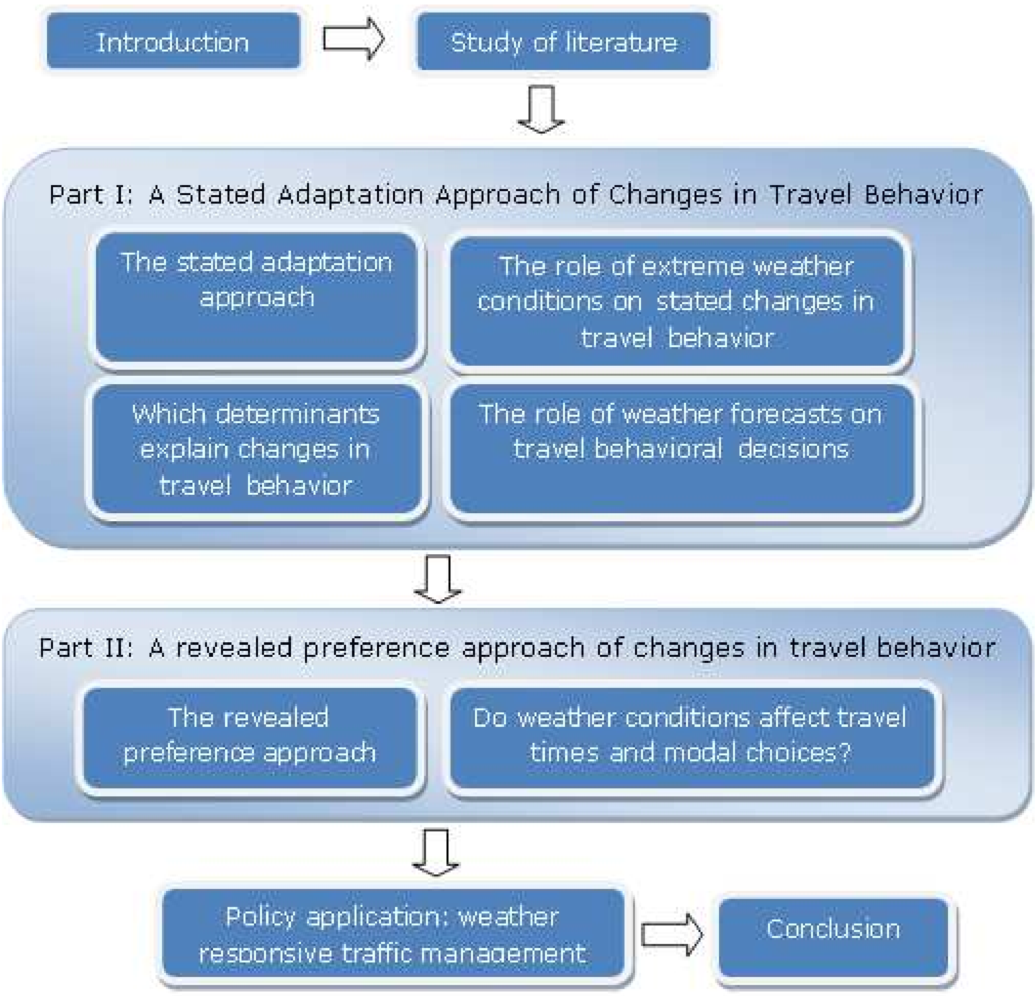

Figure 1-1: Schematic overview of the structure of the thesis

Chapter 2: Study of literature

This chapter discusses briefly the results of studies that are related to the subject of this thesis.

2.1 The impact of adverse weather and weather information on trip schedule

First, a few studies could be found that just touched upon the main subject of the thesis (Al Hassan and Barker, 1999; Nankervis, 1998; Khattack, 1991). Al Hassan and Barker (1999) reported that bad weather may result in the total cancellation of journeys and also reported mode switching from either walking or public transport to private cars during wet conditions. Nankervis (1998) found that about 25% of cyclists in a student community choose an alternative mode on days of 'poor' (not defined) weather. The majority of them (18%) claimed to switch to public transport. Similarly Khattack (1991) has reported that extreme and unusual weather, such as blizzards may induce significant travel mode shifts as well as changes in departure times and destinations.

Second, a number of studies could be found in literature that are specifically focused on alterations in travel behavior in response to weather conditions and in some cases also due to (road) weather information (Hagens, 2005; Niina, 2009; Kilpelaïnen and Summala, 2007; Khattak and De Palma, 1997; De Palma and Rochat, 1999).

By connecting weather data to the Dutch national travel survey, Hagens (2005) found that bad weather, especially rain, causes cyclists to switch to another mode. They switch in particular to car and to a lesser extent to public transport. Besides such modal shifts, also a decline in the number of trips was found. For rain, the net decrease in trips was about 2.5%. The number of bicycle trips decreased with 15%, but against this, an increase in the number of car trips by 11% was found.
To find out the underlying reasons of these effects, the investigation of Hagens was finally completed with a survey in which the influence of various weather conditions on mode choice, departure time, destination location and the cancellation of the trip was examined. Concerning mode change, the results of the survey show that respondents indicate to change their mode especially in rain (54%), ice (57.9%) and snow/hail (60.6%). The other types of weather such as fog (3.6%), cold temperatures (8.8%),

warm temperatures (9.8%) and wind (7.1%) show a rather limited influence on the modal choice of the respondents. 31.6% of the respondents indicate that they sometimes switch from bike to the car due to the weather. There is also an important switch found from bike to public transport (24.6%) and from bike to walking (11.4%). In other words, it usually concerns a transition from bike to a 'sheltered' mode of transport. This also applies to the transition from bicycle to pedestrian. In this situation one can protect themselves against rain through the use of an umbrella. Furthermore, 23% of respondents said that their choice of transport may be influenced by bad weather predictions. Postponing the trip until better weather occurs is also a common used strategy, especially in cycling trips (45.6% indicate sometimes to wait) and walking trips (14.9% wait sometimes). The waiting period varies in both cases from 5 minutes to 1 hour, depending on the purpose of the movement (shopping, leisure etc.). Only occasionally, one changes the destination due to bad weather. This depends on the trip purpose, most of the times shopping trips. One chooses for example to go to the local shop around the corner rather than to going to the supermarket further away. Last, the respondents were asked whether they ever cancel a trip due to the weather. 21.9% of the cyclists, 8.8% of the pedestrians and 3.5% of the car users indicate that they sometimes do not make their trip due to the weather.

In a Finnish study, 21% of the travelers, which were interviewed at locations along their route, said they changed or considered to change travel plans because of the weather conditions (Niina, 2009). This is significantly higher than a similar (also Finnish) survey conducted by Kilpelaïnen and Summala (2007) which found that only 6% of the respondents made changes in their trip schedule. The difference can partially be explained by a different phrasing of the question. Kilpelaïnen and Summala (2007) only asked whether the respondents changed their travel plans while Niina (2009) also asked if the respondents were considering a change in their travel plans. However, the most mentioned adaptation in both studies was allocating more time to the trip. This was indicated by 5% of the respondents in the study of Kilpelaïnen and Sumala and by 76% of the respondents in the study of Niina. This is followed by changing the departure time (respectively 3% and 27% of the respondents in both studies), cancelling the trip (12% in the study of Niina) and changing the trip route (respectively 1% and 12% in both studies). Moreover, it appears from the study of Niina (2009) that the frequencies of changing the trip planning increases with age. No less than 41% of the older drivers (over 64 years) changed or considered to change their schedules because of the weather.

This proportion decreased to 21% for the respondents aged 26-64 years and to 9% for the youngest group. In the studies from Kilpelaïnen and Sumala (2007) and Niina (2009), respectively 16.4% and 62% of the respondents said they acquired (road) weather information before the trip. This is a large difference that can partially be explained by the different investigation method. However, both studies came to the same conclusion that it is important to inform drivers about (road) weather conditions because drivers who had acquired information had also made significantly more changes to their trip schedule.

Khattak and De Palma (1997) investigated the impact of adverse weather conditions on the propensity to change travel decisions in commuting trips in the city of Brussels, Belgium. The focus of the research was to define and understand the impact of adverse weather on car user's mode change, departure time and route selection. The results of the study showed that one on two car users changed their travel decisions in response to adverse weather. Especially the impact of adverse weather on departure time seemed to be considerable. As many as 61% of the car users who revealed to change their travel decisions found the impact of weather on their departure time important, while these percentages are 27% and 36% for respectively mode change and route change. Following effects were determined by estimating ordered probit models for mode change and departure change.

First, concerning mode change, persons who drive alone or carpool are less likely to change their modes due to adverse weather than those who use a combination of car and public transport. A reason for this could be that taking transit increases the risk of exposure to the adverse weather, what one try to avoid. The survey shows that people with children who go to daycare, are less likely to change transport modes. This can be explained by a reduced flexibility due to family commitments. Next, it was found that a decrease in mode change propensity was related with higher income groups. And last, people who acquired forecasted weather are slightly more likely to change their modes than people who rely on their own observation. However, this effect was not statistically significant.

Second, concerning ordered probit models for departure time, people with low flexibility in arrival time at work are more likely to adapt their departure time compared to persons who have flexible working hours. The income effect on the departure time change is similar to that of mode change. A decrease in departure time propensity was related to higher income groups. Next, working women were more likely to change their departure time in adverse weather. Final, concerning the acquisition of forecasted weather information, the same conclusions as in the mode change model could be made.

Similar to the investigation of Khattak and De Palma (1997), De Palma and Rochat (1999) investigated the impact of adverse weather on commuter's travel decisions (mode, route and departure time) in Geneva (Switzerland). About 40% of the respondents indicated that weather has a significant influence on their travel conditions (80% are car users, 12% transit users and 8% bikers). Results show that commuters were more likely to change departure time. Up to 72.7% of the respondents who said to change their travel decisions found the impact of weather on their departure time important, while these percentages are 54.7% and 49.6% for respectively mode change and route change.

2.2 Traveler information projects

In previous studies, conflicting results could be found regarding the impact of weather forecasts on travel decisions, e.g. the Brussels survey from Khattak and De Palma (1997) found no significant effect of acquiring forecasted weather information on the probability of adapting mode and departure time while the studies from Hagens (2005), Niina (2009) and Kilpelaïnen and Summala (2007) did.

Thus, it can generally concluded that forecast and weather information to travelers might help alleviating the negative effects on the road network due to adverse weather. In practice, there are already some projects that provide road weather information to travelers.

Since 1997, Finland makes use of a traffic weather information service that gives information on forecasted driving conditions on the main roads at regional level. It classifies the driving conditions according to three levels: normal (roads are relatively bare), poor (snowfall, reduced visibility, slippery roads) and hazardous (heavy snowfall so that roads cannot be ploughed). The forecasted level is then provided on national television and radio channels as well as on the internet. Kilpelaïnen and Summala (2007) and Niina (2009) showed that this road weather information service has a clear effect on trip schedule.

The Idaho State, U.S., uses a storm warning project, which is a project of the department of intelligent transportation system (ITS). This system makes use of sensors to measure the visibility, wind speed, air temperature, humidity, surface condition and the type and amount of precipitation. This real-time information is then sent to the Idaho transportation department. Based on this information, they can provide information to motorists regarding dangerous driving conditions via telephone services or media.

The metropolitan of Hong Kong is using a model that predicts very accurately the hourly rainfall intensity. To these predictions, three warning signals are coupled, namely the Amber rainstorm signal (> 30 mm/h), the red rainstorm signal (> 50 mm/h) and the black rainstorm signal (> 70 mm/h). These signals are then communicated to travelers around two hours before the occurrence of the forecasted rainstorm. According to Lam et al (2008), this information system has a clearly impact on the travel decision in terms of route choice, mode choice and departure time choice.

Other examples of road weather information systems can be found in Pisano and Goodwin (2003). It can be concluded that all road weather information are furnished through roadside warning systems, web-based applications or interactive telephone systems.

2.3 Discussion

Five studies can be found in literature that specifically focus on alterations in travel behavior in response to weather conditions and in some cases also due to (road) weather information (Hagens, 2005; Niina, 2009; Kilpelaïnen and Summala, 2007; Khattak and De Palma, 1997; De Palma and Rochat, 1999). In addition, behavior varies across spatial and temporal context (Khattak and de Palma, 1997). As a consequence, the previous mentioned studies are not always applicable to the specific context of Flanders, Belgium. For example, the survey performed in Geneva, Suisse (De Palma and Rochat, 1999) and Finland (Niina, 2009; Kilpelaïnen and Summala, 2007). In Suisse and Finland, adverse weather conditions, such as snow and hail, occur more frequently than in Flanders. One can expect that people experience these weather phenomena differently in the two countries, because of habituation. As a consequence, people adapt their travel behavior differently in the two countries. The study from Khattak and De Palma (1997) describes the behavioral adaptations due to adverse weather from commuters in Brussels, Belgium. In the spatial context, these results can be used to have an idea of the behavioral adaptations in response to adverse weather in Flanders. Unfortunately, the results are based on data from 17 years ago and are obsolete. At last, the results from a study in the Netherlands (Hagens, 2005) is, as well as for the spatial context as for the temporal context, the most interesting study in case to get an idea of the behavioral adaptations in Flanders due to adverse weather conditions.

Moreover, previous studies have mainly focused on a limited number of behavioral adaptations due to adverse weather. E.g. Khattak and De Palma (1997) and De Palma and Rochat (1999) only focussed on departure time, mode change and route change. Kilpelaïnen and Summala (2007) even focused only on departure time and route change. However, literature indicate that there exists a wider context of adaptations in travel behavior, such as cancellation of the trip, change of activity-location, etc. (Khattak, 1991; Al Hassan and Barker, 1999; Maze et al, 2005; Lam et al, 2008; Pisano and Goodwin, 2003; Arentze et al, 2003). Moreover, most studies made no differentiation between trip purpose, except the studies from Khattak and de Palma (1997) and De Palma and Rochat (1999) where the focus is on commuting trips. This is a major shortcoming in the literature since it is expected that it is less likely to adapt travel behavior in commuting trips than in other trips, through the formation of habits. Also, most studies, except the study from Hagens (2005), don’t make a distinction between types of weather. The impact of adverse weather on travel behavior was investigated, which was not further defined. However it can be expected that some weather conditions have a greater influence on travel behavior than other types of weather. To get an accurate picture about travel behavioral adaptations due to adverse weather, the impact of different weather conditions on the full context (the full context of behavioral adaptations, trip purposes and weather types) has to be examined and not just a part of it.

It can be expected that travelers who acquire information on forecasted weather and road conditions before or during the trip, are more likely to make changes to their trip schedule. This expectancy is confirmed by empirical studies from Hagens (2005), Niina (2009) and Kilpelaïnen and Summala (2007). Although the study of Khattak and De Palma (1997) argues that acquiring forecasted weather information plays no important role in the likelihood to adapt travel behavior.

Summarized, there arises a need to investigate up to date and full context travel behavioral adaptations, due to weather conditions and forecasts, specifically for the region of Flanders. This thesis will attempt to meet this need.

Part I

A Stated Adaptation Approach of Changes in Travel Behavior in response to adverse weather conditions and -forecasts.

Chapter 3: The stated adaptation approach

In what follows, the research goals of the stated adaptation approach are refreshed and operationalized (Section 3.1). Section 3.2 gives a description of the data collection while Section 3.3 gives a description of the survey building. At last, it was checked whether the sample data is consistent with the population (Section 3.4).

3.1 Research goals

3.1.1 Objectives

The first objective of this stated adaptation approach is to explore the role of adverse weather on stated changes in travel behavior in Flanders (the Dutch speaking part of Belgium). Accordingly, a response will be given to research question I, as defined in Section 1.3. In answering this research question, an exploration of how and to what extent people change their travel behavior due to adverse weather conditions is needed. Moreover, the question can be asked whether trip purpose matter, as well as adverse weather condition and type of transport mode.

The second objective of the stated adaptation approach is to explore the role of various aspects of the weather forecast on stated changes in travel behavior in Flanders, Belgium. Therefore, an answer is given to research question II, as defined in Section 1.3. Following aspects of the weather forecast will be investigated: the degree of exposure to weather forecasts, the perceived reliability and the media source of the weather forecast.

The last objective of this stated adaptation approach is to identify which determinants explain these stated changes in travel behavior. Accordingly, a response will be given to research question III, as defined in Section 1.3.

3.1.2 Operationalization from the research goals

Three concepts from the above research questions need to be operationalized, namely trip purpose, weather conditions and behavioral adaptations.

3.1.2.1 Defining trip purposes

In the stated adaptation approach, three trip purposes are considered: 'work/school activity', 'shopping activity' (i.e. daily purchases) and 'social activities and leisure time' (e.g. visiting friends and family, sports, music, driving around with the car etc.). The remaining activities like 'not-daily purchases', 'business travel' and 'bring/get activities' are not incorporated in the stated adaptation survey to limit respondent burden. The reason why there is chosen for the first three trip purposes is because they are the most commonly executed trips in Flanders (Moons, 2009) and have consequently the greatest impact on travel demand.

3.1.2.2 Defining weather types

In the stated adaptation approach, six different weather types are considered. A first type is 'cold temperatures' (abbreviated as 'cold'). Cold temperatures are defined as the temperatures which lay below the freezing point. 'Snow and glaze ice' (abbreviated as 'snow') is a second weather type that is considered. Because 'snow' and 'glaze ice' are very similar, they are considered as one type. This is also the case for 'heavy rainfall and thunderstorms' (abbreviated as 'rain'). 'Fog' and 'warm temperatures' (abbreviated as 'warm') are the fourth and fifth weather types. Latter is defined as temperatures above 28°C. The last weather type that is considered is 'stormy weather and heavy wind' (abbreviated as 'storm'). It was found in literature that above weather types have a considerable influence on traffic demand and thus also on the behavioral adaptations (Nankervis, 1999; Al Hassan and Barker, 1999; Maze et al, 2005; Kilpelaïnen and Summala, 2007; Lam et al, 2008; Cools et al, 2007).

For a better understanding of how frequent these weather events occur in Flanders, various weather-related measures are displayed in Table 3-1 on page 27. Only snow is very rare, but when it occurs, it mostly has dramatic effects on traffic. A recent example took place in Flanders in February 2010. Sudden snowfall during the morning rush resulted in a new congestion record of 948 km, twice the previous one (Het Belang van Limburg, 2010). In addition, it is noteworthy to mention that in general, Flanders has a moderate maritime climate with mild winters and fresh summers.

Table 3-1: Weather parameters measured in Uccle (nearby Brussels, Belgium)[1]

Parameter	2007	2008	Normal[2]
Air pressure (reduced to sea level)	1017	1015.4	1015.7
Average wind speed (m/s)	3.3	3.4	3.7
Sunshine duration (h)	1472.0	1449.0	1554.0
Average temperature (°C)	11.5	10.9	9.7
Average maximum temperature	15.3	14.6	13.8
Average minimum temperature	7.8	7.2	6.7
Absolute maximum temperature	30.9	31.0	31.7
Absolute minimum temperature	-6.8	-6.1	-8.9
Number of freezing days (min < 0°C)	27	37	47
Number of wintry days (max < 0°C)	1	0	8
Number of summery days (max >= 25°C)	23	25	25
Number of heat wave days (max >= 30°C)	2	1	3
Average relative atmospheric humidity (%)	80.0	77.0	81.0
Total precipitation (mm)	879.5	861.5	804.8
Number of days with measurable precipitation (>= 0.1mm)	204	209	207
Number of days with thunderstorm	94	95	94
Number of days with snow	7	18	15

[1] Source: Royal Meteorological Institute of Belgium (KMI, 2008)

[2] Normal: long-term meteorological average (1971-2000)

3.1.2.3 Defining behavioral adaptations

Finally, there has to be an operationalization of the concept "behavioral adaptations" in response to extreme weather. After all, people can adapt their travel behavior in different ways due to extreme weather conditions. Literature identifies six possible adjustments in travel behavior, namely: changing of mode, adapt departure time (e.g. leaving earlier or later than in the normal situation), adapt activity location (e.g. choosing a supermarket closer to the living place because of heavy rainfall), cancel the trip (e.g. not going to work when it is snowing), alternate routing (e.g. taking a stroll because of the beautiful weather) and finally, no change at all (De Palma, 1997; De Palma and Rochat, 1999; Khattak, 1991; Al Hassan and Barker, 1999; Maze et al, 2005; Kilpelaïnen and Summala, 2007; Lam et al, 2008; Pisano and Goodwin, 2003; Hagens, 2005). These adaptations influence trip generation, trip distribution, modal split and the allocating phase in traffic modeling.

3.2 Data Collection

The data for the stated adaptation approach has already been collected in a previous case study, by means of a questionnaire. In total, 595 respondents completed this survey which was administered both on the internet (86.89%) as via a traditional paper-and-pencil questionnaire (13.11%). This is a high response given the length of the survey. For this purpose, the programs 'Microsoft Office Word 2003' and 'Snap 9 Professional' were used. The collected data can be found on the enclosed cd-rom in the file '1. Sncasestudy'. After cleaning the data, 586 surveys were useful for further research. This coding can also be found on the cd-rom, in the file '2. Cleaning data'. The reason why, besides the web-based survey, a paper-and-pencil questionnaire was handed out was due to the fact that a representative proportion of the population had to be reached. Some studies have demonstrated that several social classes, like older people and lower income classes, experience difficulties to access the computer and internet or to use it (Couper et al, 2007). Through the paper-and-pencil questionnaire, these groups could also be reached. This way one counteracts the sample bias that would arise when only web-based data collection is conducted.

The distribution of the survey was done in a random manner, although some groups were approached more than others. The digital questionnaire was sent to all members of the Hasselt University as well as to an office of public servants in the region of Leuven and to subscribers of a sport magazine for which an email address was available. The paper-and-pencil survey was given to family and to the circle of acquaintances. Moreover, the respondents had the opportunity to send the survey to friends and other interested parties. It can be concluded that a large variety of potential respondents was achieved and that the principles of random sampling are fulfilled.

The data was processed using the statistical software program 'SAS'.

3.3 Building the survey

The stated adaptation survey exists of two parts. The first part consists of a household- and individual questionnaire, while the second part focuses on the changes in travel behavior that the individual undertakes due to adverse weather.

First, the household- and individual questionnaire consists of general questions concerning the socio-economic characteristics (age, gender, income, etc.) and the working situation in which the respondent is rolled in with (flexible hours, telecommuting, etc.). Moreover, this part queried whether the individual has a driver license or a public transport card even as some questions related to the weather forecast. Latter is important to investigate the influence of weather information on changes in travel behavior.

In the second part, the respondents were asked to indicate how often (never, <25% of the cases, in 26-50% of the cases or >50% of the cases) they would choose for a particular change in travel behavior in a particular scenario, complemented with some open-ended questions. In this thesis, a scenario can be defined as a particular type of weather condition in response with a particular trip purpose. E.g. the respondents had to indicate how often they would cancel their work/school trip due to the prediction of snow.

Figure 3-1 on page 30 is an example of the questionnaire style concerning the cancelation of the work/school trip.

In total, 90 behavioral adaptations in response to trip purposes and weather conditions are queried. Five travel behavior adaptations (the 'no change' adaptation is implicitly taken into account by respondents that never change their travel behavior) in combination with six weather type conditions, and this replicated for three trip purposes. In this way, 90 behavioral adjustments are obtained.

Do you cancel your work/school-related trip, e.g. by taking a day off, due to any of the following weather conditions?

With 'cold temperatures' we mean temperatures below the freezing point.

With 'warm temperatures' we mean temperatures above 28 °C.

Mark the answer that corresponds mostly to your situation. Only one answer is possible for each weather condition.

	No, never	Yes, occasionally (<25% of the cases)	Yes, sometimes (<50% of the cases)	Yes, usually (>50% of the cases)
Cold temperature	O	O	O	O
Snow/glaze ice	O	O	O	O
Heavy rain/thunderstorm	O	O	O	O
Fog	O	O	O	O
Warm temperature	O	O	O	O
Storm/heavy wind	O	O	O	O

Figure 3-1: Stated adaptation question concerning the cancelation of the work/school trip

3.4 Representativeness of the data

Anderson et al (1998) defined a population as a 'collection of all relevant elements in a given investigation'. The population in this stated adaptation experiment consists of the Flemish population aged 17 years and older, because it is supposed that people from this age can make independent decisions on the facets of the travel behavior. According to data from the NIS, the population concerns 5.622.161 individuals (NIS, 2009). This extreme size makes it impossible to collect data on the entire population and therefore a sample was performed.

As a sample corresponds to a subset of the population (Anderson et al, 1998), one should check whether the sample is consistent with this population. Potential differences may be due to two types of errors that may arise in the sample. Namely sampling errors, which occur during sampling, and sample bias, which arises in the response process (Ortùzar and Willumsen, 2001). First, sampling errors are always present in a sample due to random effects. It is possible by chance that some groups of respondents are less or more frequently in the sample than in the population. Second, sample bias can arise because some groups are more inclined to response than others.

The representativeness of the sample will be examined in terms of age, gender and civil state. For this goal, data from the National Institute for Statistics (NIS) will be used. These data apply only to Flanders and refer to the year 2008 (NIS, 2009).

3.4.1 Age

Figure 3-2 indicates both the distribution of the population and the distribution of the respondents by age group. Persons under 17 years are not listed since they don't belong to the target group.

This figure shows that the age group '17-24 year' is strongly over-represented in the sample. There are almost 4 times more respondents in this category than in the population.

Contrastive, the age group '65+' is greatly underestimated in the sample despite attempts to reach this target group (Section 3.2). The same counts for the '55-64 year' age group. The other categories appear to agree well with each other, with only minimal deviations.

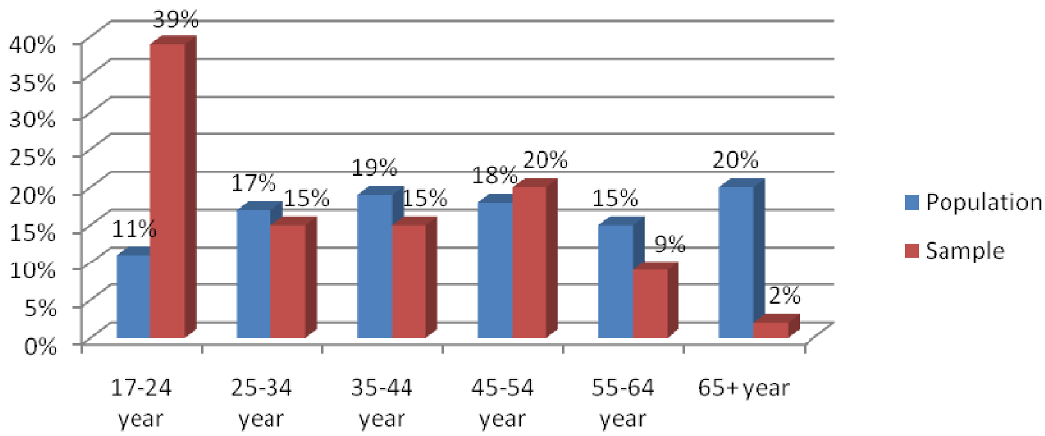

Figure 3-2: Distribution of population and sample by age group

3.4.2 Gender

Figure 3-3 indicates both the distribution of the population and the distribution of the respondents by gender.

The figure shows that the sample is moderately representative in terms of sex. There are slightly more women than men, as well as in the population as in the sample. However, men are slightly underrepresented and women are slightly overrepresented in the sample compared to the population, but these are only minor deviations.

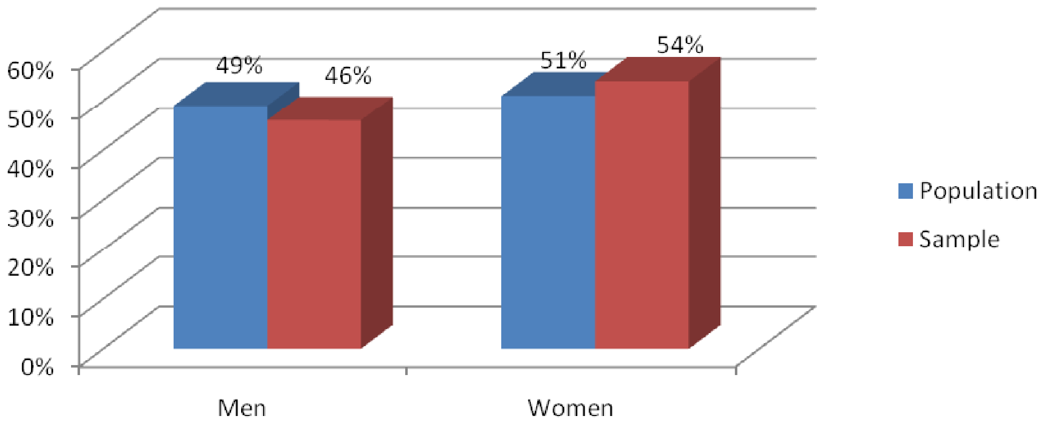

Figure 3-3: Distribution of population and sample by gender

3.4.3 Civil state

Figure 3-4 on page 33 indicates both the distribution of the population and the distribution of the respondents by civil state.

In terms of civil state, some important differences between the sample and the population can be found. The number of unmarried persons is overrepresented in the sample. This problem is probably related to the overrepresentation of the '17 - 24 year'-group as shown in Section 3.4.1. The same can be said about the group of widow(er)s. These are underrepresented and this relates probably to the low share of '+ 65 year' in the sample. The share of married or divorced people in the sample is also much lower than in the population.

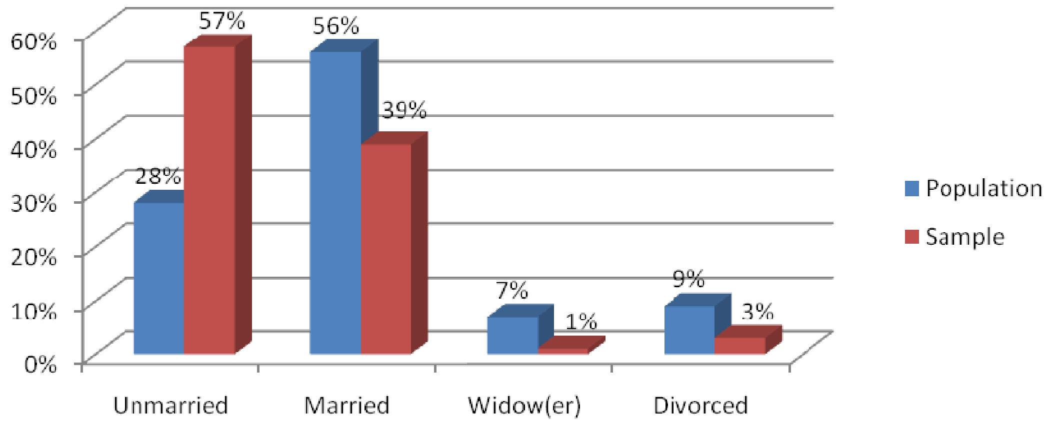

Figure 3-4: Distribution of population and sample by civil state

3.4.4 Weighting the data

The above figures show that the sample composition is quite in line with the population distribution in terms of sex, with only minimal differences, and that the sample composition is less consistent with the population distribution in terms of age and civil state. However, these are only explorative assessments and statistical analysis should be conducted to obtain an objective evaluation.

The Pearson chi-square independence test, as discussed in Section 1.5.2.2, is used to test whether the sample composition follows the population distribution. Following hypotheses are made:

H_0: Sample composition follows the population distribution.

H_a: Sample composition does not follow the population distribution.

These hypotheses are tested for the distribution by age, gender and civil state. The results are displayed in Table 3-2 on page 34. The calculations to perform this test can be found on the enclosed cd-rom, in the file '3. Chi-square analyses for testing the differences in distributions'.

For age, a P-value of <0.001 is obtained, which is below the significance level of 0.05 on which was tested. Consequently, the null hypothesis can be rejected so the alternative hypothesis is accepted. As already speculated, the sample composition differs significantly from the population distribution in terms of age.

The same conclusion can be drawn for the distribution by civil state. The P-value is below the significance level of 0.05 and therefore the null hypothesis should be rejected. Consequently, the sample composition differs significantly from the population distribution in terms of civil state.

For gender, a P-value of 0.13 is obtained. This P-value is higher than the significance level of 0.05 which means that the null hypothesis cannot be rejected. It can be concluded that the sample composition follows the population distribution in terms of gender.

Table 3-2: Chi-square analyses for testing the differences in distributions

	Chi²	**DF**	**P-value**	**Signif.[1]**
Age	558.49	5	< 0.001	***
Gender	2.25	1	0.13	n.s.
Civil state	244.09	3	<0.001	***

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

To make the survey sample composition consistent with the Flemish population, the observations in the sample are weighted. In this way, an optimal correspondence between the survey sample composition and the Flemish population is aspired. These weights are calculated by matching the marginal distributions of the sample with the marginal distributions of the population. Age, gender and civil state were the basis for this matching process. How these weights are calculated in detail and how these are assigned to the data set can be found on the cd-rom, in the file '4. Weight calculation' and the file '5. Assigning weights to the data'.

Chapter 4: The role of extreme weather conditions on stated changes in travel behavior

In this chapter, it is explored how and to what extent people change their travel plans in response to adverse weather conditions (Section 4.1) and in response to various aspects of the weather forecast (Section 4.3). Moreover, also the influence of the main transport mode on the likelihood to change mode in various weather conditions is examined (Section 4.2). The chapter terminates with an exploration of the determinants that influence these changes in travel behavior.

4.1 How and to what extent do people change their travel behavior

First, the modifications concerning commuting trips are discussed. Afterwards, the behavioral alterations in shopping trips and the adaptations in leisure trips are discussed. The results of these descriptive analyses are written in conditional probabilities rather than absolute numbers. The code that was used to obtain these results can be found on the cd-rom, in the file '6. Frequencies of changes in travel behavior'.

4.1.1 Stated changes in commuting trips

The extent to which the respondents adapt their travel behavior in commuting trips is shown in Table 4-1 on page 36. At first sight, it appears that the number of respondents making a certain travel behavior change, are rather limited in most cases.

When looking at the percentages at aggregated level (all changes), it is immediately clear that snow has the largest impact on commuting trips. Only 25% of the respondents indicates that they never change their travel behavior due to snow. Extreme temperatures, both cold and warm, turn out to have the smallest impact on travel behavior. Respectively 77% and 72% of the respondents never adjusts their travel behavior in response to these weather conditions. This is confirmed by tests for population fractions, for which the results are displayed in Table 11-1 in Appendix 1. These results indicate that significantly more people adapt their travel behavior in snow conditions compared to other types of weather. It is also clear from these tests that significantly less people adjust their travel behavior in extreme temperatures than in the case of other weather conditions, except for fog. The calculations that were performed to execute these tests can be found on the cd-rom, in the file '7. Tests for population fractions – weather conditions'.

The previous findings are confirmed by the percentages at disaggregated level (per behavioral change). The impact of the different weather conditions on each behavioral change seems to be the largest for snow and the smallest for extreme temperatures.

Furthermore, the table shows that changing the departure time is the most popular adjustment in the presence of snow, with 50% of the respondents making that choice. The adjustment of departure time is also the most common adaptation in the context of cold temperatures, rain, fog and storm. Besides adjusting the departure time, it appears that changing the route to work or school is also common practice. Changing the work/school location is the least frequent chosen behavioral adaptation.

The previous relates only to cold temperatures, snow, rain, fog and storm or in other words bad weather conditions. In contrast to these types of weather, it appears that time of day change and route change are much less chosen in the presence of warm temperatures (favorable weather). In this situation, people rather change transport mode.

Table 4-1: Frequencies of changes in commuting trips due to extreme weather conditions

Behavioral Change	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All changes	Never	76.9%	24.7%	57.0%	65.9%	71.6%	62.0%
Mode change	Never	93.8%	75.8%	84.8%	94.6%	81.6%	86.8%
	1-25%	4.4%	14.6%	7.9%	3.7%	10.5%	8.1%
	26-50%	0.9%	2.6%	1.4%	0.1%	4.4%	0.9%
	>50%	0.9%	7.0%	5.9%	1.6%	3.5%	4.2%
Time of day change	Never	89.5%	47.8%	70.3%	74.0%	94.4%	74.9%
	1-25%	6.0%	23.7%	17.0%	13.7%	2.8%	14.9%
	26-50%	2.5%	9.2%	6.9%	6.9%	1.5%	4.7%
	>50%	2%	19.3%	5.8%	5.4%	1.3%	5.5%
Location change	Never	96.6%	86.6%	94.4%	97.5%	97.0%	93.3%
	1-25%	2.2%	8.4%	3.3%	1.3%	2.0%	4.1%
	26-50%	0.6%	3.0%	1.0%	0.5%	0.8%	1.1%
	>50%	0.6%	2.0%	1.3%	0.7%	0.2%	1.5%
Trip cancellation	Never	96.2%	75.4%	93.8%	95.3%	89.0%	92.6%
	1-25%	3.4%	19.4%	5.0%	4.3%	10.0%	6.1%
	26-50%	0.4%	4.1%	0.2%	0.4%	1.0%	0.7%
	>50%	0.0%	1.1%	1.0%	0.0%	0.0%	0.6%
Route change	Never	90.5%	56.4%	85.0%	85.4%	96.4%	87.1%
	1-25%	6.3%	26.7%	9.9%	10.0%	2.4%	8.4%
	26-50%	1.8%	9.8%	2.6%	1.5%	0.9%	2.7%
	>50%	1.4%	7.1%	2.5%	3.1%	0.3%	1.8%

4.1.2 Stated changes in shopping trips

Table 4-2 on page 38 displays the percentages of respondents making a certain travel behavior alteration in shopping trips.

Percentages at aggregate level show, similar to commuting trips, that snow has the largest influence on travel behavior. In this weather condition, 82% of the respondents adjusts their travel behavior in one way or another. The travel behavior in shopping trips is also strongly affected by rain, fog and stormy weather. More than 50% of the respondents indicates that they adapt their travel behavior in response to these weather types. Similar to the commuting trips, extreme temperatures seem to have the smallest influence on travel behavior. Approximately 60% to 70% of the respondents never adapts their travel behavior in this context. The previous is validated by tests for population fractions for which the results are displayed in Appendix 1 (Table 11-1) and for which the calculations can be found on the enclosed cd-rom, in the file '7. Tests for population fractions – weather conditions'. The results of these tests show that all percentages are significantly different from each other. So one adapts their travel behavior significantly more in snow conditions than in other types of weather. Cold temperatures has the smallest impact on travel behavior, closely followed by warm temperatures.

The above is also reflected at the disaggregated level. Snow has the largest impact and extreme temperatures have the smallest impact on any of the behavioral changes.
Furthermore, the results show that adjusting the departure time is the most frequently used adaptation, regardless of the weather condition. This is followed by cancellation of the trip. In the context of snow even 70% of the respondents chooses for these adjustments. Similar to commuting trips, it seems that in the context of warm temperatures mode change is also a frequently used adaptation.

Table 4-2: Frequencies of changes in shopping trips due to extreme weather conditions

Behavioral change	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All changes	Never	69.7%	17.8%	33.3%	50.0%	60.8%	39.9%
Mode change	Never	91.5%	78.2%	85.6%	91.9%	79.7%	86.8%
	1-25%	5.2%	11.2%	6.0%	4.4%	10.2%	6.5%
	26-50%	1.4%	3.4%	2.2%	0.8%	4.9%	1.6%
	>50%	1.9%	7.2%	6.2%	2.9%	5.2%	5.1%
Time of day change	Never	80.2%	29.4%	41.8%	59.9%	80.0%	47.7%
	1-25%	13.1%	28.2%	24.1%	19.2%	13.0%	22.8%
	26-50%	3.9%	16.9%	13.6%	11.4%	4.2%	13.7%
	>50%	2.8%	25.5%	20.5%	9.5%	2.8%	15.8%
Location change	Never	86.8%	54.0%	68.4%	72.2%	83.8%	69.3%
	1-25%	7.4%	20.7%	12.6%	11.9%	10.5%	13.7%
	26-50%	2.7%	9.4%	10.7%	8.8%	2.6%	10.0%
	>50%	3.1%	15.9%	8.3%	7.1%	3.1%	7.0%
Trip cancellation	Never	86.7%	31.9%	48.4%	64.4%	82.6%	55.0%
	1-25%	7.1%	33.7%	29.3%	20.4%	13.3%	23.3%
	26-50%	3.0%	14.5%	11.6%	8.8%	2.7%	11.6%
	>50%	3.2%	19.9%	10.7%	6.4%	1.4%	10.1%
Route change	Never	93.1%	58.8%	81.7%	80.6%	93.3%	81.7%
	1-25%	4.5%	23.2%	11.0%	11.3%	4.7%	10.7%
	26-50%	1.4%	10.3%	3.7%	4.8%	0.5%	4.6%
	>50%	1.0%	7.7%	3.6%	3.3%	1.5%	3.0%

4.1.3 Stated changes in leisure trips

The extent to which the respondents adapt their travel behavior in leisure trips is shown in Table 4-3 on page 39.

Yet again, snow appears to have the largest influence on the travel behavior. Only 22% of the respondents indicates that their travel behavior is never affected due to snow. Similar to the shopping trips, also rain, fog and storms seem to have a strong influence on travel behavior. More than 50% of the respondents indicates that they would change their travel behavior in such weather conditions. Yet again, cold and warm temperatures seem to have the smallest influence on travel behavior. Respectively 68% and 58% of the respondents never changes their travel behavior in these weather conditions. Tests for population fractions show that in most cases these percentages are significantly different from each other. The results of these tests are displayed in Appendix 1 (Table 11-1) and the calculations can be found on the enclosed cd-rom (file 7). The only exception concerns the percentages between rain and storm wherefore no significant difference could be detected. Similar to the previously discussed trip purposes, there can be concluded that significantly more people adapt their travel behavior in snow conditions than is the case in other types of weather. Moreover, travel behavior is least affected by cold temperatures.

The above can also be deduced at disaggregated level. Furthermore, these results show that the most prevalent changes are time of day change and trip cancellation, which is similar as in leisure trips. No less than 65% of the respondents claims to choose these adaptations. Just as was the case in leisure trips and commuting trips, mode change is common practice in the context of warm temperatures.

Table 4-3: Frequencies of changes in leisure trips due to extreme weather conditions

Behavioral Change	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All changes	Never	68.5%	22.4%	38.5%	50.6%	58.5%	41.0%
Mode Change	Never	89.9%	74.4%	83.9%	87.3%	77.3%	85.6%
	1-25%	7.7%	13.5%	8.9%	8.1%	11.7%	8.7%
	26-50%	1.2%	3.8%	3.1%	3.5%	6.4%	3.0%
	>50%	1.2%	8.3%	4.1%	1.1%	4.6%	2.7%
Time of day Change	Never	85.3%	35.1%	54.2%	61.8%	85.3%	58.6%
	1-25%	10.5%	30.9%	26.1%	21.3%	11.5%	20.1%
	26-50%	2.0%	15.0%	12.7%	9.2%	2.0%	13.0%
	>50%	2.2%	19.0%	7.0%	7.7%	1.2%	8.3%
Location Change	Never	83.3%	70.9%	75.1%	81.5%	84.0%	74.1%
	1-25%	9.9%	14.1%	11.3%	9.3%	10.0%	13.1%
	26-50%	2.8%	6.5%	6.3%	5.3%	3.2%	6.5%
	>50%	4.0%	8.5%	7.3%	3.9%	2.8%	6.3%
Trip Cancellation	Never	79.3%	35.6%	56.1%	66.1%	82.2%	55.3%
	1-25%	14.4%	34.0%	24.2%	20.2%	13.9%	23.5%
	26-50%	4.1%	13.8%	9.6%	8.0%	3.0%	12.1%
	>50%	2.2%	16.6%	10.1%	5.7%	0.9%	9.1%
Route Change	Never	92.8%	55.1%	76.4%	78.6%	94.3%	76.9%
	1-25%	4.4%	24.4%	13.9%	13.5%	3.6%	12.4%
	26-50%	2.1%	11.9%	5.9%	4.5%	1.2%	6.9%
	>50%	0.7%	8.6%	3.8%	3.4%	0.9%	3.8%

4.1.4 Discussion

Depending on the type of weather and the trip purpose, between 15% and 85% of the respondents claims to change their travel plans due to the weather. Most values from the literature (Section 2.1) lay in this interval. E.g. De Palma and Rochat (1999) found that about 40% of the respondents indicates that weather has a significant influence on their travel plans.

Next, it is noticeable that in commuting trips people are less likely to adjust their travel behavior in comparison with the other two trip purposes. This difference applies to all types of weather, but is especially notable for rain and storms.

In all three purposes, it appears that respondents adapt their travel behavior most frequently in the presence of snow and least frequently in the context of extreme temperatures. Moreover, this appears to be the case even when each behavioral adaptation is considered separately. E.g. snow has the largest impact on the frequencies of trip cancellation, time of day change, etc.

When the focus is turned to the popularity of the various behavioral changes, it seems that adapting the departure time is one of the most chosen alterations in all weather conditions, regardless of the trip purpose. One hypothesis could be that people tend to postpone their trip until more favorable weather conditions occur. A second hypothesis could be that people take the traffic problems into account that such types of weather can bring along. Moreover, time shifts can be seen as less disruptive and easier to implement than the other alterations. Previous results are in line with international literature, as discussed in Section 2.1. Most studies indicate that especially departure time is influenced during adverse weather. E.g. De Palma and Rochat (1999) investigated the impact of adverse weather on commuter's travel decisions. They found in their study that about 29.1% of the respondents indicates that weather has an important influence on their departure time, while these percentages are 21.9% and 19.8% for respectively mode change and route change.

In commuting trips, route change is also common practice, while in leisure and shopping trips one rather opts to cancel the trip. Former is in line with literature. De Palma and Rochat (1999) as well as Khattak and De Palma (1997) investigated the impact of adverse weather on commuter's travel behavior. Both found that route change was a common alteration during adverse weather. The popularity for the cancellation of the trip in shopping and leisure trips can be explained by the fact that these are non-obligatory activities. Non-obligatory activities are more flexible than obligatory activities, such as the work activity, and are easier to cancel. Moreover, the fact that the working activity is less flexible could be a possible explanation for the popularity of changing route in commuting trips. In need to arrive on time at work, one tries to avoid traffic jams caused by the bad weather by taking a shortcut.

Various studies in literature (Section 2.1) indicated that weather may cause important shifts in modes. The descriptive analyses in this thesis show that one rather changes mode in warm temperatures than in other weather conditions and this in all three trip purposes. One explanation could be that more people are encouraged to use slow modes (cycling, walking) in favorable weather conditions than in bad weather conditions and therefore it is assumed that especially car users will shift to these kinds of modes.

Remarkable is the fact that changing the work/school location is the least frequent chosen adaptation in commuting trips. A possible elucidation why people rarely adjust the work- or school location can be that these locations are fixed, which is not the case in the other two trip purposes. Although nowadays, alternatives such as telecommuting, satellite offices, e-learning and independent learning are opportunities making location changes in commuting trips better feasible. The previous result is in line with the study from Hagens (2005). He found that if one changes location, it mostly concerns shopping trips and rarely commuting trips.

4.2 Does trip purpose matter?

The frequency analysis in Section 4.1 showed that less people will adjust their travel behavior in response to adverse weather conditions in commuting trips than in the other trip purposes. Moreover, it showed that people choose more frequently for cancellation of shopping and leisure trips than in commuting trips and that in commuting trips one chooses rather to change their route. This gives a clear indication that the frequencies of behavioral changes depends on type of activity. In this section, these hypotheses are formally tested using Pearson chi-square independence tests. The calculations to perform this analysis can be found on the enclosed cd-rom in the file '8. Dependence of behavioral changes on trip purpose'.

First, independence tests are performed on aggregated level, by which the aggregation over all behavioral changes is meant. Results of these tests are displayed per weather condition in Table 4-4. This table shows that all P-values are smaller than 0.0001 so that the null hypothesis can be rejected. This means that the extent to which people adapt their travel behavior is strongly dependent on trip purpose, regardless of the weather that occurs. The dependence is the largest in the context of snow, rain, fog and storm and the lowest in the context of extreme temperatures (but still highly significant). This can be derived from the chi²-values which have high values for snow, rain, fog and storm and lower values for extreme temperatures, but still have the same degrees of freedom. These results are in accordance to international literature as discussed in Section 1.1.3. Various studies showed that travel demand reductions are dependent on trip purpose. Moreover, the results are also in line with the frequency analysis as discussed in Section 4.1, since it was indicated that people in commuting trips modify their travel behavior to a lesser extent than in shopping and leisure trips. This difference could be due to the fact that commuting trips are frequently performed and have a fixed pattern, reducing the cognitive efforts in the decision process. Consequently, one performs the travel behavior in commuting trips with more automatism (Ouellette and Wood, 1998). People will think less about their travel behavior in the commuting trips, because of habits, compared to the other trip purposes.

Table 4-4: Dependence of behavioral changes on trip purpose (aggregated level)

Weather type	Behavioral change	Chi²	DF	P-value	Signif.[1]
All types	All changes	2180.34	238	<0.0001	***
Cold	All changes	165.59	38	<0.0001	***
Snow	All changes	473.46	38	<0.0001	***
Rain	All changes	550.79	38	<0.0001	***
Fog	All changes	382.66	38	<0.0001	***
Warm	All changes	144.80	38	<0.0001	***
Storm	All changes	462.94	38	<0.0001	***

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

Second, independence tests are performed on disaggregated level (per behavioral change) of which the results are displayed in Appendix 3.1, Table 11-17. By taking a closer look at this table, it is immediately clear that time-of-day change, change of location and trip cancellation have highly significant results and this regardless of the weather type. This means that the extent to which people choose these particular travel behavior changes strongly depends on trip purpose. The behavioral change 'trip

cancellation' has, except for warm temperatures, the largest chi²-value. In other words, the dependency between trip purpose and behavioral change frequency is the largest for trip cancellation. These results are in line with the frequency analysis. E.g. note that cancellation was common practice in the case of leisure and shopping trips but not in the case of commuting trips.
In addition, the extent to which people change their route or change their mode are not depending on trip purpose in the cases of extreme temperatures and snow.

Remark: As could been noticed from Table 11-17 in Appendix 3.1, it appears that in the context of warm temperatures the behavioral changes 'trip cancellation' and 'route change' have lower degrees of freedom. Here, an alternative independence test was tabulated because the underlying assumption, as discussed in Section 1.5.2.2 was not met. To meet this assumption, reduced answer possibilities were used (by combining the three categories of people that change their behavior) instead of the 4 frequencies that are used in the other cases (the number of people who would never change their behavior, and respectively the ones that change their behavior in 1-25%, 26-50% and more than 50% of the cases). When this test will be used in the remainder of the thesis, it will be referred to as "estimated on reduced answer possibilities" at the bottom of the table.

4.3 Does type of weather matter?

The frequency analysis in Section 4.1 showed that especially snow affects travel behavior and that the impact of extreme temperatures on travel behavior is rather limited, regardless of trip purpose. The previous indicates that the extent to which people adapt their travel behavior depends on type of weather. This hypothesis will be formally tested using Pearson chi-square independence tests. The calculations to perform this analysis can be found on the enclosed cd-rom in the file '9. Dependence of behavioral changes on weather type'.

First, independence tests are performed on aggregated level. The results are displayed for each activity in Table 4-5 on page 44. This table shows that the extent to which people adapt their travel behavior is strongly dependent on weather type, regardless of trip purpose. Indeed, all P-values are smaller than 0.0001 so the null hypothesis can be rejected. This dependence appears to be the largest for shopping trips and the smallest for commuting trips, but still highly significant (lower chi²-value, same degree of freedoms).

Table 4-5: Dependence of behavioral changes on type of weather (aggregated level)

Trip purpose	Behavioral change	Chi²	DF	P-value	Signif.[1]
All purposes	All changes	4370.95	295	<0.0001	***
Work/school	All changes	1185.76	95	<0.0001	***
Shopping	All changes	1728.95	95	<0.0001	***
Leisure	All changes	1456.25	95	<0.0001	***

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

Second, results of independence tests on disaggregated level (per behavioral change) are displayed in Table 11-18 in Appendix 3.2. A first conclusion that can be drawn from this table is the fact that all behavioral changes are strongly dependent on weather type (all P-values are smaller than 0.0001), regardless of trip purpose. For commuting trips, it appears that especially the extent to which people choose to change their route and departure time depends on type of weather (high chi² value, same degree of freedoms). The extent to which people opt for location change in commuting trips is the least dependent on weather type, although it is also highly significant. For shopping and leisure trips, the relationship is the most significant for time of day change and trip cancellation and, just as was the case for commuting trips, the least significant for location change. These results are also in line with the conclusions that were drawn in the frequency analysis.

4.4 Frequencies of mode change according to mode type

Section 4.1 showed that mode is more frequently changed in warm temperatures than in other weather conditions. It was therefore assumed that these are mainly car users switching to slow modes (cycling, walking). Furthermore, it could be assumed that in bad weather conditions especially slow mode users will switch to "sheltered" transport modes, such as the car. To give more certainty about this, the mode change row of Table 4-1, Table 4-2 and Table 4-3 should be broken down depending on which mode of transport is normally being used for the trip. The code that was used to obtain these results can be found on the cd-rom, in the file '10. Frequencies of mode change according to mode type'.

In this part, transport modes are divided into four categories. The first category refers to car users, including both car drivers and car passengers. A second category concerns the vulnerable road users, consisting of cyclists, moped riders and pedestrians. A third category consists of trips by train, bus, tram or underground which are joined under the heading of public transport users. The last category relates to other transport modes, such as motorbikes, company/school bus service and cabs. Because of the low number of observations (5.6) in this group, it will not be discussed in depth, since these percentages can be misleading.

4.4.1 Mode change according to mode type in commuting trips

Table 4-6 on page 46 displays the breakdown of the mode change row in commuting trips according to mode type.

What is striking in the category of car users is that in cold temperatures, rain, fog and storms, only a very small percentage of car users chooses to adapt their transport mode. Approximately 95% of the respondents indicates that they do not change mode in these types of weather. When car drivers do change transport mode in these weather conditions, it appears that one switches particularly to public transport or that car drivers become car passengers. Car users change their mode more frequently in warm temperatures and snow. Up to 17% switches to another mode in the context of snow while for warm temperatures this percentage comes up to 21%. Especially the switch to public transport (13.8%) is remarkable when it snows. In the context of warm temperatures, car users rather switch to slow modes (17.8%), as already was expected.

Concerning the second category, the vulnerable users, it appears that especially snow, rain and storm will cause the respondents to change their mode. In these weather conditions, around 50% of the respondents chooses another mode. As was expected, the transition to the car is very popular (35% to 40%), but also the percentage that switches to public transport is not negligible (9% to 12%).
Finally, vulnerable road users seem least influenced by warm temperatures. For only 4%, this is a reason to change their transport mode.

In the category of public transport users, it appears that especially warm temperatures cause modal shifts. In this context, approximately 23% of the respondents make use of another transport mode. The majority of them (15%) switches to slow modes.

Precipitation, both rain and snow, and storm appear to have only a moderate influence on mode change. Around 14% to 18% of the respondents stated to transfer to another mode in these weather conditions.

Table 4-6: Mode change according to mode type in commuting trips

Mode type	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
Car driver/passenger (309.7)	Never	96.4%	82.8%	95.4%	95.3%	80.8%	95.8%
	Car	1.1%	2.6%	2.2%	0.8%	0.8%	1.1%
	Slow	0.8%	0.8%	0.0%	0.7%	17.8%	0.1%
	Public	1.7%	13.8%	2.4%	3.2%	0.6%	3.0%
Vulnerable road user (90.0)	Never	80.9%	43.1%	44.2%	89.5%	91.8%	53.9%
	Car	14.1%	34.6%	45.0%	9.0%	6.0%	35.5%
	Slow	1.9%	10.5%	1.8%	0.5%	2.2%	2.1%
	Public	3.1%	11.8%	9.0%	1.0%	0.0%	8.6%
Public transport (101.1)	Never	89.3%	82.3%	85.7%	92.7%	77.4%	86.2%
	Car	5.6%	10.1%	9.1%	1.6%	5.1%	8.2%
	Slow	0.0%	2.0%	0.0%	0.0%	15.4%	0.2%
	Public	5.1 %	5.6%	5.2%	5.7%	2.1%	5.4%
Other (5.6)	Never	100%	100%	100%	100%	100%	100%
	Car	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Slow	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Public	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

4.4.2 Mode change according to mode type in shopping trips

The breakdown of the mode change row according to mode type in shopping trips is shown in Table 4-7 on page 47. Exactly like the category 'other', the category of the public transport users will not be discussed in depth because of the low number of observations (5.5).

As was also the case in commuting trips, less than 5% of the car users changes their mode in cold temperatures as well as in rain, fog and storms. Car users rather change mode in the presence of snow (13%) or when it is extremely warm (24%). In these weather conditions, one rather opts for slow modes. It is striking that less car users switch to public transport when it snows in shopping trips than in commuting trips.

In the context of vulnerable road users, the same conclusions as for commuting trips can be drawn. Snow, rain and storm appear to have the greatest impact on mode change. More than 50% of the respondents indicates that they change their mode in the presence of these weather conditions. Similar to commuting trips, they mainly shift towards the

car (40% to 55%). The percentage that switches to public transport lays considerably lower than in commuting trips.
The transport mode of vulnerable road users are least influenced by warm temperatures. Yet still 15% shifts to another travel mode, mainly to the car (13%).

Table 4-7: Mode change according to mode type in shopping trips

Mode type	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
Car driver/passenger (446.8)	Never	97.1%	86.7%	97.3%	95.6%	76.9%	96.7%
	Car	0.6%	0.9%	0.6%	0.9%	0.3%	0.6%
	Slow	2.1%	9.6%	1.4%	3.3%	22.6%	1.9%
	Public	0.2%	2.8%	0.7%	0.2%	0.2%	0.8%
Vulnerable road user (110.5)	Never	67.7%	47.1%	42.9%	77.5%	85.6%	49.1%
	Car	26.2%	40.0%	55.8%	20.5%	12.7%	43.6%
	Slow	4.4%	7.9%	2.2%	0.9%	0.9%	1.4%
	Public	1.7%	5.0%	5.1%	1.0%	0.8%	5.9%
Public transport (5.5)	Never	100%	91.2%	95.6%	95.6%	44.6%	95.6%
	Car	0.0%	4.4%	4.4%	4.4%	0.0%	4.4%
	Slow	0.0%	4.4%	0.0%	0.0%	55.4%	0.0%
	Public	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Other (5.0)	Never	100%	100%	100%	100%	100%	100%
	Car	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Slow	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Public	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

4.4.3 Mode change according to mode type in leisure trips

Table 4-8 on page 48 displays the breakdown of the mode change row according to mode type in leisure trips. Similar to shopping trips, the number of respondents that uses public transport (17.9) in leisure trips is too low to provide significant results and will not be discussed.

Similar to commuting and shopping trips, car users appear to barely switch travel mode when cold temperatures, rain, fog or storm occur. Approximately 95% of respondents claims to never change their mode due to these weather conditions.
When warm temperatures and snow occur, respectively 27% and 16% of car users changes their mode. Most of them switch to slow modes. In the context of snow, the percentage of car users that switch to public transport is considerably lower compared to commuting trips.

Concerning the vulnerable road users, the same conclusions as in previous sections (Section 4.4.1 and Section 4.4.2) can be drawn. Especially snow, rain and storm make them change from travel mode. In the presence of snow and rain, even more than 60% shifts towards a different transport mode. Especially the transition to the car seems popular (43% to 57%).
As in the previous sections, the frequencies of vulnerable road users changing mode are least influenced by warm temperatures. Yet, still 14% considers a transition towards another mode.

Table 4-8: Mode change according to mode type in leisure trips

Mode type	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
Car driver/passenger (472.5)	Never	95.0%	84.2%	95.0%	91.9%	72.8%	95.0%
	Car	0.9%	1.7%	2.0%	1.3%	0.2%	2.0%
	Slow	2.7%	7.4%	1.3%	4.2%	25.9%	1.7%
	Public	1.4%	6.7%	1.7%	2.6%	1.1%	1.3%
Vulnerable road user (82.5)	Never	61.5%	37.0%	34.0%	65.1%	86.2%	44.5%
	Car	29.3%	43.1%	57.8%	25.6%	12.1%	45.0%
	Slow	5.2%	12.8%	0.8%	5.9%	0.9%	0.3%
	Public	4.0%	7.1%	7.4%	3.4%	0.8%	10.2%
Public transport (17.9)	Never	97.3%	94.6%	94.6%	98.7%	74.5%	94.6%
	Car	1.4%	4.0%	4.0%	1.3%	1.3%	4.0%
	Slow	0.0%	0.0%	0.0%	0.0%	24.2%	0.0%
	Public	1.3%	1.4%	1.4%	0.0%	0.0%	1.4%
Other (5.0)	Never	100%	100%	100%	100%	100%	100%
	Car	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Slow	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Public	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

4.4.4 Discussion

The breakdown of the mode change row according to mode type has led to few surprises.

In all three trip purposes, less than 5% of the car users claims that they adapt their transport mode in the case of cold temperatures, rain, fog and storm. This is a logical choice since the car already protects them against the physical discomforts that are entailed by adverse weather conditions. A possible explanation for those who do change their transport mode is that they are unsure about their driving skills in such weather and that they rather opt for modes where they do not need to drive the vehicle themselves. Car users change their mode more frequently in snow (> 13%). In commuting trips, especially the transfer from car to public transport is remarkable in snow conditions. One possible explanation for this can be that they try to avoid the large traffic jams that can arise in snowy conditions, e.g. the congestion record of 948 km that arose due to sudden snowfall in the morning rush in February 2010 (Het Belang van Limburg, 2010). To avoid such traffic jams, one switches to alternative transportation modes, such as rail, which are less affected by congestion. As stated above, a second reason can be that people think they have insufficient driving skills in snow conditions and therefore prefer to opt for a safer transport mode such as bus or train. For shopping and leisure trips, the transfer from car to public transport on snowy days is remarkably lower than for commuting trips. For these trip purposes, people rather opt for switching to slow modes. A logical explanation could be that the locations of shops and leisure are closer to home than the workplace. This is also reflected by the Travel Behavior Research Flanders (TBRF) (Moons, 2009). E.g. approximately 47% of the respondents in the TBRF shops within a 2km radius from their residential location, while 47% works within a radius of 10km. Therefore, for many respondents, it is often not possible or not worthwhile to take public transport in shopping or leisure trips, while it is for commuting trips. This also explains why so few people use public transport as their main transport mode in shopping and leisure trips. As was already expected, it appears that car users especially change mode when warm temperatures arise (>20%). They rather opt to use slow modes in these weather conditions, probably because they want to enjoy the beautiful weather and therefore leave the "sheltered" car aside and go to work by bike or by foot.

Vulnerable road users respond the other way around. They especially transfer to the car in bad weather conditions (snow, rain and storms), which applies on all three trip purposes. This conclusion is in line with various studies that are discussed in Section 2.1. E.g. Hagens (2005) found that bad weather, especially rain, causes cyclists to switch mainly to the car. In commuting trips, a lot of vulnerable road users also switch to public transport. This is in line with literature. E.g. Nankervis (1998) found that about 25% of cycling students chooses an alternative mode on days of poor (not defined) weather, of which 18% claimed to transfer to public transport. Such transfers can be explained by the fact that vulnerable road users are exposed to the adverse weather conditions, resulting in physical discomforts. Therefore, in such weather conditions, they prefer transportation modes that provide shelter, like car or public transport. The large group that switches to public transport in commuting trips can be explained in two ways. Either the respondents have no alternative transport mode option so they are obliged to switch to public transport, or there are sufficient and qualitative sheltered bus stops where people can shelter from bad weather conditions while waiting on the bus. The percentage that switches to public transport in shopping and leisure trips is considerably lower than for commuting trips. The earlier mentioned reason concerning the shorter distance to shopping and leisure locations can also be cited here.

The public transport users will only be discussed in the context of commuting trips since there were not enough observations for the other two trip purposes. Public transport users claimed that they especially switch to slow modes when it gets warm. This transition may be due to a lack of air conditioning on the bus/train, but is more likely due to the fact that people want to enjoy the beautiful weather. Precipitation, both rain and snow, and storm appear to have only a moderate influence on modal change. One possible reason for this could be that there are sufficiently sheltered bus stops where people can shelter against such weather, as was explained before.

4.5 Does type of transport mode matter?

The frequency analyses in Section 4.4 showed that car users switch especially their mode in warm temperatures while vulnerable road users change rather their mode in bad weather conditions. This indicates that the frequencies of mode change depends on the mode type that is normally be used for the trip. This hypothesis will be formally tested using Pearson chi-square independence tests. The calculations to perform this analysis can be found on the enclosed cd-rom in the file '11. Dependence of mode change frequencies on mode type'.

To meet the underlying assumption, as discussed in Section 1.5.2.2, reduced answer possibilities are used in all cases. But after doing this, the underlying assumption was still not met. To solve this problem, the category 'other' was not incorporated in the analysis even as the category 'public transport users' in the context of shopping trips.

First, independence tests are performed on aggregated level for which the results are displayed in Table 4-9 on page 51. This table shows that all P-values are less than the significance level of 0.05 on which was tested. This means that the extent to which the respondents change their mode indeed depends on the type of mode that is normally be used, regardless of the trip purpose.

Table 4-9: dependence of mode change on mode type (aggregated level)

Trip purpose	Weather type	Chi²	DF	P-value	Signif.[1]
Work/school[2]	All types	384.63	22	<0.0001	***
Shopping[2,3]	All types	521.46	11	<0.0001	***
Leisure[2]	All types	444.41	22	<0.0001	***

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

[3] Based on only car users and vulnerable road users

Second, results of independence tests on disaggregated level (per weather type) are displayed in Table 11-19 in Appendix 3.3. This table shows that, except for fog in commuting trip, all P-values are highly significant. This means that the extent to which respondents change their mode depends on the mode type that is currently be used, regardless of the trip purpose and in all weather types. This dependency is the largest in the context of rain and the smallest in the context of warm temperatures, but still significant.

Chapter 5: The role of weather forecasts on travel behavioral decisions

This chapter examines the influence of various aspects of the weather forecast on changes in travel behavior. More concrete, it is explored whether the exposure to the weather forecast (Section 5.1), the perceived reliability of the weather forecast (Section 5.2) and the used media source (Section 5.3) have an influence on adaptations in travel behavior.

5.1 Influence of exposure to weather forecast on behavioral adaptations frequencies

This section gives an answer to research question II (a) as defined in Section 1.3. It can be expected that people who frequently follow the weather forecast, are taking more informed decisions regarding their travel behavior and consequently adjust their travel behavior more in response to extreme weather than those who particularly rely on their own observation of the weather conditions.

In order to answer the research question, respondents of the questionnaire were asked how often they follow the weather forecast. The results are shown in Table 5-1. This table shows that approximately 60% of the respondents follow the weather forecast on a daily basis and that only 7.5% of the respondents indicated that they follow the weather forecast sporadic.

Table 5-1: Exposure to weather forecast

Forecast Frequency	Frequency	Cumulative frequency	Percent	Cumulative Percent
Daily	347.5	347.5	59.3%	59.3%
Weekly	194.5	542.0	33.2%	92.5%
Occasional	44.0	586.0	7,5%	100.00%

Next, Table 5-2 on page 54 shows the percentage of respondents who never choose for a certain behavioral change in commuting trips according to the exposure to the weather forecast. The code that was used to obtain these descriptive results can be found on the cd-rom, in the file '12. Frequencies of changes in travel behavior according to the weather forecast frequency'.

If these percentages are seen at aggregated level (all behavioral changes), it is immediately clear that the respondents who follow the weather forecast on a daily basis adapt their travel behavior considerably more than those who follow the weather forecast occasionally. The difference can be found in all weather conditions but is especially notable in the context of fog, storm and warm temperatures (>10%). The difference is also substantially in the case of snow (7.6%). Although, results of tests for population fractions show that most of these differences are not statistically significant. The results of these tests are displayed in Table 11-2 in Appendix 1, the calculations to perform these tests can be found on file number 18 on the cd-rom. Only in the case of fog and warm temperatures a significant difference could been found between the percentages of respondents who follow the weather forecast on a daily basis and the respondents who follow the weather forecast sporadic. From this, it follows that respondents who keep up the weather forecast daily adapt their travel behavior more in these weather conditions than those who follow the weather forecast only sporadic.

The percentages on disaggregated level (per behavioral change) appear to be more ambiguous. In some cases, respondents who keep up the weather forecast daily appear to adapt their travel behavior to a lesser extent than those who follow the weather forecast occasionally. E.g. it is found that respondents who follow the weather forecast on a daily basis apparently change less of mode in all weather conditions than those who follow the weather forecast sporadic. However, this would go against the logic as such decision is planned in advance, for example after watching the weather forecast, unlike a change of the route which can be considered as a last-minute alteration. The same conclusion can be drawn for location change, e.g. in the context of snow. In other cases it appear that respondents who follow the weather forecast on a daily basis adapt their travel behavior more than those who follow the weather forecast occasionally, which is the case in "trip cancellation" and "route change". This statement is much more logic than previous one.

To determine whether these statements are significant, tests for population fractions can be used, but for reasons of simplification an alternative test is chosen, namely the Pearson's chi-square independence test. The calculations to perform this test can be found on the enclosed cd-rom in the file '13. Dependence of behavioral changes on exposure to the weather forecast'.

Table 5-2: Frequencies of changes in commuting trips in response to extreme weather conditions, according to the weather forecast frequency

Behavioral Change	Forecast Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All Changes	Daily	63.1%	21.1%	47.4%	53.5%	58.1%	51.5%
	Weekly	72.3%	20.2%	51.6%	58.7%	65.6%	55.2%
	Occasional	67.7%	28.4%	53.3%	77.0%	74.7%	62.1%
Mode Change	Daily	93.9%	75.3%	85.1%	94.6%	82.2%	86.2%
	Weekly	95.0%	77.7%	86.1%	95.4%	80.5%	88.2%
	Occasional	88.4%	71.3%	78.0%	91.8%	82.0%	85.2%
Time-of-day change	Daily	90.5%	48.1%	72.1%	74.4%	94.7%	75.0%
	Weekly	88.2%	45.2%	68.0%	69.8%	94.4%	73.9%
	Occasional	87.9%	56.2%	68.5%	88.4%	92.1%	78.2%
Location change	Daily	97.5%	89.0%	95.5%	97.0%	97.0%	94.3%
	Weekly	95.9%	85.4%	92.6%	98.0%	96.6%	91.6%
	Occasional	93.9%	76.5%	94.6%	98.5%	98.5%	94.2%
Trip cancellation	Daily	95.2%	78.2%	93.0%	93.6%	88.7%	91.8%
	Weekly	97.0%	72.2%	94.9%	97.2%	87.6%	92.2%
	Occasional	99.5%	71.1%	94.2%	98.5%	96.4%	98.9%
Route change	Daily	90.6%	56.5%	85.2%	84.1%	95.3%	87.9%
	Weekly	89.9%	53.7%	84.2%	86.0%	97.7%	85.8%
	Occasional	92.2%	67.0%	86.4%	90.6%	97.5%	87.9%

The results of the Pearson's chi-square independence test for commuting trips on aggregated level are displayed in Table 5-3 on page 55. This table shows that all P-values are higher than the 0.05 level of significance, regardless of the weather type and behavioral change. This means that the extent to which people adapt their travel behavior is not depending on the exposure to the weather forecast on aggregated level.

When the results of the independence tests are regarded on disaggregated level (Table 11-22 in Appendix 3.4), it also appears that most of the P-values are higher than the level of significance. The only exception on this is the change of route in snowy conditions, which has a slight significant P-value. So the frequencies of adjusting the route in snowy conditions depend on the frequency that one looks at the weather forecast. However, this effect is being negated at aggregated level.

Finally, it can be concluded that the extent to which people adapt their travel behavior in commuting trips is not depending on the exposure to the weather forecast. It therefore follows that respondents who frequently keep up the weather forecast do not adapt their travel behavior more or less to adverse weather than those who follow the weather forecast only sporadic. The previously discussed (disaggregated) results from the frequency analysis are not significant and are due to chance rather than due to a systematic process.

Table 5-3: Dependence of behavioral changes on exposure to the weather forecast for commuting trips (aggregated level)

Weather type	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold²	All changes	7.95	18	0.979	n.s.
Snow²	All changes	13.23	18	0.778	n.s.
Heavy rain²	All changes	5.44	18	0.998	n.s.
Fog²	All changes	13.49	18	0.762	n.s.
Warm²	All changes	6.60	18	0.996	n.s.
Storm²	All changes	5.54	18	0.997	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

The above relates only to commuting trips. The results for shopping and leisure trips are not discussed in detail, since the same conclusions can be drawn as for commuting trips, namely that the exposure to the weather forecast has no influence on the frequencies of the behavioral adaptations. The results of this analysis can be found in Appendix 3.4.

5.2 Influence of perceived reliability of the weather forecast on behavioral adaptations frequencies

This section provides an answer to research question II (b). It can be expected that people who find the weather forecast reliable adapt their travel behavior more frequently than those who think the weather forecast is rather unreliable.

To test the above statement, respondents were asked to what extent they found the weather forecast reliable. A score ranging from 1 to 10 must be given, with 1 being very unreliable and 10 being very reliable. In processing this question, it was chosen to group these data into two categories. The first category concerns the score 0 to 5 and thus contains respondents who find the weather forecast rather unreliable. A second category concerns the score 6 to 10 and includes respondents who find the weather forecast rather reasonably to very reliable. The results are shown in Table 5-4. It follows that the majority of the respondents (84.6%) confers a positive score to the weather forecast.

Table 5-4: Perceived reliability of the weather forecast

Score	Frequency	Cumulative Frequency	Percent	Cumulative percent
0 to 5	90.4	90.4	15.4%	15.4%
6 to 10	495.6	586	84.6%	100.0%

Next, Table 5-5 on page 57 shows the percentage of respondents who never choose for a certain behavioral change in commuting trips, according to the perceived reliability of the weather forecast. The code that was used to obtain these results can be found on the cd-rom, in the file '14. Frequencies of changes in travel behavior according to the perceived reliability of the weather forecast'.

If these percentages are seen at aggregated level (all behavioral changes), some remarkable discrepancies in the percentages between the two reliability categories can be noticed. For all weather conditions, it appears that the respondents who find the weather forecast rather unreliable are inclined to change their travel behavior less than those who find the weather forecast rather reliable. The differences in percentages are striking for all weather types (> -8%), but are especially noticeable for rain (-15.8%) and storm (-17.7%). Although, the results of the tests for population fractions indicate that only the percentages between the reliability categories for snow, rain and storms are significantly different to each other. For the other weather conditions, perceived weather forecast reliability plays no significant role. The results from these tests are displayed in Appendix 1 (Table 11-5) and on file 18 on the cd-rom.

The differences in percentages between the two reliability classes are also noticeable on disaggregated level. In general, the same conclusions as at the aggregate level can be drawn, namely that respondents who give a low score are less likely to choose for a certain behavioral adjustment, compared with respondents who give a high score.

In some cases, however, the differences in the rates can be negligible, e.g. adapting the departure time in the context of cold temperatures. In order to determine whether perceived weather forecast reliability plays a role in the frequencies of the various behavioral adjustments, a Pearson's chi-square independence test should be performed.

The calculations to perform this test can be found on the enclosed cd-rom in the file '15. Dependence of behavioral changes on weather forecast reliability'.

Table 5-5: Frequencies of changes in commuting trips in response to extreme weather conditions, according to the perceived weather forecast reliability

Behavioral Change	Forecast Reliability	Cold	Snow	Rain	Fog	Warm	Storm
All Changes	0 to 5	74.1%	29.6%	62.6%	63.6%	69.8%	68.5%
	6 to 10	65.1%	19.8%	46.8%	55.7%	60.4%	50.8%
Mode Change	0 to 5	96.5%	83.6%	89.6%	94.6%	83.3%	93.6%
	6 to 10	93.2%	74.1%	83.8%	94.6%	81.2%	85.4%
Time-of-day Change	0 to 5	89.5%	53.0%	74.6%	75.5%	97.6%	77.5%
	6 to 10	89.4%	46.6%	69.4%	73.7%	93.7%	74.4%
Location Change	0 to 5	95.4%	85.5%	94.0%	98.7%	96.7%	92.8%
	6 to 10	96.9%	86.8%	94.5%	97.2%	97.0%	93.4%
Trip Cancellation	0 to 5	96.5%	77.0%	95.1%	98.2%	90.2%	95.3%
	6 to 10	96.1%	75.1%	93.5%	94.7%	88.8%	92.0%
Route Change	0 to 5	86.8%	56.3%	81.6%	79.5%	96.7%	86.1%
	6 to 10	91.3%	56.5%	85.7%	86.6%	96.3%	87.4%

The results of this independence test for commuting trips at aggregated level are shown in Table 5-6 on page 58. This table shows that all P-values are close to 1 and thus are far above the significance level of 0.05 on which is tested. Although, when a lower level of aggregation is considered (Table 11-27 in Appendix 3.5), it appears that changing of mode in a storm has a slight significant P-value. This means that the frequencies of mode change in stormy weather depend on the frequency that one follows the weather forecast. However, this effect disappears at a more aggregated level as became clear in Table 5-6.

It can be concluded that the extent to which people choose for a particular behavioral change in commuting trips is not dependent on the perceived reliability of the weather forecast. Thus, the differences that were observed in the frequency table are not significant and are rather due to chance than due to a systematic process.

Table 5-6: Dependence of behavioral changes on perceived reliability of the weather forecast for commuting trips (aggregated level)

Weather type	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold²	All changes	3.57	9	0.937	n.s.
Snow	All changes	15.72	39	1	n.s.
Heavy rain²	All changes	4.08	9	0.906	n.s.
Fog²	All changes	5.58	9	0.781	n.s.
Warm²	All changes	2.48	9	0.981	n.s.
Storm²	All changes	6.07	9	0.733	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

The results for shopping and leisure trips can be found in appendix 3.5. For both trip purposes, the same conclusions as for commuting trips can be drawn, namely that the perceived reliability of the weather forecast has no influence on the frequencies of the behavioral adaptations.

5.3 Influence of the media source of the weather forecast on behavioral adaptations frequencies

This section provides an answer to research question II (c). Since it is expected that the quality of the weather forecasts are similar in the various media sources, it is not really expected that the source of media has an influence on the frequencies of the several behavioral adaptations.

In order to answer the research question, respondents of the questionnaire were asked whether they follow the weather forecast via television, radio, internet or the paper. The results of this question are shown in Table 5-7. As multiple answers could be indicated, the sum of the percentages exceeds 100. It appears from this table that television is the most used medium to follow the weather forecast, followed by the radio. Rather surprising is that just as many respondents follow the weather forecast via the internet as through the paper.

Table 5-7: Media source used by following the weather forecast

Forecast media	Percent
Television	81.2%
Radio	63.4%
Internet	23.1%
Paper	22.9%

Next, Table 5-8 on page 60 shows the percentages of respondents who never choose for a certain behavioral change in commuting trips, according to the media source used by the respondent. The code that was used to obtain these results can be found on the cd-rom, in the file '16. Frequencies of changes in travel behavior according to the media source'.

Based on the aggregated rates (all behavioral changes), clear differences can be found between the percentages of the various media sources. First, it appears that people who listen to the weather forecast by radio, apparently adjust their travel behavior more frequently than those who follow the forecast through other media. Second, also discrepancies can be found among the other media but no real trend can be drawn on which media source brings along more or less changes in travel behavior. E.g. the case of cold temperatures shows that people who follow the weather forecast through the newspaper apparently change their travel behavior less than people who follow the weather forecast through the other media sources, while at warm temperatures and fog this is rather the case for internet users. Results from the tests for population fractions, which are displayed in Appendix 1 (Table 11-8) and on file 18 on the cd-rom, indicate that indeed most rates are not significantly different from each other, with exception of some percentages in the context of cold temperatures and fog. Therefore, it can be concluded that in general the media source of the weather forecast doesn't affect the likelihood to change the travel behavior in response to adverse weather.

One can also observe some differences between the percentages at disaggregated level (per behavioral change) but these differences are rather limited. As with the aggregate level, there is not a real trend noticeable. The results of the Pearson's chi-square independence test would be decisive on this issue. The calculations to perform this test can be found on the enclosed cd-rom in the file '17. Dependence of behavioral changes on media source'.

Table 5-8: Frequencies of changes in commuting trips in response to extreme weather conditions, according to the media source of the weather forecast.

Behavioral Change	Forecast Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All changes	Television	65.2%	22.0%	47.8%	55.4%	58.3%	52.6%
	Internet	71.2%	19.2%	48.3%	67.7%	65.6%	57.1%
	Paper	74.9%	22.7%	55.2%	56.5%	60.2%	61.9%
	Radio	64.7%	16.9%	48.0%	54.3%	60.8%	51.8%
Mode Change	Television	94.0%	76.8%	85.9%	94.4%	80.0%	87.4%
	Internet	92.3%	70.7%	80.4%	92.6%	76.7%	83.4%
	Paper	95.6%	81.3%	88.3%	94.6%	77.0%	94.3%
	Radio	93.7%	74.2%	84.2%	94.1%	83.5%	86.3%
Time-of-day Change	Television	89.2%	47.0%	68.8%	72.3%	93.4%	74.1%
	Internet	90.7%	48.5%	66.6%	84.0%	95.2%	80.5%
	Paper	92.6%	44.0%	74.7%	70.0%	95.9%	80.7%
	Radio	90.2%	46.2%	70.4%	72.6%	94.0%	74.9%
Location Change	Television	95.9%	86.2%	94.0%	97.0%	96.6%	92.7%
	Internet	99.3%	89.5%	93.4%	96.9%	97.9%	94.8%
	Paper	98.6%	91.1%	96.0%	98.6%	99.4%	95.0%
	Radio	95.7%	85.3%	94.6%	96.7%	96.9%	93.1%
Trip Cancellation	Television	95.3%	76.4%	93.9%	95.3%	87.5%	92.5%
	Internet	95.7%	76.6%	92.2%	95.6%	88.9%	91.6%
	Paper	98.8%	78.5%	98.0%	99.6%	89.1%	97.6%
	Radio	95.9%	73.3%	94.3%	95.7%	87.0%	93.7%
Route Change	Television	90.5%	57.4%	85.2%	87.1%	96.0%	88.3%
	Internet	92.4%	52.9%	78.3%	86.6%	97.1%	83.9%
	Paper	95.7%	59.6%	86.2%	87.6%	97.5%	90.0%
	Radio	88.4%	51.3%	82.3%	82.3%	97.2%	85.5%

Table 5-9 on page 61 shows that all P-values are far above the level of significance of 0.05, which means that the frequencies of the various behavioral adaptations are not depending on the media source at aggregated level. When the results of the independence test are regarded at disaggregated level (Table 11-32 in Appendix 3.6), it also appears that most of the P-values are higher than the level of significance. The only exception is changing of route in the context of snow, but this effect is negated at a more aggregated level as already shown in Table 5.9. So in general, it can be concluded that the media source doesn't influence the likelihood of changing travel behavior in response to adverse weather conditions. The observed differences in the frequency table are due to chance rather than due to a systematic process.

Table 5-9: Dependence of behavioral changes on media source of the weather forecast used by the respondent for commuting trips (aggregated level)

Weather type	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold²	All changes	16.70	27	0.938	n.s.
Snow	All changes	51.26	57	0.689	n.s.
Heavy rain²	All changes	14.99	27	0.970	n.s.
Fog²	All changes	18.77	27	0.878	n.s.
Warm²	All changes	10.05	27	0.999	n.s.
Storm²	All changes	20.12	27	0.826	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

The results for the leisure and shopping trips can be found in Appendix 3.6. For these trip purposes, the same conclusions as in the case of commuting trips can be drawn, namely that the likelihood of changing travel behavior in response to adverse weather conditions is not influenced by the media source of the weather forecast.

5.4 Discussion

Previous sections (Section 5.1, Section 5.2 and Section 5.3) showed that various aspects of the weather forecast have no significant influence on the likelihood of changing travel behavior in response to adverse weather conditions in Flanders. These results are in line with the Belgian study from Khattak and De Palma (1997), which also found no significant effect of acquiring forecasted weather information on the likelihood of adapting mode and departure time. However, these results are contrary to many other international studies, as discussed in Section 2.1. These studies showed that weather forecasts have significant impacts on travel decisions. These contrary findings may be explained by the cognitive gap that is formed between the weather forecasts and the traffic and roadway conditions in Flanders. It is more difficult for people to assess what the effects of weather forecasts are on the road weather conditions compared to the own observation of the weather. The latter can be easier coupled to adverse weather experiences which one allows to make their own predictions of traffic and roadway conditions and change their travel behavior accordingly. The problem with travel behavior adaptations based on own observation is that the range of travel behavior alterations are limited to last-minute adaptations, like changing route and time of day change. Other adjustments, such as changing the location, mode and also the cancellation of the trip, are rather adaptations that should be planned ahead and thus fall by the wayside. This is the case in all three trip purposes but especially for commuting trips, and to a lesser extent shopping and leisure trips since these can be considered as more flexible activities. The existence of the gap between weather and road weather conditions is also confirmed by the descriptive analysis (Section 4.1) which showed that last minute alterations are by far more chosen as response to adverse weather conditions than the so called "planned" alterations. To encourage such "planned" adaptations, the cognitive gap between the weather forecast and the road conditions should be diminished. This is possible by linking a road weather information system to the weather forecast, to the example of Finland and Hong Kong (as discussed in Section 2.2). The Finnish studies from Kilpelaïnen and Sumala (2007) and Niina (2009) showed that such road weather information service, and thus also the weather forecasts, has a clear effect on the trip schedule. However, such road weather information system should be specifically tailored to the situation in Flanders and the Flemish weather. The usefulness of such a system was indicated in this study, but the development and its construction should be further investigated.

Chapter 6: Which determinants explain changes in travel behavior

In this chapter, it is investigated which determinants have a significant influence on the various adaptations in travel behavior.

6.1 Dependent variable: the preferred adaptation of the respondent

Section 4.1 already discussed to what extent people opts for certain behavioral changes in a given scenario. Remind that a scenario was defined as a particular type of weather condition in response to a particular trip purpose, for example heavy rain in the shopping activity. In this section we determine for each respondent which behavioral change one prefers in a given scenario, to which will be referred in the remainder of this dissertation as the preferred adaptation. The preferred adaptation will be determined by the following priorities.

Table 6-1: Prioritization for the preferred adaptation

	Mode change	Time of day change	Location change	Trip cancellation	Route change
Never			16		
Occasionally	9	15	7	6	14
Sometimes	8	13	4	3	12
Usually	5	11	2	1	10

Table 6-1 shows the various response options of the respondent in a given scenario. If the respondent replied that in a given scenario the trip is usually canceled (number 1), than this is the preferred adaptation for this scenario. If the respondent did not reply this answer possibility, the next priority should be given, namely number 2. If the respondent replied that he usually changes destination location, than one should take this adaptation as the preferred adaptation. If the respondent has also not responded this option, one should look at the next priority, namely number 3, etc.

This prioritization was inputted in the statistical software program 'SAS' so that new variables were automatically created with the preferred adaptation of the respondents.

The code for doing this can be found on the cd-rom, in the file ’19. Defining the preferred adaptation’.

To investigate which determinants explain the preferred adaptation, MNL-models will be estimated. Since we have to deal with correlated multinomial response data, the models will be estimated by use of the method developed by Kuss and Mc-Lerran (2007), as already discussed in Section 1.5.2.4. How this method is applied on the data of the stated adaptation approach can be found on the enclosed cd-rom in the file ’20. Estimating the MNL-models with correlated response data’.

6.2 Potential explanatory variables

The first category of explanatory variables that is used when estimating the MNL-models are the socio-demographic variables. The following variables are considered: children, gender, age, diploma, income, civil state, statute, the relation of the respondent with the household head and at last, the urbanization degree.

Next to the socio-demographic variables, also transport related variables are considered. This category includes the number of bikes in the household, the number of cars in the household, motorcycle ownership, moped ownership, the possession of a driving license and the possession of a public transport card.

A third category of explanatory variables concerns the frequency with which one performs the trip purpose, namely the frequency of shopping trips, the frequency of leisure trips and the frequency of work/school trips.

A fourth category applies only to the working trips. Variables like the time spent working, telework possibility, flexible working hours and worktime (full time/part time) can have significant effects on the preferred adaptation.

The final group of variables that is used for the analysis concerns the weather condition as well as some weather forecast related variables. Regarding the former, a reorganization of the data was necessary, for which the coding can be found on the cd-rom in the file ’21. Making weather type an independent variable’. Among the weather forecast related variables are the perceived reliability of the weather forecast, the exposure to the weather forecast and finally the used media source of the weather forecast (radio, television, internet or paper).

Correlation between explanatory variables may cause some important problems when estimating models, as already discussed in Section 1.5.2.7. Therefore, all the individual correlations between the variables were examined, in order to select highly correlated variables (i.e. variables with a correlation coefficient higher than 0.7). The correlation matrix showed that all the variables within the fourth category are highly correlated with each other. For this reason, only flexible working hours are considered when estimating the models. The code for obtaining the correlation matrix can be found on the cd-rom in file number 22.

6.3 Model choice and model assessment

6.3.1 Overall results

Separate models were estimated for the different trip purposes as discussed in Section 3.1.2.1. In addition, a separate model that only focuses on working trips is estimated, since the variable 'flexible working hours' is only applicable to the employed population and not to students. In all models, a significance level of 0.05 is used.

Since the preferred adaptation and some of the explanatory variables are categorical, we have to look at the results of the type III test to find out which explanatory variables are significant. These results are displayed in Table 6.2 on page 66.

This table shows that the type of weather condition is very significant in determining which behavioral adaptation one prefers (P-value <0.0001 in each model). These results are in line with the Pearson's chi-square analysis in Section 4.3, which also revealed a strong relationship between type of weather and the behavioral adaptations frequencies. Unlike the weather conditions, no significant relationship could be detected between weather forecast related variables and the preferred adaptation, which also corroborates the results from the Pearson's chi-square analyses in chapter 5. The latter is consistent with the study from Khattak and De Palma (1997), which was discussed in Section 2.1. They found that acquiring weather information did not have a significant influence on mode change and departure time.

Table 6-2: P-values of the determinants that explain changes in travel behavior

Selected variables	Commuting (only work)	Commuting (work + students)	Shopping	Leisure
Flexible working hours	0.0105	-------	-------	-------
Children	0.0562	0.0307	-------	-------
Gender	-------	-------	0.0034	-------
Age	-------	<0.0001	-------	<0.0001
Public transport card	-------	0.0051	-------	-------
Degree of urbanization	-------	0.0004	-------	-------
Driving license	-------	-------	0.0148	0.0229
Diploma	-------	-------	-------	0.0246
Statute	-------	-------	0.0224	-------
Weather condition	<0.0001	<0.0001	<0.0001	<0.0001

6.3.2 Commuting trips (only work trips)

Table 6.2 showed already that flexible working hours, children and the type of weather condition are all statistical significant variables in predicting the preferred adaptation in work trips. The parameter estimates of these variables are displayed in Table 11-36 in Appendix 4.1.

It can be derived from model equation 8, that the parameter estimates influence the odds ratio (OR). This odds ratio can be obtained by taking the exponent of the estimated parameter. Take as an example the parameter estimate of not having flexible working hours in the context of location change, which is -1.8106. The odds ratio than equals to $e^{-1.8106}$ = 0.1636. This means that the odds for location change given no flexible working hours, is only 16.36% of the odds for location change given flexible working hours. This implies that the probability of location change when having no flexible working hours is significantly lower than the probability to change the location when having flexible working hours. This conclusion can also be derived from the sign of the parameter, which in this case is negative. For simplification reasons, the parameters are interpreted as having an increasing or decreasing effect on the response probability, based on the sign of the parameters, rather than using the interpretation via the odds ratio. In what follows, the most interesting results of the parameter estimates are highlighted.

The most important conclusion that can be drawn for flexible working hours is the following: People without flexible working hours are more likely to change their departure time in response to adverse weather compared to people with flexible working hours. This means that people with low flexibility in arrival times are more likely to change their departure times, because they have to take into account delays, than people who can arrive late. The previous is consonant with international literature. Khattak and De Palma (1997) found similar results in their research, which were already discussed in Section 2.1.

A second conclusion that can be drawn concerning flexible working hours is that people who don't have flexible working hours are less likely to change their location due to adverse weather than people who do have flexible working hours. It appeared from the correlation matrix that flexible working hours and telework possibility were highly positive correlated (Pearson's correlation coefficient >0.7). This means that telework possibility and flexible working hours often go hand in hand. So it is logical that people with flexible working hours are also more likely to change their work location, purely because of the fact that they have this possibility more frequently than people without flexible working hours.

Moreover, it appears from the parameter estimates that people with flexible working hours are more likely to change their route and mode and were less likely to cancel their trips than people with flexible working hours. However, these effects were not statistically significant.

Furthermore, it follows from the parameter estimates that when one has children one changes significantly more of mode than when one has no children. This result is contradicted to the results that are found in the study of Khattak and De Palma (1997). In their research, they found that people with children going to daycare are less likely to change transport modes than people without children going to daycare. However, in this study the concept of children is broader defined than in the study of Khattak and De Palma, since all children younger than 18 years are considered and not only children going to daycare. The difference in results can then be explained because families with younger children are subject to reduced flexibility due to family commitments, while families with older children already won back some flexibility because of the growing autonomy of their children.

Section 4.1 showed that warm temperatures rather have a limited influence on travel behavior in working trips. This is now confirmed by the parameter estimates which show that the probability for the behavioral adaptations 'location change', 'route change' and 'time-of-day change' are lower for warm temperatures (the reference category) than for the other weather conditions. Of course, not all of these effects are statistically significant. The opposite is true when considering the behavioral adaptations 'mode change' and 'trip cancellation'. The parameter estimates indicate that it is more likely that people change their mode in warm temperatures than in cold temperatures, fog, rain and storm. Again, this is a confirmation of the descriptive results discussed in Section 4.1. Yet, these effects are not statistically significant in the context of rain and snow. It was also noticed that people are significantly more likely to cancel their trips in warm temperatures compared to cold temperatures, fog, rain and storm. This effect can be explained by the fact that people want to enjoy the beautiful weather by taking a day off. Moreover, Section 4.1 indicated that snow has the largest impact on travel behavior. Indeed, the parameter estimates in the context of snow have, in all adaptations, more extreme (and always positive) values than the other weather conditions, indicating a larger effect on the response. This is confirmed by the contrast results in Table 11-37 in Appendix 4.1. These results show that the parameter estimates for snow are indeed significantly different from the other weather conditions in all adaptations. The only exceptions on this are mode change, for which the parameter estimate for snow is not significantly different from the parameter estimate of warm temperatures, and time-of-day change for which the parameter estimates for snow are not significantly different from fog and rain.

6.3.3 Commuting trips (work/school trips)

As already shown in Table 6.2 age, children, public transport card, urbanization degree and the type of weather condition all have a significant influence on the preferred adaptation in response to adverse weather in commuting trips. The parameter estimates of these variables are displayed in Table 11-39 in Appendix 4.2. In what follows, the most interesting conclusions are discussed.

It appears from the parameter estimates that the probability that people adapts their activity location, transport mode, route and departure time significantly decreases with age as well as the probability to cancel their trip. One possible explanation for this effect is that younger people are unsure about their driving skills in adverse weather. With upgoing age one gains more experience in travelling under adverse weather conditions so one is more convinced that one can handle the weather.

Just as in commuting trips (only work trips) it seems that if one has children one changes mode significantly more in commuting trips than if one has no children, which is contradictory to the results in the study of Khattak and De Palma (1997). The same reason as discussed in previous section (Section 6.3.2) can also be cited here.

The only significant that can be said about the variable public transport card is that if one does not have a public transport card, it is more likely that the route change is the preferred adaptation than if you do have a public transport card. This is a quite logical effect. Public transport cards are mainly used to commute to the work or school location (Koninklijk instituut voor het duurzame beheer van de natuurlijke rijkdommen en de bevordering van schone technologie, 2006). Since public transportation is tied to fixed routes, it is unlikely that they will adjust their route to avoid traffic jams caused by the bad weather.

The most important conclusion concerning the variable urbanization degree is that people who live in the central municipalities of the most important agglomerations (which have a strong morphological and functional urbanization) are more inclined to change their transport mode than people who live in municipalities with a weak morphological urbanization. This is plausible because the range of transport modes in urban areas is much broader (metro, tram) than in rural areas where people are more chained to the same modes like car or bike.
Furthermore it appears that people living in central municipalities of the most important agglomerations are less likely to adapt their departure time compared to people living in municipalities with weak morphological urbanization. This can be explained by the fact that people living in the rural areas have to commute further to their work or school than people living in urban areas for which the work/school location is nearby. This means that they have a larger variance on their travel times and thus have more uncertainty about it, especially in extreme weather conditions. This uncertainty in travel times is than taken into account by adapting the departure time.

Regarding the variable weather condition, the same conclusions as for commuting trips (only work) can be drawn. For this reason, the parameter estimates will not be discussed again.

6.3.4 Shopping trips

It was already clear from Table 6.2 that gender, driving license, statute and the type of weather condition were all significant determinants when estimating the preferred adaptation in shopping trips. The parameter estimates of these variables are displayed in Table 11-42 in Appendix 4.3. In what follows, the most appealing conclusions are discussed.

First, from the parameter estimates of the variable gender, it can be concluded that females have a higher probability to change their location and to cancel their trips than males. This effect can be explained by persistence of the traditional role patterns. E.g. taking care of the children is mainly the task of the woman and it is generally expected that women do more in the household than men. For this reason a lot of women work part time. This appears also from the data which shows that 46% of the working women work part-time compared to only 4% of working men. Because of this, women are more flexible than men (who are more tied to their working hours) and consequently they can shift their trips easier to another day. Males in their turn, have a higher likelihood to change their mode in response to adverse weather than women, which can be explained by their reduced flexibility. They prefer rather mode change so they can still go shopping on the hours they planned for.

Second, concerning the parameter estimates of the variable driving license, it appears that people who do not have a driving license have a higher probability to cancel their shopping trips and a lower probability to change their mode compared to people who do have a driving license. This is quite logical since people without driving license have fewer transportation alternatives than people with a driving license, so instead of switching modes they are rather forced to cancel their trips.

When taking a closer look at the variable statute, the parameter estimates show that students are less likely to cancel their shopping trips than the other categories and that they are more likely to adapt their departure time than the professional actives. The latter can be explained by the fact that students are more flexible than professional actives, who are more tied to their working hours (9 to 5).

At last, the most important conclusions that can be deduced from the parameter estimates of the variable weather condition are discussed.

Section 4.1 concluded already that warm and cold temperatures had the smallest impact on travel behavior. This is now confirmed by the results of the parameter estimates. It appeared that the probabilities to cancel the trip, to adapt the departure time, to change the route or to change the shop location were in the most cases lower in warm temperatures than in the other weather conditions. Not all of these effects were statistically significant, but most of them were. Since the parameter estimates for cold temperatures and warm temperatures are not statistically different for the various adjustments, it can be concluded that both have the least impact on the preferred adaptation.
The previous is not true when considering the mode change alteration. Section 4.1 showed already that one changes mode more frequently in the context of warm temperatures compared to the other weather conditions. This is now corroborated by the parameter estimates, which show that one is significantly more likely to change transport mode in warm temperatures compared to cold temperatures, fog, rain, snow and storm.
It was concluded from the descriptive analyses that snow has the largest impact on travel behavior. This is indeed true when cancelling the trip, since the parameter estimates of snow are higher than those of the other weather conditions, indicating a larger effect on the response. The results from the contrast analyses, which are displayed in Table 11-43 in Appendix 4.3, show that the parameter estimate for snow indeed differs significantly from the parameter estimates of all the other weather conditions when cancelling the trip. When looking at the other changes, the impact of snow can be less clear interpreted. This is also reflected in the contrast results since not all parameter estimates are significantly different from the other weather conditions.

6.3.5 Leisure trips

The parameter estimates when modeling the preferred adaptation in leisure trips are displayed in Table 11-45 in Appendix 4.4. Age, driving license, diploma and type of weather condition were all significant variables in determining the preferred adaptation. In what follows, the most interesting conclusions that could be drawn from the parameter estimates are discussed.

The only significant conclusion that can be drawn about the variable driving license is that one is more likely to adapt their route if one has a driving license compared to people who have not a driving license. This effect can be explained by the fact that people without a driving license are mostly forced to use other transport modes than the car. E.g. bikes or pedestrians are less sensitive to traffic problems that arise due to adverse weather, so they do not have to switch routes to avoid delays.

Just as was the case in commuting trips (work/school trips), age was significant in determining the preferred adaptation in leisure trips. Similar as in commuting trips, it appears from the parameter estimates that the probability that people adapt their activity location, transport mode, route and departure time decreases with upgoing age. This can be deduced from the sign of the parameter estimates which are all negative. However, these effects were only significant in the case of mode change. Yet, the same explanation can be given as in the commuting trips. Younger people are unsure about their driving skills in adverse weather, but with upgoing age one gains more experience in travelling under these conditions so one is more convinced that one can handle it.

Concerning the variable diploma, it appears that people with a university diploma have a significantly lower propensity to change their routes in leisure trips than people with a diploma of a lower degree. Furthermore, it appears that people with a university diploma also have a significantly lower probability to change their modes than people with no high school diploma. Latter has especially to do with status.

Regarding the variable weather condition, about the same conclusions as in the shopping trips could be drawn. Significantly more people cancel their leisure trips in bad weather conditions compared to the warm temperatures, with exception of trips made on cold days. The propensity to change the route and to adapt the departure time is also higher in bad weather conditions than on warm days. However, the results concerning the departure time are only significant in fog and rain. These results are a confirmation of the descriptive analyses in Section 4.1.

Further, it appears from the parameter estimates that people change significantly more from transport mode in warm temperatures than in all other weather conditions, which again corroborates the descriptive analyses in Section 4.1.

When a closer look is taken at the parameter estimates of snow, it comes into sight that the parameter estimate of snow is larger when cancelling the trip than the other weather conditions, indicating a larger effect on the response. Indeed, the contrast results in Table 11-46 in Appendix 4.4 indicate that the parameter estimate of snow is significantly different from the parameter estimates of the other weather conditions when cancelling the trip. This is once more a verification of the descriptive analyses. When looking at the other changes, the contrast results show that the parameter estimates of snow are not always significantly different from the other weather types. The effects of snow on these changes can thus be less clear interpreted.

Part II

A Revealed Preference Approach of Changes in Travel Behavior in Response to Adverse Weather Conditions.

Chapter 7: The revealed preference approach

In what follows (Section 7.1) the research goals of the revealed preference approach are refreshed. Section 7.2 gives a description of the data while Section 7.3 describes the limitations of it.

7.1 Research goals

The main objective of the revealed preference part is to explore the role of extreme weather conditions on revealed travel behavior. Accordingly, a response will be given to research question IV, as defined in Section 1.3. In answering this question, it is interesting to explore whether weather conditions affect daily travel times as well as modal choices.

As will appear from Section 7.1.2, weather conditions in the revealed preference part are seen at a more detailed level than was the case in the stated adaptation approach.

7.2 Data description

For the revealed preference approach, both data about the travel behavior of people and data about the weather are necessary. Both data sources are merged based on the departure time of the trip, which was a very laborious process. The coding regarding this merge can be found on the cd-rom in the file '1. Merging data'. The purpose of this merge was to find out what weather it was at the departure time of the trip.

The weather data was provided by the Royal Dutch Meteorological Institute (KNMI). This data is ideal because it is available on hourly level, the most detailed level for which weather data is available. Section 7.1.2 provides more information about these weather data. The data on travel behavior is derived from the Mobility Research of the Netherlands (MON). These data are mainly based on travel diaries in the Netherlands which means that the data for the revealed preference approach is achieved from other respondents than was the case in the stated adaptation approach. The MON is a suitable data source because it contains a lot of information on all aspects of the displacement and also about the social-demographic characteristics of the respondent. E.g., the transport mode, distance, number of trips, departure and arrival times and the motive of the displacement are all included in the data, as well as the age and sex of the respondent. In what follows, a closer look is taken at the data collection and the data processing of MON.

7.1.1 MON

MON is a continuous ongoing investigation of the daily travel behavior of the inhabitants of the Netherlands. The aim of the study is to get a picture of the daily mobility of the Dutch people, with exception of the residents of institutions and homes. Latter are not included because it is expected that they are limited or restricted in their travel behavior. Accordingly, a random sample has been drawn from the Dutch addresses which contained up to 20.589 correct addresses for the year 2008. Each of these addresses received throughout the year a written survey, comprising of a household questionnaire, personal questionnaires and travel diaries that had to be filled in for a particular day of the year. There were no defined age limits for completing these questionnaires. For each day throughout the year, an equal number of households were approached. Respondents were motivated by telephone for completing this survey. Reminders and a new transmission (again with the questionnaires) were send to all households who had not responded one week after the expiry of a pre-specified day. This approach yielded a response rate of 70.2% (Projectteam MON, 2009).

Although an equal number of households are approached for each day of the year, there are not exactly an equal number of respondents noticeable for each of these days. Even though, this is desirable because every day of the year counts for equal weight in determining the average travel behavior. Households and individuals therefore have granted with a so-called daily-responsefactor that indicates how heavy the households and the people of those days count for. In other words: households and individuals get a high daily-responsefactor on days with a low response and vice versa (Projectteam MON, 2009).

Furthermore, it was verified whether the sample was representative for the population and weights where used to correct for sample bias and sampling errors (Section 3.4). These weights were determined by matching the distribution of variables in the sample with the corresponding distribution in the population statistics. Eventually, weights were developed based on (some combinations of) the following issues: urbanization, province, age class, household size, gender, building year of the car, fuel type of the car and age class of the owner of the car (Projectteam MON, 2009).

For simplification reasons, these weightings were brought together in three comprehensive factors, respectively for households, individuals and trips (Projectteam MON, 2009).

7.1.2 KNMI

For a detailed analysis of the influence of weather on travel behavior, also detailed weather data must be available, since weather is a very variable phenomenon. Therefore, in this study we made use of weather data on hourly level, the most detailed level for which weather data is available. The weather data was provided by the Royal Dutch Meteorological Institute (KNMI, 2010). It concerns weather data for the period 2001-2010 and was collected for 36 different weather stations in the Netherlands. The geographic locations of these 36 weather stations are shown in Figure 7-1. Every Dutch municipality was then linked to the nearest weather station. In this way, as the origin town of the displacement is known, it is possible to link weather data to the trips based on the location of the nearest weather station. When some data for a weather station were missing, data were complemented by data from the nearest weather station. E.g. when some data in the weather station of Maastricht was missing, it was complemented with data from the weather station of Ell since this station was the nearest to the station of Maastricht.

Figure 7-1: Geographic locations of the weather stations in the Netherlands

For each hour in the period 2001-2010, following data were available for each weather station:

- Mean wind direction (in degrees) during the 10-minute period preceding the time of observation
- Hourly mean wind speed (in 0.1 m/s)
- Maximum wind gust (in 0.1 m/s) during the hourly division
- Temperature (in 0.1 °C) at 1.50 m at the time of observation
- Minimum temperature (in 0.1 °C) at 0.1 m in the preceding 6-hour period
- Dew point temperature (in 0.1 °C) at 1.50 m at the time of observation
- Sunshine duration (in 0.1 hour) during the hourly division
- Global radiation (in J/cm²) during the hourly division
- Precipitation duration (in 0.1 hour) during the hourly division
- Hourly precipitation amount (in 0.1 mm)
- Horizontal visibility (in meter) at the time of observation
- Cloud cover (in octants) at the time of observation
- Relative atmospheric humidity (in percents) at 1.50 m at the time of observation
- Fog occurred during the preceding hour and/or at the time of observation
- Rain occurred during the preceding hour and/or at the time of observation
- Snow occurred during the preceding hour and/or at the time of observation
- Thunderstorm occurred during the preceding hour and/or at the time of observation
- Ice formation occurred during the preceding hour and/or at the time of observation

For a better understanding of how frequent these weather events occur in the Netherlands, various weather-related measures are displayed in Table 7-1 on page 79. In addition, it is noteworthy to mention that, in general, the Netherlands have the same climate as Flanders, namely a moderate maritime climate with mild winters and fresh summers.

Table 7-1: Weather parameters measured in De Bilt (nearby Utrecht, The Netherlands)[1]

Parameter	2008	2009	Normal[2]
Air pressure (reduced to sea level)	1014.5	1014.1	1015.5
Average wind speed (m/s)	3.6	3.4	3.3
Sunshine duration (h)	1735	1838	1524
Average temperature (°C)	10.6	10.5	9.8
Average maximum temperature	14.6	14.5	13.9
Average minimum temperature	6.5	6.2	5.8
Absolute maximum temperature	30.7	33.8	30.6
Absolute minimum temperature	-8.6	-11.1	-10.1
Number of freezing days (min < 0°C)	55	56	58
Number of wintry days (max < 0°C)	3	9	8
Number of summery days (max >= 25°C)	26	27	22
Number of heat wave days (max >= 30°C)	1	1	3
Average relative atmospheric humidity (%)	81.4	80.5	81.9
Total precipitation (mm)	881	777	793
Number of days with measurable precipitation (>= 0.1mm)	199	180	186
Number of days with thunderstorm	37	33	32
Number of days with snow	17	28	25
Number of days with fog	95	87	65

[1]Source: Royal Dutch Meteorological Institute (KNMI, 2010)

[2] Normal: long-term meteorological average (1971-2000)

7.3 Limitations of the data

Previous merged data sources have a number of limitations, which are briefly discussed in this section.

The limitations of the weather data are mainly due to the fact that a weather station is a point source, while the weather observations are used for a larger area. Thus, the weather data is aggregated in space. However, weather is a very changeable and local phenomenon. At a distance of only a few kilometers, very large differences can arise in the weather. Therefore, aggregation in space can lead to errors in determining the weather condition at a specific location. Moreover, the weather data is also aggregated in time. Although using hourly data, the most detailed level at which weather data were available, the weather can vary greatly within this hour. For instance, it might be that fog turns up suddenly but disappears completely after 10 minutes or that a cloudburst arises for 10 minutes followed by some sunny periods. By such aggregation of the data in time and space, it is unclear to what extent a specific weather observation at location x_1 (the weather station) and time t_1 (the time of the observation) corresponds to the actual weather at location x_2 (the departure point of the trip) and time t_2 (the departure time of the trip).

An important limitation with respect to the data on travel behavior implies that it is impossible to determine whether one postponed their trip due to the weather. After all, the original planned departure time of the individual is unknown. It is also unfeasible to find out to what extent one cancels a trip since only the realized trips are questioned and not the planned ones. The extent to which people change their route and location in response to the weather is also impossible to determine since there is little information available about the trip distribution in the data. Only the departure town and arrival town are known. These restrictions of the data conduct that the focus in the revealed preference part lays only on the impact of weather on the mode choice. Since the travel time of the movement is also known, it is also interesting to investigate what the impact of the weather is.

Chapter 8: Do weather conditions affect travel times and modal choices?

In this chapter, the role of various weather conditions on revealed modal choice and travel time is examined.

8.1 Dependent variables: Modal choice and travel time

The effect of weather conditions on modal choice will be investigated by estimating the MNL-model. Again, we have to deal with correlated multinomial response data. Therefore, the model will be estimated by use of the method developed by Kuss and Mc-Lerran (2007), as already discussed in Section 1.5.2.4. How this method is applied on the data of the revealed preference approach can be found on the enclosed cd-rom in the file '2. Estimating the MNL-models with correlated response data'.

To investigate the influence of weather on modal choice, the main transport mode of the displacement will be considered as the dependent variable. The main transport mode can be divided into four categories. The first category refers to car users, including both car drivers and car passengers. A second category concerns the vulnerable road users, consisting of cyclists, moped riders and pedestrians. A third category consists of trips by train, bus, tram or underground which are brought together under the heading of public transport users. The latter category relates to other transport modes, such as motorbikes, company/school bus service and cabs etc. Previous classification is the same as in the stated adaptation approach.

The dependent variable when investigating whether weather conditions affect travel times, are the recorded travel times of the displacement, which are measured in minutes. The effect of weather conditions on travel times will be investigated by estimating the Tobit model, as discussed in Section 1.5.2.5 and for which the coding can be found on the enclosed cd-rom in the file '3. estimating the Tobit model'.

8.2 Potential explanatory variables

Modal choices and travel times are the results of a whole range of factors where in addition to weather conditions also other factors can play a role. For example, it is expected that the distance of the trip is very crucial in determining the modal choice as well as for travel times. Taking into account these other factors will improve the accuracy of the parameter estimates and will consequently lead to better insights of the effects of weather on the modal choice and on the travel times. In what follows, potential variables that can have an influence on modal choice and on travel time are discussed.

The first category of explanatory variables that is used when estimating the models are the socio-demographic variables. Within this category the gender, age class, social participation, diploma and personal net income of the respondent is considered as well as the household size and the urbanization degree.

The second category of explanatory variables that is considered in the analyses concerns the transport related variables. In particular, possession of a driving license and possession of SOV-card (a free public transport card for students) are considered.

Next to the socio-demographic and the transport related variables, trip related variables are considered. This includes the trip purpose and the travel distance. It is interesting to know that in the revealed preference approach a broader approach of the concept trip purpose is used than was the case in the stated adaptation approach. Besides the work/school trips, the leisure and the shopping trips, trips with the purpose of performing services and personal care are also considered. This category includes a visit to the bank, doctor, pharmacy etc. In a final category, other trip purposes are considered, including touring/walking, business trips, transport as profession (e.g. truckers) and picking up and dropping people.

A last category of explanatory variables concerns the weather related variables. Section 7.1.2 already discussed the weather related variables that are available in the data set. However, it can be expected that some of these weather conditions are strongly correlated to each other. For example, it is likely that the hourly mean wind speed is correlated with the maximum wind gust during the hour. Such correlation may cause some important problems when estimating models, as already discussed in Section 1.5.2.7. To find out what weather conditions are correlated, a correlation matrix was composed. The code for obtaining this matrix can be found on the enclosed cd-rom in the file '4. correlation matrix'. Based on the results of this matrix, it was decided to focus on following weather conditions when estimating models:

- Maximum wind gust (in 0.1 m/s) during the hourly division
- Temperature (in 0.1 °C) at 1.50 m at the time of observation
- Sunshine duration (in 0.1 hour) during the hourly division
- Precipitation duration (in 0.1 hour) during the hourly division
- Cloud cover (in octants) at the time of observation
- Fog occurred during the preceding hour and/or at the time of observation
- Snow occurred during the preceding hour and/or at the time of observation
- Thunderstorm occurred during the preceding hour and/or at the time of observation
- Ice formation occurred during the preceding hour and/or at the time of observation

The individual correlation between all the other variables were measured too, but no high correlations (i.e. correlation coefficient >0.7) were detected. The coding for obtaining the correlation matrix can be found on the enclosed cd-rom in the file 'correlation matrix'.

8.3 Model choice and model assessment

8.3.1 Overall results

From the results of the type III test, which are displayed in Table 8-1 on page 84, it is found that many variables influence the modal choice as well as the travel time of the trip. However, our interest is mainly on the influence of the different weather conditions on the modal choice and travel time. Literature already showed that travel time (Section 1.1.2) as well as modal choice (Section 2.1) are strongly influenced by weather conditions.

When considering the travel time model, it appears that all weather conditions are highly significant (P-values are below 0.0001 for all weather conditions). However, when a closer look is taken at the modal choice model, it appears that fog has no significant influence on the modal choice. This is in line with findings from both the stated adaptation approach and the results of the study from Hagens (2005). Both show that, compared to other types of weather, relatively few people change their mode when fog arise. Next to fog, also snow and thunderstorms had no significant influence on modal choice. Contradicted to this result, Hagens (2005) found that no more than 60% of people change their mode in snowy conditions. Also in the stated adaptation approach, we came to the more modest but still considerable result that 20%-25% (dependent on the trip purpose) of the people change their mode due to snowfall. So it was quite surprising that snow as well as thunderstorm had no significant effect on the modal choice. However, this can be explained by the different methodology that is applied (revealed preference versus stated adaptation approach). While in the stated adaptation approach people claim to change their mode in adverse weather, it is not necessarily true in real life situation. When it snows or when a thunderstorm arises, it is possible that people assess the situation so dramatically that they decide to cancel their trip or to postpone it instead of changing their mode. At last, also cloud covering has no significant effect on modal choice. After all, a high cloud covering does not necessarily mean that weather is bad, so people are less inclined to adapt their travel behavior. It is more an indication that bad weather **can** arise in the near future.

Table 8-1: P-values of the type-III test for determinants that influence modal choice and travel time

Selected variables	Modal choice	Travel time
Household size	<0.0001	---------
Urbanization degree	<0.0001	---------
Social participation	<0.0001	---------
Driving license	<0.0001	---------
SOV-card	<0.0001	---------
Travel distance	<0.0001	---------
Gender	<0.0001	<0.0001
Age category	<0.0001	<0.0001
Diploma	<0.0001	<0.0001
Income	<0.0001	<0.0001
Trip purpose	<0.0001	<0.0001
Maximum wind gust	<0.0001	<0.0001
Temperature	<0.0001	<0.0001
Sunshine duration	<0.0001	<0.0001
Precipitation duration	<0.0001	<0.0001
Fog	---------	<0.0001
Cloud covering	---------	<0.0001
Snow	---------	<0.0001
Thunderstorm	---------	<0.0001
Ice formation	0.0300	<0.0001

8.3.2 Modal choice

The variables with a significant influence on modal choice already were displayed in Table 8-1. Although, it might be interesting to analyze the influence of all these variables on the choice of mode, this will go beyond the scope of this thesis. After all, our purpose is to find out how weather conditions affect this modal choice. The parameter estimates are displayed in Table 11-48 in Appendix 4.5.

It can be derived from model equation 8, that the parameter estimates influences the odds ratio (OR). This odds ratio can be obtained by taking the exponent of the estimated parameter. Take as an example the parameter estimate of maximum wind gust in the context of car use, which is 0.0017. The odds ratio than equals $e^{0.0017} = 1.0017$. This means that the odds for car use increases with 0.17% for every increase of 0.1 m/s in the maximum wind gust. This implies that the probability to take the car increase significantly for every raise in maximum wind gust. This conclusion can also be derived from the sign of the parameter, which is in this case positive. For the vulnerable road user, the opposite is true. Every 0.1 m/s increase in the maximum wind gust will lead to a decrease in the odds of slow modes with 0.18% and thus to a decrease in the probability to take slow modes. Regarding the influence of the maximum wind gust on public transport and on other transport modes, no significant results were obtained. In general, one can conclude that the intensities of vulnerable road users will decrease, while the intensities of car users will increase with freshening wind. These results are conform with international literature, as discussed in Section 2.1. Various studies indicated that windy days decrease travel demand from bikers with approximately 20% (Wilde, 2000; Emmerson, 1998; Nankervis, 1998). Moreover, previous results are in line with the results that have been obtained in the stated adaptation approach. It followed from Section 4.4 that in stormy weather (which is associated with heavy winds) especially vulnerable road users adapt their transport mode (ranging from 45% to 54%, depending on trip purpose), implying a decrease in the intensities of bikes and pedestrians. Moreover, it appears that the majority of these vulnerable road users switch to the car, which implies an increase in the intensities of the car.

Concerning the effects of temperature on modal choice, it can be derived from the parameter estimates that the odds to take public transport as well as the odds to take the car decreases with increasing temperature. More concrete, the odds to take public transport and the odds to take the car decreases respectively with 0.28% and 0.11% for every 0.1 °C increase in temperature. Thus, temperature shows a larger influence on public transport than on the car. This can be explained by the fact that, unlike the car, many buses are still not equipped with air conditioning so it is very unpleasant to travel with when it gets warm. Unlike previous results, the parameter estimates for the vulnerable road users and for the other transport modes indicate an increase in the corresponding odds with respectively 0.15% and 0.26% for every 0.1 °C increase in temperature. The considerable impact of temperature on the category 'other' can be explained by the fact that motor bikes fall into this category. It is well known that motorbikes get out of the garage once the weather allows this. In general, it can be concluded that the probability to take public transport users and the probability to take the car will decline with increasing temperature, while the probability to take slow modes and the probability to take other transport modes will increase. This is in line with international literature. De Wilde (2000) found in his research that warm temperatures leads to an increase in bicycle intensities. More concrete, Emmerson (1998) even found that a 1°C rise in temperature gives a 3% rise in daily cycle flows. Moreover, previous results are a confirmation of the results that were obtained in the stated adaptation approach. It was concluded in Section 4.4 that especially 'sheltered' transport users, such as public transport and car, will switch to slow modes to enjoy the beautiful weather.

Next, it will be discussed to what extent sunshine duration has an influence on modal choice. It appears from the parameter estimates that public transport as well as the category other transport modes are not significantly influenced by sunshine duration. Regarding the car users, it follows that the corresponding odds decreases with 3.38% for every 0.1 hour increase in sunshine duration. Unlike this result, the odds to take slow transport modes increases with 2.3% for every 0.1 hour increase in sunshine duration. In other words, more sunshine duration will lead to a decrease in the probability to take the car which will be partly offset by an increase in the probability to take slow transport modes. Again, this is in line with the results from the stated adaptation approach.

Precipitation duration also has a significant effect on modal choice. More concrete, the odds to take the car increases with 3.28%, while the odds to take slow modes decreases with 3.33%, for every 0.1 hour increase in precipitation duration. Furthermore, precipitation duration had no significant effect on public transport and also not on the category of other modes. In general, it can be concluded that higher precipitation duration leads to an increase in the probability to take the car and to a decrease in the probability to take slow modes. Previous results are in line with international literature

(Section 2.1). Al Hassan and Barker (1999) reported mode switching from walking to private cars during wet conditions and found an increase in motorized intensities from around 4%. Also Hagens (2005) indicated that especially rain causes cyclists to switch in particular to the car. Moreover, previous results are in line with the results from the stated adaptation approach, for which we came to the conclusion that vulnerable road users are subject to physical discomforts due to rain and therefore prefer "sheltered" transportation modes like the car.

The final weather condition that affects modal choice is the formation of ice. It appears from the parameter estimates that the odds to take the car given ice formation is only 24.79% of the odds to take the car when no ice occurs. For vulnerable road users, the opposite is true. The odds to take slow modes increase with 25.68% when ice was formed compared to no ice formation. At last, ice formation had no significant influence on public transport and on the other transport modes. It can be concluded from these results that the proportion of car users will decrease when ice occurs, while the share of slow transport modes will increase. This can be explained by the fact that people think they have not enough driving skills to handle the icy road and that it is safer to use slow modes which are more controllable.

8.3.3 Travel time

Table 8-1 already showed which weather conditions have a significant influence on travel time. The parameter estimates of these variables are displayed in Table 11-50 in Appendix 4.6. Although it might be interesting to analyze the influence of all these variables on travel time, our interest is mainly on the influence of weather conditions on travel time. Therefore, only the weather variables are discussed.

The estimated parameters can be interpreted as measuring the change in the expected value of the response variable when the given predictor variable is increased by one unit while all other predictor variables are held constant.

Firstly, it follows from the parameter estimates that for every 0.1 m/s increase in maximum wind gust the travel time decrease with 0.0034 minutes. Further, increasing cloud covering and ice formation lead to a decrease in travel time. Latter is contradicted to the results of Tu et al (2007). They concluded in their research that ice will increase the travel time, which was not the case in this dataset. However, previous results can be explained by the fact that people are travelling less far in heavy winds, in high cloud covering and when icy roads occur. E.g. they opt to shop in the local shop rather than in the supermarket further away.

Next, regarding the parameter estimates of temperature, it appears that every 0.1°C increase in temperature will lead to an increase in travel time of 0.0062 minutes. Also sunshine duration has an increasing effect on travel time. These results can be explained by the fact that people want to enjoy the beautiful weather by making trips to the coast or to recreation areas, resulting in increased intensities on freeways and consequently increased travel time. A second explanation can be that the coast and recreational areas are located at a considerable distance of most residential districts. Consequently, people make longer trips on beautiful days, resulting in an increased travel time.

At last, it appears that the occurrence of fog, snow and thunderstorm will lead to an increase in travel time of respectively 1.62, 0.29 and 1.36 minutes compared to the normal situation. Increasing precipitation duration will lead to an increase in travel time too. More concrete, for every 0.1 hour increase in precipitation duration, travel time will increase with 0.0089 minutes. These results are conform with the literature. Tu et al (2007) concluded in their research that fog, storm, snow but especially rain increase the travel time on freeway corridors, as already discussed in Section 1.1.2. Previous results can be explained by reduced roadway capacities during adverse weather. Various studies show that especially rain, snow and fog have reduced effects on capacities (May, 1998; Agarwal et al, 2005; Maze et al, 2005). These studies were discussed in Section 1.1.2. Since many networks are already operating near capacity in normal weather conditions and when adverse weather reduces this capacity, traffic congestion increases and affects the travel time.

Chapter 9: Policy application - weather responsive traffic management

Section 1.1 already discussed what impact adverse weather has on traffic. In order to reduce the negative impacts of inclement weather, such as congestion and increased accident risk, traffic managers can intervene through various weather-related advisory and control measures, also called weather responsive traffic management. A real-time traffic estimation and prediction system (TrEPS) can be a useful decision support tool in determining which of these measures can be best applied. However, some modifications to the original TrEPS are necessary to capture the effects of adverse weather on traffic patterns. Recently, Dong et al (2010 a) developed some methodological aspects to incorporate these effects in dynamic traffic models. Therefore, the purpose of this thesis was mainly to collect data that can be used to develop such weather-sensitive dynamic traffic models in Flanders and the Netherlands. An example of a weather sensitive TrEPS is DYNASMART-X. DYNASMART-X interacts continuously with multiple sources of weather information to anticipate for adverse weather conditions on the road network. These sources can be among others weather forecast information or roadside sensors that detect for fog or rain. When adverse weather is anticipated and when this has been communicated to the TrEPS, a prediction is generated for the traffic under that weather scenario, which can be seen as the base case. To evaluate the effectiveness of various impact reducing measures, other scenarios can run in parallel to predict traffic conditions under these interventions. Comparing the results of the different scenarios will help traffic managers to decide what measure will be best deployed (Dong et al, 2010 b).

In what follows, various traffic advisory and control measures that can be undertaken in response to adverse weather are discussed.

Firstly, a closer look is taken at the traffic advisory measures. Road weather information, such as route weather warning and route guidance can be disseminated through radio, internet, mobile devices, roadside variable message signs (VMS) and so on. It was already concluded in chapter 5 that there is a need to develop such a road weather information system in Flanders. Regarding weather warning VMS, two types can be distinguished. Firstly, there are weather warning signs that suggest travelers to reevaluate their current route. Secondly, there are VMS warning signs, indicating low visibility (fog) or slippery roads (rain and snow). These kinds of signs will generally reduce the speed (Dong et al, 2010 b). The latter is also confirmed in literature. A Finnish study by Rämä (2001) investigated the effects of a VMS that warns for slippery roads and found a speed reduction of 2.1 km/h when the sign was flashing. Also Hogema and van der Horst (1997) investigated the effects of fog warning signs, implemented in conjunction with variable speed limits, and found a decrease in mean speed by 8 to 10 km/h.

Secondly, also control measures can be deployed to handle the effects of adverse weather. Weather responsive control strategies that will be discussed include variable speed limits and traffic signal control. Variable speed limits are already being used in incident management and congestion management, but can also be applied in weather responsive management. Appropriate speeds are determined at which drivers should be traveling, given roadway and traffic conditions, and are displayed on roadside or overhead signs. For example, on a freeway in Finland speed limits are set to 120km/h for good road conditions, but speed limit decreases to 100 km/h for moderate road conditions and to 80 km/h for poor road conditions (Räma, 1999). Variable speed limits are sometimes displayed together with weather advisory VMS to inform drivers as well as to enforce traffic safety. Traffic signal timing plans are designed for clear, dry pavement conditions and are no longer efficient in adverse weather because the traffic flow parameters that were used to develop the normal-weather plans have changed. For example, Agbolosu-Amison et al (2004) indicated that inclement weather has a significant impact on saturation headways at signalized intersections, in particular once slushy conditions start. The study also reported an expected reduction of 13% in average delay and a 6% reduction in average stops per vehicle when special signal plans for inclement weather were implemented. So there are benefits to be expected from implementing special signal plans for inclement weather since roadway mobility is improved.

Chapter 10: Conclusion

In this chapter, the main conclusions of this thesis are epitomized (Section 10.1) and policy recommendations (Section 10.2) are highlighted. At last, instructions for further research are proposed (Section 10.3).

10.1 Main conclusion

The main goal of this thesis consisted of investigating whether weather conditions and weather forecasts trigger changes in our daily travel behavior. This was investigated using both a stated and a revealed preference approach. Both investigation methods found that weather clearly matters.

10.1.1 Conclusions stated adaptation approach

In the first part of this thesis, the impact of weather on stated changes in travel behavior was examined. It was found that between 18% and 85% of people claimed to change their travel plans somehow in response to adverse weather conditions. Most values from the literature lay in this interval. The extent of these percentages was depending on trip purpose and weather type.

Regarding the question how people change their travel behavior, it was found that especially adapting the departure time was common practice and this regardless of the weather type and trip purpose. Moreover, in commuting trips, route change was also frequently chosen, while in leisure and shopping trips one rather opts for cancelling the trip. At last, it was remarkable that mode change was chosen especially on warm days.

Next, it was investigated whether the mode that is normally used for the trip has a significant influence on the likelihood to change their mode in adverse weather conditions. It can be concluded that this indeed is the case.

Another goal of the thesis was to investigate whether various aspects of the weather forecast plays a role on stated changes in travel behavior. It was found that the degree of exposure to weather forecasts as well as the perceived reliability and the media source of the weather forecast do not influence the likelihood of changing travel behavior. This became clear from both the Pearson's chi-square analyses and the MNL-models. Moreover, these results were conform the Belgian study from Khattak and De Palma (1997), which found no significant effect of acquiring forecasted weather information on the likelihood of adapting mode and departure time. Although other international literature shows that weather forecasts have a clearly impact on alterations in travel behavior. These differences could be explained by the cognitive gap that is formed between the weather forecasts and the traffic and roadway conditions in Flanders.

Next, it was explored which determinants explain alterations in travel behavior in response to adverse weather conditions. Results from the MNL-models show that type of weather is a highly significant determinant, and this in all trip purposes. It was found that snow has the largest impact on travel behavior while extreme temperatures has the smallest impact. Furthermore, it appears that various socio-economic variables (like age, children, gender, diploma, statute, flexible working hours and degree of urbanization) as well as transport related determinants (like public transport card and driving license) contribute significantly to the unraveling of the preferred adaptation.

10.1.2 Conclusions revealed preference approach

In the second part of this thesis, the role of extreme weather conditions on revealed travel behavior was explored.

Using MNL-models, it was investigated whether weather conditions affect revealed modal choices. It appeared that cloud covering, fog, snow and thunderstorms did not have a significant influence on modal choice, while maximum wind gust, temperature, sunshine duration, precipitation and ice formation did. More concrete, freshening wind and increased precipitation duration lead to a decrease in the intensities of vulnerable road users, which is partially offset by an increase in the intensities of car users. The opposite is true when considering temperature, sunshine duration and ice formation. Moreover, regarding temperature, it can be said that increasing temperature leads to a decrease in the intensities of public transport and to an increase in the intensities of the other transport modes.

Tobit models were used to find out which weather conditions contribute significantly to the travel time of the trip. It was concluded that fog, cloud covering, snow, thunderstorms, maximum wind gust, temperature, sunshine duration, precipitation and ice formation all have a strong significant effect on travel time (P-values all smaller than 0.0001). More concrete, freshening wind gust, increased cloud covering and ice formation lead to a decrease in travel time while fog, snow, increased precipitation duration, thunderstorm, rising temperature and increased sunshine duration have an increasing effect on travel time.

10.2 Policy recommendations

It was concluded in this thesis that weather has a clear influence on travel behavior. This conclusion is important both in terms of traffic safety and mobility management.

Firstly, the behavioral adaptations in response to adverse weather influence traffic intensity, which is the first and primary determinant of traffic safety (Cools et al, 2007). Gaining insight in these behavioral adaptations provides policy makers with a deeper understanding of how weather conditions affect traffic intensities. These insights should be kept in mind when developing and evaluating policy measures that mitigate the negative impacts of adverse weather on traffic safety and traffic performance.

Secondly, it is recommended to integrate the effects of weather on travel behavior in weather sensitive dynamic traffic models. These kinds of models will lead to more accurate forecasts of the traffic and can be an important decision support tool for the policy maker for both long term and short-term decisions. E.g. In order to reduce the negative impacts of inclement weather, such as congestion and increased accident risk, traffic managers can intervene through various weather-related advisory and control measures, also called weather responsive traffic management. To decide which of these measures can best be applied in a particular situation, a weather sensitive traffic model can be a useful decision support tool.

At last, it is recommended to implement a road weather information system, linked to the weather forecast. In this way, it is attempted to reduce the cognitive gap that is formed between the weather forecasts and the traffic and roadway conditions in Flanders, as discussed in Section 5.4.

10.3 Further research

Besides this thesis, little research is conducted on the effects of weather on the underlying travel behavior. However, it is important to compare results of similar surveys in the context of developing a collective knowledge base. Moreover, such comparisons are challenging because often there are important methodological and contextual differences across studies that can invalidate formal comparisons. By testing behavioral hypotheses across contexts, we can begin to enrich a knowledge base that can feed the dynamic network models by making them richer and more realistic.

In this thesis, both the effects of weather on stated changes and revealed changes in travel behavior are investigated. However, further generalizations of the findings are possible by triangulation of the stated and revealed travel behavior. This should enrich the modeling and the understanding of adaptations in travel behavior. Various methods can be used to combine both data, like the use of a semi-parametric estimator method (Landry and Liu, 2008) or by use of a scale parameter (Ben-Akiva et al, 1994). It is possible to estimate such joined models with statistical software programs like MATLAB or GAUSS (Ben-Akiva et al, 1994).

In Section 1.4, a distinction was made between primary and secondary behavioral responses due to adverse weather conditions. Primary responses referred to the choice of a strategy that reduces the negative impact of adverse weather to the individual, e.g. adapting the departure time or changing the activity location. Secondary responses involved adaptations that are required to make the broader activity pattern consistent with the change. For example, switching from car to public transport may limit the possibilities for trip chaining and induce extra separate trips as a secondary response. The scope of this thesis was confined to the primary behavioral responses due to adverse weather conditions and forecasts. However, it may also be interesting to investigate the effect of adverse weather conditions on the secondary behavioral responses.

The purpose of this thesis was to investigate which influence weather has on travel behavior and it was recommended that the effects of weather should be integrated in dynamic traffic models. The results from the analyses in this thesis could therefore be used to develop such weather-sensitive dynamic traffic models in Flanders and the Netherlands. However, it still has to be investigated how these data can be integrated in existing traffic models to forge them to weather sensitive traffic models.

At last, it was recommended in Section 5.4 to develop a road weather information system in order to reduce the cognitive gap between the weather forecast and the road conditions. This road weather information system should be specifically tailored to the context of Flanders. Only the usefulness of such a system was indicated in this study, but the development, construction and its implementation should be investigated further.

References

Agarwal, M., Maze, T.H. and Souleyrette, R. (2005). *Impacts of Weather on Urban Freeway Traffic Flow Characteristics and Facility Capacity.* Submitted to the 5th Mid-Continent Transportation Research Symposium in 2005.

Agbolosu-Amison, S.J., Sadek, A.W. and El-Dessouki, W. (2004). *Inclement Weather and Traffic Flow at Signalized Intersections: Case Study from Northern New England.* Transportation Research Record: Journal of the Transportation Research Board, No. 1867, p. 163-171.

Agresti, A., 2002. *Categorical Data Analysis (Second Edition). Chapter 3: Inference for Contingency Tables.* John Wiley & Sons Inc., New Jersey, United states.

Al Hassan, Y., Barker, D.J. (1999). *The Impact of Unseasonable or Extreme Weather on Traffic Activity within Lothian Region, Scotland.* Journal of Transport Geography, No. 7, p. 209-213.

Anderson, D.R., Sweeney, D.J. and Williams, T.A. (1998). *Statistiek voor Economie en Bedrijfskunde.* Academic Service, Schoonhoven, Nederland.

Arentze, T., Hofman, F., Timmermans, H. (2003). *Predicting Multi-faceted Activity-Travel Adjustment Strategies in Response to Possible Congestion Pricing Scenarios Using an Internet-Based Stated Adaptation Experiment.* Submitted to the 82th annual meeting of the Transportation Research Board in 2003.

Attaset, V., Schneider, R.J., Arnold, L.S. and Ragland, D.R. (2010). *Effects of Weather Variables on Pedestrian Volumes in Alameda County, California.* Submitted to the 89th annual meeting of the Transportation Research Board in 2010.

Aultman-Hall, L., Lane, D. and Lambert, R.R. (2008). *Assessing the Impact of Weather and Season on Pedestrian Traffic Volumes.* Submitted to the 89th annual meeting of the Transportation Research Board in 2010.

Bartels, K., Boztug, Y. and Müller, M. (2000). *Testing the Multinomial Logit Model.* In W. Gaul and R. Decker, *Classification and Information Processing at the Turn of the Millenium (First Edition).* Springer, Heidelberg, Germany, p. 99-144.

Ben-Akiva, M., Morikawa, T., Bradley, M., Benjamin, J., Novak, T., Oppewal, H., Rao, V. (1994). *Combining Revealed and Stated Preference Data*. Marketing Letters, Vol. 5 No. 4, p. 335-350.

Billot, R. (2009). *Integrating the Effects of Adverse Weather Conditions on Traffic: Methodology, Empirical Analysis and Bayesian Modeling.* Ecole centrale Paris & Institut National de recherché sur les transports et leur sécurité, Chatenay-Malabry, France.

Brilon, W. and Ponzlet, M. (1996). *Variability of Speed-flow Relationships on German Autobahns.* Transportation Research Record: Journal of the Transportation Research Board, No. 1555, p. 91-98.

Brodsky, H. and Hakkert, A. (1988). *Risk of a Road Accident in Rainy Weather.* Accident Analaysis and Prevention, Vol. 20 No. 3, p. 161-176.

Brow, B. and Baass, K. (1997). *Seasonal Variation in Frequencies and Rates of Highway Accidents as a Function of Severity.* Transportation Research Record: Journal of the Transportation Research Board, No. 1581, p. 59-65.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences (Second Edition).* Lawrence Erlbaum Associates Inc., New Jersey, United States.

Cools, M., Moons, E., Wets, G. (2007). *Assessing the Impact of Weather on Traffic Intensity.* Submitted to the 87th annual meeting of the Transportation Research Board in 2008.

Couper, M.P., Kapteyn, A., Schonlau, M. and Winter, J. (2007). *Noncoverage and Nonresponse in an Internet Survey.* Social Science Research, Vol. 36 No. 1, p. 131-148.

Creemers, L. (2009). *Gevalstudie naar de Effecten van het Weer op het Verplaatsingsgedrag.* Opleiding Verkeerskunde, Universiteit Hasselt, België.

De Palma, A. and Rochat, D. (1999). *Understanding Individual Travel Decisions: Results from a Commuters Survey in Geneva.* Transportation, Vol. 26 No. 3, p. 263-281.

Dong, J., Mahmassani, H.S., Alfelor, R. (2010 a). *Incorporating Adverse Weather Impacts in Dynamic Traffic Simulation-assignment Models: Methodology and Application.* Submitted to the 89th annual meeting of the Transportation Research Board in 2010.

Dong, J., Mahmassani, H.S., Alfelor, R. (2010 b). *Weather Responsive Traffic Management: Deployment of Real-time Traffic Estimation and Prediction Systems.* Submitted to the 89th annual meeting of the Transportation Research Board in 2010.

Emmerson, P, Ryley, T.J., Davies, D.G. (1998). *The Impact of Weather on Cycle Flows.* Traffic Engineering and Control, Vol. 39 No. 4, p. 283-243.

Faivre D'Arcier, B., Andan, O. and Raux, C. (1998). *Stated Adaptation Surveys and Choice Process: Some Methodological Issues.* Transportation, Vol. 25 No. 2, p. 169-185.

Gazet van Antwerpen (2010). *Snelheidsbeperking van 90 km/u op Beschadigde E313.* 26/01/2010.

Hagens, A. (2005). *De Auto Laten Staan: ook als het Regent? De Invloed van Weer op de Stedelijke Verkeersvraag.* Afstudeerrapport Civiele Techniek afdeling verkeer, vervoer en ruimte, Universiteit Twente.

Hanbali, R. M. (1994). *Economic Impact of Winter Road Maintenance on Road Users.* Transportation Research Record: Journal of the Transportation Research Board, No. 1442, p. 151–161.

Het Belang van Limburg (2010). *Record: 948 km File.* 11/02/2010.

Hensher, D.A. (1993). *Stated Preference Analysis of Travel Choices: the State of Practice.* Transportation, Vol. 21 No. 2, p. 107-133.

Hensher, D.A., Button, K.J. (2000). *Handbook of Transport Modeling.* Elsevier Ltd, London, United Kingdom.

Hogema, J.H., van der Horst, R. (1997). *Evaluation of A16 Motorway Fog-signalling System with Respect to Driving Behavior.* Transportation Research Record: Journal of the Transportation Research Board, No. 1573, p. 63-67.

Hranac, R., Sterzin, E., Krechmer, D., Rahka, H. and Farzaneh, M. (2006). *Empirical Studies on Traffic Flow in Inclement Weather*. Federal Highway Administration, publication number HOP-07-073.

Ibrahim, A. and Hall, F. (1994). *Effect of Adverse Weather Conditions on Speed-Flow-Occupancy Relationship.* Transportation Research Record: Journal of the Transportation Research Board, No. 1457, p. 184-191.

Immers, L.H., Stada, J.H. (2004). *Verkeer- en Vervoersystemen: Verplaatsingsgedrag, Verkeersnetwerken en Openbaar Vervoer.* Katholieke Universiteit Leuven, Faculteit toegepaste wetenschappen.

Khattak, A., 1991. *Driver Response to Unexpected Travel Conditions: Effect of Traffic Information and Other Factors.* Civil Engineering Department, Northwestern University, Evanston, United States.

Khattak, A., Polydoropoulou, A. and Ben-Akiva, M. (1996). *Modeling Revealed and Stated Pretrip Travel Response to Advanced Traveler Informations Systems.* Transportation Research Record: Journal of the Transportation Research Board, No. 1537, p 46-54.

Khattak, A.J. and De Palma, A. (1997). *The Impact of Adverse Weather Conditions on the Propensity to Change Travel Decisions: a Survey of Brussels Commuters.* Transportation Research Part A: Policy and practice, Vol. 31, No. 3, p 181-203.

Khattak, A.J., Kantor, P. and Council, F.M. (1998). *Role of Adverse Weather in Key Crash Types on Limited Access Roadway: Implications for Advanced Weather System.* Transportation Research Record: Journal of the Transportation Research Board, No. 1621, p. 10-19.

Khattak, A.J., Knapp, K.K., Giese, K.L., and Smithson, L.D. (2000). *Safety Implications of Snowstorms on Interstate Highways.* Submitted to the 79th annual meeting of the Transportation Research Board in 2000.

Kilpelaïnen, M., Summala, H., 2007. *Effects of Weather and Weather forecasts on Driver Behavior.* Transportation research part F: Traffic psychology and behavior, Vol. 10, No. 4, p. 288-299.

KMI (2008). *Climatic Overview of 2008 (In Dutch: Klimatologisch Overzicht van het Jaar 2008).* Available at: http://www.meteo.be/meteo/view/nl/2827848-2008.html. Accessed at 10 April 2010.

KNMI (2010). *Hourly data of weather in the Netherlands.* Available at: http://www.knmi.nl/kd/uurgegevens/#no. Accessed at 20 February 2010.

Koninklijk instituut voor het duurzame beheer van de natuurlijke rijkdommen en de bevordering van schone technologie (2006). *Rail Meets Road III: Ontmoetingen rond Mobiliteit.* Brussel: Koninklijk instituut voor het duurzame beheer van de natuurlijke rijkdommen en de bevordering van schone technologie.

Kuhfeld, F.W., So, Y. (2005). *Multinomial Logit Models*. Cary, NC: SAS Institute Inc.

Kuss, O. and McLerran, D. (2007). *A Note on the Estimation of the Multinomial Logistic Model with Correlated Responses in SAS*. Computer methods and programs in biomedicine, Vol. 87, No. 3, p. 262-269.

Kutner, M.H., Nachtsheim, C.J., Neter, J., Li, W. (2005). *Applied linear statistical models.* McGraw-Hill/Irwin, New York

Kyte, M., Khatib, Z., Shannon, P. and Kitchener, F. (2001). *Effect of Weather on Free-flow Speed.* Transportation research record: Journal of the Transportation Research Board, No. 1776, p. 60-68.

Lam, W.H.K., Shao, H. and Sumalee, A. (2008). *Modeling impacts of adverse weather conditions on a road network with uncertainties in demand and supply.* Transportation Research Part B: Methodological, Vol. 42 No. 10, p. 890-910.

Landry, C.E and Liu, H. (2008). *A Semi-parametric Estimator for Revealed and Stated Preference Data: An Application to Recreational Beach Visitation.* Journal of Environmental Economics and Management, Vol. 52 No. 2, p. 205-218.

Lin, Q., Nixon, W. (2008). *Effects of Adverse Weather on Traffic Crashes: Systematic Review and Meta-analysis.* Submitted to the 87th annual meeting of the Transportation Research Board in 2008.

Long, J. S. (1997). *Regression Models for Categorical and Limited Dependent Variables.* Sage Publications Inc., California, United States.

May, A.D. (1998). *Third interim report: Capacity and Level of Service for Freeway Systems.* Publisher and place of publication unknown.

Maze, T.H., Agarwal, M. and Burchett, G. (2005). *Whether Weather Matters to Traffic Demand, Traffic Safety and Traffic Flow.* Transportation Research Record: Journal of the Transportation Research Board, No. 1948, p. 170-176.

Moons, E. (2009). *Onderzoek Verplaatsingsgedrag Vlaanderen 3 (2007-2008): Tabellenrapport.* Instituut voor mobiliteit, Diepenbeek.

Nankervis, M. (1998). *The Effect of Weather and Climate on Bicycle Commuting.* Transportation Research Part A: Policy and practice, Vol. 33 No. 6, p. 417-431.

Niina, S., 2009. *Driver Assessment of Road Weather Conditions and Road Weather Information.* Young Researchers Seminar in 2009.

NIS, 2009. Total population by age, sex and marital status. Available at: http://statbel.fgov.be/nl/modules/publications/statistiques/bevolking/Tot_bevolking_leeftijd_geslacht_bs.jsp. Accessed at 8 november 2009.

Ouellette, J., Wood, W. (1998). *Habit and Intention in Everyday Life: The Multiple Processes by which Past Behavior Predicts Future Behavior.* Psychological bulletin, Vol. 124 No.1, p. 54-74.

Ortùzar, J.D.D. and Willumsen, L.G. (2001). *Modelling Transport (Third Edition)*. *Chapter 3: Data and Space.* John Wiley & Sons Ltd, Chichester, United Kingdom.

Pan, W. (2001), *Akaike's Information Criterion in Generalized Estimating Equations*. Biometrics, Vol. 57 No. 1, p. 120-125.

Pisano, P. and Goodwin, L.C. (2003). *Surface Transportation Weather Applications.* Submitted to the annual meeting of the Transportation Engineers in 2002.

Projectteam MON, 2009. *Mobility Research of Netherland: The Research.* Ministerie van transport en openbare werken, Nederland.

Rämä, P. (1999). *Effects of Weather-controlled Variable Speed Limits and Warning Signs on Driver Behavior.* Transportation Research Record: Journal of the Transportation Research Board, No. 1689, p. 53-59.

Rämä, P. (2001). *Effects of Weather-controlled Variable Message signs on Driver Behavior.* Technical research centre of Finland, Helsinki.

SAS Institute Inc. (1999). *SAS/STAT user's guide: The Freq Procedure, version 8.* SAS Institute Inc., Cary NC, United States.

Savenhed, H. (1994). *Relationship Between Winter Road Maintenance and Road Safety.* Swedish Road and Traffic Research Institute (VTI) Sartryck, Report No. 214.

Scharsching, H. (1996). *Nowcasting Road Conditions: A system for improving traffic safety in wintertime.* Transportation Research Record: Journal of the Transportation Research Board, No. 4A Part 5, p. 141-153.

Sun, X., Hu, H., Habib, E. and Magri, D. (2009). *Quantifying Crash Risk under Inclement Weather with Radar Rainfall Data and Matched Pair Method.* Submitted for the 89th annual meeting of the Transportation Research Board in 2010.

Tu, H., Van Lint, J.W.C. and Van Zuylen H.J. (2007). *The Impact of Adverse Weather on Travel Time Variability of Freeway Corridors.* Transportation Research Record: Journal of the Transportation Research Board, No. 1642, p. 21-25.

Wilde, H. (2000). *Year 2000 Travel Survey.* University of Canterbury, Department of Civil Engineering, Canterbury, United Kingdom.

Yannis, G. and Karlaftis, M.G. (2009). *Weather Effects on Daily Traffic Accidents and Fatalities: A time Series Count Data Approach.* Submitted for the 89th annual meeting of the Transportation Research Board in 2010.

Appendices

Appendix 1: Tests for population fractions

Appendix 1.1: Tests for population fractions for weather types

Table 11-1: Tests for population fractions regarding weather types

		Cold	Snow	Rain	Fog	Warm	Storm
Work/school	**Cold**	/	16.62	6.73	3.88	1.95	5.15
	Snow	-16.62	/	-10.47	-13.18	-14.92	-11.98
	Rain	-6.73	10.47	/	-2.91	-4.82	-1.61
	Fog	-3.88	13.18	2.91	/	-1.94	1.30
	Warm	-1.95	14.92	4.82	1.97	/	3.23
	Storm	-5.15	11.98	1.61	-1.30	-3.23	/
Shopping	**Cold**	/	17.63	12.27	6.77	3.15	10.09
	Snow	-17.63	/	-5.99	-11.46	-14.83	-8.22
	Rain	-12.77	5.99	/	-5.71	-9.28	-2.31
	Fog	-6.77	11.46	5.71	/	-3.66	3.42
	Warm	-3.15	14.83	9.28	3.66	/	7.04
	Storm	-10.09	8.22	2.31	-3.42	-7.04	/
Leisure	**Cold**	/	15.74	10.22	6.20	3.53	9.39
	Snow	-15.74	/	-5.95	-9.96	-12.50	-6.79
	Rain	-10.22	5.95	/	-4.14	-6.80	-0.87
	Fog	-6.20	9.96	4.14	/	-2.70	3.28
	Warm	-3.53	12.50	6.80	2.70	/	5.95
	Storm	-9.39	6.79	0.87	-3.28	-5.95	/

Appendix 1.2: Tests for population fractions for exposure to weather forecast

Appendix 1.2.1: Commuting trips

Table 11-2: Tests for population fractions regarding exposure to weather forecast in commuting trips

		Daily	Weekly	Occasional
Cold	**Daily**	/	-2.05	-0.59
	Weekly	2.05	/	0.61
	Occasional	0.59	-0.61	/
Snow	**Daily**	/	0.23	-1.09
	Weekly	-0.23	/	-1.18
	Occasional	1.09	1.18	/
Rain	**Daily**	/	-0.88	-0.73
	Weekly	0.88	/	-0.20
	Occasional	0.73	0.20	/
Fog	**Daily**	/	-1.10	-2.93
	Weekly	1.10	/	-2.25
	Occasional	2.93	2.25	/
Warm	**Daily**	/	-1.61	-2.10
	Weekly	1.61	/	-1.16
	Occasional	2.10	1.16	/
Storm	**Daily**	/	-0.78	-1.31
	Weekly	0.78	/	-0.83
	Occasional	1.31	0.83	/

Appendix 1.2.2: Shopping trips

Table 11-3: Tests for population fractions regarding exposure to weather forecast in shopping trips

		Daily	Weekly	Occasional
Cold	**Daily**	/	0.51	0.51
	Weekly	-0.51	/	0.20
	Occasional	-0.51	-0.20	/
Snow	**Daily**	/	1.27	-1.41
	Weekly	-1.27	/	-2.13
	Occasional	1.41	2.13	/
Rain	**Daily**	/	2.41	0.65
	Weekly	-2.41	/	-0.71
	Occasional	-0.65	0.71	/
Fog	**Daily**	/	-0.53	-0.70
	Weekly	0.53	/	-0.38
	Occasional	0.70	0.38	/
Warm	**Daily**	/	-0.60	-0.91
	Weekly	0.60	/	-0.55
	Occasional	0.91	0.55	/
Storm	**Daily**	/	1.73	0.53
	Weekly	-1.73	/	-0.44
	Occasional	-0.53	0.44	/

Appendix 1.2.3: Leisure trips

Table 11-4: Tests for population fractions regarding exposure to weather forecast in leisure trips

		Daily	Weekly	Occasional
Cold	**Daily**	/	1.58	-0.78
	Weekly	-1.58	/	-1.56
	Occasional	0.78	1.56	/
Snow	**Daily**	/	2.24	-0.42
	Weekly	-2.24	/	-1.73
	Occasional	0.42	1.73	/
Rain	**Daily**	/	3.19	0.28
	Weekly	-3.19	/	-1.52
	Occasional	-0.28	1.52	/
Fog	**Daily**	/	1.11	-1.40
	Weekly	-1.11	/	-1.94
	Occasional	1.40	1.94	/
Warm	**Daily**	/	-0.49	-0.37
	Weekly	0.49	/	-0.09
	Occasional	0.37	0.09	/
Storm	**Daily**	/	3.72	-0.09
	Weekly	-3.72	/	-2.19
	Occasional	0.09	2.19	/

Appendix 1.3: Tests for population fractions for perceived reliability of the weather forecast

Appendix 1.3.1: commuting trips

Table 11-5: Tests for population fractions regarding the perceived reliability of the weather forecast in commuting trips

		0 to 5	6 to 10
Cold	**0 to 5**	/	1.63
	6 to 10	-1.63	/
Snow	**0 to 5**	/	2.04
	6 to 10	-2.04	/
Rain	**0 to 5**	/	2.70
	6 to 10	-2.70	/
Fog	**0 to 5**	/	1.36
	6 to 10	-1.36	/
Warm	**0 to 5**	/	1.65
	6 to 10	-1.65	/
Storm	**0 to 5**	/	3.03
	6 to 10	-3.03	/

Appendix 1.3.2: shopping trips

Table 11-6: Tests for population fractions regarding the perceived reliability of the weather forecast in shopping trips

		0 to 5	6 to 10
Cold	**0 to 5**	/	-1.32
	6 to 10	1.32	/
Snow	**0 to 5**	/	-1.29
	6 to 10	1.29	/
Rain	**0 to 5**	/	2.27
	6 to 10	-2.27	/
Fog	**0 to 5**	/	0.31
	6 to 10	-0.31	/
Warm	**0 to 5**	/	-1.91
	6 to 10	1.91	/
Storm	**0 to 5**	/	1.55
	6 to 10	-1.55	/

Appendix 1.3.3: Leisure trips

Table 11-7: Tests for population fractions regarding the perceived reliability of the weather forecast in leisure trips

		0 to 5	6 to 10
Cold	**0 to 5**	/	-0.81
	6 to 10	0.81	/
Snow	**0 to 5**	/	0.23
	6 to 10	-0.23	/
Rain	**0 to 5**	/	-0.27
	6 to 10	0.27	/
Fog	**0 to 5**	/	-1.10
	6 to 10	1.10	/
Warm	**0 to 5**	/	-1.67
	6 to 10	1.67	/
Storm	**0 to 5**	/	0.04
	6 to 10	-0.04	/

Appendix 1.4: Tests for population fractions for media source of the weather forecast

Appendix 1.4.1: Commuting trips

Table 11-8: Tests for population fractions regarding the media source of the weather forecast in commuting trips

		Television	Internet	Paper	Radio
Cold	Television	/	-1.25	-1.97	0.14
	Internet	1.25	/	-0.65	1.31
	Paper	1.97	0.65	/	2.01
	Radio	-0.14	-1.31	-2.01	/
Snow	Television	/	0.67	-0.16	1.71
	Internet	-0.67	/	-0.67	0.57
	Paper	0.16	0.67	/	1.38
	Radio	-1.71	-0.57	-1.38	/
Rain	Television	/	-0.10	-1.41	-0.05
	Internet	0.10	/	-1.08	0.06
	Paper	1.41	1.08	/	1.33
	Radio	0.05	-0.06	-1.33	/
Fog	Television	/	-2.45	-0.21	0.29
	Internet	2.45	/	1.80	2.58
	Paper	0.21	-1.80	/	0.41
	Radio	-0.29	-2.58	-0.41	/
Warm	Television	/	-1.46	-0.37	-0.68
	Internet	1.46	/	0.87	0.94
	Paper	0.37	-0.87	/	-0.11
	Radio	0.68	-0.94	0.11	/
Storm	Television	/	-0.89	-1.78	0.21
	Internet	0.89	/	-0.76	1.01
	Paper	1.78	0.76	/	1.87
	Radio	-0.21	-1.01	-1.87	/

Appendix 1.4.2: Shopping trips

Table 11-9: Tests for population fractions regarding the media source of the weather forecast in shopping trips

		Television	Internet	Paper	Radio
Cold	**Television**	/	1.33	-2.40	0.12
	Internet	-1.33	/	-0.91	1.38
	Paper	2.40	0.91	/	2.42
	Radio	-0.12	-1.38	-2.42	/
Snow	**Television**	/	-2.36	-0.16	0.31
	Internet	2.36	/	1.68	2.50
	Paper	0.16	-1.68	/	0.37
	Radio	-0.31	-2.50	-0.37	/
Rain	**Television**	/	-1.76	-1.99	-0.15
	Internet	1.76	/	-0.18	1.60
	Paper	1.99	0.18	/	1.82
	Radio	0.15	-1.60	-1.82	/
Fog	**Television**	/	-2.91	-2.64	0.09
	Internet	2.91	/	0.22	2.88
	Paper	2.64	-0.22	/	2.63
	Radio	-0.09	-2.88	-2.63	/
Warm	**Television**	/	-0.54	-0.46	0.49
	Internet	0.54	/	0.07	0.86
	Paper	0.46	-0.07	/	0.78
	Radio	-0.49	-0.86	-0.78	/
Storm	**Television**	/	-1.85	-2.09	-0.09
	Internet	1.85	/	-0.20	1.73
	Paper	2.09	0.20	/	1.97
	Radio	0.09	-1.73	-1.97	/

Appendix 1.4.3: Leisure trips

Table 11-10: Tests for population fractions regarding the media source of the weather forecast in leisure trips

		Television	Internet	Paper	Radio
Cold	**Television**	/	-0.83	-0.39	0.06
	Internet	0.83	/	0.36	0.85
	Paper	0.39	-0.36	/	0.42
	Radio	-0.06	-0.85	-0.42	/
Snow	**Television**	/	-0.88	-0.71	0.85
	Internet	0.88	/	0.13	1.46
	Paper	0.71	-0.13	/	1.29
	Radio	-0.85	-1.46	-1.29	/
Rain	**Television**	/	-0.65	-1.38	-0.18
	Internet	0.65	/	-0.58	0.51
	Paper	1.38	0.58	/	1.21
	Radio	0.18	-0.51	-1.21	/
Fog	**Television**	/	-2.15	-1.93	-0.43
	Internet	2.15	/	0.17	1.79
	Paper	1.93	-0.17	/	1.58
	Radio	0.43	-1.79	-1.58	/
Warm	**Television**	/	-1.41	0.47	0.26
	Internet	1.41	/	1.51	1.55
	Paper	-0.47	-1.51	/	-0.28
	Radio	-0.26	-1.55	0.28	/
Storm	**Television**	/	-0.04	-1.03	0.23
	Internet	0.04	/	-0.79	0.20
	Paper	1.03	0.79	/	1.17
	Radio	-0.23	-0.20	-1.17	/

Appendix 2: Frequency tables

Appendix 2.1: shopping trips

Table 11-11: Frequencies of changes in shopping trips in response to extreme weather conditions, according to the media source of the weather forecast

Behavioral change	Forecast Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All changes	Daily	68.5%	18.0%	36.1%	47.2%	57.5%	41.5%
	Weekly	66.3%	13.7%	25.8%	49.6%	60.2%	33.8%
	Occasional	64.7%	26.9%	31.1%	52.8%	64.7%	37.3%
Mode change	Daily	91.0%	78.4%	86.6%	90.2%	81.0%	87.5%
	Weekly	92.0%	76.7%	84.4%	93.9%	77.5%	85.0%
	Occasional	92.8%	84.1%	82.8%	97.3%	78.0%	89.0%
Time-of-day change	Daily	79.3%	30.3%	46.4%	57.5%	77.9%	51.2%
	Weekly	83.6%	28.1%	34.1%	63.2%	83.9%	42.2%
	Occasional	72.4%	27.7%	38.3%	64.8%	80.2%	44.3%
Location change	Daily	87.6%	57.7%	73.1%	72.4%	83.9%	72.9%
	Weekly	84.8%	46.4%	60.1%	69.2%	83.2%	62.8%
	Occasional	88.9%	57.4%	66.6%	82.9%	84.9%	69.2%
Trip cancellation	Daily	87.1%	33.6%	51.1%	64.6%	80.2%	58.8%
	Weekly	86.3%	28.0%	44.2%	62.0%	86.1%	49.3%
	Occasional	85.2%	34.7%	45.4%	73.8%	86.8%	50.1%
Route change	Daily	91.9%	56.5%	80.2%	78.5%	91.1%	79.7%
	Weekly	95.1%	61.1%	84.3%	84.0%	97.7%	85.2%
	Occasional	93.8%	67.6%	82.2%	82.4%	91.8%	82.2%

Table 11-12: Frequencies of changes in shopping trips in response to extreme weather conditions, according to the perceived weather forecast reliability

Behavioral Change	Forecast Reliability	Cold	Snow	Rain	Fog	Warm	Storm
All Changes	0 to 5	61.4%	12.4%	42.8%	49.9%	49.6%	46.1%
	6 to 10	68.6%	18.1%	30.4%	48.1%	60.6%	37.3%
Mode Change	0 to 5	90.3%	77.1%	90.0%	92.4%	75.9%	89.0%
	6 to 10	91.6%	78.5%	84.8%	91.9%	80.3%	86.4%
Time-of-day Change	0 to 5	76.6%	35.4%	51.7%	63.7%	81.4%	57.7%
	6 to 10	80.8%	28.3%	40.0%	59.2%	79.8%	45.9%
Location change	0 to 5	80.4%	54.8%	69.5%	75.0%	79.7%	70.9%
	6 to 10	88.0%	53.9%	68.2%	71.7%	84.5%	69.0%
Trip cancellation	0 to 5	77.8%	28.8%	56.8%	62.7%	79.7%	60.6%
	6 to 10	88.3%	32.4%	46.9%	64.8%	83.2%	54.0%
Route change	0 to 5	92.2%	61.0%	87.0%	82.4%	93.8%	86.4%
	6 to 10	93.3%	58.4%	80.8%	80.3%	93.2%	80.8%

Table 11-13: Frequencies of changes in shopping trips in response to extreme weather conditions, according to the media source of the weather forecast

Behavioral change	Forecast Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All changes	Television	66.8%	16.9%	32.2%	47.5%	59.0%	38.0°%
	Internet	72.9%	26.0%	40.4%	61.8%	61.6%	46.9%
	Paper	77.7%	17.5%	41.5%	60.5%	61.2%	48.1%
	Radio	66.4%	16.1%	32.7%	47.2%	57.3%	38.3%
Mode change	Television	91.6%	78.7%	86.8%	92.0%	80.9%	87.6%
	Internet	93.8%	84.0%	89.7%	96.2%	79.3%	89.1%
	Paper	93.4%	79.5%	87.9%	95.0%	71.6%	90.2%
	Radio	91.7%	78.2%	85.9%	92.4%	78.1%	86.7%
Time-of-day change	Television	79.4%	29.5%	41.1%	59.6%	79.0%	46.4%
	Internet	81.9%	37.3%	45.8%	66.1%	81.4%	50.5%
	Paper	83.9%	32.8%	47.4%	68.1%	82.6%	53.6%
	Radio	77.5%	26.5%	40.4%	57.5%	78.0%	46.7%
Location change	Television	86.4%	54.3%	68.5%	72.3%	83.9%	69.9%
	Internet	90.2%	58.8%	70.3%	81.6%	85.5%	72.8%
	Paper	91.1%	52.6%	71.1%	75.3%	88.7%	73.7%
	Radio	86.7%	53.0%	68.4%	70.9%	82.0%	69.6%
Trip cancellation	Television	86.0%	31.6%	48.3%	63.8%	82.3%	55.0%
	Internet	86.0%	40.7%	55.1%	75.2%	84.0%	62.9%
	Paper	91.3%	29.9%	54.2%	67.8%	85.8%	60.8%
	Radio	84.6%	30.0%	47.4%	61.0%	81.4%	53.1%
Route change	Television	92.8%	57.4%	81.7%	81.4%	92.9%	81.6%
	Internet	94.6%	64.0%	86.0%	88.0%	95.5%	87.3%
	Paper	97.3%	59.9%	89.3%	87.5%	98.9%	88.3%
	Radio	92.2%	55.2%	79.5%	76.6%	93.4%	80.4%

Appendix 2.2: leisure trips

Table 11-14: Frequencies of changes in leisure trips in response to extreme weather conditions, according to the perceived weather forecast reliability

Behavioral change	Forecast Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All changes	Daily	69.3%	24.6%	42.7%	50.7%	56.7%	45.8%
	Weekly	62.6%	16.3%	28.8%	45.7%	58.9%	29.4%
	Occasional	75.0%	27.5%	40.5%	61.9%	59.6%	46.5%
Mode change	Daily	90.8%	75.9%	86.3%	86.1%	76.7%	86.6%
	Weekly	87.5%	70.8%	80.1%	88.7%	80.2%	83.9%
	Occasional	93.3%	79.1%	81.6%	90.5%	69.3%	84.5%
Time-of-day change	Daily	85.8%	38.7%	59.5%	62.8%	83.4%	63.6%
	Weekly	82.3%	29.2%	44.8%	58.3%	88.3%	50.4%
	Occasional	94.4%	33.7%	55.7%	69.6%	86.9%	56.5%
Location change	Daily	84.6%	73.9%	77.8%	81.6%	83.2%	76.8%
	Weekly	80.9%	64.6%	69.3%	80.6%	84.4%	68.3%
	Occasional	84.3%	75.3%	79.6%	83.8%	87.4%	78.5%
Trip cancellation	Daily	81.7%	36.5%	60.1%	67.5%	80.1%	59.8%
	Weekly	74.7%	32.6%	47.8%	61.3%	83.2%	47.1%
	Occasional	80.8%	41.7%	61.9%	76.3%	94.5%	56.2%
Route change	Daily	92.6%	51.1%	74.4%	75.0%	92.1%	73.6%
	Weekly	92.6%	59.2%	76.9%	82.9%	97.3%	80.8%
	Occasional	94.9%	68.6%	90.1%	87.7%	98.5%	85.4%

Table 11-15: Frequencies of changes in leisure trips in response to extreme weather conditions, according to the perceived weather forecast reliability

Behavioral Change	Forecast Reliability	Cold	Snow	Rain	Fog	Warm	Storm
All Changes	0 to 5	63.8%	23.0%	36.7%	44.5%	49.6%	40.6%
	6 to 10	68.2%	21.9%	38.2%	50.9%	59.2%	40.4%
Mode Change	0 to 5	95.0%	80.6%	87.1%	88.9%	81.0%	90.3%
	6 to 10	89.0%	73.3%	83.3%	87.0%	76.7%	84.7%
Time-of-day Change	0 to 5	81.3%	30.7%	50.7%	55.9%	83.1%	58.0%
	6 to 10	86.0%	35.9%	54.9%	62.9%	85.7%	58.7%
Location change	0 to 5	77.8%	65.6%	74.7%	76.0%	79.4%	75.8%
	6 to 10	84.3%	71.8%	75.2%	82.4%	84.7%	73.8%
Trip cancellation	0 to 5	72.5%	36.2%	55.4%	57.2%	77.5%	55.2%
	6 to 10	80.5%	35.5%	56.2%	67.7%	83.1%	55.3%
Route change	0 to 5	93.9%	66.2%	87.8%	85.9%	96.5%	89.0%
	6 to 10	92.6%	53.2%	74.4%	77.3%	93.9%	74.7%

Table 11-16: Frequencies of changes in leisure trips in response to extreme weather conditions, according to the media source of the weather forecast

Behavioral Change	Forecast Frequency	Cold	Snow	Rain	Fog	Warm	Storm
All changes	Television	66.8%	21.9%	37.3%	49.0%	56.3%	40.0%
	Internet	70.6%	25.5%	40.4%	59.5%	63.1%	40.2%
	Paper	68.6%	24.8%	43.9%	58.5%	54.0%	45.0%
	Radio	66.6%	19.5%	37.9%	50.5%	55.4%	39.2%
Mode Change	Television	88.9%	73.9%	83.9%	86.9%	77.6%	85.7%
	Internet	91.9%	80.8%	87.7%	95.1%	79.4%	87.1%
	Paper	95.7%	78.5%	91.1%	91.4%	75.9%	92.7%
	Radio	89.9%	72.8%	84.1%	86.6%	75.5%	85.9%
Time-of-day Change	Television	84.7%	34.5%	52.5%	60.9%	84.4%	57.6%
	Internet	86.6%	40.0%	60.3%	71.7%	93.8%	64.0%
	Paper	88.5%	36.1%	60.0%	66.9%	89.2%	66.6%
	Radio	85.4%	32.9%	54.3%	60.3%	82.9%	58.6%
Location Change	Television	82.6%	69.0%	73.8%	80.0%	82.9%	72.8%
	Internet	87.6%	77.9%	79.4%	86.6%	88.6%	77.1%
	Paper	84.8%	68.2%	74.1%	81.5%	81.0%	72.5%
	Radio	82.9%	71.4%	76.8%	82.6%	83.6%	75.7%
Trip cancellation	Television	78.2%	34.5%	54.0%	65.4%	80.7%	54.3%
	Internet	79.7%	41.5%	63.5%	77.5%	86.3%	58.2%
	Paper	79.4%	34.7%	54.2%	70.6%	80.5%	59.0%
	Radio	78.6%	30.8%	54.4%	65.4%	80.4%	53.0%
Route Change	Television	91.6%	53.7%	74.6%	78.7%	93.4%	75.9%
	Internet	96.1%	60.2%	81.4%	85.9%	96.7%	81.1%
	Paper	96.4%	53.7%	80.7%	86.0%	95.6%	82.1%
	Radio	92.2%	52.9%	76.2%	77.7%	93.4%	76.2%

Appendix 3: Pearson's chi-square independence tests

Appendix 3.1: Dependence of behavioral changes on trip purpose

Table 11-17: Dependence of behavioral changes on trip purpose (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change	9.03	6	0.172	n.s.
	Time-of-day change	21.24	6	0.002	**
	Location change	50.88	6	<0.0001	***
	Trip cancellation	79.41	6	<0.0001	***
	Route change	5.12	6	0.528	n.s.
Snow	Mode change	5.07	6	0.535	n.s.
	Time-of-day change	49.55	6	<0.0001	***
	Location change	143.46	6	<0.0001	***
	Trip cancellation	271.32	6	<0.0001	***
	Route change	4.06	6	0.669	n.s.
Rain	Mode change	9.93	6	0.128	n.s.
	Time-of-day change	129.10	6	<0.0001	***
	Location change	120.21	6	<0.0001	***
	Trip cancellation	275.88	6	<0.0001	***
	Route change	15.68	6	0.016	*
Fog	Mode change	42.06	6	<0.0001	***
	Time-of-day change	30.6	6	<0.0001	***
	Location change	126.67	6	<0.0001	***
	Trip cancellation	170.08	6	<0.0001	***
	Route change	13.80	6	0.032	*
Warm	Mode change	5.41	6	0.492	n.s.
	Time-of-day change	54.23	6	<0.0001	***
	Location change	58.03	6	<0.0001	***
	Trip cancellation[2]	11.59	2	0.003	**
	Route change[2]	5.15	2	0.076	n.s.
Storm	Mode change	13.15	6	0.041	*
	Time-of-day change	97.85	6	<0.0001	***
	Location change	104.97	6	<0.0001	***
	Trip cancellation	225.54	6	<0.0001	***
	Route change	21.43	6	0.002	**

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Appendix 3.2: Dependence of behavioral changes on weather type

Table 11-18: Dependence of behavioral changes on type of weather (disaggregated level)

Trip purpose	Behavioral change	Chi²	DF	P-value	Signif.[1]
Work/school	Mode change	138.73	15	<0.0001	***
	Time-of-day change	409.06	15	<0.0001	***
	Location change	81.12	15	<0.0001	***
	Trip cancellation[2]	174.76	5	<0.0001	***
	Route change	362.53	15	<0.0001	***
Shopping	Mode change	92.23	15	<0.0001	***
	Time-of-day change	542.98	15	<0.0001	***
	Location change	235.71	15	<0.0001	***
	Trip cancellation	555.66	15	<0.0001	***
	Route change	302.37	15	<0.0001	***
Leisure	Mode change	107.91	15	<0.0001	***
	Time-of-day change	522.48	15	<0.0001	***
	Location change	62.86	15	<0.0001	***
	Trip cancellation	405.25	15	<0.0001	***
	Route change	357.76	15	<0.0001	***

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Appendix 3.3: Dependence of mode change on mode type

Table 11-19: Dependence of the frequencies of mode change on mode type (disaggregated level)

Trip purpose	Weathertype	Chi²	DF	P-value	Signif.[1]
Work/school	Cold	28.84	2	<0.0001	***
	Snow	62.58	2	<0.0001	***
	Rain	152.75	2	<0.0001	***
	Fog	5.17	2	0.075	n.s.
	Warm	15.65	2	0.0004	***
	Storm	119.63	2	<0.0001	***
Shopping	Cold[2]	91.47	1	<0.0001	***
	Snow[2]	70.37	1	<0.0001	***
	Rain[2]	187.57	1	<0.0001	***
	Fog[2]	19.91	1	<0.0001	***
	Warm[2]	8.84	1	0.003	**
	Storm[2]	143.30	1	<0.0001	***
Leisure	Cold	73.90	2	<0.0001	***
	Snow	74.32	2	<0.0001	***
	Rain	152.33	2	<0.0001	***
	Fog	28.20	2	<0.0001	***
	Warm	9.33	2	0.009	**
	Storm	106.34	2	<0.0001	***

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Based on only car users and vulnerable road users

Appendix 3.4: Dependence of behavioral changes on exposure to the weather forecast

Appendix 3.4.1: Aggregated level

Table 11-20: Dependence of behavioral changes on exposure to the weather forecast (aggregated level)

Trip purpose	Weathertype	Chi²	DF	P-value	Signif.[1]
All purposes	All types[2]	337.19	358	0.778	n.s.
Work/school	All types[2]	51.66	118	1	n.s.
Shopping	All types[2]	88.39	118	0.980	n.s.
Leisure	All types[2]	129.11	118	0.228	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Table 11-21: Dependence of behavioral changes on exposure to the weather forecast (aggregated level)

Trip purpose	Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Work/school	Cold[2]	All changes	7.95	18	0.979	n.s.
	Snow[2]	All changes	13.23	18	0.778	n.s.
	Heavy rain[2]	All changes	5.44	18	0.998	n.s.
	Fog[2]	All changes	13.49	18	0.762	n.s.
	Warm[2]	All changes	6.60	18	0.996	n.s.
	Storm[2]	All changes	5.54	18	0.997	n.s.
Shopping	Cold[2]	All changes	6.52	18	0.993	n.s.
	Snow	All changes	38.23	38	0.459	n.s.
	Heavy rain	All changes	50.77	38	0.080	n.s.
	Fog[2]	All changes	14.11	18	0.722	n.s.
	Warm[2]	All changes	15.73	18	0.611	n.s.
	Storm	All changes	41.28	38	0.329	n.s.
Leisure	Cold[2]	All changes	11.84	18	0.855	n.s.
	Snow	All changes	74.75	38	0.0003	***
	Heavy rain[2]	All changes	33.24	18	0.016	*
	Fog[2]	All changes	14.99	18	0.662	n.s.
	Warm[2]	All changes	19.18	18	0.381	n.s.
	Storm[2]	All changes	28.60	18	0.053	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Appendix 3.4.2: Disaggregated level

Table 11-22: Dependence of behavioral changes on exposure to the weather forecast for commuting trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	2.69	2	0.260	n.s.
	Time-of-day change[2]	0.70	2	0.703	n.s.
	Location change[2]	1.97	2	0.373	n.s.
	Trip cancellation[2]	2.38	2	0.305	n.s.
	Route change[2]	0.21	2	0.898	n.s.
Snow	Mode change[2]	0.90	2	0.639	n.s.
	Time-of-day change	5.13	6	0.526	n.s.
	Location change[2]	5.45	2	0.065	n.s.
	Trip cancellation[2]	2.60	2	0.273	n.s.
	Route change	13.69	6	0.033	*
Heavy rain	Mode change[2]	1.83	2	0.400	n.s.
	Time-of-day change	2.54	6	0.863	n.s.
	Location change[2]	1.83	2	0.400	n.s.
	Trip cancellation[2]	0.65	2	0.722	n.s.
	Route change[2]	0.17	2	0.919	n.s.
Fog	Mode change[2]	0.90	2	0.637	n.s.
	Time-of-day change	7.17	6	0.305	n.s.
	Location change[3]	n.d.	n.d.	n.d.	n.d.
	Trip cancellation[2]	4.22	2	0.121	n.s.
	Route change[2]	1.35	2	0.509	n.s.
Warm	Mode change[2]	0.22	2	0.898	n.s.
	Time-of-day change[2]	0.48	2	0.787	n.s.
	Location change[2]	0.43	2	0.809	n.s.
	Trip cancellation[2]	2.88	2	0.234	n.s.
	Route change[2]	2.00	2	0.368	n.s.
Storm	Mode change[2]	0.48	2	0.786	n.s.
	Time-of-day change	4.16	6	0.655	n.s.
	Location change[2]	1.38	2	0.501	n.s.
	Trip cancellation[2]	2.84	2	0.241	n.s.
	Route change[2]	0.47	2	0.789	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

[3] Not defined: The condition that 80% of the expected frequencies must be > 5 could not be fulfilled.

Table 11-23: Dependence of behavioral changes on exposure to the weather forecast for shopping trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	0.27	2	0.874	n.s.
	Time-of-day change	11.99	6	0.062	n.s.
	Location change[2]	1.00	2	0.607	n.s.
	Trip cancellation[2]	0.16	2	0.924	n.s.
	Route change[2]	1.90	2	0.388	n.s.
Snow	Mode change[2]	1.14	2	0.567	n.s.
	Time-of-day change	3.09	6	0.797	n.s.
	Location change	11.38	6	0.077	n.s.
	Trip cancellation	12.74	6	0.047	*
	Route change	7.40	6	0.285	n.s.
Heavy rain	Mode change[2]	0.77	2	0.681	n.s.
	Time-of-day change	17.75	6	0.007	**
	Location change	13.89	6	0.031	*
	Trip cancellation	5.58	6	0.472	n.s.
	Route change[2]	1.38	2	0.502	n.s.
Fog	Mode change[2]	4.13	2	0.127	n.s.
	Time-of-day change	6.49	6	0.371	n.s.
	Location change	4.53	6	0.606	n.s.
	Trip cancellation	8.54	6	0.201	n.s.
	Route change[2]	2.42	2	0.300	n.s.
Warm	Mode change[2]	0.98	2	0.613	n.s.
	Time-of-day change	7.13	6	0.309	n.s.
	Location change[2]	0.08	2	0.959	n.s.
	Trip cancellation[2]	3.40	2	0.183	n.s.
	Route change[2]	8.59	2	0.014	*
Storm	Mode change[2]	0.86	2	0.651	n.s.
	Time-of-day change	16.24	6	0.013	*
	Location change	12.53	6	0.051	n.s.
	Trip cancellation	6.37	6	0.383	n.s.
	Route change[2]	2.45	2	0.294	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Table 11-24: Dependence of behavioral changes on exposure to the weather forecast for leisure trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	2.15	2	0.342	n.s.
	Time-of-day change[2]	4.31	2	0.116	n.s.
	Location change[2]	1.31	2	0.520	n.s.
	Trip cancellation[2]	3.76	2	0.153	n.s.
	Route change[2]	0.32	2	0.853	n.s.
Snow	Mode change[2]	2.25	2	0.324	n.s.
	Time-of-day change	14.81	6	0.022	*
	Location change[2]	5.68	2	0.058	n.s.
	Trip cancellation	17.34	6	0.008	**
	Route change	14.87	6	0.021	*
Heavy rain	Mode change[2]	3.62	2	0.163	n.s.
	Time-of-day change	14.95	6	0.021	*
	Location change[2]	5.29	2	0.071	n.s.
	Trip cancellation	17.46	6	0.008	**
	Route change[2]	5.34	2	0.069	n.s.
Fog	Mode change[2]	1.18	2	0.554	n.s.
	Time-of-day change	8.27	6	0.219	n.s.
	Location change[2]	0.262	2	0.877	n.s.
	Trip cancellation	11.13	6	0.084	n.s.
	Route change[2]	6.93	2	0.031	*
Warm	Mode change[2]	2.59	2	0.274	n.s.
	Time-of-day change[2]	2.48	2	0.289	n.s.
	Location change[2]	0.55	2	0.761	n.s.
	Trip cancellation[2]	5.75	2	0.056	n.s.
	Route change[2]	7.81	2	0.020	*
Storm	Mode change[2]	0.764	2	0.682	n.s.
	Time-of-day change	19.80	6	0.003	**
	Location change[2]	5.18	2	0.075	n.s.
	Trip cancellation	20.43	6	0.002	**
	Route change[2]	5.55	2	0.062	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Appendix 3.5: Dependence of behavioral changes on perceived reliability of the weather forecast

Appendix 3.5.1: Aggregated level

Table 11-25: Dependence of behavioral changes on perceived reliability of the weather forecast (aggregated level)

Trip purpose	Weathertype	Chi²	DF	P-value	Signif.[1]
All purposes	All types[2]	158.25	179	0.866	n.s.
Work/school	All types[2]	26.79	59	1	n.s.
Shopping	All types	131.93	239	1	n.s.
Leisure	All types	114.27	239	1	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Table 11-26: Dependence of behavioral changes on perceived reliability of the weather forecast (aggregated level)

Trip purpose	Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Work/school	Cold[2]	All changes	3.57	9	0.937	n.s.
	Snow	All changes	15.72	39	1	n.s.
	Heavy rain[2]	All changes	4.08	9	0.906	n.s.
	Fog[2]	All changes	5.58	9	0.781	n.s.
	Warm[2]	All changes	2.48	9	0.981	n.s.
	Storm[2]	All changes	6.07	9	0.733	n.s.
Shopping	Cold[2]	All changes	11.79	9	0.225	n.s.
	Snow	All changes	21.80	39	0.988	n.s.
	Heavy rain	All changes	27.16	39	0.924	n.s.
	Fog	All changes	16.35	39	0.999	n.s.
	Warm[2]	All changes	2.89	9	0.969	n.s.
	Storm	All changes	18.83	39	0.997	n.s.
Leisure	Cold[2]	All changes	9.54	9	0.389	n.s.
	Snow	All changes	21.62	39	0.989	n.s.
	Heavy rain	All changes	23.32	39	0.978	n.s.
	Fog	All changes	15.26	39	1	n.s.
	Warm[2]	All changes	5.24	9	0.813	n.s.
	Storm	All changes	14.21	39	1	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Appendix 3.5.2: Disaggregated level

Table 11-27: Dependence of behavioral changes on perceived reliability of the weather forecast for commuting trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	1.38	1	0.240	n.s.
	Time-of-day change[2]	0.00	1	0.979	n.s.
	Location change[3]	n.d.	n.d.	n.d.	n.d.
	Trip cancellation[3]	n.d.	n.d.	n.d.	n.d.
	Route change[2]	1.69	1	0.193	n.s.
Snow	Mode change	6.76	3	0.080	n.s.
	Time-of-day change	1.37	3	0.713	n.s.
	Location change[2]	0.12	1	0.734	n.s.
	Trip cancellation[2]	0.14	1	0.711	n.s.
	Route change	2.56	3	0.465	n.s.
Heavy rain	Mode change	3.49	3	0.323	n.s.
	Time-of-day change	3.75	3	0.290	n.s.
	Location change[3]	n.d.	n.d.	n.d.	n.d.
	Trip cancellation[2]	0.32	1	0.571	n.s.
	Route change[2]	0.94	1	0.331	n.s.
Fog	Mode change[3]	n.d.	n.d.	n.d.	n.d.
	Time-of-day change	1.46	3	0.692	n.s.
	Location change[3]	n.d.	n.d.	n.d.	n.d.
	Trip cancellation[3]	n.d.	n.d.	n.d.	n.d.
	Route change[2]	2.88	1	0.090	n.s.
Warm	Mode change[2]	0.21	1	0.643	n.s.
	Time-of-day change[3]	n.d.	n.d.	n.d.	n.d.
	Location change[3]	n.d.	n.d.	n.d.	n.d.
	Trip cancellation[2]	0.16	1	0.693	n.s.
	Route change[3]	n.d.	n.d.	n.d.	n.d.
Storm	Mode change[2]	4.34	1	0.037	*
	Time-of-day change[2]	0.39	1	0.531	n.s.
	Location change[2]	0.05	1	0.831	n.s.
	Trip cancellation[2]	1.19	1	0.275	n.s.
	Route change[2]	0.10	1	0.752	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

[3] Not defined: The condition that 80% of the expected frequencies must be > 5 could not be fulfilled.

Table 11-28: Dependence of behavioral changes on perceived reliability of the weather forecast for shopping trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	0.17	1	0.677	n.s.
	Time-of-day change[2]	0.81	1	0.370	n.s.
	Location change[2]	3.66	1	0.056	n.s.
	Trip cancellation[2]	7.03	1	0.008	**
	Route change[2]	0.12	1	0.725	n.s.
Snow	Mode change	3.81	3	0.282	n.s.
	Time-of-day change	10.39	3	0.016	*
	Location change	0.61	3	0.895	n.s.
	Trip cancellation	2.96	3	0.398	n.s.
	Route change	4.04	3	0.258	n.s.
Heavy rain	Mode change	2.90	3	0.407	n.s.
	Time-of-day change	6.76	3	0.080	n.s.
	Location change	9.10	3	0.028	*
	Trip cancellation	5.03	3	0.170	n.s.
	Route change[2]	1.91	1	0.167	n.s.
Fog	Mode change[2]	0.03	1	0.872	n.s.
	Time-of-day change	3.97	3	0.265	n.s.
	Location change	4.39	3	0.222	n.s.
	Trip cancellation	5.22	3	0.156	n.s.
	Route change[2]	0.21	1	0.644	n.s.
Warm	Mode change[2]	0.87	1	0.351	n.s.
	Time-of-day change[2]	0.13	1	0.723	n.s.
	Location change[2]	1.23	1	0.268	n.s.
	Trip cancellation[2]	0.61	1	0.433	n.s.
	Route change[2]	0.05	1	0.822	n.s.
Storm	Mode change[2]	0.95	1	0.329	n.s.
	Time-of-day change	5.01	3	0.171	n.s.
	Location change	8.19	3	0.042	*
	Trip cancellation	1.77	3	0.622	n.s.
	Route change[2]	1.50	1	0.220	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Table 11-29: Dependence of behavioral changes on perceived reliability of the weather forecast for leisure trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	2.90	1	0.089	n.s.
	Time-of-day change[2]	1.33	1	0.248	n.s.
	Location change[2]	2.24	1	0.134	n.s.
	Trip cancellation[2]	2.88	1	0.090	n.s.
	Route change[2]	0.20	1	0.658	n.s.
Snow	Mode change	3.89	3	0.273	n.s.
	Time-of-day change	4.52	3	0.211	n.s.
	Location change	5.69	3	0.128	n.s.
	Trip cancellation	0.20	3	0.978	n.s.
	Route change	7.33	3	0.062	n.s.
Heavy rain	Mode change[2]	0.82	1	0.364	n.s.
	Time-of-day change	2.92	3	0.405	n.s.
	Location change	4.05	3	0.256	n.s.
	Trip cancellation	3.41	3	0.333	n.s.
	Route change	9.56	3	0.022	*
Fog	Mode change[2]	0.23	1	0.635	n.s.
	Time-of-day change	4.92	3	0.178	n.s.
	Location change[2]	2.01	1	0.156	n.s.
	Trip cancellation	3.78	3	0.286	n.s.
	Route change[2]	3.27	1	0.070	n.s.
Warm	Mode change	3.47	3	0.325	n.s.
	Time-of-day change[2]	0.41	1	0.520	n.s.
	Location change[2]	1.56	1	0.212	n.s.
	Trip cancellation[2]	1.55	1	0.213	n.s.
	Route change[3]	n.d.	n.d.	n.d.	n.d.
Storm	Mode change[2]	1.91	1	0.167	n.s.
	Time-of-day change	1.16	3	0.762	n.s.
	Location change	3.34	3	0.952	n.s.
	Trip cancellation	0.70	3	0.874	n.s.
	Route change	9.39	3	0.025	*

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

[3] Not defined: The condition that 80% of the expected frequencies must be > 5 could not be fulfilled.

Appendix 3.6: Dependence of behavioral changes on media source of the weather forecast used by the respondent

Appendix 3.6.1: Aggregated level

Table 11-30: Dependence of behavioral changes on media source of the weather forecast used by the respondent (aggregated level)

Trip purpose	Weathertype	Chi²	DF	P-value	Signif.[1]
All purposes	All types	740.19	1068	1	n.s.
Work/school	All types[2]	94.54	177	1	n.s.
Shopping	All types	239.08	357	1	n.s.
Leisure	All types	251.43	357	1	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Table 11-31: Dependence of behavioral changes on media source of the weather forecast used by the respondent (aggregated level)

Trip purpose	Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Work/school	Cold[2]	All changes	16.70	27	0.938	n.s.
	Snow	All changes	51.26	57	0.689	n.s.
	Heavy rain[2]	All changes	14.99	27	0.970	n.s.
	Fog[2]	All changes	18.77	27	0.878	n.s.
	Warm[2]	All changes	10.05	27	0.999	n.s.
	Storm[2]	All changes	20.12	27	0.826	n.s.
Shopping	Cold[2]	All changes	15.58	27	0.961	n.s.
	Snow	All changes	38.09	57	0.975	n.s.
	Heavy rain	All changes	35.03	57	0.990	n.s.
	Fog	All changes	52.43	57	0.647	n.s.
	Warm[2]	All changes	19.60	27	0.847	n.s.
	Storm	All changes	31.66	57	0.997	n.s.
Leisure	Cold[2]	All changes	15.56	27	0.961	n.s.
	Snow	All changes	43.79	57	0.901	n.s.
	Heavy rain	All changes	39.01	57	0.967	n.s.
	Fog	All changes	52.41	57	0.648	n.s.
	Warm[2]	All changes	21.51	27	0.762	n.s.
	Storm	All changes	38.34	57	0.973	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Appendix 3.6.2: Disaggregated level

Table 11-32: Dependence of behavioral changes on media source of the weather forecast used by the respondent in commuting trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	1.20	3	0.753	n.s.
	Time-of-day change[2]	1.23	3	0.747	n.s.
	Location change[3]	n.d.	n.d.	n.d.	n.d.
	Trip cancellation[2]	2.97	3	0.397	n.s.
	Route change[2]	5.78	3	0.123	n.s.
Snow	Mode change	8.96	9	0.441	n.s.
	Time-of-day change	2.61	9	0.978	n.s.
	Location change[2]	3.48	3	0.324	n.s.
	Trip cancellation[2]	1.63	3	0.653	n.s.
	Route change	18.90	9	0.026	*
Heavy rain	Mode change	6.90	9	0.647	n.s.
	Time-of-day change	3.15	9	0.958	n.s.
	Location change[2]	0.94	3	0.815	n.s.
	Trip cancellation[2]	4.15	3	0.246	n.s.
	Route change[2]	4.18	3	0.242	n.s.
Fog	Mode change[2]	0.624	3	0.891	n.s.
	Time-of-day change	11.48	9	0.244	n.s.
	Location change[2]	1.18	3	0.759	n.s.
	Trip cancellation[2]	4.58	3	0.205	n.s.
	Route change[2]	3.97	3	0.265	n.s.
Warm	Mode change	10.91	9	0.282	n.s.
	Time-of-day change[2]	1.35	3	0.716	n.s.
	Location change[2]	3.00	3	0.391	n.s.
	Trip cancellation[2]	0.55	3	0.909	n.s.
	Route change[2]	1.21	3	0.750	n.s.
Storm	Mode change[2]	7.19	3	0.067	n.s.
	Time-of-day change	11.27	9	0.257	n.s.
	Location change[2]	1.26	3	0.738	n.s.
	Trip cancellation[2]	4.62	3	0.202	n.s.
	Route change[2]	3.20	3	0.362	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

[3] Not defined: The condition that 80% of the expected frequencies must be > 5 could not be fulfilled.

Table 11-33: Dependence of behavioral changes on media source of the weather forecast used by the respondent in shopping trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	1.06	3	0.787	n.s.
	Time-of-day change	5.11	9	0.825	n.s.
	Location change[2]	3.13	3	0.372	n.s.
	Trip cancellation[2]	3.69	3	0.297	n.s.
	Route change[2]	4.73	3	0.193	n.s.
Snow	Mode change	3.28	9	0.952	n.s.
	Time-of-day change	8.36	9	0.498	n.s.
	Location change	7.06	9	0.631	n.s.
	Trip cancellation	11.91	9	0.218	n.s.
	Route change	7.47	9	0.588	n.s.
Heavy rain	Mode change	8.19	9	0.515	n.s.
	Time-of-day change	5.23	9	0.814	n.s.
	Location change	2.64	9	0.977	n.s.
	Trip cancellation	5.82	9	0.758	n.s.
	Route change[2]	7.83	3	0.050	*
Fog	Mode change[2]	3.87	3	0.276	n.s.
	Time-of-day change	7.57	9	0.578	n.s.
	Location change	7.37	9	0.599	n.s.
	Trip cancellation	12.78	9	0.173	n.s.
	Route change	16.96	9	0.049	*
Warm	Mode change	7.63	9	0.572	n.s.
	Time-of-day change	3.64	9	0.933	n.s.
	Location change[2]	3.51	3	0.319	n.s.
	Trip cancellation[2]	1.51	3	0.679	n.s.
	Route change[2]	7.49	3	0.058	n.s.
Storm	Mode change	4.47	9	0.888	n.s.
	Time-of-day change	3.72	9	0.929	n.s.
	Location change	5.76	9	0.764	n.s.
	Trip cancellation	6.41	9	0.698	n.s.
	Route change	11.30	9	0.256	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Table 11-34: Dependence of behavioral changes on media source of the weather forecast used by the respondent in leisure trips (disaggregated level)

Weathertype	Behavioral change	Chi²	DF	P-value	Signif.[1]
Cold	Mode change[2]	5.97	3	0.113	n.s.
	Time-of-day change[2]	1.31	3	0.728	n.s.
	Location change	5.80	9	0.760	n.s.
	Trip cancellation	3.94	9	0.915	n.s.
	Route change[2]	5.93	3	0.115	n.s.
Snow	Mode change	9.17	9	0.422	n.s.
	Time-of-day change	7.91	9	0.543	n.s.
	Location change	7.45	9	0.591	n.s.
	Trip cancellation	9.75	9	0.371	n.s.
	Route change	9.50	9	0.392	n.s.
Heavy rain	Mode change[2]	5.26	3	0.154	n.s.
	Time-of-day change	7.69	9	0.566	n.s.
	Location change	5.47	9	0.791	n.s.
	Trip cancellation	8.72	9	0.463	n.s.
	Route change	10.08	9	0.344	n.s.
Fog	Mode change[2]	9.19	3	0.027	*
	Time-of-day change	10.16	9	0.338	n.s.
	Location change	5.46	9	0.792	n.s.
	Trip cancellation	11.62	9	0.235	n.s.
	Route change	13.34	9	0.148	n.s.
Warm	Mode change	4.73	9	0.857	n.s.
	Time-of-day change[2]	11.59	3	0.009	**
	Location change	10.07	9	0.345	n.s.
	Trip cancellation[2]	2.62	3	0.454	n.s.
	Route change[2]	2.91	3	0.405	n.s.
Storm	Mode change[2]	4.83	3	0.185	n.s.
	Time-of-day change	13.76	9	0.131	n.s.
	Location change	4.06	9	0.907	n.s.
	Trip cancellation	7.69	9	0.566	n.s.
	Route change	5.77	9	0.762	n.s.

[1] Significance: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

[2] Estimated using reduced answer possibilities (yes/no)

Appendix 4: Results of the MNL-models

Appendix 4.1: Commuting trips (only workers)

Table 11-35: P-values of the type-III test when modeling the preferred adaptation in commuting trips (only workers)

Score Statistics For Type 3 GEE Analysis			
Source	**DF**	**Chi-Square**	**Pr > ChiSq**
Intercept	5	371.61	<.0001
Flexible working hours	5	14.97	0.0105
Children	5	10.77	0.0562
Weathertype	25	205.91	<.0001

Table 11-36: Parameter estimates when modeling the preferred adaptation in commuting trips (only workers)

Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Intercept	Cancellation		-1.3753	0.3756	-3.66	0.0003
Intercept	Location change		-2.5759	0.7458	-3.45	0.0006
Intercept	Mode change		-2.5666	0.3649	-7.03	<.0001
Intercept	Route change		-4.3893	0.5285	-8.30	<.0001
Intercept	Time-of day-change		-4.9144	0.4911	-10.01	<.0001
Flexible working hours	Cancellation	No flexible working hours	-0.6252	0.3639	-1.72	0.0858
Flexible working hours	Cancellation	Flexible working hours	0.0000	0.0000	.	.
Flexible working hours	Location change	No flexible working hours	-1.8106	0.4885	-3.71	0.0002
Flexible working hours	Location change	Flexible working hours	0.0000	0.0000	.	.
Flexible working hours	Mode change	No flexible working hours	0.2580	0.3065	0.84	0.3998
Flexible working hours	Mode change	Flexible working hours	0.0000	0.0000	.	.

Parameter			Estimate	Standard Error	Z	Pr > |Z|
Flexible working hours	Route change	No flexible working hours	0.3522	0.3722	0.95	0.3441
Flexible working hours	Route change	Flexible working hours	0.0000	0.0000	.	.
Flexible working hours	Time-of-day-change	No flexible working hours	0.6324	0.2933	2.16	0.0311
Flexible working hours	Time-of-day-change	Flexible working hours	0.0000	0.0000	.	.
Children	Cancellation	Yes	-0.4395	0.3243	-1.36	0.1754
Children	Cancellation	No	0.0000	0.0000	.	.
Children	Location change	Yes	-0.4918	0.5021	-0.98	0.3273
Children	Location change	No	0.0000	0.0000	.	.
Children	Mode change	Yes	0.6393	0.3135	2.04	0.0414
Children	Mode change	No	0.0000	0.0000	.	.
Children	Route change	Yes	-0.5069	0.2937	-1.73	0.0844
Children	Route change	No	0.0000	0.0000	.	.
Children	Time-of day-change	Yes	0.2574	0.2785	0.92	0.3554
Children	Time-of day-change	No	0.0000	0.0000	.	.
Weathertype	Cancellation	Cold temperatures	-1.1659	0.3229	-3.61	0.0003
Weathertype	Cancellation	Fog	-1.3842	0.3847	-3.60	0.0003
Weathertype	Cancellation	Heavy rain/thunderstorm	-1.2483	0.3326	-3.75	0.0002
Weathertype	Cancellation	Snow/freezing rain	0.8847	0.2182	4.05	<.0001
Weathertype	Cancellation	Storm/heavy wind	-0.7848	0.2863	-2.74	0.0061
Weathertype	Cancellation	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Location change	Cold temperatures	0.3547	0.4065	0.87	0.3828
Weathertype	Location change	Fog	0.2313	0.6206	0.37	0.7094
Weathertype	Location change	Heavy rain/thunderstorm	0.3387	0.5040	0.67	0.5016
Weathertype	Location change	Snow/freezing rain	1.1760	0.4471	2.63	0.0085
Weathertype	Location change	Storm/heavy wind	0.7167	0.3146	2.28	0.0227
Weathertype	Location change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Mode change	Cold temperatures	-1.3626	0.3204	-4.25	<.0001
Weathertype	Mode change	Fog	-1.1673	0.3839	-3.04	0.0024
Weathertype	Mode change	Heavy rain/thunderstorm	-0.3406	0.3012	-1.13	0.2581

Parameter			Estimate	Standard Error	Z	Pr > |Z|
Weathertype	Mode change	Snow/freezing rain	0.0944	0.2585	0.37	0.7148
Weathertype	Mode change	Storm/heavy wind	-0.5770	0.2875	-2.01	0.0448
Weathertype	Mode change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Route change	Cold temperatures	1.7697	0.5104	3.47	0.0005
Weathertype	Route change	Fog	2.1431	0.5061	4.23	<.0001
Weathertype	Route change	Heavy rain/thunderstorm	2.1085	0.5111	4.13	<.0001
Weathertype	Route change	Snow/freezing rain	2.7904	0.5072	5.50	<.0001
Weathertype	Route change	Storm/heavy wind	1.8518	0.5143	3.60	0.0003
Weathertype	Route change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Time-of day-change	Cold temperatures	1.4420	0.4432	3.25	0.0011
Weathertype	Time-of day-change	Fog	2.4971	0.4464	5.59	<.0001
Weathertype	Time-of day-change	Heavy rain/thunderstorm	2.3293	0.4412	5.28	<.0001
Weathertype	Time-of day-change	Snow/freezing rain	2.4676	0.4564	5.41	<.0001
Weathertype	Time-of day-change	Storm/heavy wind	2.0403	0.4516	4.52	<.0001
Weathertype	Time-of day-change	Warm temperatures	0.0000	0.0000	.	.

Table 11-37: Contrast results when modeling the preferred adaptation in commuting trips (only workers)

Contrast	DF	Chi-Square	Pr > ChiSq
weathertype cancel cold-fog	1	0.31	0.5795
weathertype cancel cold-rain	1	0.14	0.7116
weathertype cancel cold-snow	1	43.05	<.0001
weathertype cancel cold-storm	1	2.71	0.0994
weathertype cancel cold-warm	1	12.10	0.0005
weathertype cancel fog-rain	1	0.16	0.6858
weathertype cancel fog-snow	1	48.79	<.0001
weathertype cancel fog-storm	1	4.59	0.0321

Contrast	DF	Chi-Square	Pr > Chi Sq
weathertype cancel fog-warm	1	12.00	0.0005
weathertype cancel rain-snow	1	45.69	<.0001
weathertype cancel rain-storm	1	6.24	0.0125
weathertype cancel rain-warm	1	13.34	0.0003
weathertype cancel snow-storm	1	39.66	<.0001
weathertype cancel snow-warm	1	17.36	<.0001
weathertype cancel storm-warm	1	6.78	0.0092
weathertype location cold-fog	1	0.06	0.8056
weathertype location cold-rain	1	0.00	0.9733
weathertype location cold-snow	1	8.79	0.0030
weathertype location cold-storm	1	1.41	0.2345
weathertype location cold-warm	1	0.82	0.3643
weathertype location fog-rain	1	0.09	0.7586
weathertype location fog-snow	1	5.47	0.0193
weathertype location fog-storm	1	1.16	0.2822
weathertype location fog-warm	1	0.15	0.7006
weathertype location rain-snow	1	4.52	0.0335
weathertype location rain-storm	1	1.25	0.2643
weathertype location rain-warm	1	0.53	0.4679
weathertype location snow-storm	1	3.10	0.0783
weathertype location snow-warm	1	10.04	0.0015
weathertype location storm-warm	1	7.94	0.0048
weathertype mode change cold-fog	1	0.27	0.6011
weathertype mode change cold-rain	1	10.07	0.0015
weathertype mode change cold-snow	1	23.00	<.0001
weathertype mode change cold-storm	1	8.95	0.0028
weathertype mode change cold-warm	1	16.24	<.0001
weathertype mode change fog-rain	1	8.00	0.0047
weathertype mode change fog-snow	1	24.33	<.0001
weathertype mode change fog-storm	1	3.21	0.0731
weathertype mode change fog-warm	1	10.85	0.0010
weathertype mode change rain-snow	1	6.16	0.0131
weathertype mode change rain-storm	1	1.53	0.2158
weathertype mode change rain-warm	1	1.30	0.2533
weathertype mode change snow-storm	1	12.32	0.0004

Contrast	**DF**	**Chi-Square**	**Pr > Chi Sq**
weathertype mode change snow-warm	1	0.13	0.7146
weathertype mode change storm-warm	1	3.94	0.0472
weathertype route change cold-fog	1	2.32	0.1277
weathertype route change cold-rain	1	1.38	0.2399
weathertype route change cold-snow	1	17.62	<.0001
weathertype route change cold-storm	1	0.09	0.7584
weathertype route change cold-warm	1	12.05	0.0005
weathertype route change fog-rain	1	0.02	0.8824
weathertype route change fog-snow	1	9.33	0.0023
weathertype route change fog-storm	1	1.75	0.1863
weathertype route change fog-warm	1	20.24	<.0001
weathertype route change rain-snow	1	9.82	0.0017
weathertype route change rain-storm	1	1.57	0.2105
weathertype route change rain-warm	1	17.76	<.0001
weathertype route change snow-storm	1	13.22	0.0003
weathertype route change snow-warm	1	39.08	<.0001
weathertype route change storm-warm	1	12.62	0.0004
weathertype time-of-departure change cold-fog	1	15.08	0.0001
weathertype time-of-departure change cold-rain	1	11.33	0.0008
weathertype time-of-departure change cold-snow	1	14.30	0.0002
weathertype time-of-departure change cold-storm	1	5.14	0.0234
weathertype time-of-departure change cold-warm	1	10.02	0.0015
weathertype time-of-departure change fog-rain	1	0.90	0.3434
weathertype time-of-departure change fog-snow	1	0.02	0.8781
weathertype time-of-departure change fog-storm	1	4.72	0.0298
weathertype time-of-departure change fog-warm	1	34.08	<.0001
weathertype time-of-departure change rain-snow	1	0.40	0.5274
weathertype time-of-departure change rain-storm	1	2.35	0.1251
weathertype time-of-departure change rain-warm	1	31.03	<.0001
weathertype time-of-departure change snow-storm	1	4.19	0.0406
weathertype time-of-departure change snow-warm	1	32.49	<.0001
weathertype time-of-departure change storm-warm	1	20.39	<.0001

Appendix 4.2: Commuting trips (workers + students)

Table 11-38: P-values of the type-III test when modeling the preferred adaptation in commuting trips (workers + students)

Score Statistics For Type 3 GEE Analysis			
Source	**DF**	**Chi-Square**	**Pr > ChiSq**
Intercept	5	101.40	<.0001
Age	5	42.06	<.0001
Children	5	12.32	0.0307
Public transport card	5	16.71	0.0051
Urbanization degree	15	40.45	0.0004
Weathertype	25	272.39	<.0001

Table 11-39: Parameter estimates when modeling the preferred adaptation in commuting trips (workers + students)

Parameter			**Est.**	**Standard Error**	**Z**	**Pr > |Z|**
Intercept	Cancellation		-1.6853	0.5809	-2.90	0.0037
Intercept	Location change		-1.4986	1.3752	-1.09	0.2759
Intercept	Mode change		-1.8314	0.5312	-3.45	0.0006
Intercept	Route change		-5.2692	0.6569	-8.02	<.0001
Intercept	Time-of-day change		-3.2604	0.5309	-6.14	<.0001
Age	Cancellation		-0.0159	0.0079	-2.02	0.0438
Age	Location change		-0.0575	0.0156	-3.69	0.0002
Age	Mode change		-0.0236	0.0076	-3.12	0.0018
Age	Route change		-0.0154	0.0078	-1.98	0.0476
Age	Time-of-day change		-0.0238	0.0058	-4.07	<.0001
Children	Cancellation		-0.3015	0.2937	-1.03	0.3048
Children	Location change		-0.4087	0.4533	-0.90	0.3672
Children	Mode change		0.6858	0.2739	2.50	0.0123
Children	Route change		-0.3136	0.2661	-1.18	0.2385
Children	Time-of-day change		0.3217	0.2607	1.23	0.2172

Parameter			Est.	Standard Error	Z	Pr > |Z|
Public transport card	Cancellation	No	-0.1557	0.2734	-0.57	0.5689
Public transport card	Cancellation	Yes	0.0000	0.0000	.	.
Public transport card	Location change	No	0.0040	0.3522	0.01	0.9909
Public transport card	Location change	Yes	0.0000	0.0000	.	.
Public transport card	Mode change	No	-0.1293	0.2292	-0.56	0.5727
Public transport card	Mode change	Yes	0.0000	0.0000	.	.
Public transport card	Route change	No	1.0095	0.3152	3.20	0.0014
Public transport card	Route change	Yes	0.0000	0.0000	.	.
Public transport card	Time-of-day change	No	0.3808	0.2344	1.62	0.1042
Public transport card	Time-of-day change	Yes	0.0000	0.0000	.	.
Urbanization degree	Cancellation	Central municipalities of the most important agglomerations	-0.1783	0.4428	-0.40	0.6872
Urbanization degree	Cancellation	Municipalities with moderate morphogolical urbanization	0.3255	0.4289	0.76	0.4479
Urbanization degree	Cancellation	Municipalities with strong morphogolical urbanization	0.9189	0.4908	1.87	0.0612
Urbanization degree	Cancellation	Municipalities with weak morphogolical urbanization	0.0000	0.0000	.	.
Urbanization degree	Location change	Central municipalities of the most important agglomerations	-0.7997	0.7318	-1.09	0.2745
Urbanization degree	Location change	Municipalities with moderate morphogolical urbanization	-0.1434	0.6611	-0.22	0.8283
Urbanization degree	Location change	Municipalities with strong morphogolical urbanization	-1.8302	0.7054	-2.59	0.0095
Urbanization degree	Location change	Municipalities with weak morphogolical urbanization	0.0000	0.0000	.	.
Urbanization degree	Mode change	Central municipalities of the most important agglomerations	1.0286	0.3976	2.59	0.0097
Urbanization degree	Mode change	Municipalities with moderate morphogolical urbanization	0.3650	0.3558	1.03	0.3050
Urbanization degree	Mode change	Municipalities with strong morphogolical urbanization	-0.0011	0.4330	-0.00	0.9979

Parameter			Est.	Standard Error	Z	Pr > |Z|
Urbanization degree	Mode change	Municipalities with weak morphogolical urbanization	0.0000	0.0000	.	.
Urbanization degree	Route change	Central municipalities of the most important agglomerations	0.7807	0.4274	1.83	0.0678
Urbanization degree	Route change	Municipalities with moderate morphogolical urbanization	0.9019	0.3237	2.79	0.0053
Urbanization degree	Route change	Municipalities with strong morphogolical urbanization	0.7926	0.4379	1.81	0.0703
Urbanization degree	Route change	Municipalities with weak morphogolical urbanization	0.0000	0.0000	.	.
Urbanization degree	Time-of-day change	Central municipalities of the most important agglomerations	-0.7616	0.3667	-2.08	0.0378
Urbanization degree	Time-of-day change	Municipalities with moderate morphogolical urbanization	-0.5114	0.2809	-1.82	0.0687
Urbanization degree	Time-of-day change	Municipalities with strong morphogolical urbanization	-0.3387	0.3587	-0.94	0.3450
Urbanization degree	Time-of-day change	Municipalities with weak morphogolical urbanization	0.0000	0.0000	.	.
Weathertype	Cancellation	Cold temperatures	-1.1142	0.2902	-3.84	0.0001
Weathertype	Cancellation	Fog	-1.1772	0.3241	-3.63	0.0003
Weathertype	Cancellation	Heavy rain/thunderstorm	-0.7252	0.2395	-3.03	0.0025
Weathertype	Cancellation	Snow/freezing rain	0.9604	0.1986	4.84	<.0001
Weathertype	Cancellation	Storm/heavy wind	-0.5009	0.2378	-2.11	0.0352
Weathertype	Cancellation	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Location change	Cold temperatures	0.3823	0.3900	0.98	0.3270
Weathertype	Location change	Fog	0.3137	0.5831	0.54	0.5907
Weathertype	Location change	Heavy rain/thunderstorm	0.6993	0.4794	1.46	0.1447
Weathertype	Location change	Snow/freezing rain	1.4058	0.4458	3.15	0.0016
Weathertype	Location change	Storm/heavy wind	0.9935	0.3451	2.88	0.0040
Weathertype	Location change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Mode change	Cold temperatures	-1.2043	0.2414	-4.99	<.0001
Weathertype	Mode change	Fog	-1.2378	0.3241	-3.82	0.0001
Weathertype	Mode change	Heavy rain/thunderstorm	-0.1223	0.2488	-0.49	0.6230
Weathertype	Mode change	Snow/freezing rain	0.1946	0.2208	0.88	0.3781
Weathertype	Mode change	Storm/heavy wind	-0.3949	0.2339	-1.69	0.0914
Weathertype	Mode change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Route change	Cold temperatures	1.8210	0.4791	3.80	0.0001
Weathertype	Route change	Fog	2.2484	0.4779	4.70	<.0001

Parameter			Est.	Standard Error	Z	Pr > |Z|
Weathertype	Route change	Heavy rain/thunderstorm	2.1452	0.4809	4.46	<.0001
Weathertype	Route change	Snow/freezing rain	2.8598	0.4808	5.95	<.0001
Weathertype	Route change	Storm/heavy wind	1.9254	0.4825	3.99	<.0001
Weathertype	Route change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Time-of-day change	Cold temperatures	1.2554	0.3559	3.53	0.0004
Weathertype	Time-of-day change	Fog	2.2328	0.3530	6.33	<.0001
Weathertype	Time-of-day change	Heavy rain/thunderstorm	2.1494	0.3481	6.17	<.0001
Weathertype	Time-of-day change	Snow/freezing rain	2.1947	0.3563	6.16	<.0001
Weathertype	Time-of-day change	Storm/heavy wind	1.8613	0.3579	5.20	<.0001
Weathertype	Time-of-day change	Warm temperatures	0.0000	0.0000	.	.

Table 11-40: Contrast results when modeling the preferred adaptation in commuting trips (workers + students)

Contrast	DF	Chi-Square	Pr > ChiSq
weathertype cancel cold-fog	1	0.03	0.8531
weathertype cancel cold-rain	1	4.11	0.0426
weathertype cancel cold-snow	1	58.72	<.0001
weathertype cancel cold-storm	1	9.10	0.0026
weathertype cancel cold-warm	1	13.62	0.0002
weathertype cancel fog-rain	1	3.59	0.0580
weathertype cancel fog-snow	1	62.86	<.0001
weathertype cancel fog-storm	1	9.64	0.0019
weathertype cancel fog-warm	1	11.64	0.0006
weathertype cancel rain-snow	1	50.74	<.0001
weathertype cancel rain-storm	1	2.91	0.0878
weathertype cancel rain-warm	1	7.54	0.0060
weathertype cancel snow-storm	1	46.88	<.0001
weathertype cancel snow-warm	1	26.77	<.0001
weathertype cancel storm-warm	1	3.93	0.0473

Contrast	DF	Chi-Square	Pr > ChiSq
weathertype location cold-fog	1	0.02	0.8802
weathertype location cold-rain	1	0.65	0.4207
weathertype location cold-snow	1	17.69	<.0001
weathertype location cold-storm	1	5.33	0.0209
weathertype location cold-warm	1	1.07	0.3000
weathertype location fog-rain	1	1.75	0.1855
weathertype location fog-snow	1	10.50	0.0012
weathertype location fog-storm	1	3.35	0.0671
weathertype location fog-warm	1	0.32	0.5709
weathertype location rain-snow	1	5.83	0.0157
weathertype location rain-storm	1	1.44	0.2309
weathertype location rain-warm	1	3.20	0.0737
weathertype location snow-storm	1	4.17	0.0411
weathertype location snow-warm	1	18.83	<.0001
weathertype location storm-warm	1	17.78	<.0001
weathertype mode change cold-fog	1	0.01	0.9087
weathertype mode change cold-rain	1	15.85	<.0001
weathertype mode change cold-snow	1	29.61	<.0001
weathertype mode change cold-storm	1	13.48	0.0002
weathertype mode change cold-warm	1	20.70	<.0001
weathertype mode change fog-rain	1	17.16	<.0001
weathertype mode change fog-snow	1	35.40	<.0001
weathertype mode change fog-storm	1	9.33	0.0022
weathertype mode change fog-warm	1	17.49	<.0001
weathertype mode change rain-snow	1	5.71	0.0169
weathertype mode change rain-storm	1	2.96	0.0853
weathertype mode change rain-warm	1	0.24	0.6208
weathertype mode change snow-storm	1	13.94	0.0002
weathertype mode change snow-warm	1	0.77	0.3805
weathertype mode change storm-warm	1	2.81	0.0935
weathertype route change cold-fog	1	3.55	0.0595
weathertype route change cold-rain	1	1.53	0.2157
weathertype route change cold-snow	1	21.80	<.0001
weathertype route change cold-storm	1	0.19	0.6608
weathertype route change cold-warm	1	15.06	0.0001

Contrast	DF	Chi-Square	Pr > ChiSq
weathertype route change fog-rain	1	0.24	0.6273
weathertype route change fog-snow	1	10.75	0.0010
weathertype route change fog-storm	1	2.46	0.1168
weathertype route change fog-warm	1	26.07	<.0001
weathertype route change rain-snow	1	12.73	0.0004
weathertype route change rain-storm	1	1.34	0.2464
weathertype route change rain-warm	1	21.50	<.0001
weathertype route change snow-storm	1	15.99	<.0001
weathertype route change snow-warm	1	47.73	<.0001
weathertype route change storm-warm	1	16.31	<.0001
weathertype time-of-departure change cold-fog	1	16.80	<.0001
weathertype time-of-departure change cold-rain	1	16.03	<.0001
weathertype time-of-departure change cold-snow	1	15.47	<.0001
weathertype time-of-departure change cold-storm	1	7.29	0.0069
weathertype time-of-departure change cold-warm	1	11.44	0.0007
weathertype time-of-departure change fog-rain	1	0.29	0.5897
weathertype time-of-departure change fog-snow	1	0.05	0.8257
weathertype time-of-departure change fog-storm	1	4.04	0.0445
weathertype time-of-departure change fog-warm	1	39.13	<.0001
weathertype time-of-departure change rain-snow	1	0.06	0.8119
weathertype time-of-departure change rain-storm	1	3.22	0.0729
weathertype time-of-departure change rain-warm	1	39.93	<.0001
weathertype time-of-departure change snow-storm	1	3.27	0.0706
weathertype time-of-departure change snow-warm	1	36.61	<.0001
weathertype time-of-departure change storm-warm	1	25.68	<.0001

Appendix 4.3: Shopping trips

Table 11-41: P-values of the type-III test when modeling the preferred adaptation in shopping trips

Score Statistics For Type 3 GEE Analysis			
Source	**DF**	**Chi-Square**	**Pr > ChiSq**
Intercept	5	105.45	<.0001
Gender	5	17.66	0.0034
Driving license	5	14.13	0.0148
Statute	10	20.82	0.0224
Weathertype	25	267.98	<.0001

Table 11-42: Parameter estimates when modeling the preferred adaptation in shopping trips

Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Intercept	Cancellation		-2.6748	0.2472	-10.82	<.0001
Intercept	Location change		-3.2806	0.3143	-10.44	<.0001
Intercept	Mode change		-1.4231	0.2746	-5.18	<.0001
Intercept	Route change		-3.9136	0.7225	-5.42	<.0001
Intercept	Time-of-day change		-2.6600	0.3846	-6.92	<.0001
Gender	Cancellation	Female	0.5229	0.1847	2.83	0.0046
Gender	Cancellation	Male	0.0000	0.0000	.	.
Gender	Location change	Female	0.6118	0.2840	2.15	0.0313
Gender	Location change	Male	0.0000	0.0000	.	.
Gender	Mode change	Female	-0.6226	0.3063	-2.03	0.0421
Gender	Mode change	Male	0.0000	0.0000	.	.
Gender	Route change	Female	-0.8014	0.5904	-1.36	0.1746
Gender	Route change	Male	0.0000	0.0000	.	.
Gender	Time-of-day change	Female	-0.1556	0.2738	-0.57	0.5697

Parameter			Estimate	Standard Error	Z	Pr > |Z|
Gender	Time-of-day change	Male	0.0000	0.0000	.	.
Driving license	Cancellation	No	0.7746	0.3926	1.97	0.0485
Driving license	Cancellation	Yes	0.0000	0.0000	.	.
Driving license	Location change	No	-0.0607	0.3906	-0.16	0.8766
Driving license	Location change	Yes	0.0000	0.0000	.	.
Driving license	Mode change	No	-1.4657	0.4352	-3.37	0.0008
Driving license	Mode change	Yes	0.0000	0.0000	.	.
Driving license	Route change	No	-0.9882	0.8451	-1.17	0.2423
Driving license	Route change	Yes	0.0000	0.0000	.	.
Driving license	Time-of-day change	No	-0.1170	0.4213	-0.28	0.7812
Driving license	Time-of-day change	Yes	0.0000	0.0000	.	.
Statute	Cancellation	Professional active (e.g. employment, public servant, independent working, labourer)	0.5912	0.2165	2.73	0.0063
Statute	Cancellation	Not professional active (e.g. retired, unemployed)	0.8260	0.3823	2.16	0.0307
Statute	Cancellation	Student	0.0000	0.0000	.	.
Statute	Location change	Professional active (e.g. employment, public servant, independent working, labourer)	0.1899	0.2748	0.69	0.4895
Statute	Location change	Not professional active (e.g. retired, unemployed)	0.6655	0.4580	1.45	0.1462
Statute	Location change	Student	0.0000	0.0000	.	.
Statute	Mode change	Professional active (e.g. employment, public servant, independent working, labourer)	-0.1281	0.3006	-0.43	0.6700
Statute	Mode change	Not professional active (e.g. retired, unemployed)	-0.6660	0.4314	-1.54	0.1227
Statute	Mode change	Student	0.0000	0.0000	.	.
Statute	Route change	Professional active (e.g. employment, public servant, independent working, labourer)	-0.8329	0.4404	-1.89	0.0586

Parameter			Estimate	Standard Error	Z	Pr > |Z|
Statute	Route change	Not professional active (e.g. retired, unemployed)	0.4247	0.8360	0.51	0.6114
Statute	Route change	Student	0.0000	0.0000	.	.
Statute	Time-of-day change	Professional active (e.g. employment, public servant, independent working, labourer)	-0.7039	0.2775	-2.54	0.0112
Statute	Time-of-day change	Not professional active (e.g. retired, unemployed)	-0.9300	0.6344	-1.47	0.1426
Statute	Time-of-day change	Student	0.0000	0.0000	.	.
Weathertype	Cancellation	Cold temperatures	-0.3027	0.1864	-1.62	0.1043
Weathertype	Cancellation	Fog	0.7913	0.1517	5.21	<.0001
Weathertype	Cancellation	Heavy rain/thunderstorm	1.4710	0.1577	9.33	<.0001
Weathertype	Cancellation	Snow/freezing rain	2.2016	0.1586	13.88	<.0001
Weathertype	Cancellation	Storm/heavy wind	1.3353	0.1506	8.87	<.0001
Weathertype	Cancellation	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Location change	Cold temperatures	0.0100	0.2032	0.05	0.9608
Weathertype	Location change	Fog	0.6383	0.1953	3.27	0.0011
Weathertype	Location change	Heavy rain/thunderstorm	0.6328	0.2319	2.73	0.0064
Weathertype	Location change	Snow/freezing rain	0.5953	0.2478	2.40	0.0163
Weathertype	Location change	Storm/heavy wind	0.3376	0.2058	1.64	0.1009
Weathertype	Location change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Mode change	Cold temperatures	-1.0990	0.3027	-3.63	0.0003
Weathertype	Mode change	Fog	-1.8001	0.3988	-4.51	<.0001
Weathertype	Mode change	Heavy rain/thunderstorm	-1.1796	0.2887	-4.09	<.0001
Weathertype	Mode change	Snow/freezing rain	-1.3854	0.3222	-4.30	<.0001
Weathertype	Mode change	Storm/heavy wind	-1.2897	0.3052	-4.23	<.0001
Weathertype	Mode change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Route change	Cold temperatures	0.1271	0.2905	0.44	0.6618
Weathertype	Route change	Fog	0.8411	0.5372	1.57	0.1174
Weathertype	Route change	Heavy rain/thunderstorm	-0.4349	0.9705	-0.45	0.6540
Weathertype	Route change	Snow/freezing rain	1.0616	0.8470	1.25	0.2101
Weathertype	Route change	Storm/heavy wind	-2.5215	1.2584	-2.00	0.0451
Weathertype	Route change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Time-of-day change	Cold temperatures	0.6149	0.3191	1.93	0.0540

Parameter			Estimate	Standard Error	Z	Pr > |Z|
Weathertype	Time-of-day change	Fog	0.5551	0.3120	1.78	0.0752
Weathertype	Time-of-day change	Heavy rain/thunderstorm	0.7253	0.2815	2.58	0.0100
Weathertype	Time-of-day change	Snow/freezing rain	-0.0060	0.3022	-0.02	0.9841
Weathertype	Time-of-day change	Storm/heavy wind	0.7854	0.2848	2.76	0.0058
Weathertype	Time-of-day change	Warm temperatures	0.0000	0.0000	.	.

Table 11-43: Contrast results when modeling the preferred adaptation in shopping trips

Contrast	DF	Chi-Square	Pr > ChiSq
Weathertype cancel cold-fog	1	38.40	<.0001
Weathertype cancel cold-rain	1	108.66	<.0001
Weathertype cancel cold-snow	1	167.82	<.0001
Weathertype cancel cold-storm	1	89.77	<.0001
Weathertype cancel cold-warm	1	2.67	0.1020
Weathertype cancel fog-rain	1	29.26	<.0001
Weathertype cancel fog-snow	1	104.13	<.0001
Weathertype cancel fog-storm	1	24.14	<.0001
Weathertype cancel fog-warm	1	26.57	<.0001
Weathertype cancel rain-snow	1	43.23	<.0001
Weathertype cancel rain-storm	1	2.75	0.0975
Weathertype cancel rain-warm	1	81.28	<.0001
Weathertype cancel snow-storm	1	57.85	<.0001
Weathertype cancel snow-warm	1	152.00	<.0001
Weathertype cancel storm-warm	1	70.14	<.0001
Weathertype location cold-fog	1	8.18	0.0042
Weathertype location cold-rain	1	7.88	0.0050
Weathertype location cold-snow	1	7.56	0.0060
Weathertype location cold-storm	1	3.09	0.0788
Weathertype location cold-warm	1	0.00	0.9608
Weathertype location fog-rain	1	0.00	0.9756
Weathertype location fog-snow	1	0.05	0.8170

Contrast	DF	Chi-Square	Pr > ChiSq
Weathertype location fog-storm	1	3.12	0.0775
Weathertype location fog-warm	1	10.70	0.0011
Weathertype location rain-snow	1	0.04	0.8348
Weathertype location rain-storm	1	3.21	0.0734
Weathertype location rain-warm	1	7.62	0.0058
Weathertype location snow-storm	1	2.32	0.1278
Weathertype location snow-warm	1	6.53	0.0106
Weathertype location storm-warm	1	2.89	0.0893
Weathertype mode change cold-fog	1	6.54	0.0105
Weathertype mode change cold-rain	1	0.11	0.7377
Weathertype mode change cold-snow	1	0.99	0.3207
Weathertype mode change cold-storm	1	0.58	0.4481
Weathertype mode change cold-warm	1	15.85	<.0001
Weathertype mode change fog-rain	1	10.35	0.0013
Weathertype mode change fog-snow	1	2.32	0.1279
Weathertype mode change fog-storm	1	7.51	0.0061
Weathertype mode change fog-warm	1	31.62	<.0001
Weathertype mode change rain-snow	1	0.90	0.3438
Weathertype mode change rain-storm	1	1.61	0.2050
Weathertype mode change rain-warm	1	18.81	<.0001
Weathertype mode change snow-storm	1	0.21	0.6493
Weathertype mode change snow-warm	1	22.71	<.0001
Weathertype mode change storm-warm	1	21.15	<.0001
Weathertype route change cold-fog	1	2.57	0.1089
Weathertype route change cold-rain	1	0.32	0.5691
Weathertype route change cold-snow	1	1.65	0.1988
Weathertype route change cold-storm	1	1.93	0.1646
Weathertype route change cold-warm	1	0.21	0.6490
Weathertype route change fog-rain	1	2.38	0.1232
Weathertype route change fog-snow	1	0.13	0.7162
Weathertype route change fog-storm	1	4.92	0.0266
Weathertype route change fog-warm	1	3.28	0.0702
Weathertype route change rain-snow	1	3.46	0.0627
Weathertype route change rain-storm	1	2.04	0.1534
Weathertype route change rain-warm	1	0.17	0.6778

Contrast	DF	Chi-Square	Pr > ChiSq
Weathertype route change snow-storm	1	6.06	0.0138
Weathertype route change snow-warm	1	1.85	0.1738
Weathertype route change storm-warm	1	1.50	0.2203
Weathertype time-of-departure change cold-fog	1	0.06	0.8122
Weathertype time-of-departure change cold-rain	1	0.16	0.6890
Weathertype time-of-departure change cold-snow	1	4.22	0.0400
Weathertype time-of-departure change cold-storm	1	0.55	0.4598
Weathertype time-of-departure change cold-warm	1	3.36	0.0670
Weathertype time-of-departure change fog-rain	1	0.48	0.4884
Weathertype time-of-departure change fog-snow	1	3.39	0.0654
Weathertype time-of-departure change fog-storm	1	1.04	0.3088
Weathertype time-of-departure change fog-warm	1	2.96	0.0852
Weathertype time-of-departure change rain-snow	1	8.23	0.0041
Weathertype time-of-departure change rain-storm	1	0.11	0.7425
Weathertype time-of-departure change rain-warm	1	6.41	0.0113
Weathertype time-of-departure change snow-storm	1	7.79	0.0053
Weathertype time-of-departure change snow-warm	1	0.00	0.9841
Weathertype time-of-departure change storm-warm	1	6.96	0.0083

Appendix 4.4: Leisure trips

Table 11-44: P-values of the type-III test when modeling the preferred adaption in leisure trips

Score Statistics For Type 3 GEE Analysis			
Source	**DF**	**Chi-Square**	**Pr > ChiSq**
Intercept	5	97.02	<.0001
Driving license	5	13.05	0.0229
Age	5	47.55	<.0001
Diploma	15	27.54	0.0246
Weathertype	25	254.44	<.0001

Table 11-45: Parameter estimates when modeling the preferred adaptation in leisure trips

Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Intercept	Cancellation		-2.6767	0.3818	-7.01	<.0001
Intercept	Location change		-1.6595	0.4421	-3.75	0.0002
Intercept	Mode change		-0.0311	0.4115	-0.08	0.9398
Intercept	Route change		-7.1986	1.0411	-6.91	<.0001
Intercept	Time-of-day change		-3.1199	0.5180	-6.02	<.0001
Driving license	Cancellation	No	0.1359	0.4711	0.29	0.7731
Driving license	Cancellation	Yes	0.0000	0.0000	.	.
Driving license	Location change	No	0.1075	0.4399	0.24	0.8069
Driving license	Location change	Yes	0.0000	0.0000	.	.
Driving license	Mode change	No	-0.5499	0.3464	-1.59	0.1124
Driving license	Mode change	Yes	0.0000	0.0000	.	.
Driving license	Route change	No	-2.1552	0.7867	-2.74	0.0062
Driving license	Route change	Yes	0.0000	0.0000	.	.
Driving license	Time-of-day change	No	-1.2359	0.9718	-1.27	0.2035
Driving license	Time-of-day change	Yes	0.0000	0.0000	.	.
Age	Cancellation		0.0250	0.0081	3.07	0.0021

Parameter			Estimate	Standard Error	Z	Pr > |Z|
Age	Location change		-0.0195	0.0114	-1.71	0.0878
Age	Mode change		-0.0537	0.0078	-6.88	<.0001
Age	Route change		-0.0199	0.0123	-1.62	0.1052
Age	Time-of-day change		-0.0087	0.0111	-0.78	0.4347
Diploma	Cancellation	No secondary school diploma	-0.7633	0.4220	-1.81	0.0705
Diploma	Cancellation	Secondary school diploma	-0.2107	0.2562	-0.82	0.4109
Diploma	Cancellation	Higher not university diploma	-0.1092	0.2626	-0.42	0.6777
Diploma	Cancellation	Higher university diploma	0.0000	0.0000	.	.
Diploma	Location change	No secondary school diploma	0.4012	0.6468	0.62	0.5350
Diploma	Location change	Secondary school diploma	0.3088	0.3742	0.83	0.4093
Diploma	Location change	Higher not university diploma	-0.3629	0.4054	-0.89	0.3708
Diploma	Location change	Higher university diploma	0.0000	0.0000	.	.
Diploma	Mode change	No secondary school diploma	1.8321	0.5241	3.50	0.0005
Diploma	Mode change	Secondary school diploma	0.3672	0.3535	1.04	0.2989
Diploma	Mode change	Higher not university diploma	0.3176	0.3982	0.80	0.4251
Diploma	Mode change	Higher university diploma	0.0000	0.0000	.	.
Diploma	Route change	No secondary school diploma	2.6166	0.6841	3.82	0.0001
Diploma	Route change	Secondary school diploma	1.1721	0.5701	2.06	0.0398
Diploma	Route change	Higher not university diploma	2.1235	0.5948	3.57	0.0004
Diploma	Route change	Higher university diploma	0.0000	0.0000	.	.
Diploma	Time-of-day change	No secondary school diploma	0.0913	0.6846	0.13	0.8939
Diploma	Time-of-day change	Secondary school diploma	0.0414	0.4456	0.09	0.9259

Parameter			Estimate	Standard Error	Z	Pr > |Z|
Diploma	Time-of-day change	Higher not university diploma	-0.5613	0.4547	-1.23	0.2171
Diploma	Time-of-day change	Higher university diploma	0.0000	0.0000	.	.
Weathertype	Cancellation	Cold temperatures	0.2298	0.1670	1.38	0.1689
Weathertype	Cancellation	Fog	0.9041	0.1501	6.02	<.0001
Weathertype	Cancellation	Heavy rain/thunderstorm	1.3212	0.1481	8.92	<.0001
Weathertype	Cancellation	Snow/freezing rain	2.1767	0.1660	13.11	<.0001
Weathertype	Cancellation	Storm/heavy wind	1.3832	0.1522	9.09	<.0001
Weathertype	Cancellation	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Location change	Cold temperatures	-0.1905	0.1969	-0.97	0.3332
Weathertype	Location change	Fog	-0.0362	0.2163	-0.17	0.8672
Weathertype	Location change	Heavy rain/thunderstorm	0.0106	0.2269	0.05	0.9627
Weathertype	Location change	Snow/freezing rain	-0.2272	0.2449	-0.93	0.3535
Weathertype	Location change	Storm/heavy wind	0.1166	0.2047	0.57	0.5690
Weathertype	Location change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Mode change	Cold temperatures	-1.5799	0.2770	-5.70	<.0001
Weathertype	Mode change	Fog	-2.1352	0.3003	-7.11	<.0001
Weathertype	Mode change	Heavy rain/thunderstorm	-1.6123	0.2688	-6.00	<.0001
Weathertype	Mode change	Snow/freezing rain	-1.6032	0.2618	-6.12	<.0001
Weathertype	Mode change	Storm/heavy wind	-1.6320	0.2718	-6.00	<.0001
Weathertype	Mode change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Route change	Cold temperatures	1.7180	0.8157	2.11	0.0352
Weathertype	Route change	Fog	2.8529	0.8017	3.56	0.0004
Weathertype	Route change	Heavy rain/thunderstorm	2.7618	0.8534	3.24	0.0012
Weathertype	Route change	Snow/freezing rain	2.9835	0.8578	3.48	0.0005
Weathertype	Route change	Storm/heavy wind	2.1279	0.8877	2.40	0.0165
Weathertype	Route change	Warm temperatures	0.0000	0.0000	.	.
Weathertype	Time-of-day change	Cold temperatures	-0.5415	0.5865	-0.92	0.3559
Weathertype	Time-of-day change	Fog	0.9036	0.4596	1.97	0.0493

Parameter			Estimate	Standard Error	Z	Pr > |Z|
Weathertype	Time-of-day change	Heavy rain/thunderstorm	1.1170	0.4020	2.78	0.0055
Weathertype	Time-of-day change	Snow/freezing rain	0.4084	0.4755	0.86	0.3904
Weathertype	Time-of-day change	Storm/heavy wind	0.4147	0.4786	0.87	0.3862
Weathertype	Time-of-day change	Warm temperatures	0.0000	0.0000	.	.

Table 11-46: Contrast results when modeling the preferred adaptation in leisure trips

Contrast	DF	Chi-Square	Pr > ChiSq
weathertype cancel cold-fog	1	26.20	<.0001
weathertype cancel cold-rain	1	66.77	<.0001
weathertype cancel cold-snow	1	143.75	<.0001
weathertype cancel cold-storm	1	67.69	<.0001
weathertype cancel cold-warm	1	1.85	0.1742
weathertype cancel fog-rain	1	19.55	<.0001
weathertype cancel fog-snow	1	101.66	<.0001
weathertype cancel fog-storm	1	24.81	<.0001
weathertype cancel fog-warm	1	32.64	<.0001
weathertype cancel rain-snow	1	64.70	<.0001
weathertype cancel rain-storm	1	0.85	0.3557
weathertype cancel rain-warm	1	69.36	<.0001
weathertype cancel snow-storm	1	60.28	<.0001
weathertype cancel snow-warm	1	140.39	<.0001
weathertype cancel storm-warm	1	70.57	<.0001
weathertype location cold-fog	1	0.85	0.3569
weathertype location cold-rain	1	1.28	0.2585
weathertype location cold-snow	1	0.04	0.8457
weathertype location cold-storm	1	3.61	0.0573
weathertype location cold-warm	1	0.91	0.3401
weathertype location fog-rain	1	0.12	0.7268
weathertype location fog-snow	1	1.68	0.1947
weathertype location fog-storm	1	1.22	0.2689

Contrast	DF	Chi-Square	Pr > ChiSq
weathertype location fog-warm	1	0.03	0.8672
weathertype location rain-snow	1	4.10	0.0429
weathertype location rain-storm	1	0.76	0.3842
weathertype location rain-warm	1	0.00	0.9627
weathertype location snow-storm	1	6.06	0.0138
weathertype location snow-warm	1	0.86	0.3527
weathertype location storm-warm	1	0.33	0.5679
weathertype mode change cold-fog	1	3.04	0.0813
weathertype mode change cold-rain	1	0.02	0.8977
weathertype mode change cold-snow	1	0.01	0.9295
weathertype mode change cold-storm	1	0.05	0.8280
weathertype mode change cold-warm	1	30.57	<.0001
weathertype mode change fog-rain	1	2.74	0.0981
weathertype mode change fog-snow	1	2.67	0.1020
weathertype mode change fog-storm	1	3.40	0.0652
weathertype mode change fog-warm	1	44.11	<.0001
weathertype mode change rain-snow	1	0.00	0.9526
weathertype mode change rain-storm	1	0.02	0.8886
weathertype mode change rain-warm	1	30.64	<.0001
weathertype mode change snow-storm	1	0.03	0.8700
weathertype mode change snow-warm	1	30.32	<.0001
weathertype mode change storm-warm	1	31.95	<.0001
weathertype route change cold-fog	1	4.44	0.0351
weathertype route change cold-rain	1	3.29	0.0696
weathertype route change cold-snow	1	4.52	0.0335
weathertype route change cold-storm	1	0.42	0.5151
weathertype route change cold-warm	1	3.00	0.0832
weathertype route change fog-rain	1	0.12	0.7254
weathertype route change fog-snow	1	0.12	0.7297
weathertype route change fog-storm	1	6.11	0.0134
weathertype route change fog-warm	1	11.49	0.0007
weathertype route change rain-snow	1	0.32	0.5726
weathertype route change rain-storm	1	4.38	0.0364
weathertype route change rain-warm	1	9.09	0.0026
weathertype route change snow-storm	1	3.67	0.0555

Contrast	DF	Chi-Square	Pr > ChiSq
weathertype route change snow-warm	1	9.00	0.0027
weathertype route change storm-warm	1	4.72	0.0298
weathertype time-of-departure change cold-fog	1	12.81	0.0003
weathertype time-of-departure change cold-rain	1	14.42	0.0001
weathertype time-of-departure change cold-snow	1	5.17	0.0230
weathertype time-of-departure change cold-storm	1	5.44	0.0197
weathertype time-of-departure change cold-warm	1	0.77	0.3814
weathertype time-of-departure change fog-rain	1	0.85	0.3566
weathertype time-of-departure change fog-snow	1	3.68	0.0551
weathertype time-of-departure change fog-storm	1	3.70	0.0545
weathertype time-of-departure change fog-warm	1	5.13	0.0235
weathertype time-of-departure change rain-snow	1	5.86	0.0155
weathertype time-of-departure change rain-storm	1	7.33	0.0068
weathertype time-of-departure change rain-warm	1	10.35	0.0013
weathertype time-of-departure change snow-storm	1	0.00	0.9787
weathertype time-of-departure change snow-warm	1	0.85	0.3568
weathertype time-of-departure change storm-warm	1	0.86	0.3540

Appendix 4.5: Modal choice

Table 11-47: P-values of the type-III test when modeling modal choice

Score Statistics For Type 3 GEE Analysis			
Source	**DF**	**Chi-Square**	**Pr > ChiSq**
NewIntercept	4	286.73	<.0001
AantPers*NewIntercep	4	47.89	<.0001
NewIntercept*sted	16	748.29	<.0001
NewIntercep*Geslacht	4	28.17	<.0001
NewInterce*kleeftred	16	74.22	<.0001
NewInterc*maatpartre	20	210.65	<.0001
NewInterce*opleidred	16	1166.98	<.0001
NewInterc*inkomenred	16	109.46	<.0001
NewIntercep*Rijbewij	8	1535.08	<.0001
SOV-card	4	43.29	<.0001
NewInterc*kmotiefred	16	2100.98	<.0001
NewInterce*kafstvred	16	293924	<.0001
FX*NewIntercept	4	48.71	<.0001
T*NewIntercept	4	74.66	<.0001
SQ*NewIntercept	4	83.33	<.0001
DR*NewIntercept	4	74.52	<.0001
Y*NewIntercept	4	10.71	0.0300

Table 11-48: Parameter estimates when modeling modal choice

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Intercept	Car driver/passenger		-1.6225	0.4019	-4.04	<.0001
Intercept	Public transport		2.5389	0.5027	5.05	<.0001
Intercept	Other		-4.8788	0.9679	-5.04	<.0001
Intercept	Slow road user		-2.0317	0.3418	-5.94	<.0001
Household size	Car driver/passenger		0.0696	0.0147	4.72	<.0001

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Household size	Public transport		-0.1070	0.0324	-3.30	0.0010
Household size	Other		-0.2098	0.0690	-3.04	0.0024
Household size	Slow road user		-0.0355	0.0152	-2.34	0.0195
Urbanization degree	Car driver/passenger	Moderate urban	0.6665	0.0587	11.36	<.0001
Urbanization degree	Car driver/passenger	Not urban	0.8085	0.0603	13.41	<.0001
Urbanization degree	Car driver/passenger	Urban	0.6130	0.0563	10.88	<.0001
Urbanization degree	Car driver/passenger	Little urban	0.8470	0.0566	14.97	<.0001
Urbanization degree	Car driver/passenger	Very urban	0.0000	0.0000	.	.
Urbanization degree	Public transport	Moderate urban	-1.5344	0.1051	-14.60	<.0001
Urbanization degree	Public transport	Not urban	-1.9688	0.1134	-17.36	<.0001
Urbanization degree	Public transport	Urban	-1.0496	0.0913	-11.50	<.0001
Urbanization degree	Public transport	Little urban	-1.8864	0.1013	-18.63	<.0001
Urbanization degree	Public transport	Very urban	0.0000	0.0000	.	.
Urbanization degree	Other	Moderate urban	0.0447	0.1799	0.25	0.8039
Urbanization degree	Other	Not urban	0.0969	0.1927	0.50	0.6150
Urbanization degree	Other	Urban	-0.1510	0.1725	-0.88	0.3811
Urbanization degree	Other	Little urban	0.1025	0.1800	0.57	0.5690
Urbanization degree	Other	Very urban	0.0000	0.0000	.	.
Urbanization degree	Slow road user	Moderate urban	-0.1881	0.0597	-3.15	0.0016
Urbanization degree	Slow road user	Not urban	-0.2778	0.0625	-4.45	<.0001
Urbanization degree	Slow road user	Urban	-0.1987	0.0572	-3.47	0.0005

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Urbanization degree	Slow road user	Little urban	-0.3579	0.0577	-6.21	<.0001
Urbanization degree	Slow road user	Very urban	0.0000	0.0000	.	.
Gender	Car driver/passenger	Male	-0.0437	0.0344	-1.27	0.2035
Gender	Car driver/passenger	Female	0.0000	0.0000	.	.
Gender	Public transport	Male	-0.1661	0.0730	-2.28	0.0229
Gender	Public transport	Female	0.0000	0.0000	.	.
Gender	Other	Male	0.5223	0.1179	4.43	<.0001
Gender	Other	Female	0.0000	0.0000	.	.
Gender	Slow road user	Male	0.0474	0.0357	1.33	0.1845
Gender	Slow road user	Female	0.0000	0.0000	.	.
Age category	Car driver/passenger	+ 65 year	0.0480	0.0689	0.70	0.4867
Age category	Car driver/passenger	0-17 year	1.1027	0.3697	2.98	0.0029
Age category	Car driver/passenger	18-34 year	0.1092	0.0636	1.72	0.0860
Age category	Car driver/passenger	35-44 year	0.1609	0.0598	2.69	0.0071
Age category	Car driver/passenger	45-54 year	-0.0346	0.0563	-0.61	0.5392
Age category	Car driver/passenger	55-64 year	0.0000	0.0000	.	.
Age category	Public transport	+ 65 year	0.1734	0.1680	1.03	0.3020
Age category	Public transport	0-17 year	-1.5688	0.4238	-3.70	0.0002
Age category	Public transport	18-34 year	0.4599	0.1339	3.43	0.0006
Age category	Public transport	35-44 year	0.1675	0.1411	1.19	0.2353
Age category	Public transport	45-54 year	0.3185	0.1343	2.37	0.0177
Age category	Public transport	55-64 year	0.0000	0.0000	.	.
Age category	Other	+ 65 year	0.6816	0.1850	3.68	0.0002
Age category	Other	0-17 year	1.5018	0.7944	1.89	0.0587
Age category	Other	18-34 year	0.0764	0.2408	0.32	0.7509
Age category	Other	35-44 year	0.1024	0.2203	0.46	0.6421

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Age category	Other	45-54 year	0.5782	0.2023	2.86	0.0043
Age category	Other	55-64 year	0.0000	0.0000	.	.
Age category	Slow road user	+ 65 year	-0.1419	0.0721	-1.97	0.0493
Age category	Slow road user	0-17 year	0.0484	0.3099	0.16	0.8758
Age category	Slow road user	18-34 year	-0.2585	0.0687	-3.76	0.0002
Age category	Slow road user	35-44 year	-0.2622	0.0648	-4.04	<.0001
Age category	Slow road user	45-54 year	-0.1078	0.0611	-1.76	0.0779
Age category	Slow road user	55-64 year	0.0000	0.0000	.	.
Social particpation	Car driver/passenger	Retired	-0.5039	0.0743	-6.78	<.0001
Social particpation	Car driver/passenger	Younger than 6 year	-0.2075	0.2026	-1.02	0.3057
Social particpation	Car driver/passenger	Other/unknown	-0.2613	0.0584	-4.47	<.0001
Social particpation	Car driver/passenger	Student	-0.7128	0.1833	-3.89	0.0001
Social particpation	Car driver/passenger	Unemployed	-0.7344	0.2363	-3.11	0.0019
Social particpation	Car driver/passenger	Employed	0.0000	0.0000	.	.
Social particpation	Public transport	Retired	0.2960	0.1852	1.60	0.1100
Social particpation	Public transport	Younger than 6 year	-0.0131	0.4612	-0.03	0.9774
Social particpation	Public transport	Other/unknown	0.0564	0.1706	0.33	0.7408
Social particpation	Public transport	Student	0.4025	0.2023	1.99	0.0466
Social particpation	Public transport	Unemployed	0.8020	0.3148	2.55	0.0108
Social particpation	Public transport	Employed	0.0000	0.0000	.	.
Social particpation	Other	Retired	0.2021	0.2002	1.01	0.3129
Social particpation	Other	Younger than 6 year	-1.6225	0.4213	-3.85	0.0001
Social particpation	Other	Other/unknown	0.4899	0.2108	2.32	0.0201

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Social particpation	Other	Student	-0.1823	0.2712	-0.67	0.5016
Social particpation	Other	Unemployed	0.0799	0.7410	0.11	0.9141
Social particpation	Other	Employed	0.0000	0.0000	.	.
Social particpation	Slow road user	Retired	0.4126	0.0785	5.26	<.0001
Social particpation	Slow road user	Younger than 6 year	0.1847	0.1950	0.95	0.3436
Social particpation	Slow road user	Other/unknown	0.1922	0.0632	3.04	0.0024
Social particpation	Slow road user	Student	0.5907	0.1762	3.35	0.0008
Social particpation	Slow road user	Unemployed	0.6219	0.2631	2.36	0.0181
Social particpation	Slow road user	Employed	0.0000	0.0000	.	.
Diploma	Car driver/passenger	BO/LO/LBO/VGLO/LAVO/MAVO/MULO	-0.1104	0.1008	-1.09	0.2737
Diploma	Car driver/passenger	HBO/University	-0.5239	0.1057	-4.96	<.0001
Diploma	Car driver/passenger	Younger than 12 year	1.7750	0.1293	13.73	<.0001
Diploma	Car driver/passenger	MBO/HAVO/Atheneum/Gymnasium/MMS/HBS	-0.1562	0.1023	-1.53	0.1266
Diploma	Car driver/passenger	Other/unknown	0.0000	0.0000	.	.
Diploma	Public transport	BO/LO/LBO/VGLO/LAVO/MAVO/MULO	-0.1899	0.2289	-0.83	0.4067
Diploma	Public transport	HBO/University	0.5720	0.2311	2.47	0.0133
Diploma	Public transport	Younger than 12 year	-1.1674	0.3426	-3.41	0.0007
Diploma	Public transport	MBO/HAVO/Atheneum/Gymnasium/MMS/HBS	0.1210	0.2281	0.53	0.5958
Diploma	Public transport	Other/unknown	0.0000	0.0000	.	.
Diploma	Other	BO/LO/LBO/VGLO/LAVO/MAVO/MULO	0.0199	0.3586	0.06	0.9558
Diploma	Other	HBO/University	-0.2982	0.4029	-0.74	0.4592

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Diploma	Other	Younger than 12 year	0.7876	0.4942	1.59	0.1110
Diploma	Other	MBO/HAVO/Atheneum /Gymnasium/MMS/HBS	-0.0373	0.3684	-0.10	0.9194
Diploma	Other	Other/unknown	0.0000	0.0000	.	.
Diploma	Slow road user	BO/LO/LBO/VGLO/LAVO/MAVO/ MULO	0.1294	0.1111	1.16	0.2442
Diploma	Slow road user	HBO/University	0.4435	0.1165	3.81	0.0001
Diploma	Slow road user	Younger than 12 year	-1.7062	0.1383	-12.34	<.0001
Diploma	Slow road user	MBO/HAVO/Atheneum /Gymnasium/MMS/HBS	0.1109	0.1129	0.98	0.3260
Diploma	Slow road user	Other/unknown	0.0000	0.0000	.	.
Income	Car driver/passenger	15 000 - 30 000	0.0117	0.0518	0.23	0.8213
Income	Car driver/passenger	< 15 000	-0.1572	0.0560	-2.81	0.0050
Income	Car driver/passenger	>= 30 000	0.2706	0.0635	4.26	<.0001
Income	Car driver/passenger	No own income	-0.1924	0.0790	-2.44	0.0149
Income	Car driver/passenger	Unknown	0.0000	0.0000	.	.
Income	Public transport	15 000 - 30 000	0.0596	0.1209	0.49	0.6220
Income	Public transport	< 15 000	0.2138	0.1324	1.61	0.1064
Income	Public transport	>= 30 000	-0.1113	0.1379	-0.81	0.4195
Income	Public transport	No own income	0.3741	0.1751	2.14	0.0326
Income	Public transport	Unknown	0.0000	0.0000	.	.
Income	Other	15 000 - 30 000	-0.1220	0.1965	-0.62	0.5346
Income	Other	< 15 000	-0.0544	0.2046	-0.27	0.7904
Income	Other	>= 30 000	-0.0642	0.2527	-0.25	0.7996
Income	Other	No own income	-0.8029	0.2586	-3.11	0.0019
Income	Other	Unknown	0.0000	0.0000	.	.
Income	Slow road user	15 000 - 30 000	-0.0345	0.0569	-0.61	0.5438
Income	Slow road user	< 15 000	0.1372	0.0608	2.26	0.0239
Income	Slow road user	>= 30 000	-0.2850	0.0692	-4.12	<.0001
Income	Slow road user	No own income	0.1995	0.0847	2.36	0.0185

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Income	Slow road user	Unknown	0.0000	0.0000	.	.
Driving license	Car driver/passenger	Yes	2.6565	0.3200	8.30	<.0001
Driving license	Car driver/passenger	Younger than 18 year	0.0000	0.0000	.	.
Driving license	Car driver/passenger	No	0.9245	0.3240	2.85	0.0043
Driving license	Car driver/passenger	Unknown	0.0000	0.0000	.	.
Driving license	Public transport	Yes	-2.9457	0.3466	-8.50	<.0001
Driving license	Public transport	Younger than 18 year	0.0000	0.0000	.	.
Driving license	Public transport	No	-1.1346	0.3558	-3.19	0.0014
Driving license	Public transport	Unknown	0.0000	0.0000	.	.
Driving license	Other	Yes	-0.1768	0.7153	-0.25	0.8047
Driving license	Other	Younger than 18 year	0.0000	0.0000	.	.
Driving license	Other	No	1.5194	0.7145	2.13	0.0335
Driving license	Other	Unknown	0.0000	0.0000	.	.
Driving license	Slow road user	Yes	-1.2338	0.2480	-4.98	<.0001
Driving license	Slow road user	Younger than 18 year	0.0000	0.0000	.	.
Driving license	Slow road user	No	-0.4007	0.2540	-1.58	0.1146
Driving license	Slow road user	Unknown	0.0000	0.0000	.	.
SOV-card	Car driver/passenger	No	0.7369	0.2070	3.56	0.0004
SOV-card	Car driver/passenger	yes	0.0000	0.0000	.	.
SOV-card	Public transport	No	-1.0757	0.1990	-5.40	<.0001
SOV-card	Public transport	yes	0.0000	0.0000	.	.
SOV-card	Other	No	0.4565	0.4117	1.11	0.2674
SOV-card	Other	yes	0.0000	0.0000	.	.
SOV-card	Slow road user	No	-0.0834	0.1965	-0.42	0.6712
SOV-card	Slow road user	yes	0.0000	0.0000	.	.
Trip purpose	Car driver/passenger	Services and personal care	0.3181	0.0683	4.66	<.0001
Trip purpose	Car driver/passenger	Other	-0.7137	0.0430	-16.59	<.0001

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Trip purpose	Car driver/passenger	Social recreative, visite	-0.0881	0.0395	-2.23	0.0257
Trip purpose	Car driver/passenger	Work/school trips	-1.1623	0.0444	-26.20	<.0001
Trip purpose	Car driver/passenger	Shopping trips	0.0000	0.0000	.	.
Trip purpose	Public transport	Services and personal care	-0.4052	0.2537	-1.60	0.1102
Trip purpose	Public transport	Other	-0.7892	0.1336	-5.91	<.0001
Trip purpose	Public transport	Social recreative, visite	-0.7283	0.1143	-6.37	<.0001
Trip purpose	Public transport	Work/school trips	0.4375	0.1035	4.23	<.0001
Trip purpose	Public transport	Shopping trips	0.0000	0.0000	.	.
Trip purpose	Other	Services and personal care	1.1056	0.1699	6.51	<.0001
Trip purpose	Other	Other	0.9109	0.1465	6.22	<.0001
Trip purpose	Other	Social recreative, visite	0.2078	0.1405	1.48	0.1392
Trip purpose	Other	Work/school trips	0.5444	0.1682	3.24	0.0012
Trip purpose	Other	Shopping trips	0.0000	0.0000	.	.
Trip purpose	Slow road user	Services and personal care	-0.4146	0.0748	-5.54	<.0001
Trip purpose	Slow road user	Other	0.7290	0.0441	16.54	<.0001
Trip purpose	Slow road user	Social recreative, visite	0.1620	0.0395	4.10	<.0001
Trip purpose	Slow road user	Work/school trips	0.9497	0.0453	20.98	<.0001
Trip purpose	Slow road user	Shopping trips	0.0000	0.0000	.	.
Travel distance	Car driver/passenger	0,1 - 0,5 km	-4.8384	0.0930	-52.01	<.0001
Travel distance	Car driver/passenger	0,5 - 1,0 km	-3.7986	0.0628	-60.53	<.0001
Travel distance	Car driver/passenger	1,0 - 2,5 km	-2.5691	0.0424	-60.60	<.0001
Travel distance	Car driver/passenger	2,5 – 10 km	-1.1153	0.0376	-29.66	<.0001
Travel distance	Car driver/passenger	> 10 km	0.0000	0.0000	.	.
Travel distance	Public transport	0,1 - 0,5 km	-39.7342	0.0863	-460.32	<.0001
Travel distance	Public transport	0,5 - 1,0 km	-7.4177	0.7664	-9.68	<.0001
Travel distance	Public transport	1,0 - 2,5 km	-3.3661	0.1659	-20.29	<.0001

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			Estimate	Standard Error	Z	Pr > |Z|
Travel distance	Public transport	2,5 – 10 km	-1.6720	0.0762	-21.95	<.0001
Travel distance	Public transport	> 10 km	0.0000	0.0000	.	.
Travel distance	Other	0,1 - 0,5 km	-0.9663	0.2486	-3.89	0.0001
Travel distance	Other	0,5 - 1,0 km	-1.0507	0.1860	-5.65	<.0001
Travel distance	Other	1,0 - 2,5 km	-1.0512	0.1406	-7.47	<.0001
Travel distance	Other	2,5 – 10 km	-0.6893	0.1251	-5.51	<.0001
Travel distance	Other	> 10 km	0.0000	0.0000	.	.
Travel distance	Slow road user	0,1 - 0,5 km	5.9396	0.1040	57.12	<.0001
Travel distance	Slow road user	0,5 - 1,0 km	5.0530	0.0695	72.67	<.0001
Travel distance	Slow road user	1,0 - 2,5 km	3.8616	0.0540	71.54	<.0001
Travel distance	Slow road user	2,5 – 10 km	2.3433	0.0504	46.45	<.0001
Travel distance	Slow road user	> 10 km	0.0000	0.0000	.	.
Max. wind gust	Car driver/passenger		0.0017	0.0004	4.80	<.0001
Max. wind gust	Public transport		0.0003	0.0008	0.44	0.6582
Max. wind gust	Other		-0.0018	0.0012	-1.52	0.1274
Max. wind gust	Slow road user		-0.0018	0.0004	-4.81	<.0001
Temperature	Car driver/passenger		-0.0011	0.0003	-4.23	<.0001
Temperature	Public transport		-0.0022	0.0006	-3.95	<.0001
Temperature	Other		0.0026	0.0008	3.13	0.0018
Temperature	Slow road user		0.0015	0.0003	5.60	<.0001
Sunshine duration	Car driver/passenger		-0.0240	0.0036	-6.70	<.0001
Sunshine duration	Public transport		0.0074	0.0079	0.93	0.3500
Sunshine duration	Other		0.0099	0.0114	0.87	0.3858
Sunshine duration	Slow road user		0.0227	0.0037	6.07	<.0001
Preciptiation duration	Car driver/passenger		0.0323	0.0052	6.18	<.0001
Preciptiation duration	Public transport		-0.0107	0.0116	-0.92	0.3571
Preciptiation duration	Other		0.0066	0.0196	0.34	0.7366

Analysis Of GEE Parameter Estimates						
Empirical Standard Error Estimates						
Parameter			**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Preciptiation duration	Slow road user		-0.0328	0.0055	-5.94	<.0001
Yce formation	Car driver/passenger	no occurrence	0.2215	0.1153	1.92	0.0547
Yce formation	Car driver/passenger	occurred during the preceding hour	0.0000	0.0000	.	.
Yce formation	Public transport	no occurrence	0.3323	0.2768	1.20	0.2300
Yce formation	Public transport	occurred during the preceding hour	0.0000	0.0000	.	.
Yce formation	Other	no occurrence	-0.0962	0.3861	-0.25	0.8032
Yce formation	Other	occurred during the preceding hour	0.0000	0.0000	.	.
Yce formation	Slow road user	no occurrence	-0.2967	0.1263	-2.35	0.0188
Yce formation	Slow road user	occurred during the preceding hour	0.0000	0.0000	.	.

Appendix 5: Results of the Tobit-model (travel time)

Table 11-49: P-values of the type-III test when modeling travel time

Type III Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
Gender	1	38355705.1	<.0001
Age category	5	44449543.1	<.0001
Diploma	4	82835844.3	<.0001
Income	4	16057819.4	<.0001
Trip purpose	4	543717121	<.0001
Max. wind gust	1	474253.347	<.0001
Temperature	1	4192965.97	<.0001
Sunshine duration	1	6548244.24	<.0001
Precipitation duration	1	10884.3138	<.0001
Fog	1	1419325.75	<.0001
Cloud covering	1	535107.987	<.0001
Snow	1	26831.9014	<.0001
Thunderstorm	1	441429.046	<.0001
Yce formation	1	29729.6649	<.0001

Table 11-50: Parameter estimates when modeling travel time

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept		1	15.1336	0.0037	1.649E7	<.0001
Gender	Man	1	2.3888	0.0004	3.836E7	<.0001
Gender	Vrouw	0	0.0000	.	.	.
Age category	+ 65 jaar	1	0.3480	0.0007	221200	<.0001
Age category	0-17 jaar	1	-2.3112	0.0010	4903856	<.0001
Age category	18-34 jaar	1	0.5542	0.0007	707620	<.0001
Age category	35-44 jaar	1	-2.8369	0.0007	1.834E7	<.0001
Age category	45-54 jaar	1	-1.2743	0.0007	3655178	<.0001
Age category	55-64 jaar	0	0.0000	.	.	.

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > Chi Sq
Diploma	BO/LO/LBO/VGLO/LAVO/MAVO/MULO	1	-0.8122	0.0011	531336	<.0001
Diploma	HBO/University	1	1.9049	0.0012	2717622	<.0001
Diploma	Younger than 12 year	1	-7.4033	0.0014	2.898E7	<.0001
Diploma	MBO/HAVO/Atheneum/ Gymnasium/MMS/HBS	1	0.3335	0.0011	89319.4	<.0001
Diploma	Other/unknown	0	0.0000	.	.	.
Income	15 000 - 30 000	1	0.0368	0.0007	2929.83	<.0001
Income	< 15 000	1	-1.0503	0.0007	2218132	<.0001
Income	>= 30 000	1	1.8109	0.0008	5162067	<.0001
Income	No own income	1	-0.3085	0.0009	120553	<.0001
Income	Unknown	0	0.0000	.	.	.
Trip purpose	Services and personal care	1	1.6099	0.0010	2587205	<.0001
Trip purpose	Other	1	9.3152	0.0006	2.74E8	<.0001
Trip purpose	Sociaal recreatief, Visite/logeren	1	8.4801	0.0005	2.454E8	<.0001
Trip purpose	Work/school trips	1	12.1457	0.0006	4.725E8	<.0001
Trip purpose	Shopping trips	0	0.0000	.	.	.
Max. wind gust		1	-0.0034	0.0000	474253	<.0001
Temperature		1	0.0062	0.0000	4192966	<.0001
Sunshine duration		1	0.1629	0.0001	6548244	<.0001
Precipitation duration		1	0.0089	0.0001	10884.3	<.0001
Fog	no occurrence	1	-1.6195	0.0014	1419326	<.0001
Fog	occurred during the preceding hour	0	0.0000	.	.	.
Cloud covering		1	-0.0549	0.0001	535108	<.0001
Snow	no occurrence	1	-0.2946	0.0018	26831.9	<.0001
Snow	occurred during the preceding hour	0	0.0000	.	.	.
Thunderstorm	no occurrence	1	-1.3560	0.0020	441429	<.0001
Thunderstorm	occurred during the preceding hour	0	0.0000	.	.	.
Yce formation	no occurrence	1	0.4424	0.0026	29729.7	<.0001
Yce formation	occurred during the preceding hour	0	0.0000	.	.	.
Scale		1	23.4112	0.0001		

Auteursrechtelijke overeenkomst

Ik/wij verlenen het wereldwijde auteursrecht voor de ingediende eindverhandeling:
Do weather conditions and weather forecasts trigger changes in our daily travel behavior

Richting: **master in de verkeerskunde-mobiliteitsmanagement**
Jaar: **2010**

in alle mogelijke mediaformaten, - bestaande en in de toekomst te ontwikkelen - , aan de Universiteit Hasselt.

Niet tegenstaand deze toekenning van het auteursrecht aan de Universiteit Hasselt behoud ik als auteur het recht om de eindverhandeling, - in zijn geheel of gedeeltelijk -, vrij te reproduceren, (her)publiceren of distribueren zonder de toelating te moeten verkrijgen van de Universiteit Hasselt.

Ik bevestig dat de eindverhandeling mijn origineel werk is, en dat ik het recht heb om de rechten te verlenen die in deze overeenkomst worden beschreven. Ik verklaar tevens dat de eindverhandeling, naar mijn weten, het auteursrecht van anderen niet overtreedt.

Ik verklaar tevens dat ik voor het materiaal in de eindverhandeling dat beschermd wordt door het auteursrecht, de nodige toelatingen heb verkregen zodat ik deze ook aan de Universiteit Hasselt kan overdragen en dat dit duidelijk in de tekst en inhoud van de eindverhandeling werd genotificeerd.

Universiteit Hasselt zal mij als auteur(s) van de eindverhandeling identificeren en zal geen wijzigingen aanbrengen aan de eindverhandeling, uitgezonderd deze toegelaten door deze overeenkomst.

Voor akkoord,

Creemers, Lieve

Datum: **25/05/2010**