Weather and Travel Behaviour

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Weather and travel behaviour

Weer en reisgedrag

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VRIJE UNIVERSITEIT

WEATHER AND TRAVEL BEHAVIOUR

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door

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geboren te FR Kohat, Pakistan

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PREFACE

Today is a big day of my life, as I have reached a milestone which I dreamed of years ago. When, I look back over the past years, I see them as a journey of seeking knowledge and learning that first started at a school in Federally Administered Tribal Areas of Pakistan, and now ends with PhD at the VU University, Amsterdam, the Netherlands. However, I believe that this is not "the end" but the beginning of a new journey with new learning and challenges to come. I cannot forget all those people who have supported me one way or another during all these years. I want to thank all of them though it would be literally impossible to mention each and every one here.

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I am lucky to be blessed with a big and loving family. I want to take this opportunity to thank all my cousins for their encouragement. In particular, I want to thank Muhammad Imran for his help and support during all my academic career. In other family members I would like to thank Senator Abdul Raziq, Habib ur Rehman, Imran Khan Afridi and Muhammad Kamran Khan. Special thanks to Muhammad Shohaib and Naveed ur Rehman for their help and support in my study period in Karachi. I also want to thank all of my school friends in particular, Muhammad Ali, Shahid ur Rehman, Raifullah and Riazullah. I am very much indebted to Haji Shahjahan and Haji Ghuloon for their love and support throughout my academic career and in life, particularly encouraging me to do my Masters in Economics from Peshawar University.

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M. Sabir,
Amsterdam, the Netherlands
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Chapter 1

Introduction

1.1 Setting the scene

Weather plays an important role in almost all kinds of day-to-day activities. Travelling is one of them. However, there are many issues to consider regarding the effects of weather on travel behaviour. For example, weather may affect the generalized cost of travel by delaying the trip due to reduction in speed. It may influence the comfort and safety of the travellers. Additionally, weather may influence mode choice and destination choice decisions. Also, it can have implications for the maintenance of road, rail and public transport. For example, extreme weather may cause the road infrastructure to deteriorate quickly.

The degree of influence of weather on travel behaviour is country-specific given differences in transport infrastructure. Travel behaviour in countries which rely mostly on the automobile, such as the United States or the United Kingdom, are less sensitive to daily weather variations compared with those countries where people are more dependent on non-motorized transport, in particular the bicycle (e.g. China, and the Netherlands).

The effect of weather conditions on daily activities may also change over time. Nowadays, travellers have access to information on the exact weather conditions using modern technology and also have access to advanced knowledge of weather forecasting. Additionally, this information is mostly available free of charge. The discussion of the role of weather in travelling is further heating up as a result of the possibility of climate change and global warming, because the transport sector is likely to be vulnerable to climate change. This increases the need to investigate the role of weather and climate on transportation.

1.2 The science of weather and climate change

Frequently, weather and climate are treated as synonyms. However, climate and weather are quite different. Weather is the state of the atmosphere at a particular place and time, as regards heat, cloudiness, dryness, sunshine, wind, rain, etc. Climate, on the other hand, refers to the weather conditions prevailing in an area in general over a long period. In other words, weather refers to the daily variation in the atmosphere, and climate refers to the general conditions we would expect over long time period in a given location.

Climate change refers to the changes in the weather over a longer period of time that ranges from decades to millions of years. The climate of the world appears to have changed as a result of a number of factors, among which Green House Gases (GHGs) are likely one of the most important.

GHGs are emitted into the atmosphere mainly due to burning of fossil fuels. GHGs cause global warming, which in turn leads to climate change. There is disagreement on the extent and the exact impacts of climate change. But, with the available knowledge, there are certain issues on which many scientists agree. These include the likely occurrence of climate change including the increase in average temperature of the globe, rising sea level, changes in the pattern of wind and precipitation, and more frequent extreme weather events (IPCC 2007). However, these changes will be not spread equally across globe. The effects of climate change will be mostly region-specific. Details of these future climate changes are presented in Appendix 1A.

1.3 Weather and transport: literature review

The literature on weather and transport can be divided into two main categories. First, studies which focus on the emissions from transport sector and hence on the impacts of transportation on weather and climate. For example, Lenzen (1999), Hatzopoulou and Miller (2010), Fomunung et al. (2009), and Holmen and Niemeier (1998) are just few recent studies from this vast literature. Second, studies which focus on the influence of weather on the transportation sector. Clearly, our study belongs to the latter research studies.

Koetse and Rietveld (2009) provide a survey of the empirical literature concerning the effects of weather and climate change on transport sector. Here, we will briefly present a literature survey similar to that of Koetse and Rietveld (2009), but with a specific focus on car and public transport, while ignoring air, sea and water transport. Furthermore, the focus of the literature is on the impacts of individual weather components on travel behaviour.

Temperature

Temperature is one of the important components of weather. Examples of research on this topic includes, Wyon et al. (1996), Nofal and Saeed (1997), Stern and Zehavi (1990), Fridstrøm et al. (1995). Some studies focus on temperature along with other weather components. For instance, Wyon et al. (1996) did an experimental study to see the effects of moderate heat stress on Swedish drivers' vigilance in a moving vehicle. The car compartment temperature was set at either 21^{o}C or at 27^{o}C. They found that heat stress has a negative effect on the vigilance of the drivers. Additionally, the response time of drivers was 22 per cent longer in the higher temperature as compared with the moderate temperature. Also, deliberate driving errors were more observable at the higher temperature than at the moderate temperature. This suggests that effective air conditioning may be able to substantially increase driver vigilance in warm weather, and may thereby reduce accident frequency. Nofal and Saeed (1997) also suggest hot weather as an important factor that leads to increased stress and decreased performance in intellectual tasks, and hence is a hazard to the safety and health of drivers. Stern and Zehavi (1990) studied road safety in warmer weather. They use data on the Arava road in Israel from 1979 to 1985, and found that road accident risk increases with severity of temperature. Moreover, the majority of accidents that happened in warmer weather are those in which one person's judgment is involved (this especially concerns running off the road). These studies suggest that warmer weather in general is a hazard for road travel.

Besides affecting safety, temperature may also influence the demand for travel and the mode-choice decision. For instance, Cools et al. (2010) focus on the impact of weather on the traffic intensity by observing the number of cars passing through a specific road segment. They found that high temperatures increase traffic intensity. Hassan and Barker (1999) study the variation in traffic activity in the Lothian region in Scotland during extreme weather conditions between 1987 to 1991. Their extreme weather measurement was based on the 10 per cent of days with either the highest or lowest values for each meteorological variable (i.e. the extremes) for both weekdays and weekends. They found an increase in weekday traffic activity associated with higher sunshine hours, and with higher than expected maximum and minimum temperatures. Additionally, they found strong positive effects of unseasonable sunshine hours, maximum temperature, minimum temperature, and rainfall on traffic activity during weekdays compared with weekends. Richardson (2000) quantified the effects of temperature variation on the propensity of cycling in the Melbourne metropolitan area, Australia. He found that cyclists are less likely to ride in very low or very high temperatures. Brandenburg et al. (2004) also reported that cyclists are vulnerable to weather conditions. In addition, recreational cycling trips are more sensitive to temperature as compared with commuting cycling trips.

Temperature may play a role in the decision for a destination choice and may affect the travel demand or mode choice decision. However, these studies mostly consider international destination choices. For example, Bigano et al. (2006) find that tourists are attracted to sunny yet mild climate locations. They suggest that the optimal average temperature of the destination is equal to 16.2^{o} C ± 2.05^{o} C. Hamilton (2004) found that Northern European countries become relatively more attractive than the southern European countries for German tourists. A similar kind of study has been done by Maddison (2001) for British tourists. These studies consider the link between weather and international destination choices. Not very, many empirical studies have been done on the weather and destination choice within the country and its implications for travelling decisions.

Wind

Gentle wind may encourage travelling, as recreational and sports activities such as surfing on the beach may increase. However, strong wind usually has negative implications for transportation mostly related to decreased safety. Strong wind affects moving vehicles and may create obstacles by blowing snow or sand, etc. It also affects transport infrastructure such as overhead cabling if trees are blown down onto it. There is some literature available on the impact of strong wind on transportation. For example, Young and Liesman (2007) investigate the impact of strong wind on truck crashes between 1994 to 2003 in Wyoming, USA. They found significant effects of strong wind on truck-overturning crashes.

Baker and Reynolds (1992) analysed the wind induced vehicle accidents that occurred in the UK during a windstorm. They found that most common wind-induced road accidents are overturning (47 per cent), followed by course-deviation accidents (19 per cent), and those involving trees (16 per cent). They also obtained a threshold speed of wind for traffic management in the presence of strong wind. Their finding suggests that the majority of overturning accidents in South East of England and on the M1 motorway happened during a wind speed higher than 20m/s. They propose that traffic should be restricted if wind storms are stronger than 17m/s. Hermans et al. (2006) confirm these finding and reported increases in crashes with increasing wind in the Netherlands. Edwards (1996) also analyses the relationship of weather and the frequency of road accidents in England and Wales. She finds a positive influence of strong wind on accident frequency (although in some counties the pattern was not clear). Wind may also overturn lightweight trains and trams. However, not much empirical work has been done on this topic.

Strong wind also influences the demand and supply equilibrium for transport. On the demand side, strong wind may cause people to cancel their trips (depending on the purpose of trip), or they may switch to other modes of transportation (e.g. from bicycle to car). On the supply side, wind may affect the infrastructure of the urban transport or of inter-city highways and rail because of falling trees or because of overturning. Perry and Symons (1994) report that the lanes on the Severn Bridge between England and South Wales have had to be closed for some 130 hours per annum on 20 days annually during the 1980s. Additionally, such lane closures occur mostly in autumn and winter, with an average time of closure of around 7 hours. They reported that over 100 people were killed and nearly 700 injured because of wind on British roads between 1962 and 1980. These fatalities are 0.1 per cent of total fatalities.

Precipitation

Perhaps precipitation is the most studied weather component for travel and transport as compared with other weather components. Satterthwaite (1976), Fridstrøm et al. (1995), Chung et al. (2005), Hogema (1996), Bertness (1980), Edwards (1996), Brodsky and Hakkert

(1988), Keay and Simmonds (2006), Van Berkum et al. (2006), Sabir et al. (2010a, b) are just a few among a vast literature.

The above studies focus on different aspects of the impact of precipitation on transportation ranging from safety to delay in travel time. The risk of accidents is reported to increase during rainy conditions. For instance, Chung et al. (2005) find that accidents increase during rainy conditions on weekends in Japan. Brodsky and Hakkert (1988) reported a higher risk of accidents in Israel due to occasional rains compared with the more persistent rains of the winter season. Rainy weather contributes to about 6 per cent of weekday vehicular injury accidents in Israel. Additionally, their study found that rain followed by a drier spell is more risky. Similarly, for the United States, Brodsky and Hakkert (1988) find that a higher proportion of wet time does have higher indices of risk (see also Keay and Simmonds 2006). Talab (1973) investigates the relationship between rainfall and road accident frequencies of London and Huddersfield using accident data from 1966 and 1967. His study shows more accidents in London compared with Huddersfield during rainy conditions. Additionally, rainfall during the night and in the spring month has severe effects.

Andrey and Yagar (1993) find that the risk of a road accident is 70 per cent higher during rain compared with normal conditions. Satterthwaite (1976) also reported that the number of accidents doubled on state highways of California during wet days compared with dry days. They also reported more single-vehicle accidents during wet days compared with other types of road accidents. Hermans et al. (2006) reported an increase of 6.5 per cent in number of hourly crashes for each additional 10 minutes of precipitation. However, a higher amount of precipitation has a smaller impact suggesting that people adapt to the situation or drive more carefully.

All these studies reported an increase in road accidents during precipitation. However, there are some studies which reported reverse effects. For example, Eisenberg (2004) found a negative (fatal accidents reduce by 3.73 per cent per 10cm of precipitation) and statistically significant relationship between monthly precipitation and monthly fatal crashes, for US crash data from 1975 to 2000. One explanation for this contrary finding is the lag effect of precipitation over a number of days, due to the clearing of oil that accumulates during dry periods. Also, people may adapt to driving in wet conditions. However, the relationship between daily weather and daily crashes was strongly positive.

The severity of accidents also varies during rain as compared with fine weather. However, the literature on the relationship between precipitation and the severity of accidents has mixed findings. For example, Edwards (1998) finds that accident severity decreases during rain compared with fine weather. This finding is contrary to Bertness (1980), who reported that crash severity increases with rain in rural areas.

Another aspect of the relationship between rain and travelling concerns travel demand. It is likely that people may take fewer trips during precipitation, or may take more recreational trips during nice weather. Chung et al. (2005) observed lower traffic demand during rainy days, especially on weekends. Khattak and De Palma (1997) did a commuter survey in Brussels and asked commuters about their daily commuting behaviour. They report that adverse weather causes commuters to alter their departure time choice, mode choice and route choice decisions. Rochat and De Palma (1999) confirmed the finding of Khattak and De Palma (1997) for Geneva's commuters.

Hogema (1996) studied the effects of rain on daily traffic volume and on driving behaviour on a highway (the A16) in the Netherlands. He reported that precipitation has no effect on traffic volume, and there is a reduction in speed. Cools et al. (2010) found that snowfall, rainfall, and wind speed diminish traffic intensity. Sabir et al. (2010a) also found that rain alone has no influence on commuting trips made by car in the Netherlands. However, rain during congestion does have an influence on these trips, and the welfare costs associated with rain is up to 12 per cent of the overall commuting costs.

It may be noted that snow, hail and sleet are also part of precipitation. However, they are measured separately. Snow is most common among these. Snow may have an influence on demand and supply of transportation and may also pose safety risks. On the demand side, extreme snow can reduce the total demand by cancellation of trips (based on trip purpose). On the supply side, the roads may be covered with snow and hence have a lower capacity, or public transport supply may be limited due to technical reasons. The supply-side phenomena can be observed from recent snow events in December-2009 and January 2010, during which, over 80 per cent of the Dutch national railways were not able to function (mainly for technical reasons), and people were advised to not travel by train. FHWA (2006) studied the impact of severe weather on traffic flow. They found that snow and rain influence free-flow speed, speed at capacity depending on the intensity of snow.

Snow can also be potentially dangerous for traveller safety. Empirical research has mixed findings on the role of snow in road accidents. For instance, Edwards (1996) found seasonal affects of snow (but a relatively insignificant role) in overall accidents for England. On the other hand, Jean et al. (2003) reported an increase in traffic accidents in snow and sleet. Andreascu and Frost (1998) also found an increase in accidents with an increase in snow and rainfall. Nofal and Saeed (1997) found a negative correlation between road accidents and the amount of precipitation, snow and hail. Fridstrøm et al. (1995) also found that in Nordic countries rainfall increases the accident counts, whereas during snow the number of accidents falls, but this may be due to people's adaptive behaviour when driving in snow in the Nordic countries.

Besides its effects on road safety, snow may have role in traffic congestion, as vehicles may move slowly in snow due to low visibility, or due to the presence of snow on roads. Nookala (2006) found that during severe snow the traffic demand drops significantly on freeways. This reduces the traffic volume, thus easing the freeway congestion.

Other forms of precipitation such as sleet, hail etc. may also influence transport. However, not much empirical research has been done on these particular events, separately. Major reasons are unavailability of suitable data and the less frequent occurrence of these phenomena.

Fog

Fog is a less frequent weather component in many parts of the world, yet one of the most important related to traffic safety. Fog reduces visibility and increases the risk of the accidents. An interesting scientific study was done by Snowden et al. (1998). They found, in a virtual environment driving simulator, that drivers drove faster as the scene became foggier because drivers underestimate their speed during foggier conditions. The main reason for this behaviour is that drivers check their speed from the speedometers, and for this they have to divert their gaze and attention from the road to the speedometer. During foggy conditions, the drivers are reluctant to divert their gaze from road to the speedometer for fear of missing an object emerging from the fog. Thus drivers mostly underestimate their speed, and hence increase accident risk. In the UK around 2 per cent of annual accidents occur in fog, and the majority of these accidents are reported in the last quarter of the year, where fog plays a role with ice and wind. (Edwards 1996).

During foggy conditions, multiple-vehicle crashes are more common. Whiffen et al. (2002) document some fog-related road accidents in Canada. In the two worst of these multiple-vehicle accidents 145 and over 200 vehicles, respectively, were involved causing many fatalities and injuries in both these accidents. Whiffen et al. (2002) also reported an increase of fog related fatal accidents in Canada during the 10-year period 1988 to 1997, even though, overall, fatal road accidents and the occurrence of fog events fell during this period.

Fog may also reduce the overall speed of traffic flow and thus cause travel delays. Normally, such speed reduction is for safety reasons, and is imposed by road control authorities. In some countries, the highways maybe closed completely during fog for safety reasons. However, there are not many scientific studies that specifically focus on the impact of fog on road accidents, mainly because fog happens less frequently.

Other Weather components

There are other weather components, such as dew point temperature, relative humidity, clouds, global radiation, air pressure, etc. However, these components do not receive much attention in academic work and have been ignored from most of the empirical studies.

Extreme weather events

Extreme weather events such as severe winter storms, flooding, hurricanes, etc. can cause damage worth millions of dollars to the transport infrastructure, can lead to evacuations, and can be a risk to the life of the people living in affected area. But mostly these events fall under the heading of natural disasters, and hence are beyond the scope of this thesis.

1.4 Role of weather and climate changes for travel behaviour

The above discussion leads to the question: Are weather and climate change important for travel behaviour? Clearly weather has strong influence on travel behaviour, as discussed in Section 1.2. On the other hand, the effect of climate changes on travel behaviour does not seem that important right now, (as climate change refers to long term changes in weather). But this does not mean that it can be totally neglected for transportation in the short run (TRB, 2008) because it is possible that, as a result of raising global temperature, the normal variability in weather will become amplified in the near future. Another point is that transport infrastructure is normally built for a longer period of 20 to 80 years. So current decisions are made (and have implications) when considering future infrastructure and land use. Transport professionals already consider weather and climate-related factors in designing and operating the transportation infrastructures. But deviation from normal circumstances may create new problems.

Climate change also has implications for travel behaviour. Appendix 1A presents a summary of the major future expected climate changes. Based on these projections one can easily draw some inferences that climate change may have a strong influence on travel behaviour. These effects can be divided into two main groups: first, the positive impacts of climate change on transportation; and second, the negative impacts of climate change on transportation.

On the positive side, an increase in average temperature for some areas will bring a longer duration of summer. For example, countries with a longer winter, such as the Nordic countries or the countries in higher altitudes will likely to have a longer summer. This implies more economic activities for those regions in these months, and hence more demand for transportation. Another important aspect is the potential for increases in tourism. The areas which were not common tourist destinations due to extreme cold may have less extreme weather due to climate change and tourists may be attracted to these destinations, which means more transportation demand and the development of new transport infrastructure in those areas.

There is already some evidence that the ice sheet on the North Pole is melting and scientists are expecting that in few decades, this may lead to opening the Northern route for the shipping between East and West. This may lower transportation costs for trade between East and West. Travel time and fuel costs may be as low as 50 per cent compared with alternative routes for a ship going from Rotterdam via the Northern route to Japan. Besides the opening of Northern route for trade, there will be the possibility to exploit important natural and mineral resources below the ice sheet, which was not possible before. This has implications for increased road, sea transport activities and the development of new transport infrastructure in those areas.

Another aspect is of less snow during winter, which means less safety concerns and less spending on the maintenance of roads during winter (e.g. less salting required). Accordingly, Miller (1989) reported $US 4.5 million cost reduction due to the reduction in annual snowfall from 50 to 8 inches due to climate warming in Cleveland, Ohio, USA. There may be less failure and disruption of public transport due to adverse weather.

On the negative side, an increase in mean temperature may cause modal shift phenomena in countries which rely on the non-motorized mode of transportation. This may have huge implications for the policy makers of those countries. However, to what extent the changes in mean temperature will affect model shift is an empirical question. Increased mean temperature may also have implications for travel demand in those countries. The demand for vehicles equipped with modern technology to face warmer weather will increase. Furthermore, the cost of road surface maintenance may increase, especially in those regions where roads are constructed for colder and moderate warmer weather.

Another important issue is rise in sea level. This may influence housing and road infrastructure located near the coast. The higher sea level may also add to the intensity of the possible flooding in the coastal region, and hence the risk of the damage to the transport infrastructure on the coast may be even higher.

Besides raising mean temperature and sea-level, climate change will bring more precipitation with increased intensity. This may cause higher maintenance costs for transport infrastructure in general, and for road infrastructure in particular.

Modal split and travel demand are not the only decisions which may be influenced by climate change. Another aspect is road safety which may be adversely affected because of unusual weather conditions. For example, the literature suggests that there will be more road accidents with more precipitation. But the question remains unanswered whether the relationship between precipitation and road accidents will remain stable in future (accidents increase with increase in precipitations), given that people may adapt to new climates.[1] Also

[1] There is already some evidence that car travel during inclement weather has become less risky over the past two decades in Canada (Andrey 2010). There has been a downward trend in relative risk during rainfall from 1984 to 2002 – both overall and when further disaggregated by injury severity combined with precipitation amount, city group, and time of day. By contrast, the overall relative risk of casualties during snowfall shows no significant change over time.

the role of future technologies cannot be ignored, which may bring safer vehicles and better road surfaces. How people will react to all these changes is not easy to answer.

This discussion highlights the role of climate change for transportation. However, climate changes refer to long-term changes and analysing travel behaviour in the far future involves considering many issues (e.g. state of future technology, people preferences for travelling, state of the road, etc.) along with the predicted weather conditions. The uncertainty about those additional factors is probably great enough to create only a generalized scenario. Therefore, it makes more sense to confine ourselves to analysing the impacts of weather on travel behaviour, given that we are able to obtain the real-time, micro-level detailed data from the real-world situation. However, where relevant, we will occasionally generalize our empirical findings in the context of future climate change.

1.5 Scope of the thesis

On the basis of Section 1.2, the potential impacts of different weather conditions on travel behaviour can be summarized below in Table 1.1, which is self-explanatory. The variation in temperature, precipitation, wind, snow and visibility may cause the changes in travel behaviour. Temperature variation may lead to variation in travel demand (and supply), destination choice, etc. For example, people may take fewer trips during bad weather, or on a good day there will be more people going to the beach instead of going to the city or crowded areas for recreational trips.

Similarly, precipitation can also cause travel delays as the traffic flow may slow down in the presence of precipitation for safety reasons and hence possibly cause of delay in the overall trip. Strong wind can disrupt the operation of the public transport, especially urban transport.

Table 1: Weather and Travel behaviour[1]

	Potential Impacts on Travel behaviour						
Changes in Weather*	Trip generation	Modal shift	Destination choice	Travel delays	Road capacity	Accident risks	Disruption of transport
Wind	?[2]	+	?	?	0	+	+
Temperature	+	+	+	?	?	?	?
Precipitation	+	+	–	+	–	+	?
Snow	?	–	?	?	–	+	+
Fog	–	?	?	–	–	+	?

Notes:
(1) It may be noted that these are the weather components mostly used in the transportation literature. There are many more weather variables, just to mention few, sunshine, hail, tornadoes, flood, coastal storms, thunder storms, etc. But most of them happen less frequently or are not very important compared with the basic weather components.
(2) The symbols +, –, 0 and "?" mean increase, decrease, no relationship and ambiguous, respectively.

The aim of this thesis is to quantify the impacts of weather on travel behaviour, and on the basis of these findings suggest policy measure for the Dutch government to take possible corrective measures in transport management during various weather conditions. Under this research theme, following research questions are investigated in this thesis:

- How does weather influence the destination choice for recreational trips? (Chapter 2)
- How does weather influence individual travel demand? (Chapter 3)
- How does weather influence the mode choice decision of individuals? (Chapter 4)
- How does weather influence the travel time for commuting trips? (Chapters 5 and 6)
- How does weather play role in road accidents? (Chapter 7)

1.6 Research organization

This thesis is organized in eight chapters consisting of six empirical studies (See Figure 1.1). Chapter 2 studies the influence of weather on the decision to go to the beach, together with mode choice and the distance to travel. A nested logit model is employed to investigate these three decisions simultaneously.

Chapter 3 describes how individual travel demand responds to varying weather conditions. Two measures of travel demand are used. These are the number of trips made by individuals during a single day and the daily distance travelled by individuals. An analysis is also made for different trip purposes and for different travel modes.

Chapter 4 investigates the role of weather in the mode choice decision of individuals. Different multinomial models are estimated for different trip purposes and also a combined model has been estimated to obtain a general overview of the mode choice decision of individuals. Moreover, substitution among different modes of transportation in different weather conditions is also investigated.

Chapters 5 and 6 focus on adverse weather and travel time. Chapter 5 considers car commuting trips and estimates the welfare loss caused by weather due to loss in travel time. Chapter 6 also considers the role of weather in commuting trips' travel time in public transport. The focus of the chapter is on the role of public transport in integrated transport systems.

Chapter 7 investigates the role of weather in hourly accidents. The main objective is to analyse the role of weather in the number of accidents that happen during different hours of a day. Additionally, severity of accidents in various weather conditions has also been discussed.

Finally, Chapter 8 provides the summary and conclusions of the research.

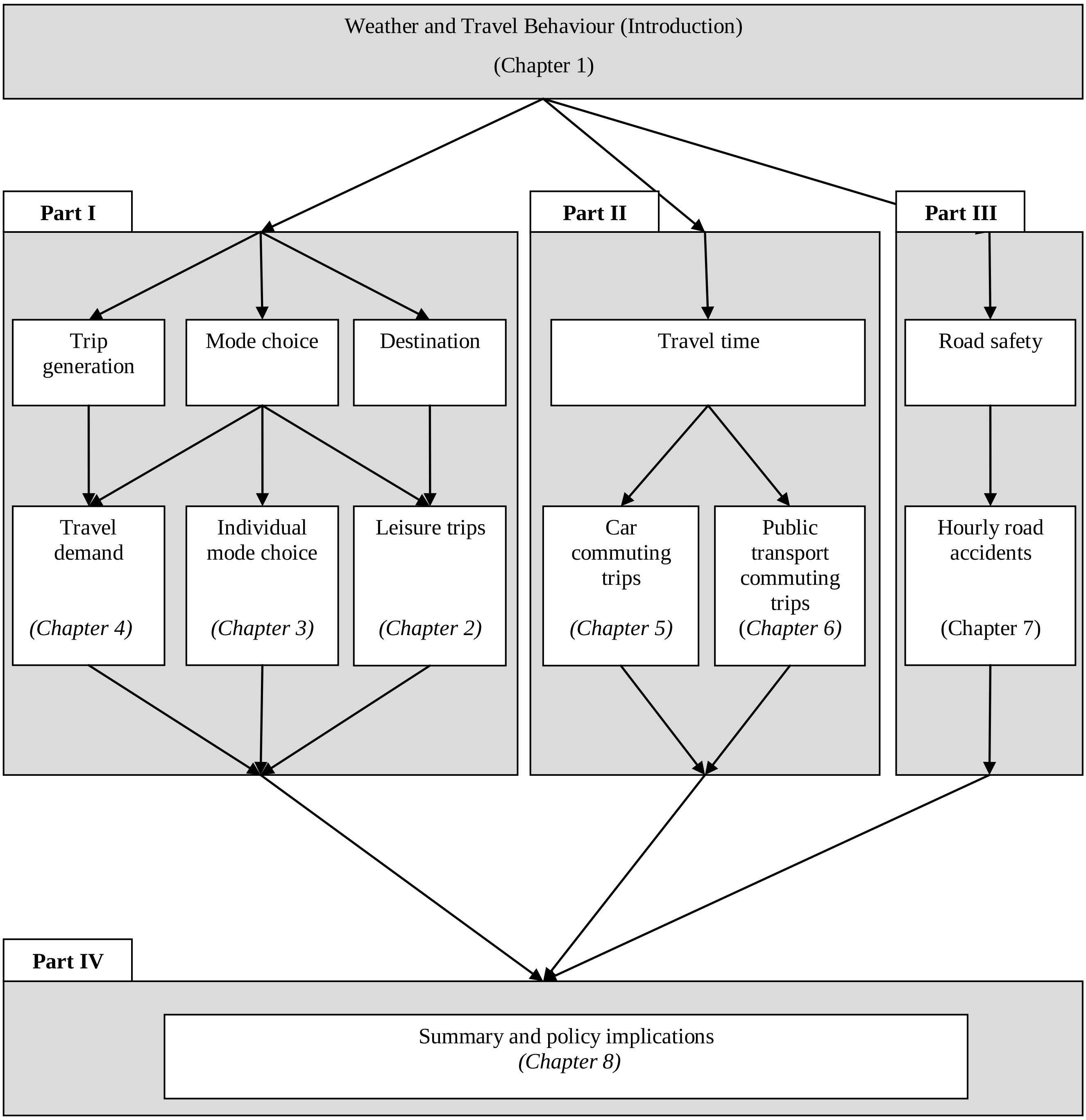

Figure 1.1: Thesis layout

Appendix 1A

Table 1A: Summary of major future climate change expectations

Temperature The global surface mean temperature is expected to rise by 1.8°C to 3.4°C (depending on different models) by end of this century compared with the 1999 level. This increase will be not be equal across the globe. It is very likely that heatwaves will be more intense, more frequent, and long-lasting in a future warmer climate. The annual mean temperature is likely to increase more in Europe compared with global annual mean temperature. Also within Europe the increase will be not proportional. The warming in northern Europe is likely to be greatest in winter, and in the Mediterranean area greatest in summer. Furthermore, the lowest winter temperature in northern Europe is less likely to increase more than average winter temperature. Also the highest summer temperature is likely to increase more than the average summer temperature in southern and central Europe. KNMI (2006) climate change scenarios for the Netherlands suggest that temperature in the Netherlands will continue to rise over the next 50 years, i.e. milder winters and warmer summers. Van Oldenborgh and van Ulden (2003) find that temperature in De Bilt in the Netherlands has risen by 1° C over the 20th century.[2]
Precipitation Precipitation is expected to increase globally. There will be more average mean precipitation, globally. However, in the subtropics precipitation is expected to decrease in future warmer climate. Annual precipitation is very likely to increase in most of northern Europe and decrease in most of the Mediterranean area. Extremes of daily precipitation, and the annual number of precipitation days are very likely to increase in northern Europe. In central Europe, precipitation is likely to increase in winter and decrease during summer. KNMI (2006) report that annual precipitation in the Netherlands has increased by 20 per cent since 1900. Moreover, KNMI (2006) also predicted that winter will become wetter and extreme precipitation will increase in the Netherlands as a result of climate change. Extreme showers during summer will also become more common, although the number of rainy days in summer will decrease.
Wind pattern Certainty about future changes in windiness is relatively low, but it seems more likely that there will be an increase in average and extreme wind speeds in northern Europe. KNMI (2006) predict that the calculated changes in wind speed are expected to be small compared with natural fluctuations in the Netherlands.
Snow The duration of the snow season is very likely to shorten all over Europe and snow depth is likely to decrease in most of Europe.
Sea level rise Sea level is projected to rise by 0.18m to 0.59m (depending on different models) by end of this century compared with the 1980-1999 level.

Source: IPCC (2007) and KNMI (2006).

[2] The station De Bilt is representative for the mean climate conditions in the Netherlands. Its temperature and wind direction records are considered the most homogeneous long-term records of the Netherlands (van Oldenborgh and van Ulden 2003).

PART I

WEATHER AND INDIVIDUAL TRAVEL CHOICES

Chapter 2

Weather to travel to the beach

2.1 Introduction

Weather plays an important role in most day-to-day activities. Leisure activities, in particular, are strongly affected by weather. For example, a nice sunny day may bring thousands of people to the beach. The importance of weather for leisure activities increases more with increasing knowledge about the weather forecasts and climate changes.

Climate change may change the weather of some countries considerably. In countries with extreme cold, summer is anticipated to be longer and warmer. This may increase the demand for certain domestic leisure trips and destinations.[3] Stated preferences studies suggest that demand for beach holidays may change due to climate change (see Braun et al. 1999).[4] The findings by Ibarra (2010) for Spain, and Moreno et al. (2008) for the Netherlands suggest that temperature is an important factor which brings more people to the beaches.

This study focuses on the impacts of weather on destination choice, i.e. the choice between going to the beach or to non-beach destinations for leisure activities. Previous studies differ considerably from our study. For example, De Freitas (2006) and Adams (1973) show that bad weather conditions have a negative effect on going to the beach using stated preference methods, but do not consider the mode of transportation. The current study considers the impacts of weather conditions on *revealed* beach trips choice and mode choice simultaneously.

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[3] For a survey, see Moreno and Amelung (2009), Hamilton and Maren (2004), and Becken (2010).

[4] For example, Braun et al. (1999) report that climate change will have a negative influence on the north German coastal region as a vacation destination. For example, Bigano et al. (2006), who analysed destination choices of the tourists from 45 countries, report that tourists are attracted to a sunny yet mild climate. Hamilton (2004) shows that European countries are more attractive for German tourists during summer months, in particular, the northern European countries. See, similarly, Maddison (2001) for British tourists. Lise and Tol (2002) show that beaches and a nice climate attract tourists. The optimal holiday temperature for international tourists is above 20^{o} C.

One of our contributions to the literature is methodological. To fully understand transport decision making, one has ideally to include the decision to make a certain type of trip (e.g. visiting a restaurant), the decision where to travel (which depends, for example on both the spatial choice set of restaurants, and the quality of the restaurants) and the travel mode decision. Usually, one of the decisions is ignored or made exogenous (e.g. by choosing only trips to restaurants). One of the difficulties is that transport is a derived demand, so when weather conditions change, this will affect not only typical transport decisions, such as which transport mode to choose, but also whether or not to make a certain type of trip. This is of particular importance in the context of leisure trips, because it is particularly these types of trips, which are influenced by weather conditions. This is not the case with all types of trips. For example, the decision to work does not depend directly on weather, so the demand for commuting is not affected by weather through a change in demand for working.

In the current chapter, we focus on travel to the beach from residence locations. This enables us to make simplifying assumptions. First, from each residence location in the Netherlands, there is an extremely limited range of attractive beach locations. For each municipality location to each beach location in the choice set, we know the travel distance. So for each residence municipality, we are able to calculate the average travel distance to the beach (based on actual trips made). Because most persons in a certain municipality choose the same beach, it is useful to consider the beach choice decision as being one-to-one with the travel distance decision. Second, we assume that the average travel distance to the beach is exogenous with respect to the residence location. In other words, it is assumed that households who choose their residence location do not include beach trips in that decision. This seems a reasonable assumption as almost all households make only a few trips to the beach each year.

To simplify the interpretation of the empirical results, we use a selective sample of car-owning individuals who make leisure trips during the summer months (so we exclude commuting, business, and shopping trips). In essence, we model the decision to visit the beach conditional on the decision to make a leisure trip. The latter makes sense, because few workers really have to choose between a commuting or a beach trip. Note that we only include car-owning individuals. It would be also possible to include individuals without cars, but, as these refer to only 8 per cent of the sample and these individuals have a different choice set, interpretation is facilitated by focusing on car-owning individuals. Given this set-up of the model, it is possible to estimate a standard nested logit model, where individuals: (i) make a decision to travel to a certain beach location which defines the travel distance: and (ii) make a mode choice decision when travelling to the beach. By estimating the standard nested logit model, we are able to calculate the (marginal) effect of weather conditions (and other variables) on the decision to travel to the beach by a certain travel mode conditional on the spatial choice set of each individual. Thus, the number of kilometres travelled, the type of destination, and the transport mode decision are modelled as simultaneous decisions.

The rest of the chapter is organized as follows: Section 2.2 describes the empirical data, which consists of details of the explanatory variables included in the model. Section 2.3 presents the estimation results and discusses the results. Section 2.4 concludes the Chapter.

2.2 Data

We use the Transportation Surveys of Dutch Central Bureau of Statistics (OVG/MON) from 1996 till 2005.[5] Over the course of an entire year, individuals were asked to fill out a questionnaire on their travel behavior *during a certain day*. The survey contains information about the origin and destination of the trip at municipality level and details of the trip, along with important socio-economic characteristics of travellers. The weather data, provided by Royal Netherlands Meteorological Institute (KNMI), contains information about weather conditions measured on an hourly basis by 32 weather stations spread all over the Netherlands. The average distance to a weather station is about 12 to 13 km, which means that our measurement of weather conditions is local.[6]

We select leisure trips (of car-owning households) made during four summer months (May, June, July, and August). In a national travel survey, it is not explicitly reported whether or not trips are to the beach. We solve this issue by assuming that leisure trips to municipalities that have a beach are beach trips. This assumption is plausible because these municipalities are small.[7] Furthermore, we exclude trips originating from beach municipalities, as many of these trips may not be to the beach. The total sample then consists of 154,261 leisure trips of which 1,405 (0.9 per cent) are to the beach. The beach locations are given in Figure 2.1.

As explained in the introduction, we select leisure trips because it is plausible that most individuals choose to go to the beach conditional on the decision to be involved in a

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[5] OVG and MON are almost similar surveys. MON has fewer reported trips and individuals than the OVG survey but has some additional variables not used here.

[6] We have estimated the average distance as follows: The total land area of the Netherlands is 33,889 km^2. Given the assumption that stations are homogenously spread over the country, and that each weather station covers a circular area, the maximum distance is 18.78 km. The average distance from the centre of a circle is 2/3 of the maximum distance, so the average distance to a station is 12.52 km.

[7] Although The Hague has a beach, we did not label trips to this municipality as a beach trips, because The Hague is a large city.

leisure activity. Analysis of the data in this way enables us to model *three* decisions in *one* standard nested logit model, because the distance to the (nearest) beach is given, so we are able to combine type of trip (beach or non-beach) destination (the location of the beach) and mode choice decisions in one single standard model.

A priori, it is unclear how weather conditions must be measured (e.g. on departure at home or on arrival at the destination). We use weighted daily weather conditions at the residence (instead of, for example, hour of arrival of weather conditions), where the weights are proportional to the aggregate number of recreational trips made during certain hours of the day. By using the weather conditions of the residence, we avoid the issue that the weather conditions depend on the destination choice decision. So, for each observed trip, we use the weighted weather conditions of the weather station that is nearest to the individual's residence municipality. Weather variables included in the model are temperature (lower than 20^{o} C, from 20^{o} C to 24^{o} C, and higher than 24^{o} C), wind strength (in metres per second) and its square, in order to capture any non-linearity in wind strength. Precipitation is measured by a dummy variable.

Besides weather variables, we include other explanatory variables such as weekends, income, gender, age, and work status of individuals. Importantly, we use a beach distance variable measured by the *mean* distance to the beach from the residence municipality, where the mean is taken over all beach trips made by persons living in that municipality. This means that every person living within the same municipality has the same distance to the beach, no matter which beach is selected. This way of measuring of distance enables us to use beach distance as an *exogenous* control variable to explain the decisions regarding mode choice and weather to go to the beach. We also control for a time trend by including a linear time trend variable.

We do not include seasonal variation, such as, monthly dummies for two reasons. First, we use a reduced sample. Second, we are using a selected sample of summer months which automatically controls for seasonal variations. The descriptives of explanatory variables are presented in Appendix 2A.

Figure 2.1: Beach Locations in the Netherlands

2.3 Estimation Results

We have estimated several nested logit models (NLMs) and tried several tree structures to find the best decision tree. Figure 2.2 presents the preferred tree structure for an NLM based on model fit and a global utility maximization principle.[8] The full results of the NLM are presented in Appendix 2A. The results are plausible, and almost all the variables have the

[8] It may be noted that the Inclusive Value (IV) parameter is 0.99, implying that MNL and NL have similar results.

'correct' intuitive signs. We focus on the marginal effects of weather variables, which are presented in Table 2.1.[9]

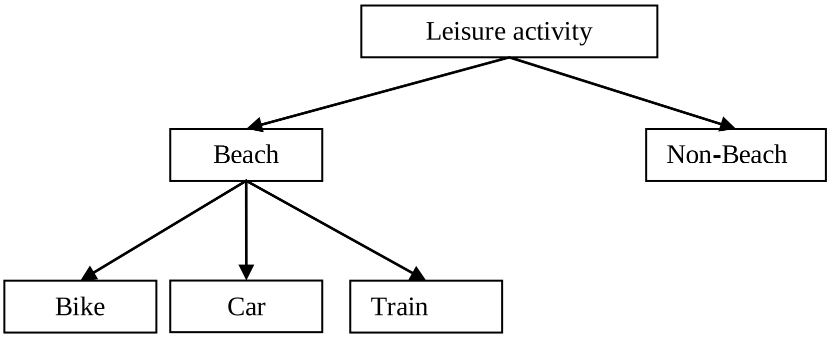

Figure 2.2: Destination choice and mode choice

Table 2.1 presents the percentage point changes in the probabilities of choice decisions. The first two columns give the marginal effect on mode choice, conditional on going to the beach. As one may expect, weather has a strong influence on travel to the beach decisions, as well as on mode choices. For example, the probability of going to the beach by bike increases by 6.3 percentage points for temperatures above 24^{o} C (compared with temperatures lower than 20^{o} C). Similarly, the probability of going to the beach by train increases with an increase in temperature of 3.7 and 5.3 percentage points, respectively, for the two higher temperature intervals. Clearly, a higher temperature makes the biking activities more attractive. These are rather substantial variations in probabilities of these two modes given that the probabilities of going to the beach by these modes of transportation are very small (12 and 10 per cent respectively). These results suggest that people use train and bicycle (for short distances) to go the beach in order to avoid car congestion on roads to the beach and at parking places. This may also reflect that cycling is more pleasant when the temperature is high.

Wind has no statistically significant effects on train trips compared with car trips. For bicycle trips, the effects of wind strength, combined with negative effects for its square, implies that the biking probability starts falling after a certain threshold level, which appears to be slightly higher than the mean wind strength. These findings are plausible if some wind

[9] The marginal effects of continuous variables are obtained at their mean values (see Hensher et al. 2005). For dummy variables, the marginal effects are obtained for a change in value from 0 to 1.

is considered pleasant, but too high wind levels are considered unpleasant or even dangerous. Finally, the probability of going to the beach by bike falls on a rainy day. However, the effects of precipitation are statistically not significant for train travel. The latter is intuitive, we believe.

Table 2.1: The marginal effects of weather conditions from the Nested Logit model

	Beach by different modes (Conditional on beach trips)		Going to beach decision
	Bike	Train	All Modes
Weather variables			
Wind strength (m/s)	**0.0703**	0.0178	**0.0036**
Wind strength square (m/s)	**-0.0044**	-0.0004	**-0.0002**
Temperature 20 °C to 24 °C	0.0264	**0.0367**	**0.0015**
Temperature >24 °C	**0.0637**	**0.0533**	**0.0023**
Rain (dummy)	**-0.0626**	-0.0144	**-0.0032**
Non-Weather Variables			
Weekends	0.0121	0.0300	**0.0021**
Distance to the beach (log)	**-0.0977**	**0.0211**	**-0.0035**
Income (log)	**0.0110**	0.0033	-0.00002
Employed worker	**-0.0033**	**-0.0200**	**0.0019**
Male	0.0011	-0.0044	-0.0004
Age < 18	**0.1548**	**-0.0367**	0.0020
Age between 30 and 60	0.0406	**-0.0956**	0.0004
Age > 60	**0.0812**	**-0.0967**	0.0005
Annual trend	**0.0132**	0.0056	**0.0007**

Notes:
(1) Coefficients in bold are significant at the 10% level of significance. Going to the beach by car is the reference category.
(2) The Reference categories of explanatory variables are : Temperature < 20° C, age and 18-30 years.

The probability of going to the beach is also affected by weather conditions. As one would expect during higher temperatures beach destinations become more attractive for leisure activities. The analysis shows that the probability of going to the beach increases by 0.15 and 0.23 percentage points, respectively, in the two higher temperatures intervals, which is substantial, as the average probability is 0.9 per cent. Similarly, gentle wind attracts more people to the beach for sea sports and recreational activities, but as it crosses some threshold level, it discourages beach trips (as indicated by the negative and statistically significant coefficient of the wind square variable). Leisure activities at the beach are strongly reduced by precipitation. This implies that people prefer to go to non-beach destinations for leisure activities if it rains.

The results of non-weather variables also provide some interesting results. During weekend there is no change in the probability of going to the beach by bicycle and train (compared with working days). However, the probability of going to the beach destination increases by 0.212 percentage points during weekends. This implies that people have a strong preference to go to beach destinations during weekends compared with working days. In our set-up, we are able to distinguish between the effect of distance on destination choice, as well as on mode choice. We show that the probability of going to the beach by bike decreases as distance increases. The opposite is true for train travel. Also, distance has strong negative effects on the beach (destination) choice. For example, the doubling of the distance to the beach decreases the probability of going to the beach by about 20 per cent. This effect is as strong as the effect of rain on the probability of going to the beach.

2.4 Conclusions

In this chapter, the focus was to investigate the influence of weather conditions on beach destination and mode choice decisions for leisure trips. We were able to combine three separate decisions (type of destination, distance travelled, and mode choice) in a single standard nested logit model. As anticipated, for higher temperatures there is a higher probability of going to the beach.

The results indicate that colder weather, strong wind, and precipitation decrease the probability of cycling to the beach. The probability of going to beach by bike and train increases with higher temperatures, where the latter is likely to occur to avoid car congestion on roads and parking places.

Appendix 2A

Table 2A.1. Descriptives of Variables

Variables	Mean	Variables	Mean
Weather Variables		*Non-Weather Variables*	
Wind strength (m/s)	4.93	Age less than 18 years	0.18
Wind strength square	28.65	Age between 18 to 30 years	0.14
Temperature < 20 ^{o}C	0.45	Age between 30 to 60 years	0.50
Temperature 20^{o} to 24^{o} C	0.32	Age greater than 60	0.16
Temperature > 24 ^{o}C	0.22	Income log	9.17
Rain	0.58	Male	0.48
		Worker (dummy)	0.47
Modal split beach trips (%)		Distance log	3.27
Bicycle	12.38	Weekends	0.21
Car	77.65	Beach trips	0.091
Train	9.96		

Note:
All variables are dummy variables, except wind strength, income log and distance log.

Table 2A.2: Nested Logit model for Destination choice and Mode choice (car is the reference category)

	Bike to the beach	**Train to the beach**	**Going to the beach Destination *(vs non-beach destination)***
	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)
Wind strength (m/s)	**0.304** (0.189)	-0.005 (0.117)	**0.460** (0.048)
Wind strength square (m/s)	**-0.030** (0.016)	-0.0001 (0.007)	**-0.018** (0.003)
Temperature 20 ^{o}C to 24 ^{o}C	0.241 (0.188)	**0.386** (0.197)	**0.161** (0.082)
Temperature >24 ^{o}C	**0.546** (0.198)	**0.672** (0.214)	**0.193** (0.118)
Rain (dummy)	**-0.350** (0.171)	**0.456** (0.183)	**-0.439** (0.065)
Weekends	-0.090 (0.189)	-0.089 (0.199)	**0.271** (0.072)
Distance to the beach (log)	**-0.656** (0.241)	**0.998** (0.320)	**-0.516** (0.110)
Income (log)	**0.169** (0.040)	**0.102** (0.037)	-0.024 (0.026)
Worker	**-0.553** (0.207)	**-0.815** (0.206)	**0.409** (0.128)
Male	0.150 (0.156)	0.151 (0.165)	-0.064 (0.066)
Age < 18	**0.785** (0.372)	**-0.643** (0.319)	0.224 (0.172)
Age between 30 and 60	0.241 (0.266)	**-1.026** (0.193)	**0.164** (0.122)
Age > 60	0.461 (0.328)	**-2.034** (0.341)	0.120 (0.171)
Trend	**0.069** (0.037)	0.012 (0.037)	**0.082** (0.014)
Constant	**-2.411** (1.122)	**-5.191** (1.183)	**5.626** (0.430)
IV Parameter			
Beach	0.99		
Non-Beach	1.00 (fixed)		
Number of observations	15 4, 261		
Log Likelihood	-9805.025		

Note:
Coefficients in bold are significant at the10 % level of significance.

Chapter 3

Weather and daily Travel Demand

3.1 Introduction

In this study we are interested in the effect of weather on travel demand. Travel demand is influenced by a large number of factors including price of transportation, fuel prices, taxes and weather. The role of weather is particularly important in a country like the Netherlands, where about 25 per cent of the population make use of the bicycle on a daily basis. Cycling is more sensitive to weather variation compared with other modes of transportation. Therefore, any abrupt change in weather may have substantial effects on travel demand in general, and on bicycle use in particular.

The Royal Netherlands Meteorological Institute (KNMI) predicts that the temperature in the Netherlands will continue to rise in the future. Mild winters and hot summers are anticipated to become more common. There may be more extreme precipitation, and on average, winters may be wetter. Furthermore, the summer is likely to have more intense rain, but with a reduction in the number of rainy days (KNMI, 2006). Given the expected future climate change, the impact of weather on travel demand is therefore an important consideration for policy makers and future planners. This study aims to investigate the impact of weather on individual travel demand for different trip purposes and for different modes of transportation.

Generally, we expect a negative effect of rain and extreme temperatures on transportation demand.[10] For example, Richardson (2000) finds negative effects of both rain and temperature, with rainfall and both high and low temperature decreasing the number of cycling trips in the metropolitan area of Melbourne, Australia (see also, Van Berkum et al. 2006). Goetzke and Rave (2006) confirm these findings. Chung et al. (2005) show that the number of car trips made on the Tokyo Expressway in Japan are lower during rainy days, in particular during weekends. Hofmann and O'Mahony (2005) study urban bus performance on selected routes in Ireland and report that ridership is reduced during rainy days. In addition,

[10] A general overview of empirical findings concerning the influence of weather on transportation is given by Koetse and Rietveld (2009).

rain increases congestion, which reduces the reliability of bus services.[11] Winters et al. (2007) show that utilitarian cycling in Canadian cities is negatively influenced by precipitation and low temperatures. Bertness (1980) also studied the impact of summer precipitation in the Chicago area. He reported a 3-5 per cent reduction in ridership of mass transit systems during rainfall due to a fall in discretionary riders such as shoppers. However, his study focuses on the impact of rainy days during summer only. Hence, his study excludes the impact of rain on public transit ridership during winter. Seasonal variations may also be important for travel demand. For example, Thomas et al. (2008) found that travel demand is at a maximum during spring, whereas summer and winter are relatively quiet.

Changes in weather may also cause a modal shift. Khattak and De Palma (1997) study traveller behaviour in Brussels, and find that adverse weather causes changes in mode and route choice, as well as on the departure time of car commuters. Furthermore, changes in departure time due to adverse weather conditions appear to be of more importance for automobile commuters than changes in route and mode choice.[12] Bergström and Magnusson (2003), using a survey of employees of four major companies in two Swedish cities, show that the number of car trips is 27 per cent higher while the number of bicycle trips is 47 per cent lower in winters compared with summers. Van Berkum et al. (2006) find that precipitation not only causes modal shift and cancellation of bike trips, but also causes postponement of bicycle trips. They reported that about 7 per cent of bicycle trips are postponed for an hour on a rainy day. Aaheim and Hauge (2005) find for Bergen (Norway) that increases in precipitation and wind increase the likelihood of the use of public transportation compared with walking and cycling.[13]

Despite their useful insights, these studies have some drawbacks. First, the weather indicators used in these studies were recorded only once a day, or only a few values of a limited number of weather indicators were available. In countries in which weather is subject to hourly changes, such as the Netherlands, such an approach is inaccurate at least. Second, most studies are based on surveys that cover only a few months. Since climate change is likely to have a differential effect on weather conditions in different seasons, covering only a few months is insufficient if the focus of research is on the general impact of climate change

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[11] Some studies also reported slightly different results. For example, Nankervis (1999) finds only trivial effects of precipitation on bicycle use in Melbourne. However, his study is based on students, who can be expected to have fewer substitution possibilities.

[12] De Palma and Rochat (1999) conducted a similar survey among Geneva commuters and found similar results.

[13] At the regional level, their analysis shows that weather conditions do not induce a switch between public and private transport. Furthermore, at the macro-level the expected impact of climate change on travel patterns appears small for Norway.

on travel demand. Third, the number of observations used in these studies is small, which makes it difficult to obtain precise estimates. Fourth, travel demand for other modes of transportation, such as bus, tram, metro, train, etc., is not studied thoroughly. Fifth, the focus of previous studies is mostly on commuting and recreational trips (e.g. Richardson, 2000; De Palma and Rochat, 1999) while ignoring other trip purposes. Finally, previous studies compare the influence of weather on individual travel demand across different days, but leave regional variation out of the equation.

In this chapter we aim to examine the influence of weather conditions on individual travel demand, while using data that have a large coverage in terms of geographical location, time duration, and weather indicators. We distinguish between several modes of transportation and trips undertaken for different purposes. An important contribution of this chapter is that local, hourly measured weather data are used. The data cover the entire Netherlands for a 10-year period. Additionally, we use day-specific panel data, thereby measuring the influence of weather on travel demand across the country on the same day. That is an improvement over methodologies used in previous studies which study the same phenomenon but across different days. Our analysis should give more exact and precisely estimated effects of weather on measures of travel demand.

The remainder of the chapter is organized as follows. Section 3.2 is devoted to the data, its sources, and the variables used in analysis. Section 3.3 contains model specifications for travel demand, while Section 3.4 presents the estimation results. Section 3.5 concludes.

3.2 Data and variables

We use data from two sources. First, Transportation Surveys of Statistics Netherlands (OVG/MON Surveys) for the years 1996 to 2005.[14] Second, we use KNMI weather data for the same period. The details of both data sets are presented in Section 2.3 in Chapter 2. In total, we have around 1 million individuals and 3.5 millions trips. The number of people and the reported trips for each year are presented in Appendix 3A. It may be noted that weather conditions used in our analyses are temperature, wind strength (BFT), precipitation duration (minutes of precipitation), precipitation intensity (mm), snow and visibility.

Transportation and weather data sets were matched so that each observed trip was assigned the weather conditions of the hour during which the trip took place, and from the weather station that was nearest to the place of departure. The average distance to a weather

[14] We combined the OVG and MON data sets to get data for 10 years from 1996. Some variables which were part of the OVG data set are not included in the MON data set; also, some variable categories have been changed over the years. For these reasons, some of the variable categories (such as age) are defined so that they become consistent with the next years' surveys in order to merge them.

station is about 12 to 13 km, which means that our measurement of weather conditions is local.

We are interested in the influence of weather on transportation demand. The transportation surveys used in this study provide the exact time of the trip made by a person during a specific day. We measure daily travel demand by the number of trips made by a person during a specific day, so we use an aggregate approach.[15]

Individuals may vary their travel distance, while the numbers of trips remains the same. We therefore also use the daily distance travelled as a measure of individual travel demand. This measure addresses the possible distance effects of weather. To obtain a more a comprehensive picture of the impacts of weather and climate changes on transportation demand, we will employ both measures.

We focus on daily travel demand, so we need a measure of daily weather conditions in the Netherlands. We use a weighted average of weather variables per day, where weights are based on the distribution of trips made during different hours of the day.[16] Hence, the weather of those hours in which more trips are made (such as peak hours), is assigned a larger weight than it is at other hours of days.

We specified different measures of weather. We measure temperature according to five intervals: (below or equal to 0^o C, 0^o C to 10^o C, 10^o C to 20^o C, 20^o C to 25^o C and temperatures higher than 25^o C).[17]

In order to measure the effect of precipitation we include a dummy variable for precipitation up to 0.1 mm per hour, a dummy variable for precipitation greater than 0.1 mm per hour and precipitation duration per hour (in minutes). Wind strength is measured in Beaufort (Bft).[18] A dummy variable is used, which is equal to 1 when the hourly weighted average of wind strength is equal to or exceeds 6 Bft.

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[15] A disaggregate approach with a daily level of trip may also be used (see, e.g., Chapter 4). However, the main advantage of an aggregate approach is that one may address travel demand and mode choice decisions simultaneously. Furthermore, the aggregate approach provides total travel demand for the whole day, whereas the disaggregate approach provides only travel demand per trip. Therefore, aggregation at a day level is useful.

[16] A simple average will not be an adequate measure for weather conditions as most of the trips are made during the daytime, and there are substantial differences in weather conditions of day and night.

[17] Because of climate change we would expect more extreme weather events especially on summer days as, on average, the temperature will increase. Therefore, the dummy variable for temperatures greater than 25^o C will reflect the expected effects of climate change on travel demand.

[18] The Beaufort scale (Bft) measures wind strength on a scale of 1 to 12. On this scale, 6 Bft represents powerful winds with a speed between 39 and 49 kilometres per hour (or 10.8 to 13.8 metres per second) over a period of at least 10 minutes. Similarly, 12 Bft represents a hurricane with wind speeds greater than 117 kilometres per hour (or greater than 32.6 metres per second).

Visibility is measured by a dummy variable which is equal to 1 when (the hourly weighted average) horizontal visibility is less than 300 metres during a day.

The effect of snow on the demand for travel is measured by a dummy variable. Unfortunately, we do not have an explicit measure of falling snow or snow on the ground. However, we use a proxy for snowfall by including an interaction effect of precipitation and temperatures below or equal to 0^{o} C. Measuring snow in this way probably only captures the effect of falling snow, and *does not* control for the effects of snow on the ground.

Furthermore, we control for regional differences in the Netherlands by controlling for provinces. We also include seasonal dummy variables to control for seasonal variation. Similarly, to see whether travel demand is different on different days of the week, we include a dummy for weekdays. Descriptives of all explanatory variables are given in Appendix 3A.

3.3 Theoretical model and estimation methods

3.3.1 Demand measured by number of trips

The advantage of using the daily number of trips as a measure of travel demand is that it is easy to apply, and it can be used to measure total travel demand, travel demand for specific transport modes, or travel demand for different trip purposes. The number of trips is a count variable. The benchmark model for count data is the Poisson regression model (Gurmu and Trivedi 1996; Greene 2007; Cameron and Trivedi 2005). The Poisson model is based on the assumption of equality of mean and variance both being equal to the Poisson parameter λ. To identify and estimate the effects of systematic factors on the number of trips made per person, we can specify this parameter as $\lambda_i = \exp(\beta x_i)$, where β is a vector of regression coefficients and x_i is a vector of independent variables. Then the Poisson regression model can be specified as, $\mathrm{P}(Y_i\!=\!y_i)\!=\!\exp(-\beta x_i)\,(\beta x_i)^{y_i}/y_i\,!$, where $\mathrm{P}(Y_i\!=\!y_i)$ is the probability of daily trips (y_i) made by an individual (y_i = 0,1, 2,……). However, a limitation of the Poisson model is that it cannot cope with the case that the variance exceeds the mean, a feature called overdispersion (Cameron and Trivedi, 2005).[19] The alternative model suggested in the literature is the negative binomial model. One way of deriving the negative binomial model is by introducing an unobserved effect into the conditional mean of the Poisson model (Cameron and Trivedi, 1986). This redefines the equation $\lambda_i = \exp(\beta x_i)$ into $\lambda_i = \exp(\beta x_i + \varepsilon_i)$, where ε_i is the disturbance term. This implies that:

[19] This approach also fails to account for conditional interdependence of counts because counts may be dependent on the previous occurrence of an event.

$$\mathrm{P}(Y_\mathrm{i} = y) = \frac{\exp(-\beta x_i + \varepsilon_i)\,(\beta x_i + \varepsilon_i)^{y_i}}{y_i!}. \qquad (3.1)$$

Equation (3.1) was called the compound Poisson model by Cameron and Trivedi (1986). The negative binomial model can be derived from the compound Poisson model by specifying a gamma distribution for ε_i, and allowing λ_i to vary randomly. In other words, the compound Poisson model, with ε_i having a gamma distribution, gives the negative binomial distribution.[20] We will estimate a negative binomial model with *day-specific fixed effects*, as it will provide the influence of weather on travel demand of different individuals across the country during the same day. In the absence of fixed effects, the model provides the effects of weather on travel demand across different days. We prefer the former approach because it is an improved technique and is more relevant for the type of weather data available in this study.

3.3.2 Demand measured by total distance travelled

Another possibility of estimating travel demand is to consider the distance travelled by an individual during a day. Let Y_i be the distance (km) travelled by a person per day (or by a specific mode or for a specific trip purpose), then we have $Y_i = \beta_i x_i + \varepsilon_i$, where β represents a vector of coefficients on explanatory variables x_i. This model can be estimated by OLS. However, OLS will produce inefficient and inconsistent estimates because of the excess number of zeros in the dependent variable, as not every person makes trips by each mode of transportation or for every trip purpose on the same day (Cameron and Trivedi, 2005). This problem can be addressed by using the Tobit model. Therefore, we specify our model as a Tobit model for total distance travelled per person per day; distance travelled by different modes of transportation; and distance travelled for different trip purposes. Hence $Y_i^* = \beta_i x_i + \varepsilon_i$, where Y_i^* is called a latent variable (because we do not observe it directly). This model is estimated with the condition: $Y_i = Y_i^*$ if $Y_i^* > 0$, and $Y_i = 0$ if $Y_i^* \leq 0$.

[20] In the present case, Y_i is the number of trips made by an individual during a day; and x_i is the vector of variables such as weather variables, seasonal variables, and the location of the trip origin.

3.4 Empirical results and discussion

3.4.1 Number of Trips

Different binomial models are estimated for (1) total travel demand: (2) travel demand for different modes of transportation; and (3) travel demand for different trip purposes. In this section we discuss the results from estimating the models day-specific fixed effects. The results of the weather variables are summarized in Table 3.1. The complete results of the model are given in Appendix 3B. The results are plausible and show the expected signs for almost all variables. A general observation for Figures 3.1 to 3.3 is that the shares of the various transport modes vary strongly (high for car and bicycle, low for public transport) (as also presented in Appendix 1, Table 3A.2). Therefore, we will consider both the absolute changes and the relative changes while interpreting the results. For example, a relative change in Bus, Tram and Metro trips (BTM) of say 20 per cent is smaller in absolute terms than a relative change in bicycle trips of say 5 per cent, simply because the modal share of the bicycle is much larger than that of BTM in the Netherlands. The same is true for train trips compared with car and bicycle trips.

Strong wind has a negative impact on individual travel demand, as shown in Table 3.1 and Figure 3.1. Total travel demand is about 2 per cent lower in strong wind conditions as compared with normal wind. The demand for walking and car trips is 2 and 3 per cent lower, respectively, during strong wind as compared with normal wind. The largest reduction happens for demand of the BTM, which show a reduction of about 22 per cent in windy conditions. These findings imply that total travel demand is sensitive to strong wind, and this holds true in particular for BTM. There may be two reasons for it. On the supply side, during strong wind, there may be limited operations of the services because of failure or for safety reasons. At the demand side, people may not take many trips under strong windy conditions, especially, if a weather warning/alert is given as well.

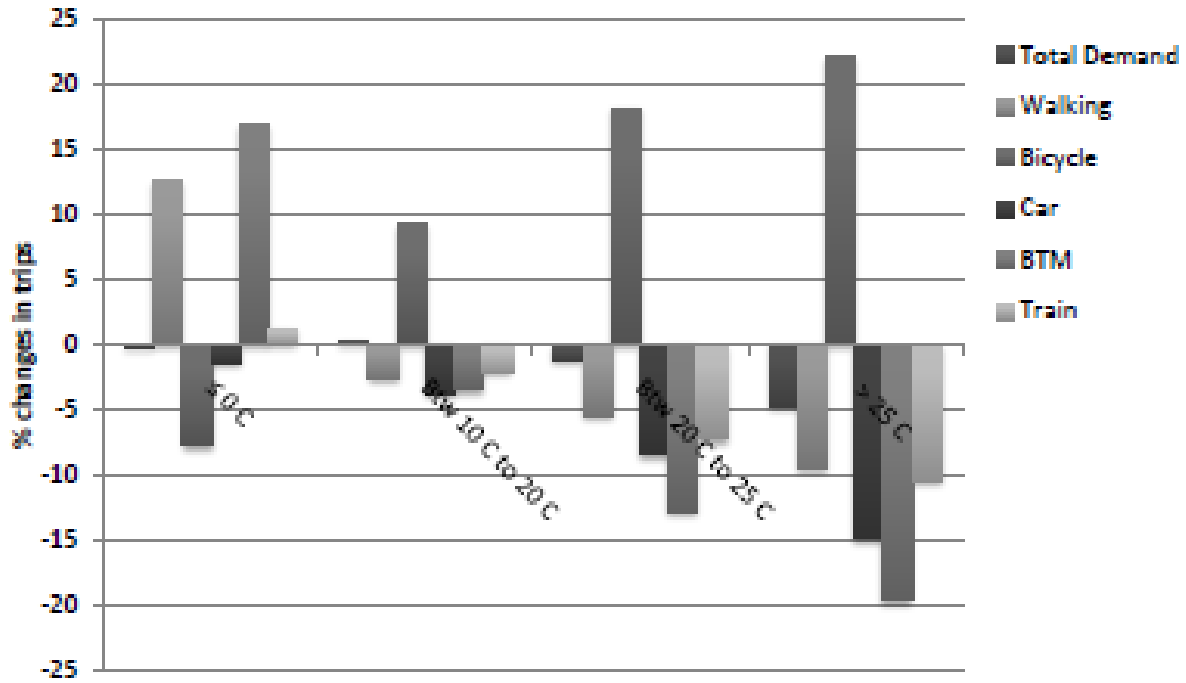

Figure 3.1: Temperature variation and relative changes in number of trips (the reference category is temperatures between 0 ^{o}C-10 ^{o}C)

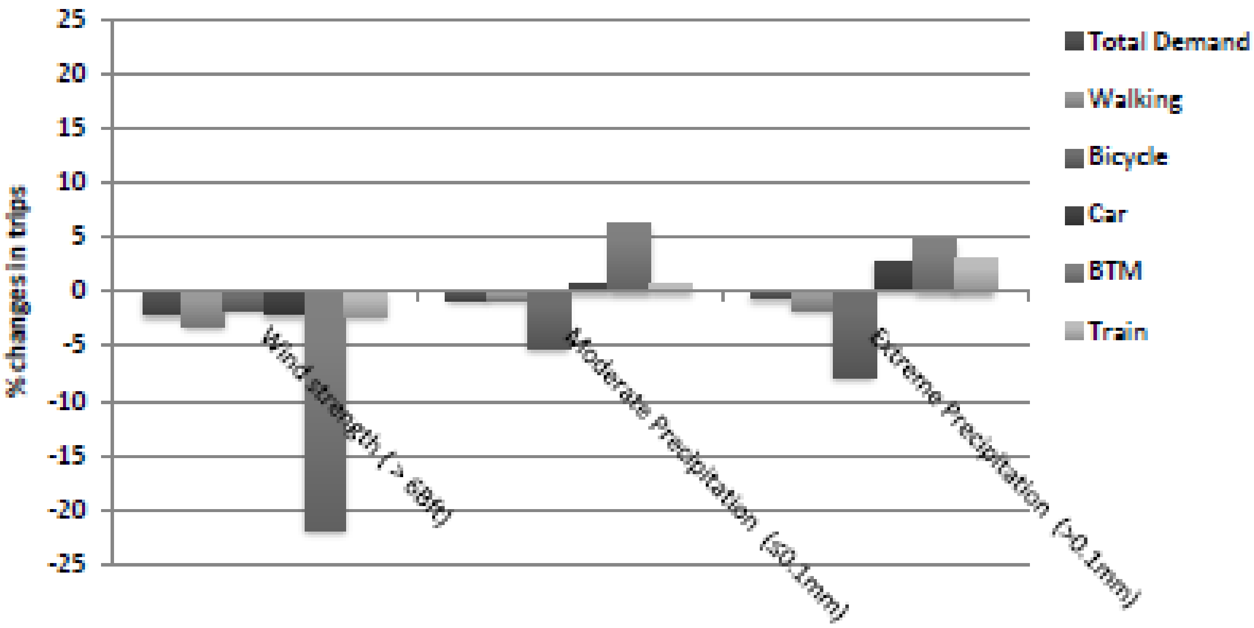

Figure 3.2: Impact of variation in wind and precipitation on number of trips; relative changes (the reference categories are wind strength < 6Bft and no precipitation)

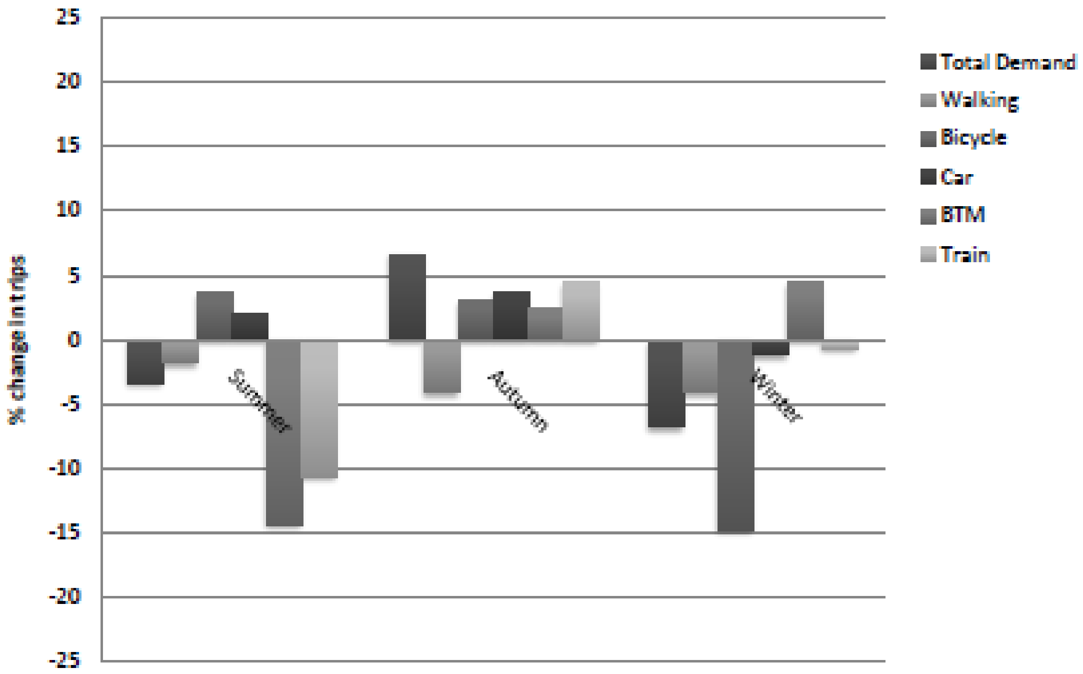

Figure 3.3: Seasonal variation and relative changes in number of trips (the reference category is Spring)

Total travel demand is not affected in *extremely cold weather* (temperature less than 0 ^{o}C). However, modal split effects occur, as shown in Fig 3.2. During extremely cold weather, the demand for bicycle falls by about 7.7 per cent and that of BTM increases by about 16.9 percent compared with demand at temperatures between 0^{o} C to 10^{o} C. The demand for walking trips also increases by about 12.5 per cent in these cold weather conditions. The demand for car and train are not affected in extreme cold weather conditions. Lower demand for bicycle trips is a plausible finding, as one would expect fewer of such trips during extreme cold weather, given that cyclists are more vulnerable to extreme weather conditions. The increase in walking trips may be a surprise. Approximately, a shift occurs towards very short distance trips.

Table 1: Impacts of weather conditions on individuals' daily trips (percentage changes in number of trips)

		Wind Strength	**Temperature**				**Precipitation**			**Snow**	**Visibility**	**Seasonal**		
		Wind Bft	≤ 0^o C	10^o C to 20^o C	20^o C to 25^o C	> 25^o C	Minutes	Up to 0.1 mm	> 0.1 mm	Dummy	< 300m	Summer	Autumn	Winter
Analysis I	All Trips	**-2.04**	-0.20	0.27	-1.17	**-4.87**	**-0.16**	**-0.74**	-0.63	**-3.88**	2.31	**-3.36**	**6.65**	**-6.84**
Analysis II	Walking	**-3.15**	**12.56**	**-2.60**	**-5.47**	**-9.58**	**-0.25**	-0.65	*-1.61*	1.38	3.38	*-1.83*	**-4.10**	-4.10
	Bicycle	-1.59	**-7.76**	**9.19**	**18.11**	**21.95**	**-0.73**	**-5.20**	**-7.89**	-4.08	-6.27	**3.66**	**3.00**	**-14.76**
	Car	**-2.07**	-1.40	**-3.90**	**-8.47**	**-14.80**	*0.06*	**0.68**	**2.85**	-2.75	4.11	**2.05**	**3.58**	-1.23
	Bus/Trams/ metros	**-21.73**	**16.88**	*-3.44*	**-12.90**	**-19.62**	**0.26**	**6.19**	*4.73*	**-14.97**	43.15	**-14.39**	2.35	*4.52*
	Train	-2.30	1.21	-2.21	**-7.19**	-10.45	-0.05	0.61	2.90	-10.19	11.88	**-10.65**	**4.41**	-0.79
	Other	-1.64	-1.22	**12.32**	**10.97**	**17.53**	**-0.28**	**-4.11**	**-8.30**	-11.12	-8.75	4.02	***-4.04***	**-12.47**
Analysis III	Commuting	-1.07	-10.94	0.53	-0.48	-3.86	-0.09	-1.038	*-2.11*	6.77	4.19	**-19.42**	**10.13**	**-6.33**
	Business	-2.46	-12.66	-1.73	*-6.88*	**-13.69**	-0.06	0.24	0.54	8.34	-7.80	**-7.37**	1.17	-0.74
	Shopping	**-5.50**	**4.64**	-0.05	-1.43	*-4.75*	**-0.19**	**1.32**	1.00	-9.40	-0.47	**13.71**	0.35	-0.74
	Recreational and Sports	-0.19	**-4.37**	**5.17**	**10.23**	**8.26**	**-0.36**	**-2.64**	*-1.45*	**10.39**	-4.54	**-5.07**	**-3.47**	**-10.01**
	Educational	-1.65	5.11	**-2.68**	**-5.72**	-7.25	-0.01	**-1.90**	**-3.22**	**-9.16**	1.17	**-45.17**	**6.47**	-0.83
	Visiting family & Friends	**-3.24**	*6.25*	0.80	1.89	**7.97**	**-0.26**	**-3.99**	**-6.05**	-3.19	*9.44*	**4.75**	**-3.59**	**-10.28**

Notes:

The figures indicate the percentage change in daily number of trips made per person per day. The bold and italic numbers are significant at the 5% and 10% level of statistical significance, respectively. The reference categories for wind, temperature, precipitation (mm), snow, visibility and seasonal variables are, respectively, wind strength greater

Similar to the demand response in extremely cold weather, total travel demand also shows an interesting pattern in *warmer weather* (temperatures between 10^{o} C to 20^{o} C), as can be seen in Fig 3.1. The demand for walking falls slightly in warmer weather. However, travel demand for car falls by around 4 per cent in warmer weather compared with normal weather. Also, the demand for BTM trips falls by around 3.5 per cent in same weather conditions. On the contrary, demand for cycling increases by 9.2 per cent in these weather conditions. Finally, we observe that total travel demand is hardly affected during warmer weather. In temperatures between 20^{o} C to 25^{o} C there is a big reduction in travel demand for car and BTM. However, demand for cycling increases by around 18 per cent in these weather conditions. Given that total travel demand is only slightly affected, this implies that people have a strong tendency to switch to biking from car and public transportation during warmer weather conditions. It may be noted that modal shift is stronger during higher temperatures. Even stronger effects are found for extremely high temperatures (above 25^{o} C), compared with temperature betweens 0-10^{o} C. The number of bicycle trips increases by 22 per cent; all other modes show decreasing numbers of trips from 10 to 20 per cent. As a result, we find a substantial decrease in the total number of trips of about 5 per cent.

We analysed the effects of *precipitation* on travel demand in two ways: first, using the duration of precipitation (measured by minutes of precipitation during an hour); Second, the intensity of precipitation (measured in millimeters of precipitation). The duration variable shows that total travel demand for individuals is negatively affected by precipitation. Total travel demand reduces by 1.6 per cent for 10 minutes of precipitation. In particular, bicycle use is very sensitive: for the same amount of precipitation the demand for bicycle decreases by about 7 per cent. This is partly compensated by public transport: travel demand for BTM trips increases by about 2.5 per cent for every 10 minutes of precipitation. Car trips also increase by about 0.7 per cent. This suggests that people switch from cycling to BTM and car as the duration of precipitation increases. Therefore, public transport may be more crowded and roads may be more congested when the duration of rain increases, which may be especially problematic during peak hours.

The effects of precipitation on travel demand are presented in Figure 3.2. There is a minor fall in total travel demand during moderate precipitation compared with no precipitation, while demand for bicycle trips falls by about 5 per cent during moderate precipitation compared with no precipitation. Demand for BTM increases by about 6.2 per cent and car trips increase by about 0.70 per cent. As Figure 3.2 shows, the effects of extreme precipitation follow the same pattern as moderate precipitation, but on average the effects are somewhat larger.

We tried several measurements for the *visibility* variable to analyse the effects of visibility on travel demand, but we could not find any statistically significant impact on total travel demand, on the demand for different modes of transportation, and on the demand for transportation for different trip purposes. Apparently, visibility apparently is not important for transportation demand in the Netherlands.

Total travel demand is about 4 per cent lower when it snows.[21] Travel demand for BTM falls by about 15 per cent, while travel demand for other modes of transportation is not affected. This suggests that people prefer to cancel their public transport trips instead of switching to other modes of transportation during snow. This argument is supported by findings in Chapter 6.

The lower part of Table 3.1 shows the effects of weather on the number of trips made for *different trip purposes*.[22] As expected, the demand for commuting and business trips is hardly affected by weather. This confirms that it is difficult to cancel or delay such trips. The demand for recreational and sports trips decreases in extreme cold, and increases in higher temperatures compared with normal temperatures. Furthermore, strong wind, precipitation duration and precipitation intensity reduce the demand for recreational and sports trips by about 2 per cent. We find that the demand for recreational and sport trips is more sensitive to weather conditions compared with other trips. Trips made for visiting family and friends are also sensitive to weather conditions compared with other trips. These trips are more flexible and can be easily rescheduled or cancelled, especially compared with commuting and business trips. Trips for visiting family and friends are generally more flexible, i.e. they can be postponed or delayed compared with commuting trips, but are less flexible compared with recreational and sports trips. Precipitation duration has minor effects on travel demand for visiting family and friends. In addition, moderate precipitation also reduces these trips by about 4 per cent compared with no precipitation. Demand for educational trips falls by about 5.8 per cent in warm weather conditions. This may be because of the summer vacation period during which all schools are closed. Shopping trips also fall in warm weather conditions.

The seasonal variation shows total travel demand is lower during summer and winter. Summer is the holiday season, so one would expect lower travel demand, and the results do indeed show a drop in travel demand for almost all types of trips. The demand for bicycle and car also increase during summer suggesting that people are more likely use these modes of transportation during their vacations. On the other hand, bicycle trips are lower during winter suggesting people avoid cycling during the winter period.

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[21] It may be noted that snow in this analysis only measures the effects of *falling* snow. It *does not* control for snow on roads or snow on cycle routes, which may have different effects.

[22] It may be also noted that commuting and business-related trips demand are estimated after selecting only those trips which are made by people who do have work in order to avoid any kind of selection effects.

Sensitivity analysis

We also estimated the three models excluding the seasonal variables and not using day-specific fixed effects. In this model the modal shift measures the influence of weather on travel demand across different days, rather than on the same day across different parts of the country. The results of these two analyses are *comparable in most cases* (e.g. total travel demand or demand for car or bicycle). This implies that both methodologies provide similar results, even though they are slightly different.

3.4.2 Total distance travelled

Distance travelled by individuals during a day is another aspect of this analysis. We therefore repeat the three different analyses of individual transportation demand, but now travel demand is measured by distance per person per day (dependent variable). Note that, in using this alternative measure of travel demand, we mainly measure the impact of weather on travel demand across days.[23] As stated earlier, instead of OLS, the Tobit model is used. The coefficients of the Tobit model provide the marginal effects of the explanatory variables on the latent variable (i.e., Y^* in the current case), whereas we are interested in the effects of weather on the actual distance travelled. For this reason, we estimate the marginal effects of all X variables on Y. The changes in distance travelled per person per day due to weather conditions are presented in Table 3.2.[24]

The results show that strong winds reduce the average total distance by 2.3 km. This is about a 7.4 per cent reduction in average total distance travelled. This is consistent with findings of the previous section, though here the effects are larger, which implies that strong wind does not only lead to less trips, but also to shorter trips. Similarly, strong winds reduce the average distance travelled by BTM by about 19 per cent. This finding is also consistent with the previous section, which suggests about a 20 per cent reduction in the demand for BTM.

[23] We did not use day-specific fixed effects for the Tobit models for two reasons. First, the results of day specific fixed effects negative binomial and those of without day-specific fixed effects were comparable. Second, to estimate the Tobit model with day-specific fixed effects was computationally cumbersome through the software package STATA.

[24] The marginal effects are presented in Appendix 3C.

Table 3.2: Impacts of weather conditions on daily distance travelled per person (percentage changes in daily average distance)

		Wind Strength	**Temperature**				**Precipitation**			**Snow**	**Visibility**	**Seasonal**		
		Wind Bft	$\leq 0^{o}$ C	10^{o} C to 20^{o} C	20^{o} C to 25^{o} C	$> 25^{o}$ C	Minutes	Up to 0.1 mm	> 0.1 mm	Dummy	< 300m	Summer	Autumn	Winter
Analysis I	All Trips	**-7.41**	**-2.70**	**3.56**	*1.56*	**-7.25**	-0.76	**-0.19**	-0.10	**-8.59**	2.07	0.57	**4.58**	**-4.20**
Analysis II	Walking	-8.0	**38.0**	**-14.0**	**-30.0**	**-60.0**	4.0	**-2.0**	2.0	**90.0**	30.0	**-16.0**	**-14.0**	**18.0**
	Bicycle	**-13.04**	**-13.04**	**22.17**	**49.57**	**57.83**	**-19.57**	**-1.74**	**-11.74**	-10.00	1.74	**8.26**	**6.96**	**-26.09**
	Car	**-3.86**	*1.80*	**-1.18**	**-6.71**	**-13.90**	**3.68**	**0.09**	**2.28**	**-11.49**	-1.80	**1.36**	*0.83*	**-2.72**
	Bus/Trams/ metros	**-18.67**	*7.33*	*-3.33*	**-14.67**	**-18.00**	0.67	**0.33**	*3.33*	**-18.00**	19.33	**-14.67**	**9.33**	**9.33**
	Train	-6.39	-1.94	0.56	-5.28	-11.95	2.50	-0.03	-1.11	-14.72	23.89	**-10.28**	**13.33**	4.72
	Other	0.43	**-17.14**	**18.57**	**25.71**	**28.57**	**-12.86**	**-0.43**	**-8.57**	-10.00	*-27.14*	2.86	-1.43	**-11.43**
Analysis III	Commuting	**-4.92**	**6.56**	-0.49	**-10.00**	**-14.10**	**3.94**	*-0.16*	**5.58**	**-10.82**	**33.46**	**3.12**	**14.92**	0.16
	Business	-5.91	-4.09	0.91	0.45	4.09	2.27	*0.23*	2.27	-14.54	-6.82	**-9.54**	**5.45**	1.36
	Shopping	**-2.70**	**1.89**	0.11	**-1.08**	**-6.75**	**2.16**	**-0.05**	**1.89**	**-4.05**	*-3.24*	**4.05**	*-0.54*	-0.54
	Recreational and Sports	-0.82	**-2.65**	**4.08**	**6.73**	**11.42**	**-1.63**	**-0.20**	**-2.65**	**12.85**	-3.67	-0.20	**-1.02**	**-4.28**
	Educational	-0.17	-0.42	**-0.42**	**-1.25**	**-1.67**	-0.42	0.001	-0.04	-0.83	0.83	**-3.33**	**1.67**	**0.42**
	Visiting family & Friends	-1.05	-1.23	**3.33**	**5.44**	**8.24**	**-3.33**	-0.02	**-2.10**	0.70	**2.10**	**4.03**	**-3.33**	**-2.98**

Notes:

The figures indicate changes in average distance (Km) per person per day. The numbers in bold and italic are significant at 5% and 10% level of significance, respectively. The reference categories for wind, temperature, precipitation (mm), snow, visibility and seasonal variables are, respectively, wind strength greater than 6 Bft, temperature between 0 ^{o}C to 10^{o}C, no precipitation, no snow, visibility greater than 300 metres, and spring.

The changes in distance travelled by different mode of transportation due to increasing temperatures in Table 3.2 are similar to those reported in Table 3.1. Specifically, the variation in daily distance travelled by BTM, car and train are comparable to the variation in the number of trips. The percentage changes in distance travelled by bicycle are higher compared with changes in the number of daily trips. This is possibly due to an increase in longer distance trips by bicycle for recreational purposes when temperatures increase. This can also be observed from the increase in distance travelled for recreational and sports trips when temperatures increase.

Total average distance travelled per person is reduced by about 9 per cent because of snowfall, whereas average distance by car and BTM are reduced by 11.5 and 18 per cent, respectively. This suggests there is an overall reduction in total travel demand during snowfall. Additionally, average distance walked increases by 90 per cent, suggesting that people shift to walking when it snows.

The average distance of business trips is not significantly affected by weather conditions. However, the average distance of recreational and sports trips is most sensitive to weather conditions, followed by visiting family and friends, compared with other trip purposes. These findings are similar to those in Section 3.1.

We also allow for seasonal variations. Total travel demand is lower during winter. However, during autumn there are increases in total travel demand followed by increases in demand for car, bicycle and train trips, as compared with spring. These are also plausible findings because we would expect people are then coming back from vacations and back to their normal routine. Total travel demand falls during winter, with the greatest fall in cycling trips, whereas there are increases in the BTM trips. These results are also plausible as one would expect less demand during winter because of the vacation period and a reduction in the recreational and sports activities because of cold weather, as can be also noted by fall in the demand for recreational and sports trips. All these findings are plausible.

3.5 Conclusions and policy implications

This chapter has investigated the impact of weather conditions on individual travel demand. We use individual travel data of Dutch travellers for the 1996-2005 period. These data are matched with locally-measured hourly meteorological weather data. The weather variables were divided into various categories in order to give a clear picture of the effects of different weather conditions on travel demand.

We use two approaches to measure travel demand: first, daily number of trips per person; and second, daily distance travelled per person. The results from both approaches are comparable and consistent, with only a few exceptions (probably due to differences in the estimation method). Weather, in general, has an influence on individual travel demand.

Second, unlike total travel demand, there is strong variation in the demand for trips made by different modes of transportation in different weather conditions, suggesting that weather causes model shifts. Third, extreme weather conditions (cold/warm) show a strong modal shift among bicycle, car and public transportation. During extreme cold weather, cycling is substituted by an increase in public transport and walking. During extremely warm weather, car and public transport are substituted by bicycle. Fourth, substitution between different modes also occurs during precipitation. There is strong substitution from bicycle to bus, tram and metros during moderate precipitation, whereas extreme precipitation induces people to switch to the car. However, substitution from bicycle to BTM is stronger than substitution from bicycle to car. Fifth, snow substantially reduces the total number of daily individual trips, but the relative demand for different modes of transportation is not affected by snow, except for a reduction in demand for BTM. Sixth, there are hardly any statistically significant effects of visibility on individual travel demand. Seventh, the demand for commuting and business trips is not affected by weather conditions, but we do find negative weather effects on recreational and sports trips. Finally, we also use distance travelled by individuals as a proxy for demand for transportation. The results support the findings obtained from the negative binomial panel model on the number of trips.

This study quantifies the influence of weather on demand for transportation, along with discussing the role of weather in modal shift. It has implications for the transport planners and managers. On the one hand, it suggests that, during extremely colder weather and during precipitation, public transport will be more extensively used, and vice versa. On the other hand, modal shift in favour of cycling is evident, during increasing temperatures. These findings suggest that Dutch travellers are still not vulnerable to the expected climate changes which predict an increasing temperature in future, because there is still an increasing demand for cycling even in higher temperatures.

A direction for future research could be the quantification of these results, and to portray the future travel demand situation in the post-climate change era while using KNMI (2006) Climate Change Scenarios for the Netherlands.

Appendix 3A

Table 3A.1 : Number of recorded trips and individuals

Year	Trips	Individuals
1996	471463	137322
1997	465285	128451
1998	450519	122486
1999	407922	124610
2000	405311	126994
2001	367477	114174
2002	287428	88469
2003	223432	68839
2004	217908	63258
2005	206139	60775
Total	3502884	1035378

Table 3A.2: Mode shares (Percentages) Year 1996-2005

Modes	Trip Purposes						*Overall averages*
	Commuting	Business related	Educational	Shopping	Visiting family & Friends	Recreational & Sports	
Walk	3.8	3.0	21.6	16.1	19.0	24.4	*14.7*
Bicyle	23.4	9.6	42.6	29.9	23.0	24.6	*25.5*
Car	56.3	79.4	13.7	48.9	51.1	45.6	*49.2*
Bus/Tram/Metro	4.8	1.2	9.3	2.4	1.9	1.4	*3.5*
Train	8.4	4.2	10.1	1.1	2.7	1.9	*4.7*
Other	3.2	2.6	2.6	1.6	2.2	2.1	*2.4*

Table 3A.3: Descriptives of daily weighted averages of variables[1]

Weather variables	Mean	Other variables	Mean
Wind strength (Bft)	0.034	Spring	0.255
Temperature < 0 °C	0.049	Summer	0.230
Temperature 0 °C to 10 °C	0.409	Autumn	0.262
Temperature 10 °C to 20 °C	0.462	Winter	0.253
Temperature 20 °C 25 °C	0.067	Age < 18 years	0.226
Temperature > 25 °C	0.013	Age 18 to 30 years	0.134
No Precipitation	0.361	Age 30 to 60 years	0.459
Precipitation ≤ 0.1 mm	0.384	Age > 60 years	0.181
Precipitation > 0.1 mm	0.254	Male	0.493
Precipitation Duration (minutes/h)	4.280	Weekday	0.722
Snow	0.018		
Visibility < 300 metres	0.002		
Visibility > 300 metres	0.998		

Notes

Weather variables are weighted daily average of hourly weather variables. Weights are assigned on the basis of the number of trips made in different hours of the day.

Table 3A.4: Descriptives for trips and distances per person per day

Variables	Mean	
	Number of Trips	Distance(km)
Total	3.34	31.4
Walking	0.54	0.5
Cycling	0.87	2.3
Car	1.61	22.8
Bus\tram\metro (BTM)	0.10	1.5
Train	0.13	3.6
Other	0.07	0.7
Commuting	0.40	6.1
Business	0.10	2.2
Education trips	0.33	2.4
Recreational & sports	0.64	4.9
Family & friend visiting	0.53	5.7
Shopping	0.79	3.7
Other trip purpose	0.30	3.2
Unknown purpose	0.31	3.3

Appendix 3B

Table 3B.1: Negative binomial model of number of trips per person per day (for various transport modes) [1, 2, 3]

Variables	Total		Walking		Bicycle		Car		Bus/Tram/ Metro		Train		Other	
Weather Variables	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**
Wind strength (Bft)	**-0.02**	0.005	**-0.03**	0.01	-0.02	0.01	**-0.02**	0.01	**-0.24**	0.04	-0.02	0.03	-0.017	0.035
Temperature < 0 °C	-0.002	0.01	**0.12**	0.02	**-0.08**	0.01	-0.01	0.01	**0.16**	0.04	0.01	0.04	-0.012	0.045
Temperature 0 °C to 10 °C	0.003	0.005	**-0.03**	0.01	**0.09**	0.01	**-0.04**	0.01	*-0.04*	0.02	-0.02	0.02	**0.116**	0.021
Temperature 20 °C 25 °C	-0.01	0.01	**-0.06**	0.01	**0.17**	0.01	**-0.09**	0.01	**-0.14**	0.04	**-0.07**	0.04	**0.104**	0.034
Temperature > 25 °C	**-0.05**	0.01	**-0.10**	0.03	**0.20**	0.02	**-0.16**	0.02	**-0.22**	0.08	-0.11	0.07	**0.162**	0.064
Precipitation ≤ 0.1 mm	**-0.01**	0.003	-0.01	0.01	**-0.05**	0.01	*0.01*	0.004	**0.06**	0.02	0.01	0.02	**-0.042**	0.016
Precipitation >0.1 mm	-0.01	0.004	*-0.02*	0.01	**-0.08**	0.01	**0.03**	0.01	*0.05*	0.03	0.03	0.03	**-0.087**	0.025
Precipitation Duration (Minutes)	**-0.002**	0.0002	**0.003**	0.001	**-0.01**	0.0005	**0.0006**	0.0003	**0.003**	0.001	-0.0005	0.001	**-0.003**	0.001
Snow	**-0.04**	0.01	0.01	0.03	-0.04	0.03	-0.03	0.02	**-0.16**	0.08	-0.11	0.08	-0.118	0.089
Visibility less than 300 metres	0.02	0.02	0.03	0.05	-0.06	0.04	0.04	0.03	**0.36**	0.11	0.11	0.12	-0.092	0.146
Summer	**-0.03**	0.01	*-0.02*	0.01	**0.04**	0.01	**0.02**	0.01	**-0.16**	0.03	**-0.11**	0.03	0.039	0.026
Autumn	**0.06**	0.01	**-0.04**	0.01	**0.03**	0.01	**0.04**	0.01	0.02	0.02	**0.04**	0.02	*-0.041*	0.023
Winter	**-0.07**	0.01	-0.02	0.01	**-0.16**	0.01	-0.01	0.01	*0.04*	0.02	-0.01	0.02	**-0.133**	0.027
Other Variables														
Age less than 18 years	**-0.05**	0.002	**0.55**	0.01	**0.66**	0.01	**-0.54**	0.004	**-0.90**	0.02	**-1.97**	0.02	**0.225**	0.016
Age between 30 to 60 years	**-0.02**	0.002	**0.16**	0.01	**0.05**	0.01	**0.17**	0.003	**-1.30**	0.01	**-1.29**	0.01	**-0.539**	0.016
Age greater than 60 years	**-0.42**	0.003	**0.26**	0.01	**-0.25**	0.01	**-0.46**	0.005	**-1.06**	0.02	**-1.95**	0.02	**-0.489**	0.020
Male	**-0.04**	0.001	**-0.25**	0.004	**-0.21**	0.003	**0.16**	0.002	**-0.36**	0.01	**0.08**	0.01	**0.456**	0.011
Weekday	**0.32**	0.010	**-0.07**	0.01	**0.46**	0.01	**-0.27**	0.01	**0.54**	0.02	**0.74**	0.02	**0.141**	0.021
Number of Groups	3653		3653		3653		3653		3538		3554		3594	
Log likelihood	-2265508.4		-910137.33		-1191510.9		-1735822.8		-183260.39		-189723.73		-187584.42	
Wald Chi ^{2} (31)	37082.66		13937.93		51749.54		70125.69		13097.81		22468.82		6166.36	

Notes:

(1) This model has been estimated controlling for 12 provinces and day specific fixed effects.
(2) The bold and italic numbers are significant at the 5% and 10 % level of significance, respectively.
(3) **The reference categories** for wind, temperature, precipitation (mm), snow, visibility and seasonal variables are, respectively, wind strength greater than 6 Bft, temperature between 0 °C to 10°C, no precipitation, no snow, visibility greater than 300 metres, and spring.

Table 3B-2: Negative binomial model of number of trips per person per day (for various trip purposes) [1, 2, 3]

	Commuting		Business		Shopping		Educational		Sports & Recreational		Visiting family & friends	
Variables	**Coff.**	**S.E**	**Coff.**	**S.E**	**Coff.**	**S.E**	**Coff.**	**S.E**	**Coff.**	**S.E**	**Coff.**	**S.E**
Weather Variables												
Wind strength (Bft)	-0.01	0.01	-0.02	0.03	**-0.06**	0.01	-0.02	0.01	-0.002	0.012	**-0.03**	0.01
Temperature < 0 ^oC	-0.12	0.07	-0.14	0.18	**0.05**	0.02	**0.05**	0.02	**-0.045**	0.016	**0.06**	0.02
Temperature 0 ^oC to 10 ^oC	0.01	0.01	-0.02	0.02	-0.001	0.01	**-0.03**	0.01	**0.050**	0.008	0.01	0.01
Temperature 20 ^oC 25 ^oC	-0.005	0.02	*-0.07*	0.04	-0.01	0.01	**-0.06**	0.02	**0.097**	0.013	0.02	0.01
Temperature > 25 ^oC	-0.04	0.04	**-0.15**	0.07	*-0.05*	0.03	-0.08	0.05	**0.079**	0.025	**0.08**	0.03
Precipitation ≤ 0.1 mm	-0.01	0.01	0.002	0.02	**0.01**	0.01	**-0.02**	0.01	**-0.027**	0.006	**-0.04**	0.01
Precipitation >0.1 mm	*-0.02*	0.01	0.01	0.02	0.01	0.01	**-0.03**	0.01	-0.015	0.009	**-0.06**	0.01
Precipitation Duration (Minutes)	-0.001	0.001	-0.001	0.001	**-0.002**	0.0004	-0.0001	0.001	**-0.004**	0.0005	**-0.003**	0.0005
Snow	0.07	0.07	0.08	0.18	**-0.10**	0.03	**-0.10**	0.04	**0.099**	0.027	-0.03	0.03
Visibility less than 300 metres	0.04	0.05	-0.08	0.13	-0.005	0.04	0.01	0.06	-0.046	0.048	**0.09**	0.05
Summer	**-0.22**	0.03	**-0.08**	0.03	**0.13**	0.01	**-0.60**	0.02	**-0.052**	0.010	**0.05**	0.01
Autumn	**0.10**	0.03	0.01	0.02	0.003	0.01	**0.06**	0.02	**-0.035**	0.009	**-0.04**	0.01
Winter	**-0.07**	0.03	-0.01	0.03	-0.01	0.01	-0.01	0.02	**-0.105**	0.010	**-0.11**	0.01
Other Variables												
Age less than 18 years	**-0.13**	0.02	**-0.94**	0.13	**-0.45**	0.01	**1.56**	0.01	**0.031**	0.007	**0.13**	0.01
Age between 30 to 60 years	**-0.11**	0.005	**0.46**	0.02	**0.38**	0.01	**-2.35**	0.01	**0.120**	0.006	**-0.12**	0.01
Age greater than 60 years	**-0.33**	0.02	**0.81**	0.03	**0.42**	0.01	**-3.27**	0.03	**0.057**	0.007	**-0.18**	0.01
Male	**0.16**	0.004	**0.76**	0.01	**-0.53**	0.004	**-0.02**	0.005	**-0.038**	0.004	**-0.07**	0.004
Weekday	**3.63**	0.02	**1.56**	0.04	**-0.43**	0.01	**3.97**	0.04	**-0.557**	0.007	**-0.67**	0.01
Number of Groups	2552		3403		3650		3183		3653		3653	
Log likelihood	-371129.13		-154067.01		-1062107.4		-407438.15		-1025604.3		-947279.53	
Wald Chi ^{2} (31)	29978.34		6434.3		55477.16		160883.44		7241		12346.38	

Notes:

(1) This model has been estimated controlling for 12 provinces and day specific fixed effects.
(2) The bold and italic numbers are significant at the 5% and 10 % level of significance respectively.
(3) **The reference categories** for wind, temperature, precipitation (mm), snow, visibility and seasonal variables are, respectively, wind strength greater than 6 Bft, temperature between 0 ^oC to 10^oC, no precipitation, no snow, visibility greater than 300 metres, and spring.

Appendix 3C

Table 3C.1: Marginal effects of the Tobit model for number of kilometres travelled per person per day (for various transport modes) [1, 2, 3]

Variables	Total		Walking		Bicycle		Car		Bus/Tram/ Metro		Train		Other	
	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
Weather Variables														
Wind strength (Bft)	**-2.33**	0.31	-0.04	0.06	**-0.30**	0.07	**-0.88**	0.22	**-0.28**	0.05	-0.23	0.19	0.003	0.03
Temperature < 0 °C	**-0.85**	0.31	**0.19**	0.06	**-0.30**	0.07	*0.41*	0.22	*0.11*	0.06	-0.07	0.19	**-0.12**	0.03
Temperature 0 °C to 10 °C	**1.12**	0.15	**-0.07**	0.03	**0.51**	0.03	**-0.27**	0.11	*-0.05*	0.03	0.02	0.09	**0.13**	0.02
Temperature 20 °C 25 °C	*0.49*	0.28	**-0.15**	0.05	**1.14**	0.07	**-1.53**	0.19	**-0.22**	0.05	-0.19	0.17	**0.18**	0.03
Temperature > 25 °C	**-2.28**	0.53	**-0.30**	0.09	**1.33**	0.13	**-3.17**	0.35	**-0.27**	0.10	-0.43	0.33	**0.20**	0.06
Precipitation ≤ 0.1 mm	**-0.06**	0.01	**-0.01**	0.00	**-0.04**	0.00	**0.02**	0.01	**0.00**	0.00	0.00	0.01	**-0.003**	0.001
Precipitation >0.1 mm	-0.03	0.14	0.01	0.02	**-0.27**	0.03	**0.52**	0.10	*0.05*	0.03	-0.04	0.09	**-0.06**	0.01
Precipitation Duration (Minutes)	-0.24	0.22	0.02	0.04	**-0.45**	0.05	**0.84**	0.15	0.01	0.04	0.09	0.14	**-0.09**	0.02
Snow	**-2.70**	0.66	**0.45**	0.13	-0.23	0.15	**-2.62**	0.44	**-0.27**	0.11	-0.53	0.40	-0.07	0.07
Visibility less than 300 metres	0.65	1.24	0.15	0.23	0.04	0.27	-0.41	0.86	0.29	0.26	0.86	0.84	*-0.19*	0.11
Summer	0.18	0.19	**-0.08**	0.03	**0.19**	0.04	**0.31**	0.13	**-0.22**	0.03	**-0.37**	0.11	0.02	0.02
Autumn	**1.44**	0.16	**-0.07**	0.03	**0.16**	0.03	*0.19*	0.11	**0.14**	0.03	**0.48**	0.10	-0.01	0.02
Winter	**-1.32**	0.18	**0.09**	0.03	**-0.60**	0.04	**-0.62**	0.13	**0.14**	0.04	0.17	0.11	**-0.08**	0.02
Other Variables														
Age less than 18 years	**-23.70**	0.17	**2.08**	0.05	**3.04**	0.05	**-16.14**	0.11	**-1.17**	0.02	**-6.88**	0.07	**0.13**	0.02
Age between 30 to 60 years	**-10.72**	0.17	**0.40**	0.03	**-0.38**	0.04	**3.15**	0.12	**-2.15**	0.03	**-7.00**	0.10	**-0.45**	0.02
Age greater than 60 years	**-26.18**	0.16	**1.48**	0.05	**-1.32**	0.04	**-11.37**	0.12	**-1.25**	0.02	**-5.84**	0.06	**-0.29**	0.02
Male	**8.58**	0.11	**-0.74**	0.02	**-0.64**	0.02	**8.76**	0.08	**-0.50**	0.02	**0.59**	0.07	**0.45**	0.01
Weekday	**4.76**	0.13	**-0.15**	0.02	**2.28**	0.02	**-3.98**	0.09	**1.04**	0.02	**3.46**	0.07	**0.32**	0.01

Notes:

1. This model has been estimated controlling for 12 provinces and day specific fixed effects.
2. The bold and italic numbers are significant at the 5% and 10 % level of significance respectively.
3. **The reference categories** for wind, temperature, precipitation (mm), snow, visibility and seasonal variables are, respectively, wind strength greater than 6 Bft, temperature between 0 °C to 10°C, no precipitation, no snow, visibility greater than 300 metres, and spring.

Table 3C.2: Marginal effects of the Tobit model for number of kilometres travelled per person per day (for various trip purposes) [1, 2, 3]

Variables	**Commuting**		**Business**		**Shopping**		**Recreational and Sports**		**Educational**		**Visiting family and friends**	
	Coeff.	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**
Weather Variables												
Wind strength (Bft)	**-0.30**	0.11	-0.13	0.08	**-0.10**	0.02	-0.04	0.04	-0.004	0.004	-0.06	0.05
Temperature < 0 ^{o}C	**0.40**	0.11	-0.09	0.08	**0.07**	0.02	**-0.13**	0.04	-0.01	0.004	-0.07	0.05
Temperature 0 ^{o}C to 10 ^{o}C	-0.03	0.05	0.02	0.04	0.004	0.01	**0.20**	0.02	**-0.01**	0.002	**0.19**	0.02
Temperature 20 ^{o}C 25 ^{o}C	**-0.61**	0.09	0.01	0.08	**-0.04**	0.02	**0.33**	0.04	**-0.03**	0.003	**0.31**	0.05
Temperature > 25 ^{o}C	**-0.86**	0.17	0.09	0.16	**-0.25**	0.03	**0.56**	0.08	**-0.04**	0.01	**0.47**	0.09
Precipitation ≤ 0.1 mm	*-0.01*	0.004	*0.005*	0.003	**-0.002**	0.001	**-0.01**	0.00	0.00002	0.0002	-0.001	0.002
Precipitation >0.1 mm	**0.34**	0.05	0.05	0.04	**0.07**	0.01	**-0.13**	0.02	-0.001	0.002	**-0.12**	0.02
Precipitation Duration (Minutes)	**0.24**	0.08	0.05	0.06	**0.08**	0.01	**-0.08**	0.03	-0.01	0.003	**-0.19**	0.03
Snow	**-0.66**	0.22	-0.32	0.17	**-0.15**	0.04	**0.63**	0.10	-0.02	0.01	0.04	0.11
Visibility less than 300 metres	**2.04**	0.49	-0.15	0.31	*-0.12*	0.07	-0.18	0.16	0.02	0.02	**0.12**	0.20
Summer	**0.19**	0.06	**-0.21**	0.05	**0.15**	0.01	-0.01	0.02	**-0.08**	0.002	**0.23**	0.03
Autumn	**0.91**	0.06	**0.12**	0.04	*-0.02*	0.01	**-0.05**	0.02	**0.04**	0.002	**-0.19**	0.02
Winter	0.01	0.06	0.03	0.05	-0.02	0.01	**-0.21**	0.02	**0.01**	0.002	**-0.17**	0.03
Other Variables												
Age less than 18 years	**-1.06**	0.20	**-1.00**	0.14	**-0.42**	0.01	**0.11**	0.03	**0.27**	0.005	**0.34**	0.03
Age between 30 to 60 years	**-1.02**	0.05	**0.91**	0.03	**0.47**	0.01	**0.30**	0.02	**-0.48**	0.01	**-0.19**	0.03
Age greater than 60 years	**-2.33**	0.11	**3.45**	0.25	**1.04**	0.02	**0.73**	0.03	**-0.26**	0.003	**0.39**	0.03
Male	**1.91**	0.04	**1.59**	0.03	**-0.61**	0.01	*0.03*	0.02	**0.01**	0.002	**-0.15**	0.02
Weekday	**7.89**	0.04	**2.38**	0.03	**-0.09**	0.01	**-1.92**	0.02	**0.38**	0.004	**-3.47**	0.03

Notes:

(1) This model has been estimated controlling for 12 provinces and day specific fixed effects.
(2) The bold and italic numbers are significant at the 5% and 10 % level of significance respectively.
(3) **The reference categories** for wind, temperature, precipitation (mm), snow, visibility and seasonal variables are, respectively, wind strength greater than 6 Bft, temperature between 0 ^{o}C to 10^{o}C, no precipitation, no snow, visibility greater than 300 metres, and spring.

Chapter 4

The Impacts of Weather Conditions on Mode Choice

4.1 Introduction

The choice of transport mode is an important issue in transport planning. It affects the general efficiency of travel and the space devoted to transport functions (Mandel et al. 1997). Mode choice decisions are influenced by many factors, such as travel time, travel costs, and socio-economic characteristics of the trip maker. These decisions are also sensitive to the occurrence of unforeseen and key events such as accidents, extreme weather, and substantial changes in one's personal life, such as change of residence, a change of workplace and children (Van Waerden et al. 2003). All these factors are expected to motivate changes in mode choice decisions.

The role that weather plays in mode choice decisions may change as a result of changes in the climate system. Global temperature is predicted to rise by 2^{o} C to 3^{o} C within the next 50 years, on the basis of current temperature trends, and furthermore by 5^{o} C by 2100 (Stern 2006). Stern (2006) also predicts an increase in the frequency of extreme weather due to global warming. An example of an extreme weather event can be seen from the snow during the Winters of 2008 and 2009 in Europe which had the heaviest snow in last few decades.

The climate of the Netherlands may respond to the future expected climate change as explained in Appendix 1A in Chapter 1. The three prominent modes of transportation in the Netherlands are *car*, *bicycle* and *walking*. These three modes cover around 90 per cent (CBS) of all Dutch individual trips. Walking and cycling are more vulnerable to weather conditions, especially in extreme weather situations. Since, global temperature will increase during the coming decades and extreme weather events will become more frequent, it is likely that the weather is going to play a more dominant role in transportation in general, and in mode choice in particular.

Many studies are available on the relationship between weather and transport. Most of these studies focus on road safety (e.g. Eisenberg 2004; Andrey et al. 2001; Edwards 1996) or vulnerability of transport infrastructure to extreme weather conditions (e.g. Waalkes 2003). The literature that focuses on the impact of weather on mode choice decisions is limited. However, there are a few studies on weather and mode choice decision. For example, Khattak and De Palma (1997) studied traveller behaviour in Brussels. They find that adverse weather causes changes in the mode choice, route choice, and departure time of car commuters. Changes in departure time are more important for car commuters than changes in route and mode choice. Car users constrained by family commitments and those who drove alone were found to change their mode choices less often due to bad weather. De Palma and Rochat (1999) conduct a similar survey among Geneva commuters. The patterns found are similar to the ones found in Khattak and De Palma (1997). Adverse weather leads to changes in mode choice, route choice, and departure time choice, with the latter again being most important.

A more recent study by Aaheim and Hauge (2005) uses micro-level information on individual transport behaviour in Bergen (Norway) to study the impact of weather conditions on mode choice decisions. They find that the likelihood of use of public transport increases with intensity of precipitation and wind, as compared with walking and biking. Additionally, they extend the analysis to the regional and national level. They find no switching between public and private transport at the regional level. Furthermore, the impact of climate change on travel patterns appears to be small at the country level.

Despite their useful insights, these studies have some major limitations. First, the relatively short survey periods in Aaheim and Hauge (2005), De Palma and Rochat (1999) and Khattak and De Palma (1997) imply that there is relatively little variation in weather conditions. It is therefore difficult to draw general conclusions from these studies. More specifically, if the focus of research is on the general impact of climate change on transport choices, periods covering only a few months are insufficient, since climate changes are likely to have a differential effect on weather conditions in different seasons. Second, the weather indicators used in these studies were recorded once a day, or only a few values of a limited number of weather indicators were available. In countries in which weather is subject to hourly changes, such as the Netherlands, such an approach is not viable. Furthermore, the numbers of observations used in these studies are small. This makes it difficult to generalize the findings.

Clearly, there is a need to analyse the influence of weather conditions on mode choice decisions using data that have a wide coverage in terms of geographical location, time duration, and weather indicators. The aim of this chapter is to study the influence of weather conditions on individual mode choice decisions, while using data that meet to all of these criteria. We use hourly data for all weather variables that covers the entire Netherlands from 1996 till 2005. We analyse weather and mode choice separately for different trip purposes.

The chapter is organized as follows. Section 4.2 explains the data and its sources. This section also provides a detailed discussion of the explanatory variables and also presents some descriptive statistics from the data. In addition, we discuss the model used. Section 4.3 presents the model results and a discussion. Section 4.4 concludes the chapter.

4.2 The data and model specification

4.2.1 The data and its sources

We use the Transportation Surveys from the Dutch Central Bureau of Statistics (OVG/MON Survey) and KNMI hourly weather data reports for the period 1996 till 2005. The details of both these two data sets are given in Section 2.3, in Chapter 2. It may be noted that weather conditions in this chapter refer to temperature, wind strength (Bft), precipitation duration (minutes of precipitation), precipitation intensity (mm) and snow.

The transportation data set is matched with weather data in such a way that each observed trip is assigned the weather conditions of the same hour when the trip took place and from the weather stations which are nearest to individual places of departure. The assumption is that an individual based his mode choice decision on the weather conditions prevailing at the hour of departure.

Table 4.1: Percentage of mode share for different trip purposes (1996-2005)

Purpose of Trips	**Walk**	**Bike**	**Car**	**BTM***	**Train**	**Other**	**Total**
Commuting	3.8	23.4	56.3	4.8	8.4	3.2	100
Business-related	3.0	9.6	79.4	1.2	4.2	2.6	100
Educational	21.6	42.6	13.7	9.3	10.1	2.6	100
Shopping	16.1	29.9	48.9	2.4	1.1	1.6	100
Visiting family & Friends	19.0	23.0	51.1	1.9	2.7	2.2	100
Recreational & Sports	24.4	24.6	45.6	1.4	1.9	2.1	100
Overall averages	*14.7*	*25.5*	*49.2*	*3.5*	*4.7*	*2.4*	*100*

*BTM = Bus, tram and metro.

Excluding the observations with missing values, the sample used here consists of about 1 million individuals with about 3.5 million trips. Table 4.1 presents the modal share for different trip purposes. The modal share varies for different trip purposes. The use of car for business trips is almost 80 per cent, whereas for educational trips it is about 14 per cent. Similarly, the share of walking trips is about 24 per cent in recreational and sports trips, but about 4 per cent in commuting trips. These descriptives motivate us to do a separate mode-choice analysis for each kind of trip purpose.[25]

[25] Another possibility for analysis is to combine the similar trip purposes, for example, combining work-related trips, such as commuting and business trips and analyse them jointly. But, given that the

Figures 4.1 to 4.4 provide information on the relationship between weather and mode choice. The share of car trips decreases, whereas the share of bicycle trips increases with temperature; however, this increase is small in the highest temperature category. Other modes change with temperature, but a clear pattern is difficult to observe. Figure 4.2 shows that the share of bicycle declines marginally with wind strength. The share of car trips fractionally increases with increases in wind strength. Figure 4.3 shows a decreasing share of bicycle trips with increasing rain, whereas for car trips the reverse happens. The percentage share of walks appears unaffected.

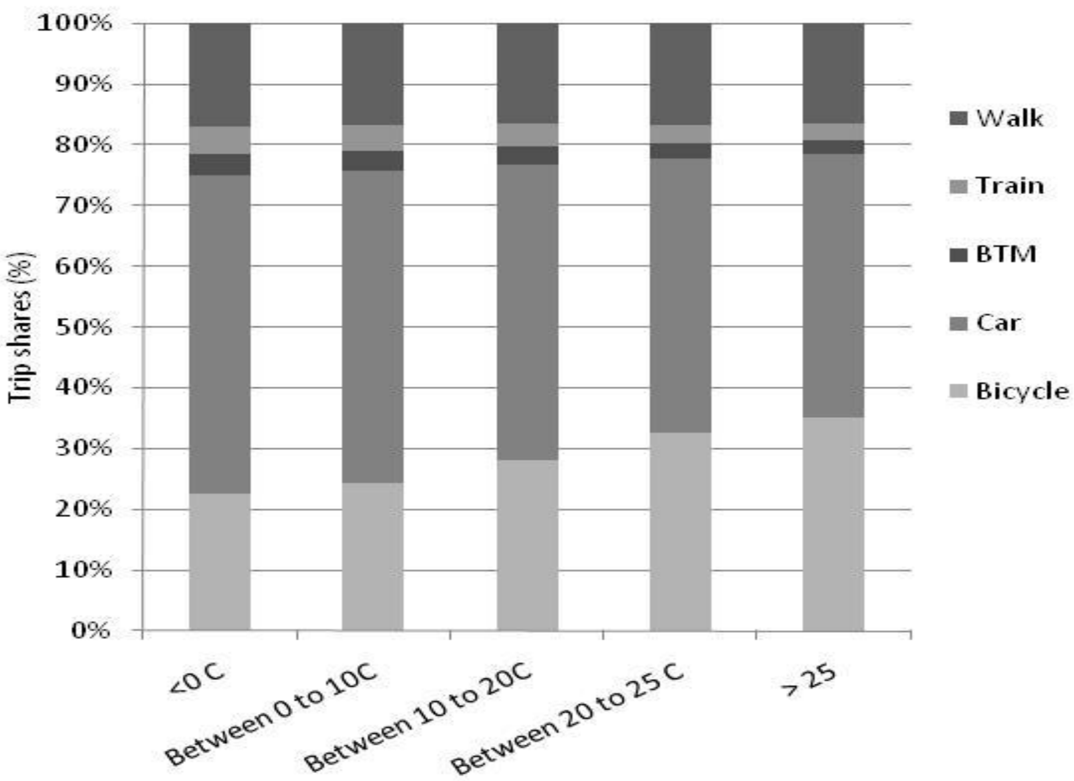

Figure 4.1: Temperature and mode choice

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mode shares of both work-related trips (commuting and business-related) are reasonably different, combining both kinds of trips (and any other two or more trip purposes) will cause loss of information.

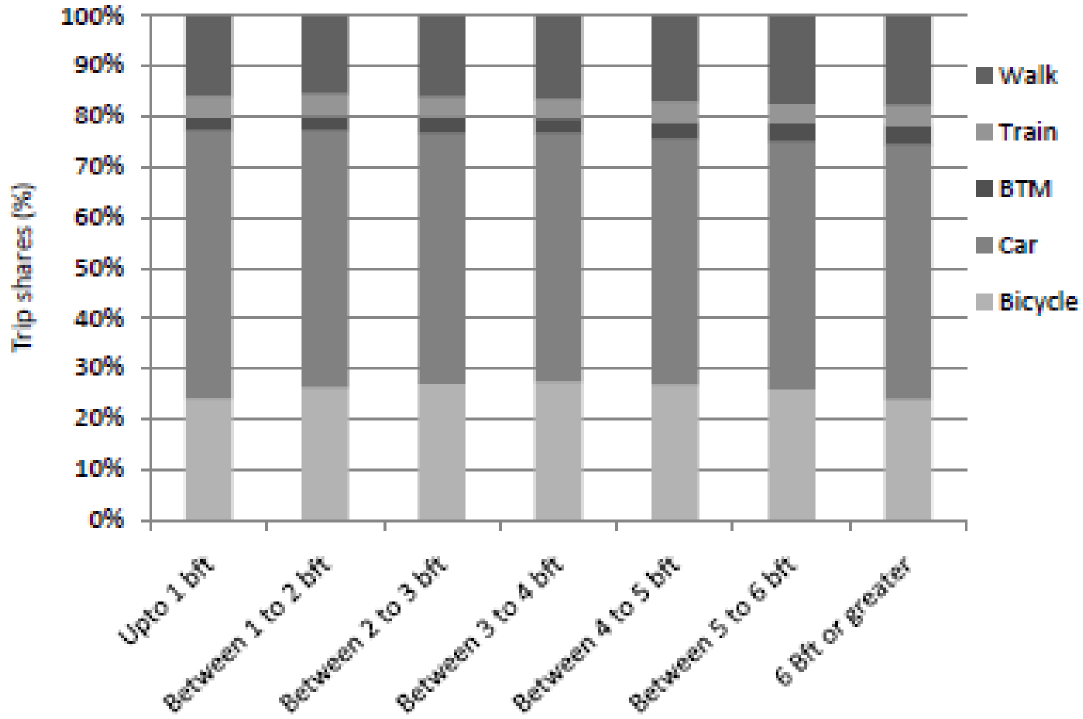

Figure 4.2: Wind strength and mode choice

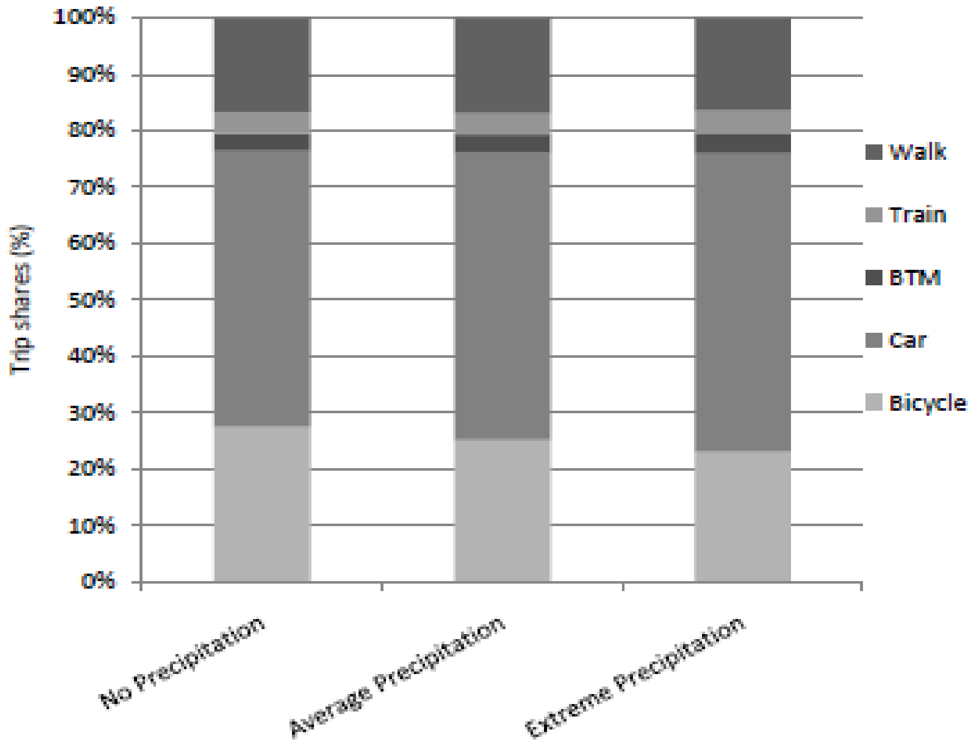

Figure 4.3: Precipitation per hour and mode choice

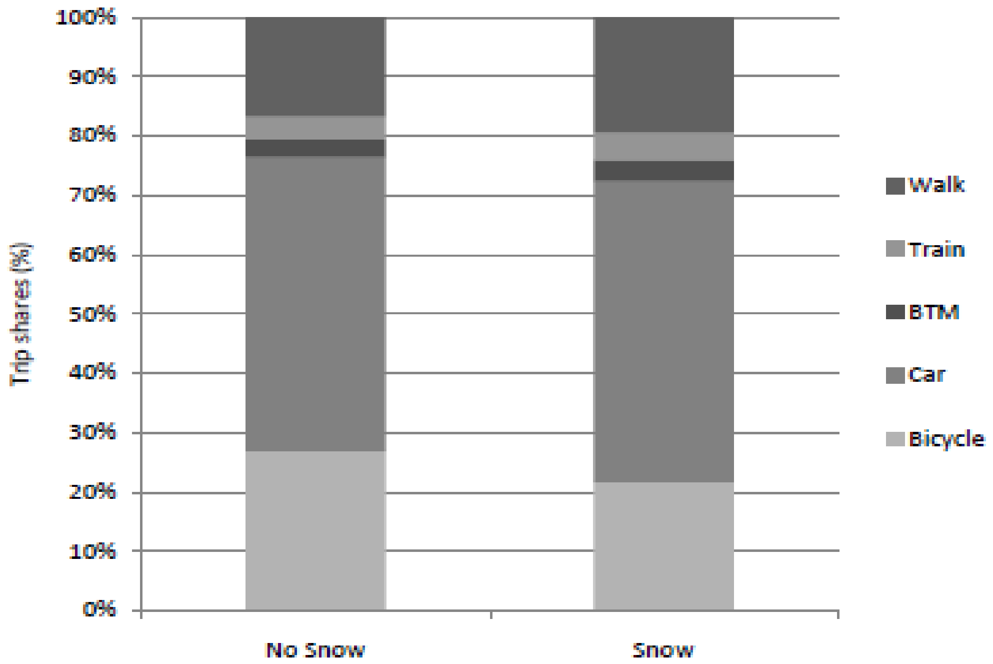

Figure 4.4: Snow and mode choice

4.2.2 Model specification and explanatory variables

In order to analyse model choice a Multinomial Logit Model (MNL) is used based on a utility function given below;

$$V_j = \alpha_j + \sum_{n=1}^{N} \beta_{n,j} x_n + \varepsilon_j \ , \tag{4.1}$$

where α_j is a transport mode specific constant; *j* represents the transport mode; and *N* is the number of explanatory variables. The coefficients of the explanatory variables vary across modes. We assume that each individual faces the same choice set of six different modes of transportation, i.e. walking (reference category), bicycle, car, bus/tram/metro (BTM), train and other (moped, motor, scooter, taxi, truck, delivery van).

We measure temperature by five dummy variables: temperature below or equal to 0^o C, between 0^o C to 10^o C, between 10 ^{o}C to 20 ^{o}C, between 20^o C to 25^o C, and greater than 25^o C. The last dummy variable for temperature is of interest for an assessment of the potential impact of a warmer climate on modal choice. Similarly, we defined several ranges for other weather variables. For instance, we define precipitation up to 0.1 mm (average precipitation) and precipitation higher than 0.1 mm (extreme precipitation) during the travellers' hour of departure. Another rain-related variable we use is the duration of precipitation (in minutes) of the hour of departure. Wind strength is measured using the Beaufort scale. A dummy variable is used if wind strength is equal to or greater than 6 Bft. Snow is an important weather variable. Unfortunately, we do not have an explicit measure of snow. [26] Therefore, we use a proxy for snowfall by including an interaction effect of precipitation and temperature less than or equal to 0^{o} C. However, measuring snow this way can only capture the effects of falling snow, and therefore it does not control for the effects of snow on the ground.

We also include a range of non-weather variables, namely; age, income, gender and car ownership and dummy variables for seasonal variations, for working and non-working days of the week and for different levels of urbanization. Finally, we included the hour of departure in the model in order to control for differential effects of travel during peak and non-peak hours. Three dummy variables are used for the hour of departure, which include dummy variables for the peak hours (morning peak from 07:00 to 10:00 and evening peak from 16:00 to 19:00) and a dummy variable for off-peak hours.[27]

4.3 Estimation and results

4.3.1 Estimation

We have a set of six categories of trip purposes: commuting, education, recreational and sports, business, and shopping, visiting family and friends. We estimated a Multinomial logit model (MNL), for each trip purpose separately, and also a combined model. Therefore, we have seven estimated models. The general results of all models are presented in Table 4.2. The specific results which show the percentage point changes in the share of different modes of transportation for the most important (the first three trip) purposes, i.e. commuting, educational and recreational trips, as well as for the combined trips, are presented in Section 4.3.3 in Tables 4.3 to Tables 4.6, and are also discussed in the text. The marginal effects of all the MNL models are presented in Appendix 4B.

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[26] It may be noted that in the initial analysis horizontal visibility was also used, but since fog seldom happens in the Netherlands and was badly measured during the study period, it is not included in the results presented.

[27] The results of these variables are not presented but can be received upon request.

4.3.2 General results

This section presents a general overview of the overall findings from the 7 estimated MNL models. The objective is to summaries the findings from all these MNL models and obtain a general idea. The summary of all MNL model estimations are given in Table 4.2 below. Table 4.2 is constructed as follows; first, we assigned -1, 0 and +1 to the negative and statistically significant coefficients, statistically insignificant coefficients, and positive and statistically significant coefficients, respectively. Second, we counted how many times a specific weather variable coefficient has -1, 0 or +1 value. Finally, we added them up to produce Table 4.2.

The interpretation of Table 4.2 can be illustrated by an example. Car is influenced by strong wind both positively and negatively for different trip purposes (2 times positive and 2 times negative in each of the different MNL models). It is also statistically insignificant in three of the MNL models. Therefore, car gets the values -2, 0, +2 for wind strength under the different models, and 0 overall (i.e. (-1) x (2) + (0) x (3)+ (+1) x(2) = 0). We interpret this “0” as no effect of strong winds on car trips. However, strong wind has different effects for different trip purposes, which are discussed in Section 4.3.3 in detail.

Table 4.2: Weather and mode choice decision (summary of findings)[1]

	Walking	**Bicycle**	**Car**	**BTM**	**Train**
Wind Strength (> 6 BFT)	0	-2	0	+4	+3
Temperature < 0^o C	+3	-4	+4	-1	-3
Temperature 10^o C to 20^o C	+1	+6	-5	-3	-2
Temperature 20^o C to 25^o C	0	+6	-5	-4	-3
Temperature > 25^o C	+2	+5	-5	-6	-4
Precipitation duration	0	-4	+3	-1	+1
Precipitation up to 0.1 mm	-3	-4	+4	+3	+1
Precipitation > 0.1mm	-3	-2	+5	+3	+2
Snow	+4	+3	-1	0	+1

Notes:

(1) The reference categories are wind up to 6 Bft, temperatures between 0^o C and 10^o C, and no precipitation.

Table 4.2 presents an interesting picture of weather and mode choice decision. We can see, that the modal shift phenomena from bicycle to car during extreme cold temperatures. However, there is a modal shift from car and BTM to cycling during increasing temperature. The walking trips also show an increase during increasing temperature, though the effects are small compared with car or cycling.

Precipitation also shows modal shift from cycling to car and BTM. In general, we would expect strong effects of modal shift during heavy precipitation. This can also be observed from those findings where modal shift in favour of car and BTM are stronger during extreme precipitation compared with average precipitation. However, snow and wind strength have an influence on mode choice decision, but a clear pattern of modal shift on the aggregate level is not clear from this table.

These findings mean that weather influences the mode choice decision of individuals. Among the weather variables, temperature and precipitation appear to be more influential in the mode choice decision.

4.3.3 Specific results

Commuting trips

The percentage-point changes in share of commuting trips caused by the weather are presented in Table 4.3. The weather variables show that weather does have an influence on the mode choice for commuting trips. Car and bicycle are more sensitive to weather conditions compared with other modes of transportation. The probability of cycling increases with temperature, but the coefficients are statistically not significant. The probability of selecting the car for commuting reduces by 1.81, 3.12 and 5.17 percentage points respectively, for the temperatures between 10^{o} C to 20^{o} C, temperatures between 20^{o} C to 25^{o} C, and temperature greater than 25^{o} C, compared with temperature between 0^{o} C to 10^{o} C. This suggests that the absolute share of bicycle increases in total commuting trips during warmer weather. The absolute share of car trips decreases. Furthermore, the probabilities of bus, tram and metro (BTM) and trains fall during higher temperatures although the effects are below 1 percentage point in most of the cases.

The coefficients of the precipitation variables have the expected signs, but most of them are statistically insignificant. Further, the statistically significant coefficients of precipitation are small. This implies, that although precipitation has little effect on mode choice for commuting trips, nevertheless people are reluctant to shift to other modes of transportation. There is a small substitution from cycling to car during extreme precipitation as compared with no precipitation. Snow strongly reduces the probability of selecting train for commuting by about 0.35 percentage points because of the delay and unreliability of the train travel time and the railway operational system during snow.[28]

[28] This was also observed during an extreme example, when 80 per cent of Dutch train services were closed down during December 2009 and January 2010 because of an extreme snow event, and people were advised to travel by train only if it was very important. However, we cannot measure the full effects of such an event here, given that our snow measure is crude.

Educational Trips

The mode choice decision for educational trips seems unaffected by strong winds (see Table 4.4). The probability of selecting BTM changes slightly during strong wind. There are noticeable changes in probabilities of travel modes in different temperatures. For instance, the probability of selecting cycling increases by 2.2 percentage points in temperatures between 10^{o} C to 20^{o} C relative to temperatures between 0^{o} C to 10^{o}. This increase is more visible during temperatures greater than 25^{o} C, where the probability of cycling increases by about 5.8 percentage points. This means that the absolute share of bicycle trips in all educational trips increases from 42.6 per cent to 48.4 per cent in temperatures higher than 25^{o} C. The probabilities of car and BTM fall during warmer weather. This indicates modal shift from BTM and car to biking for educational trips.

Table 4.3: Commuting trips (percentage-point changes)[1,2]

	Walk	Bike	Car	BTM	Train	Other
Wind strength > 6Bft	0.004	-0.574	0.356	0.373	0.112	-0.271
Temperature < 0^{o}	0.002	-0.282	1.471	-0.071	0.004	**-1.124**
Temperature between 10^{o} to 20^{o} C	**0.006**	1.264	**-1.810**	-0.034	0.075	0.500
Temperature between 20^{o} to 25^{o} C	**0.015**	2.803	**-3.115**	**-0.546**	**-0.161**	1.004
Temperature > 25^{o} C	**0.028**	4.472	**-5.174**	**-0.053**	**-0.191**	0.917
Precipitation duration (minutes)	-0.00001	-0.009	0.006	0.005	-0.001	-0.001
Precipitation up to 0.1mm	0.001	-0.608	0.386	**0.452**	0.035	-0.265
Precipitation > 0.1 mm	-0.004	-1.212	1.359	0.029	0.146	-0.319
Snow	-0.001	0.495	-0.703	0.183	-0.359	0.385

Notes:

(1) Coefficients in bold and italics are statistically significant at 5% and 10%, respectively.

(2) The reference categories are: wind up to 6 Bft, temperatures between 0^{o} C and 10^{o} C, and no precipitation.

(3)

Table 4.4: Educational Trips (percentage-point changes)[1,2]

	Walk	Bike	Car	BTM	Train	Other
Wind strength > 6Bft	0.066	-0.040	*-0.720*	**0.497**	**0.012**	0.186
Temperature < 0^{o}	**0.397**	-1.701	1.679	**0.038**	0.007	**-0.420**
Temperature between 10^{o} to 20^{o} C	-0.056	**2.256**	**-1.824**	**-0.355**	-0.003	-0.018
Temperature between 20^{o} to 25^{o} C	**0.165**	**5.210**	**-4.377**	**-0.671**	0.005	**-0.332**
Temperature > 25^{o} C	**0.464**	**5.775**	**-5.975**	**-0.370**	**-0.008**	0.114
Precipitation duration (minutes)	0.003	-0.045	0.041	*-0.005*	**-0.0002**	0.006
Precipitation up to 0.1mm	-0.066	-2.208	**2.179**	**0.126**	**0.008**	-0.040
Precipitation > 0.1 mm	-0.146	-3.481	**2.965**	**0.769**	**0.018**	-0.125
Snow	**0.484**	**-3.105**	0.990	0.755	0.018	0.859

Notes:

(1) Coefficients in bold and italics are statistically significant at the 5% and 10%, respectively.

(2) The reference categories are: wind up to 6 Bft, temperatures between 0^{o} C and 10^{o} C, and no precipitation.

Table 4.5: Recreational and sport trips (percentage-point changes)[1,2]

	Walk	Bike	Car	BTM	Train	Other
Wind strength > 6Bft	**-1.690**	**-0.387**	**1.956**	**0.074**	**0.017**	**0.030**
Temperature < 0^{o}	**-3.093**	**-5.512**	**8.538**	**0.044**	**-0.008**	**0.032**
Temperature between 10^{o} to 20^{o} C	**1.571**	**5.477**	**-7.527**	**-0.111**	**-0.016**	**0.605**
Temperature between 20^{o} to 25^{o} C	**2.118**	**14.279**	**-17.013**	**-0.267**	**-0.051**	**0.934**
Temperature > 25^{o} C	-0.151	**19.630**	**-20.006**	**-0.358**	**-0.042**	**0.927**
Precipitation duration (minutes)	-0.007	**-0.061**	**0.067**	**-0.001**	**0.001**	0.001
Precipitation up to 0.1mm	**-1.555**	**-3.938**	**5.607**	**0.118**	-0.002	-0.231
Precipitation > 0.1 mm	**-1.011**	**-4.231**	**5.455**	0.007	-0.005	-0.273
Snow	**3.495**	**3.417**	-6.993	0.013	0.031	-0.074

Notes:
(1) Coefficients in bold and italics are statistically significant at the 5% and 10%, respectively.
(2) The reference categories are: wind up to 6 Bft, temperatures between 0^{o} C and 10^{o} C, and no precipitation.

Table 4.6: All trips combined *(*percentage-point changes)[1,2]

	Walk	Bike	Car	BTM	Train	Other
Wind strength > 6Bft	**-0.392**	**-5.909**	**6.241**	**0.125**	**0.022**	-0.085
Temperature < 0	**0.122**	**-2.966**	**3.460**	**-0.179**	**-0.011**	**-0.426**
Temperature between 10 to 20C	**0.051**	**3.845**	**-4.203**	**-0.080**	**-0.011**	**0.397**
Temperature between 20 to 25 C	0.040	**9.552**	**-10.007**	**-0.217**	**-0.0004**	**0.674**
Temperature > 25C	0.001	**13.160**	**-13.662**	**-0.238**	**-0.045**	**0.785**
Precipitation duration (minutes)	0.0004	**-0.066**	**0.064**	-0.0003	-0.00001	0.002
Precipitation up to 0.1mm	**-0.369**	**-2.841**	**3.357**	**0.109**	**0.009**	-0.265
Precipitation > 0.1 mm	**-0.520**	-3.203	**3.920**	**0.200**	**0.023**	-0.420
Snow	**0.861**	**2.358**	**-4.037**	0.241	0.040	0.538

Notes:
(1) Coefficients in bold and italics are statistically significant at the 5% and 10%, respectively.
(2) The reference categories are: wind up to 6 Bft, temperatures between 0o C and 10o C, and no precipitation.

If there is 10 minutes of precipitation during the hour of departure, the probability of cycling falls by 0.45 percentage points, whereas the probability of car increases by 0.41 percentage points. Additionally, during average precipitation conditions the probability of biking is lower, and that of the car and BTM is higher as compared with no precipitation. Furthermore, the change in probability of car and bicycle is higher for extreme precipitation as compared with average precipitation.

This suggests a modal shift from cycling to car and BTM during precipitation for educational trips. In the case of snow, the probability of selecting the bicycle for educational trips reduces by about 3 percentage points whereas that of the BTM increases by 0.75 percentage points, as compared with no snow. However, there are no significant changes in the probability of selecting car. Given that students have less substitution possibilities, and also that public transport for students is subsidized in the Netherlands, the switching from cycling to BTM is obvious.

Recreational and sports trips

Recreational and sports trips are influenced more by weather conditions than by any other kind of trips (see Table 4.5). The strong variation occurs in probability of cycling and car. As one would expect, that during extreme cold weather the probability of cycling falls by 5.5 percentage points compared with temperature between 0^o C to 10^o C. But during extreme cold weather the probability of selecting car as a mode of transportation for recreational trips increases by 8.5 percentage points. This shows that during extreme cold weather the modal share of car increases from 45.6 per cent to 54 per cent. The bicycle share reduces from 24.6 per cent to 19 per cent during extreme cold, whereas the share of walking falls from 24.4 to 21.3 per cent. These are considerable effects. These findings reveal the sensitivity of recreational and sports trips to the weather variation.

The probability of cycling increases and that of the car decreases as temperature increases above 10^o C. It may be noted that cycling for recreational trips is more sensitive to weather conditions than any other trip purpose. The biggest changes happen during temperatures above 25^o C when the probability of cycling increases by 19.5 percentage points and the probability of car decreases by about 20 percentage points, compared with a temperature range between 0^o C to 10^o C.

These changes may be considered big changes, given the absolute share of car and bicycle (45.6 per cent and 24.6 per cent, respectively) for recreational and sports trips. Walking trips also occur more frequently with higher temperatures. However, there is about 0.15 percentage points reduction in the probability of walking if the temperature is above 25^o C. So people seem to avoid walking on days when the temperature is above this level. The probability of BTM reduces with increasing temperature, although the changes in probability are less than 1 percentage point.

The probability of selecting car increases by more than 5 percentage points if there is average or extreme precipitation. The probability of cycling decreases by about 4 percentage points and of walking about 1 percentage point in average precipitation and also about by same magnitude during extreme precipitation conditions compared with no precipitation.

Interestingly, during falling snow there is an increase in the probability of walking and (even) cycling, whereas the probability of selecting car decreases. This is unexpected. A possible explanation might be that during snow people predominantly make short distance trips for recreational and sports activities. [29]

Other trip purposes

The results of other trip purposes such as business, visiting family and friends, and shopping are presented in Appendix 4B. A general impression of the results from business-related trips is that the mode choice decision for business trips is hardly affected by the weather. The coefficients have plausible signs but are small in size as compared with other trip purposes (e.g. commuting or recreational and sports).[30]

The results of shopping trips and visiting family and friend trips are comparable. The change in the probability of selecting car (fall in car probability) is almost the same size as the changes in the probability of cycling (increase in probability) under the same weather conditions and vice versa. For example, during temperatures higher than 25^{o} C the probability of biking for visiting family and friends increases by about 17 percentage points, and that of car decreases by about 18 percentage points compared with temperatures between 0^{o} C to 10^{o} C. A similar pattern holds for shopping trips. This suggests that bicycle is the best substitute for car when making these kinds of trips.

The changes in the probabilities of the remaining modes of transportation due to the remaining weather variables are mostly less than 1 percentage point. This implies that the individual mode choice decision for visiting and for shopping trips is not sensitive to weather conditions. It is only car and bicycle which are affected by the weather for such kinds of trips.

Overall mode choice decision

The percentage point changes in overall mode share due to weather conditions are presented in Table 4.6. The substitution from car to bicycle use due to different temperatures is more visible in the combined model for all kinds of trips. For example, during higher temperature bicycle appears to be absorbing the fall in the absolute share of car trips in total trips. The same holds true for the precipitation duration and precipitation intensity.

A statistically-significant fall in the share of BTM and train trips can also be observed with increasing temperature, but the changes in the percentage share are less than 1 percentage point. These changes are changes in the absolute share of BTM. The modal share of BTM is around 3.5 pe rcent. The interesting findings are the increase in the relative share of BTM during average and extreme precipitation by 3.1 and 5.7 per cent, respectively. This shows that people switch to BTM from bicycles and walking during precipitation.

[29] In the Netherlands, for short distance trips people mostly use bicycle and walking. However, it may be noted that snow measures only the effects of falling snow, hence we cannot observe the mode choice decision in the case when the snow is on the ground.

[30] About 80 per cent of business trips are made by car which is less vulnerable to weather.

Despite slightly different research questions and methodologies, the findings of Chapter 3 and 4 are comparable. For instance, Chapter 4 focuses on individual trips, and shows that there is modal shift in favour of biking with an increase in temperature. Chapter 3 showed the same behavioural response using aggregate daily trips data. Other behavioural patterns found in Chapter 3 are also comparable with the findings in Chapter 4. For example, more use of public transport and car during precipitation or the strong influence of weather on recreational and sports trips.

4.4 Conclusions and policy implications

This chapter presents the influence of hourly weather conditions on the mode-choice decisions of individuals in the Netherlands. We estimated a set of multinomial logit models (MNL) to analyse the impact of weather on mode choice decisions. We estimated different models for various trip purposes.

The results of the models for different trip purposes show a more or less similar picture, though the size of the coefficients of the weather variables are different for different trip purposes. Wind discourages cycling, but increases the propensity to use the car. The effects of temperature show a decreasing percentage share of bicycle trips and an increasing percentage share of car and public transport trips at low temperatures. The opposite is true when temperatures increase up to 25^{o} C. Finally, the probability of selecting the bicycle decreases and the probability of using the car and public transportation increases as the amount of precipitation increases.

These findings on the effect of weather on mode choice can be summarized as follows: bicycle seems to be an almost perfect substitute for car trips. *Nicer weather* causes an increase in the absolute share of the bicycle trips, and the opposite happens to the car trips. However, during *bad weather* bicycles are replaced by car. The substitution is higher during warmer weather as compared with rainy conditions. This suggests that a warmer/colder day has more influence on modal share compared with a wet day.

These findings imply that, if temperature varies due to climate change, this would not create a problem for Dutch transport planners. In the Netherlands, people still prefer to bicycle even if the temperature is above 25^{o} C. Therefore, in next few decades no big policy shift is required. However, if temperatures in the range 30^{o} C - 35^{o} C become more frequent, people may switch from bicycle to car and BTM. Such a situation will have major implications for Dutch transport planners given that the decision to investment in bicycle/road infrastructure will have to be revised, and an additional supply of road or the extension of current roads may be required. This will also have more implications for road congestion as a result of the excess demand created by modal shift. Also, BTM need to be equipped for warmer weather (for example being provided with modern air-conditioning system). However, these considerations are only relevant over a very long time scale.

Appendix 4A

Table 4A: Descriptive of variables

Variable	Mean	Std. Dev.
Wind strength > Bft	0.005	0.071
Temperature < 0	0.052	0.223
Temperature between 0° to 10° C	0.391	0.488
Temperature between 10° to 20° C	0.447	0.497
Temperature between 20° to 25° C	0.076	0.265
Temperature > 25° C	0.023	0.150
Precipitation duration (minutes)	4.210	13.154
No precipitation	0.789	0.408
Precipitation up to 0.1mm	0.120	0.325
Precipitation > 0.1 mm	0.091	0.287
Snow	0.008	0.088

Appendix 4B

Table 4B.1: MNL models' fit

Trip Purpose	Number of Observations	Pseudo R^2
Commuting Trips	429194	0.3183
Business Trips	106594	0.3223
Educational Trips	348959	0.4494
Recreational and Sports Trips	670286	0.2886
Visiting family and Friend	562605	0.3107
Shopping	746023	0.2966
All trips	3512645	0.3222

Table 4B.2: Marginal effects of MNL models[1,2]

Commuting Trips	Walk	Bike	Car	BTM	Train	Other
Wind strength > Bft	0.00004	-0.0057	0.0036	0.0037	0.0011	-0.0027
Temperature < 0^{o}	0.00002	-0.0028	0.0147	-0.0007	0.00004	**-0.0112**
Temperature between 10^{o} to 20^{o} C	**0.0001**	0.0126	**-0.0181**	**-0.0003**	0.0008	0.0050
Temperature between 20^{o} to 25^{o} C	**0.0002**	0.0280	**-0.0312**	**-0.0055**	**-0.0016**	0.0100
Temperature > 25^{o} C	**0.0003**	0.0447	**-0.0517**	**-0.0005**	**-0.0019**	0.0092
Precipitation duration (minutes)	-0.0000001	-0.0001	0.0001	0.0001	-0.00001	-0.00001
Precipitation up to 0.1mm	0.00001	-0.0061	0.0039	0.0045	0.0003	-0.0027
Precipitation > 0.1 mm	-0.00004	-0.0121	0.0136	0.0003	0.0015	-0.0032
Snow	-0.00001	0.0049	-0.0070	0.0018	-0.0036	0.0039
Business Trips						
Wind strength > Bft	-0.0001	-0.0062	0.0026	-0.0001	-0.0004	**0.0042**
Temperature < 0^{o}	0.0001	-0.0004	0.0056	0.0011	-0.0001	**-0.0064**
Temperature between 10^{o} to 20^{o} C	0.00001	**0.0058**	-0.0071	**-0.0019**	0.0003	0.0030
Temperature between 20^{o} to 25^{o} C	-0.0001	**0.0055**	-0.0147	*-0.0029*	**0.0023**	0.0099
Temperature > 25^{o} C	-0.0001	*0.0077*	-0.0102	**-0.0054**	**0.0040**	0.0039
Precipitation duration (minutes)	0.000004	*-0.0001*	-0.0002	0.0001	0.0001	0.0001
Precipitation up to 0.1mm	-0.00003	-0.0019	0.0048	0.0001	-0.0013	-0.0017
Precipitation > 0.1 mm	-0.0002	-0.0031	0.0129	-0.0025	-0.0022	-0.0049
Snow	0.0002	-0.0045	0.0069	-0.0037	0.0020	-0.0009
Educational Trips						
Wind strength > Bft	0.0007	-0.0004	*-0.0072*	**0.0050**	**0.0001**	0.0019
Temperature < 0^{o}	**0.0040**	-0.0170	0.0168	**0.0004**	0.0001	**-0.0042**
Temperature between 10^{o} to 20^{o} C	-0.0006	**0.0226**	**-0.0182**	**-0.0036**	-0.00003	-0.0002
Temperature between 20^{o} to 25^{o} C	**0.0017**	0.0521	**-0.0438**	**-0.0067**	0.0001	**-0.0033**
Temperature > 25^{o} C	**0.0046**	**0.0577**	**-0.0597**	**-0.0037**	**-0.0001**	0.0011
Precipitation duration (minutes)	0.00003	-0.0005	0.0004	*-0.00005*	**-0.000002**	0.0001
Precipitation up to 0.1mm	-0.0007	-0.0221	**0.0218**	**0.0013**	**0.0001**	-0.0004
Precipitation > 0.1 mm	-0.0015	-0.0348	**0.0296**	**0.0077**	**0.0002**	-0.0012
Snow	**0.0048**	**-0.0310**	0.0099	0.0075	0.0002	0.0086
Recreational and Sports Trips						
Wind strength > Bft	**-0.0169**	**-0.0039**	**0.0196**	**0.0007**	**0.0002**	**0.0003**
Temperature < 0^{o}	**-0.0309**	**-0.0551**	**0.0854**	**0.0004**	**-0.0001**	**0.0003**
Temperature between 10^{o} to 20^{o} C	**0.0157**	**0.0548**	**-0.0753**	**-0.0011**	**-0.0002**	**0.0061**
Temperature between 20^{o} to 25^{o} C	**0.0212**	**0.1428**	**-0.1701**	**-0.0027**	**-0.0005**	**0.0093**
Temperature > 25^{o} C	-0.0015	**0.1963**	**-0.2001**	**-0.0036**	**-0.0004**	**0.0093**
Precipitation duration (minutes)	-0.0001	**-0.0006**	**0.0007**	**-0.00001**	**0.00001**	0.00001
Precipitation up to 0.1mm	**-0.0156**	**-0.0394**	**0.0561**	**0.0012**	-0.00002	-0.0023
Precipitation > 0.1 mm	**-0.0101**	**-0.0423**	**0.0546**	0.0007	-0.0001	-0.0027
Snow	**0.0349**	**0.0342**	-0.0699	0.0013	0.0003	-0.0007

Visiting family and Friends						
Wind strength > Bft	**0.0125**	**-0.0036**	**-0.0131**	**0.0029**	0.0002	**0.0011**
Temperature < 0^o	**0.0166**	**-0.0169**	**0.0046**	**-0.0017**	0.0002	**-0.0028**
Temperature between 10^o to 20^o C	**-0.0023**	**0.0477**	**-0.0515**	-0.0008	**-0.0002**	**0.0071**
Temperature between 20^o to 25^o C	**-0.0051**	**0.1174**	**-0.1230**	*-0.0016*	**-0.0006**	**0.0129**
Temperature > 25^o C	-0.0021	**0.1720**	**-0.1805**	**-0.0033**	**-0.0007**	**0.0146**
Precipitation duration (minutes)	-0.00005	**-0.0007**	**0.0008**	*-0.00004*	-0.000003	-0.00001
Precipitation up to 0.1mm	**-0.0035**	**-0.0297**	**0.0330**	**0.0017**	-0.00001	-0.0016
Precipitation > 0.1 mm	**-0.0102**	**-0.0381**	**0.0498**	**0.0031**	**0.0001**	-0.0047
Snow	**0.0170**	**0.0103**	**-0.0483**	0.0044	0.0004	**0.0161**
Shopping trips						
Wind strength > Bft	**0.0039**	**0.0071**	**-0.0122**	0.0007	-0.00001	0.0006
Temperature < 0^o	**0.0082**	**-0.0178**	**0.0130**	**-0.0012**	**-0.0001**	**-0.0021**
Temperature between 10^o to 20^o C	**-0.0025**	**0.0292**	-0.0284	**0.0001**	**0.00004**	**0.0016**
Temperature between 20^o to 25^o C	**-0.0027**	**0.0656**	**-0.0658**	-0.0004	-0.00002	**0.0033**
Temperature > 25^o C	*-0.0025*	**0.0882**	**-0.0899**	*-0.0015*	-0.00001	**0.0057**
Precipitation duration (minutes)	0.00003	**-0.0011**	**0.0010**	*0.00003*	**0.000003**	-0.000001
Precipitation up to 0.1mm	-0.0005	**-0.0248**	**0.0280**	-0.0003	**-0.0001**	**-0.0023**
Precipitation > 0.1 mm	-0.0039	-0.0267	**0.0339**	-0.0002	*-0.0001*	**-0.0030**
Snow	0.0025	0.0202	-0.0276	-0.0004	**0.0003**	0.0050
All Trips						
Wind strength > Bft	**-0.0039**	**-0.0591**	**0.0624**	**0.0012**	**0.0002**	-0.0008
Temperature < 0^o	**0.0012**	**-0.0297**	**0.0346**	**-0.0018**	**-0.0001**	**-0.0043**
Temperature between 10^o to 20^o C	**0.0005**	**0.0385**	**-0.0420**	**-0.0008**	**-0.0001**	**0.0040**
Temperature between 20^o to 25^o C	0.0004	**0.0955**	**-0.1001**	**-0.0022**	**-0.0004**	**0.0067**
Temperature > 25^o C	0.00001	**0.1316**	**-0.1366**	**-0.0024**	**-0.0005**	**0.0079**
Precipitation duration (minutes)	0.000004	**-0.0007**	**0.0006**	-0.000003	-0.0000001	0.00002
Precipitation up to 0.1mm	**-0.0037**	**-0.0284**	**0.0336**	**0.0011**	**0.0001**	-0.0027
Precipitation > 0.1 mm	**-0.0052**	-0.0320	**0.0392**	**0.0020**	**0.0002**	-0.0042
Snow	**0.0086**	**0.0236**	**-0.0404**	0.0024	0.0004	0.0054

Notes:

(1) Coefficients in bold and italics are statistically significant at the 5% and 10%, respectively.

(2) The reference categories are: wind up to 6 Bft, temperature between 0^o and 10^oC, no precipitation.

PART II

WEATHER AND TRAVEL TIME

Chapter 5

Adverse Weather and Commuting Speed[31]

5.1 Introduction

In the current chapter, we will introduce a number of methodological improvements in the econometric analysis of congestion, weather conditions and travel speed. The econometric approach is applied to car commuters in the Netherlands, with an emphasis on the effect of weather on speed. We are particularly interested in whether adverse weather conditions reduce the welfare of transport users by a reduction in the speed.

The effects of weather on speed are clearly relevant for the theme of accessibility, as they are a measure of the potential for spatial interaction for individuals, firms or other organizations. Most indicators of accessibility are based on the concept of generalized costs, defined as the weighted sum of monetary costs, travel time and possibly other types of costs. For an analysis of accessibility, it is therefore essential that appropriate measures are available for travel speed under various conditions. The contribution of the present chapter is that it focuses on the impact of weather on travel time, this being one of the components of generalized costs.

Most of the literature available on the effects of weather on road transport focuses on traffic accidents and traffic speed (for an overview of the empirical literature, see Koetse and Rietveld 2009). Most of the evidence shows an increasing effect of precipitation on the frequency of accidents, but the impact on accident severity appears to be not as pronounced.

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[31] This chapter is based on Sabir et al. "Adverse Weather and Commuting Speed", *Networks and Spatial Economics*, forthcoming.

Similarly, some studies analyse the impact of weather on traffic speed. For instance, Maze and Agarwal (2006) use a data set which includes 4 years of traffic data from the freeway system in the Minneapolis/St. Paul metropolitan area and weather data from three weather stations near to the freeway network. They show that adverse weather causes clear reductions in traffic speed: up to 6 per cent for rain; up to 13 per cent for snow; and up to 12 per cent for reduced visibility. Similarly, Ibrahim and Hall (1994) analyse the effects of adverse weather on the speed-flow and flow-occupancy relationships for Canadian travellers (see also Brilon and Ponzlet 1996; Hall and Barrow 1988). They find a small but statistically significant effect of light rain and light snow on the free-flow speed. The effects of heavy rain and heavy snow are much larger, causing a reduction in the free-flow speed of 5–10 km/hour and 38–50 km/hour, respectively.

We offer a number of methodological improvements. First, in the literature it is common to focus on traffic speed/reliability measured for a specific segment of a road of typically 100 metres (see, e.g., Ibrahim and Hall 1994), in the context of weather. This implies that only a small part of a whole trip is analysed. This approach is less insightful because the travellers' utility and therefore the welfare effects of weather depend on the total travel time, so the interpretation of results for a specific road segment requires assumptions of changes in speed for other parts of the trip. To address this issue, our observations are at the trip level, implying that we focus on the average speed of the whole trip instead of only part of the trip.

Second, we focus on commuting, because, in general, daily variation in demand for employment, and therefore daily variation in demand for commuting, hardly depends on weather conditions (see, e.g., Chapter 3). The welfare loss associated with a reduction in derived demand is therefore negligible, implying we can focus on the welfare effect of transport users. This most probably does not hold for trips related to other activities: for example, demand for recreational and leisure trips is likely to be negatively affected by adverse weather conditions.

Third, we apply panel data techniques using variation of car commuting trips within the day. We use local weather data measured on an hourly basis, which allows us to use daily variation in weather (previous studies tend to use the average weather per day). One of the main methodological advantages of focusing on commuting trips is that it allows one to apply panel techniques, as for most commuters two trips on the same day are observed under different weather circumstances. This is relevant as it allows us to deal with potentially important issues related to unobserved heterogeneity and data selection.[32]

[32] Given individual-specific fixed effects, self-selection bias is reduced, because a constant is included for each commuter, and therefore controls for individual preferences.

In the Netherlands, almost a quarter of commuters use the bicycle.[33] The welfare effects of adverse weather for bicycle users are not so much caused by delay in trips, but more strongly by the inconvenience of adverse weather itself, which is motivation to focus exclusively on car commuters. The main objective of the current chapter is therefore, to analyse the welfare effects of adverse weather associated with changes in the speed of car commuting trips. In this chapter, we will largely ignore the possible welfare effects of adverse weather through changes in travel time
reliability. We leave this issue for further research.

The remainder of this chapter is organized as follows. Section 5.2 explains the empirical model and the econometric methodology to derive welfare effects of weather through changes in commuting speed. Section 5.3 describes the data, as well as the explanatory variables included in the model. Section 5.4 provides the empirical results, and discusses the welfare effects of adverse weather conditions for the Netherlands. Finally, Section 5.5 concludes.

5.2 Theory and estimation methods

5.2.1 Theoretical background

Our empirical analysis is based on standard microeconomic theory (e.g. Van Ommeren and Dargay 2006; Fosgerau 2005). Let us assume that the traveller's utility is a concave function of speed, and that the travel cost function is a convex function of speed. It can then be shown, quite intuitively, that the optimal speed is chosen, such that the marginal benefits of speed (a reduction in travel time given the distance) equals the marginal costs of speed. Given the assumption that the monetary costs are a power function of speed, it can be shown that the double-log model is the preferred statistical model.

Van Ommeren and Dargay (2006) show then that the marginal effect of an exogenous environmental characteristic, such as weather, on the logarithm of speed can be interpreted as the marginal effect of this characteristic on the logarithm of the commuter's total commuting costs (the sum of travel time costs and any other costs that vary with speed). So, it is meaningful to estimate the welfare consequences of the weather conditions using loss in travel time. For our empirical analyses, we will use the following logarithmic specification, which is in line with the theoretical considerations above:

[33] In the data set used in this study the commuting shares of the different transport modes are 56 per cent for car, 23 per cent for bicycle, 14 per cent for public transport, 4 per cent for walking, and 3 per cent for other modes.

$$log(S_{it}) = \beta_o + \beta_1 W_{it} + \beta_2 log(D_{it}) + \beta_3 log(y_{it}) + \beta_4 X_{it} + \beta_5 F_{it} + \xi_{it}, \qquad (5.1)$$

where subscript *i* represents individuals; *t* represents hour of departure; and *d* represents day of the year. Furthermore, *S* is speed; *W* is a vector of individual-specific time-varying variables (including weather variables); *D* denotes the distance travelled; y is the income of individuals; *X* is a vector of individual variables (including gender, age, etc); and *F* refers to time-specific characteristics such as degree of urbanization, hour of travel, day of the year, and seasonal variation. Finally, the *β's* are parameters to be estimated by the model; and ξ denotes an unobserved error term.

5.2.2 Assumptions regarding conditions of error terms

In order to analyse the impact of road conditions such as weather on the speed of commuting trips, we employed fixed effects techniques. Individual-specific fixed effects allow us to control for unobserved differences in preferences among individuals and other unobserved features of individuals (such as the exact location of the individual). These unobserved features are correlated with weather variables. For example, in the western part of the Netherlands, weather tends to be warmer and wetter in the winter than in the rest of the Netherlands. The western part of the Netherlands is also the most congested part, so not controlling for residence location may cause a spurious correlation between weather and speed. Furthermore, the interaction of weather with other explanatory variables (such as the presence of congestion in the individual-specific region of residence) is likely correlated with unobserved individual-specific variables. For example, it is plausible that commuters who are more likely to be affected by congested roads (independent of weather conditions) have a lower speed on average.

For the same reasons discussed above, it may be relevant to control for day-specific and hour-specific fixed effects. For instance, it is plausible that all commuters are affected by a common factor on the same day (apart from weather), which is correlated with weather (for example, summer holidays reduce traffic). Similarly, it is plausible that all commuters are affected by a common factor during the same hours, which is correlated with weather patterns (for example, temperature tends to be higher during the day than during the evening rush hour). Ultimately, we estimate fixed-effects panel data models with *day-specific*, *individual-specific* and *hour-specific* effects. Fixed effects models include a dummy variable for each observation in the same group (where a group refers to an individual, a day, or an hour). Note that some commuters have two different distances even when using the same day, which allows us to identify the effect of distance using individual fixed effects.

5.3 Data and model specification

The data used in this chapter are taken from two sources. We make use of the National Transport Survey provided (OVG) by Statistics Netherlands for 1996. The second data source is a weather database available from the Royal Netherlands Meteorological Institute (KNMI) for 1996. The details of both data sets are provided in Section 2.3, in Chapter 2. It may be noted that weather conditions in this chapter refer to temperature (we distinguish between temperatures above and below 0^{o} C), wind speed (wind strengths exceeding 6 Bft), rain and falling snow. Falling snow is measured as the interaction effect of rain and temperatures equal to or below 0°C. Note that our snow measure only captures falling snow and not the level of snow on roads, which may be the more relevant variable in the current context. Hence, for each commuting trip, we have the local weather conditions of the hour in which the trip took place. Nevertheless, as precipitation is much more localized, and variation of precipitation within 1 hour is much higher than captured by our measure, it is plausible that due to (random) measurement error, our weather effects are downward-biased.

As already mentioned in the introduction, we select only car commuting trips for our analyses. There are a number of economic and statistical reasons for this. First, and most importantly, we select commuting trips because the demand for commuting is derived from the demand for labour, which does not directly depend on weather, whereas the derived demand for other trips (in particular, leisure trips) is affected by daily variation in weather conditions. Hence, for commuting trips, interpretation of the welfare effect of weather is more straightforward. Second, commuting distance can be instrumented, avoiding problems with the endogeneity of distance to speed, whereas this may be more difficult for other travel purposes (Van Ommeren and Dargay 2006). Third, we select car trips because for other modes, and in particular cycling, which is the main alternative for car use in the Netherlands, the welfare of commuting is directly affected by the weather and not so much through its effects on traffic speed. A possible critique of our sample selection is that it may generate biased estimates (for example, Wooldridge 2003). However, by including individual-specific fixed effects, one also controls for individual-specific selection effects that may occur, as we have a selected sample of car commuters because the individual-specific dummies included control for unobserved individual preferences for speed.

Given these restrictions, our sample contains 42,534 car commuting trips made by 17,248 commuters. Average trip distance is 20 km; average speed is 43.9 km/h; and average commuting time is 24.5 min. The means and standard deviations of other explanatory variables are provided in Appendix 5A. Most explanatory variables included in the model are self-explanatory, and are included to control for differences in ‘demand’ for speed (for example, gender), as well as for characteristics that effect the cost of speed (for example, degree of urbanization). Some variables need some additional explanation. Van Ommeren and Dargay (2006) use the wage rate in the specification of their theoretical speed model but, because of lack of data on wages, they use individual income for their empirical analysis. We will also use individual income instead of the wage rate for the same reason. Further, we estimate the effect of rush hours (morning and evening rush hours) which is useful to capture general congestion effects. In a separate analysis, we distinguish between morning and evening rush hours. The results are almost identical and can be provided on request. Furthermore, adverse weather may have stronger effects on speed during rush hours, due to increased demand for car travel, or to an increase in the minimum distance between cars, which is necessary for safety reasons. The interaction of (morning and evening) rush hours and rain are therefore included in the model. We include interaction effects for the rain variable but not for temperature and wind because the main effects of these weather variables are small. In addition, the inclusion of more interaction effects makes interpretation of the effects cumbersome.

We estimate the effect of travelling on above-average congested routes by distinguishing trips longer than 10 km that are directed towards or originate from one of the four major cities in the Randstad in the morning and evening peak. The Randstad consists of an urban ring formed by the four largest cities in the Netherlands (Amsterdam, Utrecht, Rotterdam, the Hague) and their surrounding areas. The population of the Randstad is over 7 million inhabitants, which is almost 50 per cent of the total population of the country. These four cities contain the main centres of employment and business activities, so in the morning, congestion occurs on roads leading towards the four cities while in the afternoon it occurs on their exit roads.

Specifically, a morning peak congestion dummy is equal to 1 when a trip is longer than 10 km, is directed towards one of the four major cities, and takes place between 07.00 and 09.00 in the morning. An evening peak dummy is equal to 1 when a trip is longer than 10 km, originates from one of the four major cities, and takes place between 16.00 and 18.00 in the evening. Since most traffic jams occur at highways near the major cities, the model should pick up the effects of congestion on speed. Furthermore, we interact the morning and evening peak congestion variables with a rain dummy in order to test whether rain has a stronger impact on speed on already congested routes than during free-flow. We select the trips longer than 10 km to increase the probability that a trip takes place partly on highways. In order to control for carpooling effects, we control for the number of people in the vehicle (Rietveld et al. 1999). Seasonal effects are captured by seasonal dummy variables.

5.4 Results

5.4.1 Speed

The results of the various model estimations are provided in Table 5.1. In general, the results are robust with respect to the type of model estimated. The signs and magnitudes of the effects are comparable across the models with few exceptions.

The results suggest that adverse weather conditions generally have a rather limited impact on car commuting speed except for falling snow and strong wind, given the hour-fixed effects specification. Extreme wind strengths appear to have a negative effect on speed of approximately 2 per cent, and falling snow of about 7 per cent.
There appears to be no effect of rain, suggesting that free-flow speed is not affected by rain. Therefore, although there appear to be some negative welfare consequences of adverse weather conditions, these seem to be close to negligible, except for snow and maybe extreme winds. To estimate these welfare costs we focus on the average commuter. For that commuter the average commuting time is 0.41 hour (see Appendix 5A).

To estimate the welfare effect of weather through changes in traffic speed, we use information on the average value of travel time (see, e.g., Small and Verhoef 2007). Based on a meta-analysis of 56 value-of-time (VOT) estimates from 14 different countries, Waters (1996) finds an average ratio of VOT equal to 48 per cent of gross wage rate, and a median ratio of 42 per cent for commuting trips made by automobile.

In another review, Wardman (1998) finds similar values. In the Netherlands, gross hourly wage rates for car commuters are about € 16, suggesting a value of time of about € 8 per hour. This figure has been derived from the Dutch National Household Survey, which includes employees who commute by car. Therefore, the welfare effect of falling snow through loss in travel time is around € 0.23 (0.41×0.07×€ 8) per commuting trip.

For extreme winds the welfare loss is around € 0.07 (0.41×0.07×€ 8) per commuting trip. Since both types of weather conditions rarely occur, the overall welfare costs are negligible.

With respect to the impact of other variables, speed is reduced by around 4 per cent during rush hours. Trips made in the morning and evening peaks and on congested routes are also substantially slower. Congestion in the morning and evening peak both cause a speed reduction of at least 7 per cent compared with non-peak times. The congestion-related welfare losses amount to € 0.23 (0.41×0.07×€ 8) per commuting trip in both morning peak and evening peak. Carpooling also strongly reduces trip speed by about 7 per cent, the likely underlying causes being waiting times and detours made to pick up passengers.

Table 5.1: Analysis of logarithm of speed of car commuting trips

	Day-specific Fixed effects		Individual-specific Fixed effects		Hour-specific Fixed effects	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Weather variables						
Wind strength > 6 Bft	−.022	0.014	−.005	0.018	**−.026**	0.013
Temperature < 0°C	−.002	0.011	0.018	0.012	0.006	0.007
Rain	0.002	0.012	0.002	0.013	−.001	0.007
Falling snow	−.057	0.036	0.012	0.043	**−.075**	0.033
Rush hour × rain	−.011	0.014	−.001	0.015	–	–
Congestion morning peak × rain	−.030	0.042	−.026	0.048	−.037	0.042
Congestion evening peak × rain	*−.068*	0.042	**−.122**	0.046	*−.068*	0.041
Other explanatory variables						
Rush hour	**−.042**	0.004	**−.034**	0.005	–	–
Congestion morning peak	**−.031**	0.012	**−.076**	0.017	**−.041**	0.013
Congestion evening peak	**−.042**	0.013	**−.069**	0.017	**−.035**	0.013
Carpooling	**−.071**	0.006	**−.054**	0.01	**−.068**	0.006
Income (Ln)	0.000	0.004	–	–	0.002	0.004
Distance travelled (Ln)	**0.406**	0.002	**0.436**	0.003	**0.412**	0.002
Very urbanized	**−.167**	0.009	–	–	**−.167**	0.009
Urbanized	**−.141**	0.006	–	–	**−.142**	0.006
Moderately urbanized	**−.100**	0.006	–	–	**−.102**	0.006
Little urbanized	**−.034**	0.005	–	–	**−.036**	0.005
Gender (Males)	**0.032**	0.005	–	–	**0.039**	0.005
Age between 30 and 40 years	−.004	0.005	–	–	−.008	0.005
Age between 40 and 65 years	**−.032**	0.005	–	–	**−.034**	0.005
Age greater than 65 years	**−.138**	0.027	–	–	**−.155**	0.027
Weekends	–	–	–	–	**0.052**	0.007
Summer	–	–	–	–	**0.026**	0.006
Autumn	–	–	–	–	−.008	0.005
Winter	–	–	–	–	**−.012**	0.006
R^2	0.581		0.883		0.576	
Number of observations	42,435		42,435		42,435	
Number of groups	366		17, 248		24	

Notes:
(1) Coefficients in bold and italics are statistically significant at the 5 % and 10% level of significance, respectively.
(2) The reference categories for temperature, urbanization, age, and seasonal variables are, respectively, temperature > 0°C, rural, age between 18 and 30 years, and spring.

In contrast to Fosgerau (2005), who also focuses on car commuting trips, we find no statistically significant effect of income on speed. Furthermore, we find that the distance elasticity is around 0.40 to 0.44 (in line with Van Ommeren and Dargay 2006). The degree of urbanization strongly reduces trip speed, with around 17 per cent speed reduction in very urbanized areas (see also Van Ommeren and Dargay 2006). This result is plausible because trips made in urban areas experience more congestion, and encounter more road signals and crossing points compared with trips made in rural areas. Some other results are that older people drive slower, that trips made during weekends are faster than trips made on working days, and that male commuters drive slightly faster than female commuters. The latter is consistent with the literature (see, e.g., Rietveld et al. 1999; Van Ommeren and Dargay 2006).

Finally, the interactions of rain show interesting results. The effect of rain on the speed of trips made during the both rush hour is negative but small and statistically insignificant. This finding is in line with our previous finding that rain has relatively limited negative welfare consequences. However, although rain during the morning peak on congested routes appears to have hardly any effect, there does appear to be a substantial negative impact of rain on the speed of trips made on congested routes during the evening peak.

The difference between these estimates for morning and evening peak times may be entirely due to random variation, but may also be due to additional congestion caused by adverse weather before the evening peak. The additional impact of rain on speed reduction for evening trips ranges from 7 to 12 per cent. Hence, this suggests that the welfare loss of rain when commuters face congested roads turns out to be substantial and between 7 and 12 per cent of total commuting costs.

Note that the average commuting time of trips in the evening peak on congested routes is 0.51 hour (see Appendix 5A), which means that the additional welfare loss through increases in travel time due to rain is around € 0.50 (0.51× 0.12×€ 8) per commuting trip in the evening peak on congested routes.

It may be argued that the distance variable included in the model is endogenous since the distance travelled may depend on speed (van Ommeren and Dargay 2006). In order to address this problem the model has been re-estimated by instrumental variables (IV), using the education of commuters as an instrument of distance. The results are almost identical, so the IV estimates are not reported here. We have also investigated other weather variables (such as sunlight), but did not find any effect. Furthermore, our results are robust by selecting sub-samples (such as the selection of commuters who are observed exactly twice). Adverse weather may not only affect average speed but also speed variation. In the log-linear model, the estimated standard error of residuals has a direct effect on estimated expected traffic speed, which implies that adverse weather may also have an effect through the standard error of residuals. In order to analyse whether this is the case, we allow the variance of the error term to vary with weather and several other variables in the model with individual-specific fixed effects. This exercise shows that adverse weather has only a small and statistically insignificant effect on the standard error of residuals. Consequently, our estimates are robust with respect to the specification of the variance.

5.4.2 Reliability

One may argue that our estimates of the effect of bad weather on welfare is an underestimate of the real welfare effect, because we have ignored the welfare effects of increased unreliability and arrival times at work due to bad weather. To test for the presence of unreliability, we have estimated a linear speed model with heteroskedasticity due to adverse weather. These analyses show that rain during the peak hours strongly increases the variance, but this effect largely disappears for the fixed-effects model. These results suggest that adverse weather increases between-day unreliability but does not increase within-day unreliability. We have attempted to estimate the welfare losses of increased unreliability, making use of the conceptual framework of Small (1982). According to this model, increased unreliability in travel times implies that workers leave earlier from home in order to be at work in time. To address this issue, we have estimated the effect of the weather variables on the morning departure time of the car drivers (after 6 o'clock and before 12 o'clock). Hence, the dependent variable is a duration variable. The explanatory variables included are the individual (including commuting distance) and household variables (including the urbanization degree of the region of residence) that were included in the previous analyses, as well as the weather variables which are allowed to vary by hour. Clearly, the hazard rate of departing time varies strongly by hour. We have therefore estimated semi-parametric duration models using a partial likelihood approach, as these models do not require any parametric assumptions on the effect of hour time on the departure time (see Lancaster, 1990). Our estimates do not show any evidence that bad weather makes people depart earlier for work. In fact, we even find a small positive effect of snow on the departure time (workers leave about 5 minutes later). This finding is consistent with the studies by Arnott et al. (1991, 1999), as well as by De Palma and Lindsey (1998), in which stochastic bottleneck models are analysed.

5.5 Conclusions

In this chapter we have analysed the effects of weather on the speed of car commuting trips for the Netherlands. We use micro-data at the trip level based on the national transportation survey and detailed local time-specific weather conditions for the Netherlands for the year 1996. One novelty of the approach used in the current chapter is that our observations are at the trip level, implying that we focus on the average speed of the whole trip instead of on only part of the trip, which is the standard approach in the literature. We estimate panel data models with a range of fixed effects. In our models, we use a large number of explanatory variables, such as distance travelled, age, gender, degree of urbanization, income, and hours of the day. Our main interest is in the effect of weather variables, such as temperature, rain, snow, and wind strength. We also include interaction effects of the weather variables with congestion specific variables. We have taken the potential endogeneity of distance into account.

In general, the results are robust with respect to model specification and type of model estimated. Snow is the only weather condition that clearly reduces trip speed, the reduction being around 7 per cent. However, since snowfall is rare the associated welfare loss in the Netherlands is limited. What is interesting is the speed reduction in the morning and evening peaks on congested routes, which is around 7 per cent. The associated welfare loss through increases in travel time is around € 0.23 per commuting trip. These effects are exacerbated by rain, which has a strong negative effect on trip speed on congested routes, especially during the evening peak. The welfare effect of rain for these trips ranges between 9 per cent and 12 per cent of total commuting costs, and amounts to at least € 0.50 per commuting trip.

By our analysis of weather dependence of speed we provide an enrichment of the accessibility concept. Accessibility depends on, among other things, travel times, and, given the impact of weather on travel times, we find that weather is one of the determinants of accessibility.

Appendix 5A

Table 5A.1: Descriptive statistics of variables used in the empirical model (N= 45,534)

	Mean	S.D
Continuous variables		
Speed (km/hour)	43.90	31.90
Income (in 000's euros)	14.20	5.04
Income (Ln)	2.54	0.54
Distance (in km)	20.10	25.10
Distance (Ln)	2.41	1.14
Commuting time (in hours)	0.41	1.38
Commuting time non-congested roads (in hours)	0.40	0.38
Commuting time congestion morning peak(in hours)	0.45	0.35
Commuting time congestion evening peak (in hours)	0.51	0.37
Dummy variables		
Strong wind (Bft)	0.024	
temperature <= 0 C	0.166	
Rain	0.091	
Falling snow	0.004	
Rush hour	0.603	
Rush hour x rain	0.055	
Carpooling	0.114	
Males	0.699	
Age between 18 and 30 years	0.242	
Age between 30 and 40 years	0.299	
Age between 40 and 65 years	0.448	
Age greater than 65 years	0.005	
Very urbanized	0.058	
Urbanized	0.190	
Moderately urbanized	0.224	
Little urbanized	0.227	
Rural	0.251	
Weekends	0.077	
Spring	0.262	
Summer	0.215	
Autumn	0.253	
Winter	0.270	
Congestion morning Peak	0.045	
Congestion evening peak x rain	0.004	
Congestion evening peak	0.039	
Congestion evening peak x rain	0.003	

Chapter 6

Weather and Travel Time of Public Transport Trips[34]

6.1 Introduction

The main modes of transportation in the Netherlands are car, bicycle and walking. They cover about 90 per cent of all trips. About 50 per cent of trips are made by car, and the main alternative for the car is the bicycle, with a share of about 25 per cent. Distance appears to be an important moderator, as people prefer to not use the bicycle for longer distances. About 75 per cent of all bicycle journeys to work are less than 5 kilometres, 20 per cent are between 5 and 10 kilometres, and 5 per cent are longer than 10 kilometres (Statistics Netherlands 2008). Longer commuting trips are mostly made either by car or by public transportation. Since using the car is not always a viable option, e.g. because no driver's licence is available or because of parking restrictions (especially in the Randstad region), public transport in the Netherlands is frequently a good alternative for trips over longer distances. Public transport will be classified in two main categories, i.e. trips made by bus, tram and metro (BTM), on the one hand, and trips made by train on the other.[35]

Public transport in the Netherlands has about an 8 per cent share of trips. When travelling by public transport, an individual has to go to an access point (bus stop, train station, etc.). The more time that is spent getting to an access point, the larger the total time required to reach the final destination. Transferring between trains or buses during a trip has a similar effect. Furthermore, waiting time, delays and adverse weather may also influence the

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[34] This chapter is based on Sabir et al. 2010b, The Effects of Weather and Individual Characteristics on the Speed of Public Transport Trips: An Empirical Study for the Netherlands, in M. Givoni and D. Banister (eds) (2010), *Integrated Transport: From Policy to Practice*, Routledge, USA (pp. 275-288).

[35] We combine trips made by bus, tram and metro (BTM) for two main reasons. First, the average speed, distance, and travel time of trips made by BTM are similar. Second, BTM are mostly used for medium distance trips, unlike the train which is mostly used for long-distance trips.

speed of a trip, and hence total travel time. Thus, the need for, and importance of, integrating the different segments of the journey is clear.

Compared with car trips, the speed of public transport is often a weak element of multimodal transport chains. In the large majority of the cases, car trips are considerably faster than public transport trips, and it is therefore not surprising that the modal share of the car is much higher than that of public transport. There are two exceptions to this, leading to market segments where public transport tends to perform relatively well: in congested areas and for long distance trips where the high speed of trains is a great advantage. The first sub-market is an example where push factors (congestion on the road, parking problems in cities) are an important factor which contributes to the success of public transport. In all cases, it is clear that a key success factor for integrated public transport is that it achieves speeds that are competitive with those offered by car transport.

A related consideration is that reliability of transport services is an important determinant of the quality of multimodal trips: when delays occur in part of a trip, travellers may miss their connection, leading to extra waiting time at transfer points and possibly high scheduling costs (when one is late for an important appointment). Thus variations in speed in a certain part of a trip chain may lead to substantial extra waiting or travel time in the rest of the trip.

The potential success of integrated transport therefore depends considerably on the degree of its reliability. To make integrated public transport successful, it is therefore important that transport organizations can cope with these uncertainties in an adequate way, i.e. such that the effects for the travellers are minimized. Elements of such policies are that timetables are made in such a way that there is some slack at transfer points. This may make the average speed slightly slower, but it would reduce the negative impact of disturbances (Rietveld et al. 2001). Another element would be a high level of integration between services at the operational level: for example, the bus driver waits a few minutes when it is known that the train will be some minutes late.

This underlines the importance of various ‘soft’ dimensions to achieve integrated public transport of high quality. One is the dimension of human resource management: drivers should be motivated to serve passengers properly. Timetables should be obeyed where possible, but, in case of disturbances, flexibility is needed. Another important aspect of integrated public transport is the institutional dimension: when one integrated company is responsible for the overall quality of a multimodal chain, this creates favourable conditions for high quality, reliability, and flexibility. On the other hand, when there is one integrated (bus-rail) company, the potential benefits of competition may be lost. This leads to challenging questions concerning how to combine the better elements of both worlds.

In the present chapter we carry out an analysis of speed fluctuations as a determinant of the quality of public transport. We do this by focusing on a special cause of unreliability:

variations in weather conditions. We find that this is a relatively under-explored theme of research. We will focus on commuting trips. This is an important part of the trips made by public transport. The advantage of focusing on commuting is that weather variations will most probably not affect the decision of travellers to stay at home, which might lead to selectivity effects. This makes it easier to analyse commuting trips compared with, for example, recreational trips. It should be noted that by 'travel time of a trip' we mean travel time of a complete door to door trip, i.e. it not only includes the in-vehicle time but also includes time spent on access and/or egress modes, waiting times, and delays.

During the past decades comparatively little attention has been paid to the effects of weather on transportation in general, and on public transport in particular. An overview of the empirical literature on weather and transport can be found in Koetse and Rietveld (2009). Most of the available empirical studies on weather and transport report a reduction in speed during adverse weather conditions (see, e.g., Martin et al. 2000; Hranac et al. 2006; Maze and Agarwal 2006). The major reduction in speed of road transport is due to precipitation and snow. Martin et al. (2000) report a 10 per cent speed reduction in wet conditions, and a 25 per cent reduction in slushy and wet conditions. These results are confirmed by Hranac et al. (2006) using detailed traffic and weather data from 2002 to 2004 for the Baltimore, Seattle and Minneapolis-St. Paul metropolitan areas. They find that light rain reduces the free flow speed by 3 per cent, and the speed at full capacity by 9 per cent. Reduction in speed increases with rain intensity, with maximum reductions of around 6-9 per cent for free-flow speed and 8-14 per cent for speed at capacity (see also Ibrahim and Hall 1994; Hall and Barrow 1988; Maze and Agarwal (2006). Finally, Sabir et al. (2010a) report negative but small effects of adverse weather on the speed of car commuter trips. However, the effect of snow is substantial, with speed reductions of around 7 per cent. Furthermore, although the effects of rain on speed are small in general, rain causes a speed reduction of 10-15 per cent for trips made during rush hours on congested routes.

Interestingly, these studies mainly focus on road transport (but, for an exception, see Hranac et al. 2006). Public transport is largely ignored. Whereas trip speed reductions for car transport are mainly caused by congestion, public transport delays are also and perhaps mainly caused by technical failures. Therefore, the current study contributes to the limited available empirical evidence by providing a closer insight into the effects of weather conditions on the speed of public transport commuting trips and the welfare affects associated with the changes in travel time.

The rest of the chapter is organized as follows. Section 6.2 discusses the data as well as the descriptive statistics of the variables. Section 6.3 explains the econometric methodology used to analyse the effects of weather and individual characteristics on the speed of commuting trips made by public transport. Section 6.3 also discusses the explanatory variables included in the model. Section 6.4 provides the empirical results and discusses the welfare effects of weather conditions for the Netherlands. Section 6.5 then assess the welfare effects of weather through changes in travel time. Section 6.6 concludes.

6.2 Data

We use transportation survey (MON) and hourly weather data of KNMI for the years 2004 and 2005. The details about the data are provided in Section 2.3, Chapter 2. The MON data sets contain information about 130,000 persons who reported the trips they made on one particular day during these two years, leading to about 450,000 reported trips during 2004 and 2005.[36] The weather conditions in this chapter refer to temperature, wind speed, visibility, rain, and snow. By combining these two data sources, we are able to analyse for each trip the local weather conditions of the hour in which the trip took place.

We select only commuting trips for a number of economic and statistical reasons. First, this is because the demand for commuting is derived from the demand for workers, which does not directly depend on weather, whereas the derived demand for other trips (in particular, leisure trips) is affected by weather conditions. Hence, for commuting trips, the interpretation of the welfare effect of weather is more straightforward. Second, commuters are a relatively homogeneous group of travellers, for whom assumptions on the value of time are likely to be more accurate. Third, we select public transport trips because for other trips, in particular bicycle trips, the welfare of commuting is directly affected by weather, e.g. it is unpleasant to take the bicycle on a rainy day because one gets wet, and not so much because of reductions in speed. Fourth, the selection of a sample may generate biased estimates of the coefficients of variables (Wooldridge 2003). Fifth, adverse weather may increase the risk of travel speed for car use on account of accidents, but this is less likely for public transport users. Finally, as commuters generally take at least two trips per day, panel estimation techniques can be employed to deal with this issue.

Given these selections, our sample contains 13,618 public transport trips made by 2,225 commuters. The average trip distance is 32.9 km, the average trip speed is 31.7 km/hour, and the average travel time per trip is 57.5 minutes. The descriptive statistics for BTM, and train are given, along with other explanatory variables in Appendix 6A.

It is important to realize that the speed as we measure it is based on the travel time of the *whole* trip rather than only in-vehicle travel time. This implies that this travel time also includes the time to reach the access point, waiting time, in-vehicle time, and the time to get to the final destination after the arrival. The average in-vehicle travel time for public transport is 24.6 minutes. The average in-vehicle travel time for BTM is 21.6 minutes, whereas, the average in-vehicle travel time for train is 30 minutes. It appears that the share of in-vehicle

[36] The exact number of individuals in the sample is 130,534. These people reported 453,885 trips, of which 13,618 were made by public transport .

time in the total trip time of BTM trips and train trips is about 50 per cent and 45 per cent, respectively. This implies that public transport travellers spend a significant part of their total travel time on access/aggress modes or in waiting time. Additionally, this also explains why the average speed of public transport trips is low.

6.3 Model specification and estimation procedure

Similar to Sabir et al. (2010a), the interpretation of our empirical analysis is based on standard microeconomic theory, such as, that used in Van Ommeren and Dargay (2006), who derived a structural model for commuting speed, and then used that model for Great Britain, as well as in Fosgerau (2005), who applied it to Denmark.[37]

Van Ommeren and Dargay (2006) assume that commuters optimally choose their speed given a specified cost function (the only restriction is that the cost function is a power function of speed) and the travel time costs are proportional to the wage. Furthermore, they show that the marginal effect of an exogenous environmental characteristic, such as weather, on the logarithm of speed can be interpreted as the marginal effect of this characteristic on the logarithm of the commuter's total commuting costs (the sum of the travel time and other costs, which vary with speed, e.g. accident costs and fuel costs). Given an estimate of an average worker's value of time (VOT), it is meaningful to estimate the effect on the welfare of commuters through loss in travel time only. We will use a log specification in line with the theoretical considerations discussed in Van Ommeren and Dargay (2006). It takes the form:

$$\ln S_{itd} = \beta_0 + \beta_1 W_{itd} + \beta_2 \ln D_{itd} + \beta_3 \ln y_i + \beta_4 X_i + \beta_5 F_{td} + \xi_{itd}, \qquad (6.1)$$

where the *β's* are parameters to be estimated; subscripts *i* represent individuals; *t* represents hour of departure; and *d* represents day of the year. *S* is speed; *W* is a vector of individual-specific time-varying variables (including weather variables); *D* denotes the distance travelled; *y* is the income of individuals; *X* is a vector of individual variables (including gender and age); *F* refers to time-specific characteristics such as urbanization, hour of travel, and seasonal variations; and ξ denotes an unobserved error term.

Using OLS for analysing the impact of weather on the speed of commuting trips is not ideal since it assumes that the residuals are uncorrelated. We face two drawbacks if we employ OLS estimation for equation (6.1). First, OLS does not control for differences in unobserved preferences of individuals and differences in other unobserved features (such as

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[37] We improve on the statistical analyses of Fosgerau (2005) and Van Ommeren and Dargay (2006) by explicitly taking the time dimension of the moment of travel (in time of days, hours) into account, as well as unobserved heterogeneity of commuters.

the exact location of the individual). We therefore exploit the panel structure inherent in the data to control for these issues. Specifically, we include individual fixed-effects in order to control for selection and unobserved heterogeneity.[38] Second, using OLS for analysing the impact of weather on the speed of commuting trips is not ideal since it assumes that the residuals are uncorrelated. This implies that, if a person makes two trips on the same day, the residuals from the model of both trips are assumed to be uncorrelated. This obviously does not hold in the current case.[39] As a result, OLS is inefficient (Wooldridge 2003). Therefore, a random-effects panel data model that controls for the correlation between errors is employed.

Most of the variables included in model are self-explanatory. However, some other variables need additional explanation. We include personal characteristics because they may affect the optimally chosen travelling speed to and/from the access point. Furthermore, in this way we control for selection effects. The travel time of a trip may be different during peak and off-peak hours because of the difference in the frequency of the service, difference in the number of people using the public transport, etc. Therefore, a dummy variable is included for rush hours.[40] In order to control for congestion effects on roads for bus and tram trips, we distinguish between trips on congested roads and those on non-congested roads. Specifically, we distinguish those trips that originate in non-congested areas during the morning peak hours, and that are directed towards congested areas. Similarly, we distinguish those trips during evening peak hours that are directed from congested areas to non-congested areas (see Sabir et al. 2010a). Ultimately, we include a congestion dummy variable that controls for these specific trips.

In order to analyse the effects of weather on travel time, we use hourly measured wind strength, temperature, precipitation, snow and visibility. Dummy variables are used to measure the effects of most weather variables. Wind strength is measured by a dummy variable that represents wind strengths larger than 6 Bft. We define three temperature categories, i.e. a dummy for temperatures less than 0 ^{o}C, a dummy for temperatures between 0^{o} C and 25^{o} C, and a dummy for temperatures higher than 25^{o} C. Precipitation effects are captured by using a dummy variable that is equal to 1 for the presence of precipitation during the hour in which the trip took place. The visibility variable measures the horizontal visible distance; and a dummy is used to indicate a visibility distance less than 300 metres. We do not have an exact measure of snow. However, we use the interaction effects of temperature lower than or equal to 0^{o} C and the presence of rain as a proxy for measuring snow. But, it

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[38] Note that some commuters have two different distances on the same day, which allows us to identify the effect of distance using individual-fixed effects.

[39] The correlation between the two errors is higher than 0.80 for all public transport modes.

[40] Morning peak hours are from 06:00 to 10:00, evening peak hours from 16:00 to 18:00, and all other hours are off-peak hours.

may be noted that this is a crude measure of snow, and it will only capture the effects of *falling* snow.

6.4 Results and discussion

6.4.1 Speed of bus, tram and metro trips

The estimation results are presented in Table 6.1. The results are robust and most of the variables have plausible signs. Observe that, although temperature does not have a strong impact, snow, limited visibility and rain on congested routes all substantially reduce the speed of BTM trips. Remember that trip speeds are computed on the basis of the sum of in-vehicle time and other time components, including access and egress times, waiting times and delays. Apparently, these three specific circumstances (snow, limited visibility and rain) cause an increase in travel time by affecting one or more of these components.

The fixed-effects model shows that the speed of BTM trips is reduced by 12 per cent in snow. A potential reason, at least for bus trips, and maybe partly for tram trips, is that it is more risky to drive in snow, and that the capacity of roads is reduced because of the increased distance that is necessary to preserve between vehicles. Another reason may be that snow causes people to switch from cycling and walking to public transport, thereby increasing the demand for public transport. This may mean that more and longer stopping and waiting times are required for passengers to enter and leave the vehicles. Although rain in general has no effect on trip speeds, it does have a substantial impact on trip speeds on already congested routes (meaning that the results are mainly driven by the effect of rain on the speed of bus trips). Specifically, rain reduces trip speed on congested routes by approximately 18 per cent.

This result is consistent with the result obtained in Sabir et al. (2010a), who reported a 10-15 per cent reduction in the speed of car commuting trips under the same circumstances. There also is a 6 per cent reduction in trip speeds when visibility is under 300 metres (this effect is also likely to be driven by the effects of visibility on the speed of bus trips). This finding is plausible, as one would expect people and vehicle operators to change their behaviour under risky conditions such as limited visibility. The effects of other weather variables are small and, except for strong wind, statistically insignificant. The effect of distance on the speed of BTM is around 60 per cent, i.e. on average, trip speed increases by 60 per cent when distance increases by 1 kilometre. This makes sense because longer trips are likely to make more use of roads with higher speed limits than shorter trips. The congestion variable shows a reduction of 8 per cent in trip speed, which is comparable to the results of Sabir et al. (2010a), who reported an 8 per cent reduction in the speed of car commuting trips on congested routes. The effects of other characteristics on the speed of BTM commuting trips are generally small and most are statistically insignificant. An exception is commuting trips made in highly urbanized areas, which are on average, 11 per cent slower compared with trips made in rural areas. This makes sense, since in these areas public transport is confronted with a larger number of crossings and traffic lights. Also the speed of the access mode (walking or cycling) to the public transport stop will be lower in highly urbanized areas.

Table 6.1: Analysis of the logarithm of speed of public transport commuting trips (individual-specific effects) [1,2]

	Bus, Tram and Metro				Train			
	Fixed Effects		Random Effects		Fixed Effects		Random Effects	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Strong Wind (6 bft)	**–.005**	.002	**–.004**	.001	.001	.001	.0003	.001
Temperature <= 0° C	.02	.02	.01	.02	**.04**	.01	**.04**	.01
Temperature >25° C	–.01	.02	–.01	.02	**–.04**	.01	**–.03**	.01
Rain	.01	.01	.01	.01	.003	.00	.005	.005
Snow	**–.12**	.04	**–.08**	.04	**–.06**	.02	**–.05**	.02
Limited visibility	**–.06**	.02	**–.06**	.02	.03	.02	.03	.02
Congestion x Rain	**–.18**	.05	**–.17**	.05	-	-	-	-
Congestion	*–.08*	.04	–.01	.01	-	-	-	-
Rush Hours	–.01	.01	*–.06*	.03	**.02**	.01	**.01**	.01
Distance	**.56**	.02	**.57**	.01	**.62**	.02	**.52**	.01
Gender (Males)	-	-	.01	.02	-	-	–.02	.01
Age less than 18 years	-	-	.04	.07	-	-	–.02	.09
Age between 30 and 40 years	-	-	.02	.03	-	-	**.05**	.02
Age between 40 and 65 years	-	-	–.01	.02	-	-	.02	.02
Age greater than 65 years	-	-	–.14	.12	-	-	*–.19*	.12
Weekdays	-	-	–.05	.04	-	-	–.01	.04
Very Urbanized	-	-	**–.11**	.04	-	-	**–.08**	.03
Urbanized	-	-	–.05	.04	-	-	–.04	.03
Moderately Urbanized	-	-	–.05	.04	-	-	.0004	.03
Little Urbanized	-	-	.02	.04	-	-	–.04	.04
Summer	-	-	.002	.02	-	-	.003	.01
Autumn	-	-	–.03	.02	-	-	.01	.01
Winter	-	-	**.05**	.02	-	-	–.01	.01
Constant	-	-	**1.66**	.06	-	-	**1.73**	.06
R^2	.95		-		.94			
Number of groups	1124		1124		1441		1441	
Variance of random error	-		.02		-		.01	
Variance of group specific error	-		.09		-		.06	
Correlation between error terms	-		.84		-		.83	

Notes:

(1) Coefficients in bold and italic are statistically significant at the 5%, and 10% level of significance, respectively.

(2) The reference categories for temperature, urbanization, age, and seasonal variables, are, respectively, temperature between 0° C and 25° C , rural, age between 18 and 30 years, and spring.

Our analysis shows that snow, fog, wind, and rain do indeed have an impact on the speed of BTM trips. One reason is that the speed of these vehicles themselves will be affected, implying increases in in-vehicle time. Another part of the explanation is that adverse weather leads to longer waiting times at platforms, in particular when people miss a connection, and leads to longer access and egress times. It should be noted that adverse weather has a doubly negative effect on integrated public transport: not only does it lead to longer and less reliable travel times, but also the comfort at transfer points will be worse. This provides a challenge to operators who aim to offer integrated transport services. Timetables should be made in such a way that they are reasonably robust under conditions of adverse weather, and also the comfort levels at transfer points should be adequate under varying weather conditions.

6.4.2 Speed of train trips

The results of the fixed-effects model on the speed of train commuting trips show that, at temperatures below 0^{o} C, train trips are 4 per cent faster than train trips made at temperatures between 0 ^{o}C and 25^{o} C. Similarly, train commuting trips made during temperatures higher than 25^{o} C are 4 per cent slower compared with trips made in normal temperatures. Remember that trip speeds are computed on the basis of the sum of in-vehicle time and other time components, including waiting times, delays, access and egress times to get to the station by foot, bicycle, bus, car, etc. A likely explanation is therefore that people may prefer to walk or cycle rather than use public transport to go to or from a train station. Another reason may be that demand for train trips is lower in cold weather, which may result in a smaller number of people at access points, implying lower probabilities of delays. Similarly, if demand for train trips is higher in warm weather, we would observe an increased probability of delays. The results furthermore show that also train trips are slower during snow; the speed reduction is around 5 per cent. Comparing the effects of snow on the speed of BTM trips, on the one hand, and train trips on the other, shows that train trips are less affected by snow. This is not surprising, given the technology of the train compared with the bus. Both types of trips share the possible delay during the access and egress mode, but the bus (and to some extent trams) travel on road networks with other vehicles, whereas the train has a separate network. Trains will therefore suffer less congestions and one may expect a smaller effect of snow on the speed of train trips compared with the effect for other modes.

Again the effects of other characteristics are small and generally insignificant for train commuters. However, the age variable shows some interesting results. The results suggest that trips made by people in the oldest age category are 19 per cent slower compared with trips made by younger people. This probability reflects that older people take more time to reach access points, and spend more time transferring between trains. It is also possible that older people have less access to cars, so they have to use public transport even when they live at a distance further away from an access point. Another interesting finding is the speed reduction in very urbanized areas compared with rural areas. This probably reflects a difference in access modes: residents of highly urbanized areas typically will not use the car to get to the railway station, and other access modes are typically slower than the car.

We find that, compared with BTM trips, the impact of weather on rail trips is considerably smaller. The main effect we observe relates to snow, and this most probably is a consequence of the impact of snow on the access and egress modes used, not on the railway trip itself. This robustness makes rail an attractive transport mode compared with BTM, and also compared with the car. This does not mean that reliability is not an issue in rail trips, because it certainly is. It does mean that that weather is not an important factor here and that the negative effects of certain weather conditions on rail trips is confined to the comfort level at railway stations. Thus, from the perspective of adverse weather, the main challenge to railway operators who aim to provide quality public transport services is to build railway stations that are comfortable under various weather conditions.

6.5 Welfare effects through changes in travel time

An important purpose of the current study is to assess the welfare effects of weather through changes in the travel time of public transport.[41] For this we use information on the average value of travel time (VOT). There is a vast empirical literature on the VOT (see, e.g. Small and Verhoef 2007). Based on a meta-analysis of 56 VOT estimates from 14 different countries, Waters (1996) finds an average ratio of VOT equal to 48 per cent of the gross wage rate and a median ratio of 42 per cent for commuting trips made by car. In another review, Wardman (1998) finds similar values. In this chapter we follow the standard literature on VOTs, and use 50 per cent of hourly gross wages as our measure. In the Netherlands the average gross hourly wage rate is about € 18, implying a VOT of € 9 per hour (Statistics Netherland).[42] The welfare effects are based on the estimates from the fixed effects models, and are obtained by taking the product of the percentage effects, the average travel time, and the value of time. The results are presented in Table 6.2.

The highest welfare loss due to adverse weather is observed for BTM trips. The welfare loss for these trips due to snow is € 0.76 per commuting trip per person.[43] Similarly, BTM

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[41] The calculation for welfare effects are computed on a per person basis, implying that the total welfare loss for a trip by train or bus should be multiplied by the average load factors. This holds for all welfare calculations in this study.

[42] The gross hourly wage is € 19 (for the whole population). It may be noted that the gross wage can be lower for bus commuters and a higher for train commuters. Therefore, the results will be slightly biased.

[43] There is a 12 per cent reduction in speed of BTM when it snows. This implies an increase of 0.0852 hours in average travel time (0.12 x 0.71 = 0.0852). Given a VOT of € 9 per hour, the welfare loss due to snow is 0.0852 x 9 € = € 0.76.

commuting trips made in rainy conditions and on congested routes experience a welfare loss of € 1.78 per commuting trip per person. Furthermore, the welfare loss due to limited visibility is around € 0.38 per commuting trip per person. The highest welfare loss for train trips is that of snow, which leads to a loss of € 0.50 per commuting trip per person. Additionally, train trips made during high temperatures experience a loss of € 0.40 per commuting trip per person.

However, there is a gain of € 0.40 per commuting trip per person when trips are made during temperatures below 0 °C. Note that these calculations only address the travel time element, and disregard the comfort element of adverse weather. No doubt the comfort levels of waiting at platforms and walking to access points will be lower under such circumstances. It is beyond the scope of the present study to provide estimates for this aspect.

Table 6.2: Welfare effects of weather through changes in travel time

	Welfare loss/gain (in €)	
Variables	**Bus, Tram and Metro**	**Train**
Wind strength (Bft)	–0.03	0
Temperature <= 0 °C	0	0.40
Temperature > 25 °C	0	–0.40
Rain	0	0
Rain x Congestion	–1.78	-
Snow	–0.76	–0.50
Visibility	–0.38	0

6.6 Conclusions

In this chapter we have analysed the effects of weather on the speed of commuting trips made by public transport in the Netherlands. We used micro-data at the trip level obtained from a national transportation survey for the Netherlands. The data cover trips made by BTM and train during 2004 and 2005. Hourly measured weather data for this period are obtained from the Royal Netherlands Meteorological Institute. The weather and transport data are matched in such a way that each trip was assigned the weather data for the hour in which that trip took place and from the weather station that was nearest to the place of departure.

We estimated panel data models with individual-specific fixed and random effects in order to control for possible selection problems and unobserved heterogeneity. We used a large number of variables in our model to explain the speed of public transportation. Our main interest, however, is in the effect of weather variables on the speed of public transport and the associated welfare effects.

In general, the results are robust and most of the coefficients have plausible signs. The results show that wind strength has only a small negative effect on the speed of bus, BTM commuting trips. Snow has a substantial negative effect on the speed of public transport. The associated welfare loss is 53 eurocents per commuting trip per person made by train, and 76 eurocents per commuting trip per person made by BTM. Rain strongly affects the speed of BTM commuting trips on congested routes. The associated welfare loss is € 1.15 per commuting trip per person.

The effects of other characteristics are generally absent. However, one interesting finding is that train trips made by older people are 19 per cent slower than those made by younger people. This may indicate that older people have fewer options to take the car on their way to the train station. They may also walk more slowly to their final destination on the egress part of their trips. It may, of course, be that they are just less in a hurry, but one should not forget that in our analysis we focus on commuting trips.

In terms of integrated transport we find that the effects of weather on trip speed are relatively strong in the case of BTM trips. These effects may well lead to changes in in-vehicle time, but most probably also in waiting times at transfer points. This implies a challenge to public transport operators to develop timetables and operating routines that lead to reasonably robust outcomes for travellers. In the case of railway trips, the impact of weather on speeds is clearly smaller. For both types of trips a general observation is that the comfort of trips under adverse weather probably depends substantially on the quality of the facilities at transfer points such as bus stops and railway stations. This is one of the fields where efforts to improve the quality of integrated transport should focus.

Appendix 6A

Table 6A1: Descriptive statistics of variables included in the empirical analyses

	Bus/Tram/Metro		**Train**	
	Mean	**S.D**	**Mean**	**S.D**
Speed (km/hr)	21.19	11.29	38.17	14.93
Travel Time (h)	0.71	0.34	1.11	0.48
Travel Time Congested Areas (h)	1.10	0.34	-	-
Distance (km)[1]	15.63	13.15	43.34	29.10
Strong Wind (Bft)	0.02	0.16	0.02	0.16
Temperature <= 0° C	0.05	0.22	0.05	0.23
Temperature >0 to <=25	0.93	0.26	0.93	0.25
Temperature >25	0.02	0.15	0.02	0.12
Rain	0.19	0.40	0.19	0.39
Snow	0.01	0.10	0.01	0.09
Visibility	0.02	0.14	0.01	0.11
Morning Peak Hours	0.45	0.50	0.47	0.50
Evening Peak Hours	0.37	0.48	0.40	0.49
Non Peak Hours	0.18	0.39	0.13	0.34
Weekday dummy	0.94	0.24	0.98	0.16
Spring	0.25	0.43	0.22	0.41
Summer	0.21	0.41	0.23	0.42
Autumn	0.32	0.46	0.34	0.47
Winter	0.22	0.42	0.21	0.41
Very Urban	0.37	0.48	0.23	0.42
Urbanized	0.30	0.46	0.41	0.49
Moderately Urbanized	0.11	0.32	0.21	0.41
Little Urbanized	0.13	0.34	0.09	0.29
Rural	0.09	0.28	0.05	0.22
Age less than 18 years	0.02	0.15	0.00	0.07
Age between 18 to 30 years	0.31	0.46	0.25	0.43
Age between 30 and 40 years	0.19	0.39	0.27	0.44
Age between 40 and 65 years	0.47	0.50	0.47	0.50
Age greater than 65 years	0.01	0.07	0.00	0.05
Male	0.42	0.49	0.59	0.49
Congestion	0.05	0.21	-	-
Congestion x Rain	0.01	0.08	-	-
Number of Observations	5126		8492	

Notes:

(1) This is the average distance of the entire trip. This implies that it includes not only in-vehicle distance but also distance travelled by access/aggress modes. The average in-vehicle distance for BTM trips and train trips is 13.1 km and 36.7 km, respectively.

PART III

WEATHER AND ROAD SAFETY

Chapter 7

Weather and Hourly Road Accidents

7.1 Introduction

Safety is one of the considerations that people take into account when they choose between travel alternatives. The safety of trips depends on behavioural, technological and environmental factors (Edwards 1996). Weather is one of the factors that determine the frequency and severity of road accidents. Weather may affect the number of road accidents and the severity of road accidents in three ways. First, it may affect the number of kilometers travelled. Second, it may affect travel mode conditonal on kilometers driven. For instance, switching from car to bicycle during warmer weather may increase the risk of an accident, given that bicyclists face higher risk per kilometer driven compared with a car user. Third, it may affect the severity of the accident outcome conditonal on an accident. In some cases these effects will partly compensate each other. For example, with snow the accident rate will most probably increase, even though speed adjustments will have a dampening effect on the severity. As a consequence of these mechanisms it is not all obvious what will be the effect of various weather conditions on the total number of accidents.

For certain purposes it is important that the overall effect of weather on accidents can be decomposed. For example, for effective interventions to improve road safety it is important to know to what extent high accident frequencies are due to high accident rates per km, or due to changes in traffic volumes. But for other purposes, there is not much need to decompose the two mechanisms. For example, the hospital administration will just be interested in knowing, whether they should expect more (or less) patients under certain weather conditions. Similarly, for insurance companies, it is sufficient to know that they may expect less material damage claims if certain kinds of weather reduce the number of accidents with material damage. In the present chapter we will address the overall influence of weather on road accidents, although in our interpretations we will, from time to time, pay attention to the possible underlying behavioural mechanisms, in particular the changes in traffic flows, as already discussed in Chapters 3 and 4.

There is a vast literature on the role of weather in road accidents which measures the effects of weather on road accidents. This literature can be classified in several ways: for instance, by statistical methodology, by level of aggregation, time period, geographic location, explanatory variables, and on the basis of the type of weather measurements (e.g. hourly, daily or monthly) etc. A relevant question is which weather conditions are important for analysing road accidents. Is it the weather at the moment when an accident happens? Or are daily averages of the weather variables more relevant? Another important issue concerns the aggregation level of weather and road accidents. Monthly aggregation studies may cover seasonal influences, but may be rather imprecise on the effect of specific weather conditions, and may not be valid for countries which have considerable weather variations within a month. Aggregating on a daily level may not take into account factors which vary per hour: for example, the hourly variation of traffic flow or hourly travel demand, which may influence the relationship between weather and road accidents. Hourly-level aggregation may incorporate all hourly variations but will, of course, have fewer observations during each interval. There are not many studies which investigate the relationship of weather and road accidents on an hourly basis with the exception of studies like Hermans et al. (2006) and Brijs et al. (2008). The main reason is availability of appropriate data.

The current study investigates the influence of weather on hourly road accidents on all Dutch road networks during 2000 until 2009. We focus on the overall influence of weather on road accidents, and also distinguish among between types of accidents, while controlling for hour-and region-specific effects.

The rest of the chapter is organized as follows: Section 7.2 provides the findings of previous studies on weather and road accidents. Section 7.3 presents the derivation of the econometric model used in the Chapter. Section 7.4 discusses the data and its sources, and also presents the overview of the weather and non-weather variables used. Section 7.5 contains the estimation results and discussion of major findings. Section 7.6 investigates the percentage share of road accident in varying weather conditions given that an accident happens. Section 7.7 concludes.

7.2 Literature survey

SWOV (2009) provides an overview of the literature of weather on road accidents. It concludes that weather has a rather strong influence on road safety. In particular, there is a higher risk of road crashes during rainfall, fog, snow, and stronger wind. It may be noted that there are large country differences with regard to transport infrastructure, weather and climate conditions. Therefore, studies from different countries are not necessarily comparable. For instance, many researchers find that the total number of road accidents increases with precipitation (Satterthwaite 1976; Brodsky and Hakkert 1988; Edwards 1996; Andrey et al. 2003; Andrey and Yagar 1993; Keay and Simmonds 2006; Bijleveld and Churchill 2009). Total number of road accidents also increases with snow (Edwards 1996; Nofal and Saeed 1997; Brijs et al. (2008). On the other hand, a few studies report a decrease in total accidents in the presence of precipitation and snow (see, e.g., Fridstrøm et al. 1995; Eisenberg 2004). Road accidents also increase with temperature. For instance, Nofal and Saeed (1997), and also Stern and Zehavi (1990), report increased total road accidents during warmer weather (see, also Wyon et al. 1996).[44] However, some studies report different results. For example, Brijs et al. (2008) do not find a straightforward relationship of temperature and accidents. They reported more accidents at lower temperatures compared with temperatures greater than 20^o C. However, when the daily mean temperature exceeds the monthly mean temperature, there are more crashes. Hermans et al. (2006) also report a negative influence of temperature on accidents. Wind is another component of weather which may cause road accidents. Young and Liesman 2007, and also Baker and Reynolds (1992) reported an increase in road accidents with wind. However, other studies report weak effects of wind. For example, Hermans et al. (2006) find positive and rather weak influence of wind on hourly road accidents in the Netherlands. Given the variation in empirical findings presented above, it is difficult to generalize the findings of these studies.

Studies on weather and accidents adopt different methodologies to accommodate exposure (Chapman 1973) and other confounding factors. Many studies use a matched sample approach to control for exposure (e.g. Andrey and Yagar 1993). The main idea is that the event and control period are spaced just one week apart, and they match in terms of clock time and weekday. In other words, control period and post-control periods are defined. A control period is the time that coincides with the clock time of the accident occurrence exactly one week prior to, or following the event, to control for all kinds of time-dependent variation. This is a good method to cope with overall variations in traffic volumes from hour to hour, but it cannot correct for the weather-specific effect on traffic flows.[45] Other studies use difference in means or wet payment index methods (e.g. Brodsky and Hakkert 1988). Furthermore, some studies use vehicle-miles travelled or traffic volume (e.g. Eisenberg 2004; Keay and Simmonds 2006) as a control variable. This

[44] Wyon et al. (1996) did an experimental study to analyse the effects of moderate heat stress on Swedish driver's vigilance in a moving vehicle. They found that heat stress has a negative effect on the vigilance of the drivers.

[45] Note that this matched sample approach comes close to the use of time-specific dummies in our estimation approach of Section 7.5.

would indeed be a good way to isolate the separate effect of weather on accident rates per km, and on total traffic volumes. Some studies use innovative methodologies or a superior data set. For example, Brijs et al. (2008) use a Poisson Integer Autoregressive Model (INAR) to investigate the relationship of weather and road accidents on three Dutch cities (Utrecht, Dordrecht and Haarlemmermeer). Hermans et al. (2006) use *hourly* weather and road accident data of a primary Dutch road system.

Another issue related to road accidents is the nature of road accidents. Most studies are based on data from countries where motorized transport is the major contributor in road accidents with the exception of Brijs et al. (2008) and Hermans et al. (2006). These studies are based on Dutch data, where non-motorized modes, namely, bicycle trips (about 25 per cent) have a significant shares in modal split.

In research on the impact of weather on traffic safety an important issue is the incorporaton of weather conditons. Some studies use weather conditons as reported by the police (e.g. Edwards 1996). Police reported data may be easily available for analysis, these data have a risk of personal errors and may not have exact weather conditions .Some studies use weather data from other sources, mostly from meteorological reports (e.g. Eisenberg 2004; Hermans et al. 2006). Meteorological data are normally difficult (or expensive) to obtain. Another important issue about measurements of weather conditions is the number of weather factors. Some studies focus on just one weather factor (mostly precipitation), while other studies focus on more than one. Precipitation is the most significant and most studied weather factor, followed by snow, temperature, fog, wind, etc. However, with advancement in the measurement of weather conditions and easy availability of the data, studies may use more detailed information. For example, Hermans et al. (2006) use factors like duration of sunshine, cloudiness, global radiation, relative humidity, etc., along with precipitation and temperature.

We focus on the effects of weather on hourly road accidents on all Dutch roads between 2000 and 2009. Our research will contribute to the existing literature, as we will be using a large number of weather variables (as will be explained in Section 7.4), while controlling for exposure via a time and region-specific fixed effects methodology. Additionally, we distinguish between different types of accidents (material damage only versus accidents with injuries), while using a rather large data set. We use hourly weather measured conditions (an improvement over, for example, Bijleveld and Churchill 2009). This analysis focuses on the Netherlands where the share of bicycles and pedestrians in the total number of victims is greater compared with most other studies. In short, our analysis adds several elements to the research done on this specific issue in past.

7.3 Econometric model

Road accidents are assumed to occur randomly per hour. The number of injury accidents is limited and includes many zeros, so it is useful to use a count model. Therefore, we employ the Poisson model as explained in Section 3.3.1, Chapter 3. However, it may be noted that, in current case, the main assumption of mean and variance equality of the Poisson model does not hold for material damage and total accidents . For these types of accidents the mean is much greater than the variance (see Table 7.2). To address this issue, the negative binomial models are employed, as explained by Equation 3.1 in Section 3.3.1 in Chapter 3. In the current case, we have $log\,\partial E(y_i \mid X_i)/\partial X_i = \beta_i$, so β can be interpreted as the marginal effect of X on the *log* of the expected value of the number of hourly accidents. In both models the percentage change in the expected number of accidents for a δ unit change in X_i, holding all other variables constants can be computed as $[exp(\beta_i \text{ x } \delta)\text{-}1]$ x *100*.

7.4 Data

This study uses accidents on Dutch road networks for the years 2000 to 2009: the BRON data set. This data set was obtained from the Transport Research Centre DVS, working under the Dutch Ministry of Transport and Public Works. It contains information about all police-recorded accidents including the parties and victims involved in the accidents, as well as the accident characteristics such as time, date, location and injury outcome. Because it only contains police-recorded accidents, it contains hardly any minor accidents (such as parking accidents). In the data, the annual number of material-damage accidents fell over time, because of a change in the reporting of this type of accidents. However, given the reasonable assumption that under-reporting of material-damage accidents is independent of the weather condition, *this will not affect our findings*.

The outcomes of the accidents are categorized as: fatal, serious injury, minor injury, other injuries, and material damage, respectively. A fatal accident implies that at least one fatality is involved. A serious injury accident implies that one or more persons are treated in hospital. A minor injury is when at least one person receives first aid. There is also a category of “other injuries”. Finally, material-damage accidents are those accidents which involve exclusively material damage.

Table 7.1 shows the aggregate number of accidents from 2000 to 2009. About 17 per cent of (police-recorded) accidents involve personal injuries.

To estimate the impact of the hourly weather conditions on hourly variation in road accidents, we use the *hourly* number of accidents *per region*. The Netherlands maybe divided into 32 weather regions based on the nearest weather stations of the Royal

Netherlands Meteorological Institute (KNMI). Table 7.2 presents the descriptives of hourly road accidents. It is clear from Table 7.2 that the means of the number of all types of accidents that include injuries are almost equal to their variances, consistent with the assumption that the means of road accidents are Poisson-distributed. However, the material-damage (and therefore total accidents) variance is much greater than the mean, which suggests that these accidents are affected by over-dispersion. In total, we have 2,805,504 hourly observations for 10 years (32 regions x 24 hours x 3653 days). The average accident rate per region is 0.585 per hour. The average fatal accident rate is 0.003, whereas, for the three other injuries types this rate is around 0.03.

Table 7.1: Road accidents in the Netherlands (2000-2009)

Accidents	**Numbers**	**% Shares**
Fatal	7,820	0.5
Serious injury	85,680	5.2
Minor injury	91,631	5.6
Other injuries	101,507	6.2
Material damage	1,359,389	82.6
Total	*1,646,027*	

Source: BRON 2000-2009.

Table 7.2: Descriptives of hourly road accidents per region (2000-2009)

Numbers of accidents	**Mean**	**Max**	**S. D**	**Variance**
Fatal	0.003	2	0.053	0.003
Serious injury	0.031	5	0.179	0.032
Minor injury	0.033	5	0.190	0.036
Other injury	0.036	5	0.199	0.040
Material damage	0.483	24	1.011	1.022
Total Accidents	*0.585*	*25*	*1.15583*	*1.336*

Hourly weather data for each region was obtained from KNMI. This includes temperature, wind speed, duration of sunshine, presence of fog, snow and clouds, etc.[46] In the econometric model, we distinguish between five different temperature categories (less than 0^o C, 0^o C to 10^o C, 10^o C to 20^o C, 20^o C to 25^o C and higher than 25^o C). We include wind speed and its squared power. One would expect that the impact of wind is non-linear, as stronger wind has a stronger (marginal) effect than gentle wind. Precipitation is measured by two variables. First, precipitation intensity is captured by millimetres of precipitation (per hour). Second, precipitation duration is included in minutes (per hour). Sunlight duration is also measured in minutes. Clouds in the sky are represented on a scale

[46] If weather stations have missing values, we use weather measurements from the nearest weather station.

from 0 to 9. Value 0 represents a clear sky, while 9 represents a fully-covered sky. Dummy variables are used for the presence of snow, thunderstorm, and fog.

In the econometric model, we further include the hourly-fixed effects (the reference category is the hour between 12:00 to 13:00) and 32 region-fixed effects. Controlling for hourly-specific effects is useful because it aims to control for other factors (other than weather) which may affect accidents but cannot be observed with data used in the current study, e.g. traffic flow and traffic congestion during specific hours of the day. Descriptives of the explanatory variables are provided in Appendix 7A.

7.5 Estimation and findings

The hourly number of road accidents is our dependent variable. We distinguish between the five different types of road accidents. We estimated Poisson and negative binomial models while controlling for different hours of the day and regional-specific dummy variables. The results for the Poisson and negative binomial models are almost identical, so we focus on the better ones. The full results of the Negative Binomial models are presented in Appendix 7B. [47]

In general, the results are plausible and comparable with previous research findings with few exceptions. The percentage changes in different types of road accidents due to varying weather conditions are presented in Table 7.3.[48] The results indicate, for example, that the number of fatal accidents *increases* by 8.4 per cent in temperatures between 0^{o} C to 10^{o} C, and rise even 50 per cent higher when the temperature exceeds 25^{o} C, compared with the number of fatal accidents in freezing temperature. Other injury (non-fatal) accidents also increase with temperature in a similar fashion. However, interestingly, the number of material damage accidents, and the total number of accidents, decreases with temperature. This suggests that the severity of accidents increases strongly with temperature. These findings are consistent with Nofal and Saeed (1997), Stern and Zehavi (1990) and Wyon et al. (1996) and are slightly different from Brijs et al. (2008) and not consistent with Hermans et al. (2006). There may be a few reasons for this postive effect of temperature on the severity of accidents. First, it may be due to an increase in human error,

[47] For fatal accidents it is also possible to estimate a binary logit model because there are only 11 observations for which more than 1 fatal accident happened. However, the results of the Poisson and the binary logit models were identical. We present the results of the *Poisson model for fatal accidents* in Appendix 7C.

[48] The last column in Table 7.3 shows the effects of weather on the overall number of road accidents (sum of fatal, injury crashes accidents and material-damage accidents). Note that, total accidents' includes all types of accidents, but it is dominated by material-damage accidents due to their higher share in total accidents.

given that human response times during warmer weather increase (Wyon et al. 1996). However, nowadays this explanation is not so plausible, given that more and more vehicles have air-conditioning systems. Second, it may also possible that it is due to the use of what is called “zoab asphalt”, which is good for absorbing precipitation water and noise, but it may be less effective in warmer weather.[49] Third, during warmer temperatures older people may participate more in traffic activities and, given that the risk of severity of injury is higher for older people compared with younger people, there is an increase in the severity of accidents.[50] The most likely explanation is that increases in temperature lead to increased demand for other modes of transportation, mostly bicycles.[51] This means that different types of vehicles use the same roads which leads to high potential risks, especially for non-motorized (bicyclists) users (Shefer and Rietveld 1997). Given that an accident involving vehicle-bicycle may be more severe compared with a vehicle-vehicle accident, we would also expect more severe accidents with increasing temperature.[52]

The risk of having more severe accidents also changes with other weather variables. For instance, during snow, the number of fatal and serious injury accidents falls by about 7.6 and 10 per cent, respectively, whereas the number of material-damage and, therefore, total accidents increases, by 17 per cent and 13 per cent, respectively. This implies that during snow the probability of an injury crash will be lower and of a material-damages crash higher. This is a plausible finding, given that drivers reduce their speed during snow because of bad visibility in falling snow or the reduced capacity of roads if it snows for longer periods.[53] Additionally, slow-moving vehicles may cause congestion which increases the chances of small accidents compared with injury or fatal accidents.

An hour of sunlight increases all types of accidents by around 12 per cent. The main reason may be that during a sunny period, the road surface may be more reflective, or the sun reaches an angle which reduces sight, so the risk of accidents may increase. Sunny weather also encourages other traffic activities, such as cycling and walking. This may increase the risk of more severe accidents. This can be seen from the results that the accidents with injuries increase slightly more than the total number of accidents, which suggest that there is a slight increase in severity of accident with increase in sunlight. On the other hand, clouds reduce the risk of accidents, especially fatal accidents (consistent

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[49] Zoab stands for “Zeer open asfaltbeton” referring to the asphalt used for pavements in the Netherlands and Belgium. This asphalt has 20 percent more hollow space compared with normal asphalt.

[50] This hypothesis cannot be explored further due to the aggregate approach used in this chapter.

[51] The probability of selecting bicycle as mode of transportation increases by around 13 per cent, whereas the demand for bicycle trip increases by around 22 per cent if the temperature exceeds 25^{o} C, compared with temperatures lower than 0^{o} C (see Chapters 3 and 4).

[52] We cannot test this hypothesis because we are using aggregate data.

[53] Snow reduces the speed of car and public transport (see, e.g., Chapters 5 and 6).

with Hermans et al. 2006). As most of the literature suggested, precipitation has a strong positive influence on all types of road accidents. The total number of road accidents increases by 41 per cent for a full hour of precipitation, but the effects on the number of fatal accidents are relatively smaller (see also Hermans et al. 2006).

Fog increases the number of accidents (but interestingly enough this effect cannot be indentified for fatal ones). Finally, wind has no statistically significant effects for most of the accident types. This is consistent with Brijs et al. (2008). This is also plausible as really strong wind is an exception in the Netherlands, but it is difficult to test.

Table 7.3: Percentage changes in the number of hourly road accidents due to weather conditions[1,2]

Variables	Fatal	Injure Crashes (Accidents)				Material Damage	Total Accidents
		Serious	Minor	Other	Total		
Wind speed (m/s)	1.88	–0.72	–0.24	–0.18	–0.41	0.18	0.11
Wind speed square (m/s)	–0.22	–0.01	0.001	–0.05	–0.02	**0.02**	0.01
Temperature 0^o to 10^o C	**8.36**	**13.40**	**6.89**	**6.56**	**8.80**	**–7.73**	**–5.26**
Temperature 10^o to 20^o C	**16.03**	**23.67**	**14.02**	**16.56**	**17.94**	**–11.46**	**–7.09**
Temperature 20^o to 25^o C	**32.58**	**34.67**	**22.94**	**25.98**	**27.66**	**–18.18**	**–11.43**
Temperature > 25^o C	**49.23**	**33.68**	**30.47**	**27.25**	**30.26**	**–20.23**	**–12.83**
Sunshine (in minutes)	**0.20**	**0.37**	**0.34**	**0.30**	**0.33**	**0.19**	**0.21**
Precipitation duration (in minutes)	**0.25**	**0.55**	**0.68**	**0.68**	**0.64**	**0.71**	**0.69**
Precipitation mm	1.39	**–0.38**	–0.14	–0.14	–0.18	0.35	0.26
Snow	–7.65	**–9.99**	**–13.92**	**–17.20**	**–13.74**	**17.55**	**13.15**
Clouds	**–2.07**	**–1.14**	**–0.88**	**–0.98**	**-0.99**	**–0.20**	**–0.38**
Fog	–4.53	**7.43**	**8.40**	**9.92**	**8.52**	**9.23**	**9.06**
Thunder	6.04	**3.35**	4.24	**12.69**	**6.94**	**6.46**	**6.52**
Weekend	1.54	**–16.38**	**–28.14**	**–31.86**	**–25.82**	**–27.60**	**–26.85**
Autumn	**13.78**	**5.69**	**9.12**	**8.30**	**7.75**	**4.44**	**5.04**
Winter	5.38	**1.28**	**1.42**	–0.42	0.68	**3.06**	**2.77**
Summer	–4.43	–10.42	**–9.90**	–11.38	**–10.54**	**–6.74**	**–7.34**
Hour dummies (23)	included *(see figures 2 and 3)*						
Regional dummies (31)	included						
Year dummies (9)	included						

Notes:

(1) Bold coefficients are statistically significant at the 5 % level.

(2) Reference categories for temperature, snow, fog, thunder, seasonal variables are, respectively, temperature lower than 0^o C, no snow, no fog, no thunder, and spring.

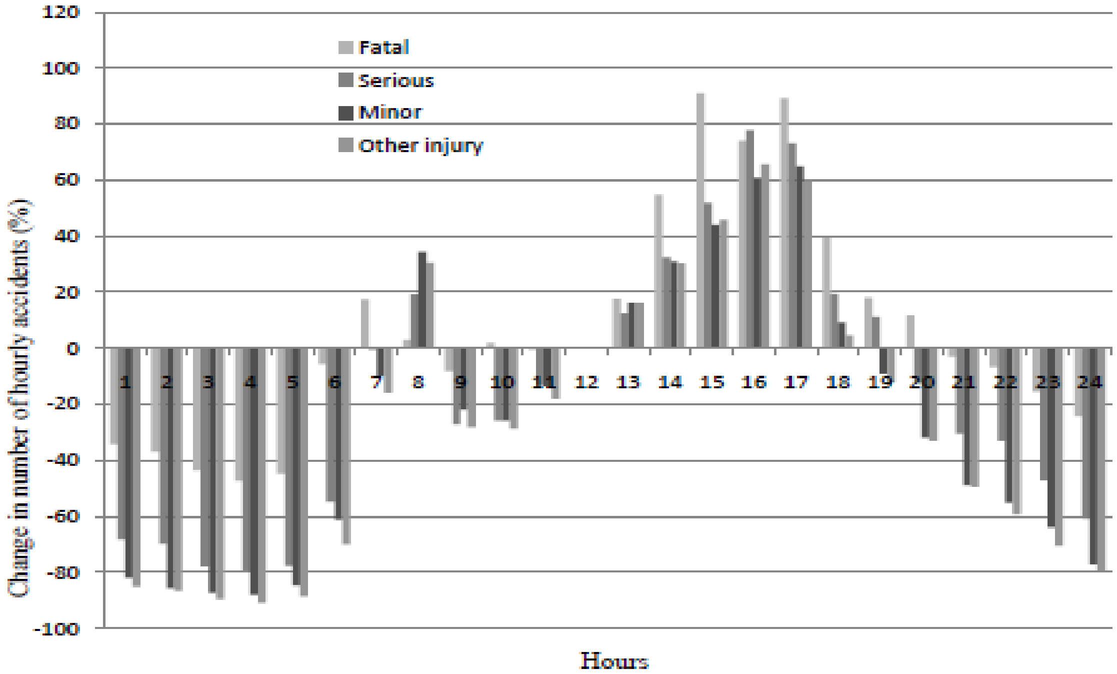

Figure 7.1: Hourly road accident outcomes (fatal, serious, minor and other injury) (reference period: 12.00-13.00)

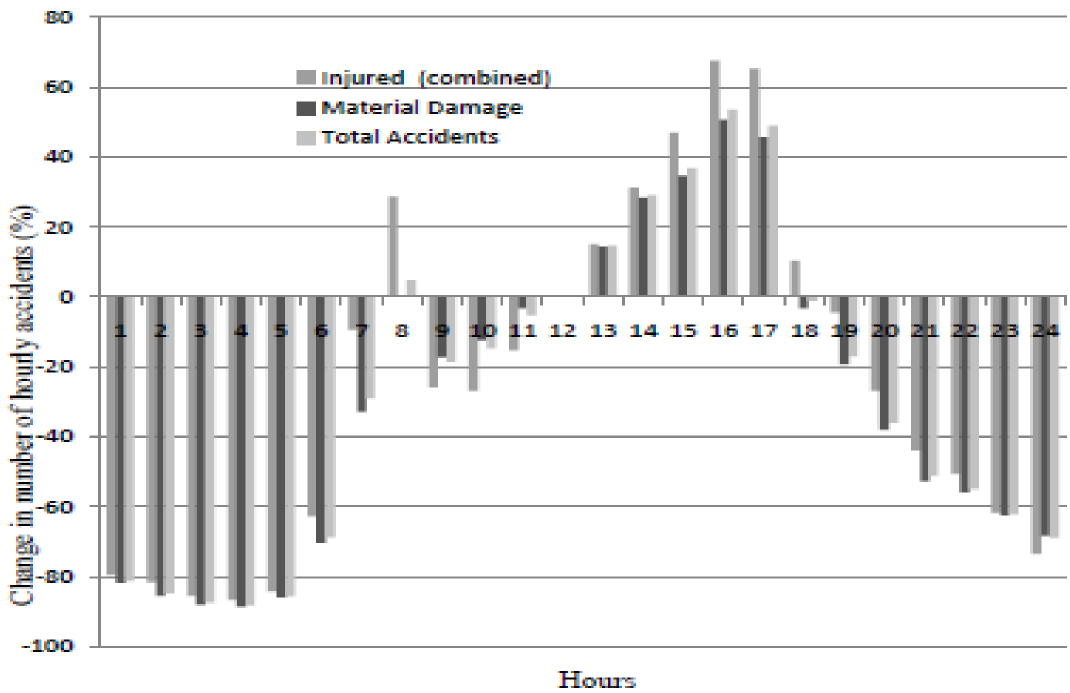

Figure 7.2: Hourly road accidents outcomes (material damage, total injured, and total accidents) (reference period: 12:00-13:00)

The hourly dummy variables show an interesting pattern, as shown in Figures 7.1 and 7.2. As expected, there are fewer accidents during the night until the morning peak hours (between 20:00 until the morning peak hours). This is likely to be mainly due to the presence of less traffic during these hours. However, the number of accidents increases from 12:00 hours, and peaks during the evening peak (around 17:00). For example, around 17:00 the number of fatal accidents is almost 90 per cent higher than around 12:00 (See Figure 7.1). Importantly, the number of accidents during the evening peak is much higher than during the morning peak, which cannot be explained by the difference in higher traffic flow. We can only speculate why we find this important result. One plausible explanation is that there is a higher share of non-motorized traffic (because of shopping and recreational trips), which greatly increases fatality rates. Another reason is that people are more tired in the evening, which may reduce the alertness of drivers, and this may cause more accidents during evening peak hours, but it seems unlikely that this can explain such a large effect. Also alcohol use during the day may play a role.

Sensitivity Analysis

One way to improve the analysis of the impacts of weather on total hourly accidents is to use a dummy variable for every hour of the day for the whole study period (87,672 hourly fixed effects). One advantage of this is that it is then possible to improve control for any kind of hourly regional variations: for example, differences in regional travel demand or traffic flow. However, there are certain limitations in applying this method to all types of accidents. As is clear from Table 7.2, average hourly fatal and serious injuries accidents are 0.003 and 0.031 per region, per hour, respectively. This means that there are many hours which have no fatal or any injury accident in most of the regions. Therefore employing hourly-fixed effects for these accidents will not be appropriate. On the other hand, total hourly and material-damage road accidents are around 0.50 per region. Therefore, we can apply hourly-fixed effects only to these types of accidents only. The results of the hourly-fixed effects for material-damage and total hourly accidents are presented in Appendix 7C. The percentage changes in these accidents under various weather conditions are presented in Table 7.4.

The results in Table 7.4 are comparable with the earlier results in Table 7.3. For instance, the effects of sunlight, precipitation, snow and clouds are comparable with Table 7.3. However, some weather variables are slightly different. For example, the effects of temperature on material-damage accidents are slightly lower for material-damage accidents in Table 7.4. The main reasons for the difference in the two analyses is that hourly-fixed effects control for all kinds of non-weather variation in each region.

Table 7.4: Percentage change in the number of hourly road accidents due to weather conditions[1,2]

	Material	Total Accidents
Wind speed (m/s)	**-1.49**	**-1.19**
Wind speed square (m/s)	**0.03**	**0.001**
Temperature 0^o to 10^o C	**-4.40**	**-4.21**
Temperature 10^o to 20^o C	**-4.88**	**-4.02**
Temperature 20^o to 25^o C	**-9.24**	**-7.50**
Temperature > 25^o C	**-11.57**	**-10.24**
Sunshine (in minutes)	**0.20**	**0.20**
Precipitation duration (in minutes)	**0.30**	**0.30**
Precipitation mm	**-0.03**	**-0.20**
Snow	**14.11**	**12.75**
Clouds	**-0.49**	**-0.50**
Fog	**3.98**	**3.45**
Thunder	**-2.17**	-1.88

Note:
(1) Bold coefficients are statistically significant at the 5 % level.
(2) Reference categories for temperature, snow, fog, thunder, seasonal variables are, respectively, temperature lower than 0^o C, no snow, no fog, no thunder, and spring.

7.6 Weather and percentage share of road accidents

Analyses in earlier sections that provide the role of weather in road accidents suggest that the share of different types of road accidents in total accidents varies with weather conditions. Therefore, we also investigated explicitly the effect of weather on the share of different types of accidents. For example, we estimated models to explain the share of type of accidents in total accidents during an hour as a function of weather and non-weather variables. So, we are now able to obtain the probability of having a fatal accident, *given that an accident happens* during *certain* weather conditions. We use OLS to estimate the effects of weather on the share of all types of hourly road accidents in total accidents with the same controls as used earlier. [54]

The results are presented in Appendix 7D. The percentage change in shares of the different types of accidents during various weather conditions are presented in Table 7.5. As discussed earlier, fatal accidents increase by around 50 per cent during extremely warm temperatures (see Table 7.4), However, it is 109 per cent more likely to have that there will be a fatal accident, *given that an accident happens,* in extremely warm temperatures,

[54] We also estimated the Tobit model instead of using OLS, but the results of both models were nearly identical.

compared with temperatures lower than 0^o C. Similarly, the share of serious and minor accidents in total accidents increases by about 76 and 58 per cent respectively, *given that an accident happens*, although these types of accidents increase by about 33 and 31 per cent respectively, in extremely warmer temperatures. Additionally, for the same interval of temperature, the share of material damage accident reduces by about 15 per cent, *given that an accident happens*. This implies that in higher temperatures the severity of the accidents increases and the material damage share in total accidents is substituted by injury accidents. This may be due to increased numbers of non-motorized (mostly cyclists) during increasing temperatures (e.g. see Chapter 3 and 4).

As is clear from Section 7.2, all kinds of hourly road accidents increase with duration of precipitation, However, the share of fatal and injury accidents falls with duration of precipitation, whereas the share of material-damage accidents increases, slightly.

The share of different types of accidents varies in different hours of the day, as shown in Figures 7.3, 7.4 and 7.5. Figure 7.3 shows the variation in percentage shares of fatal accidents during different hours of the day, while Figures 7.4 and 7.5 show the variation in percentage shares of different types of injury and material damage accidents, respectively. The share of fatal and serious injury accidents is highest between 01:00 and 06:00. This implies that a person is more likely to have a fatal or serious injury accident during these hours (01:00 to 06:00), *given that an accident happens,* compared with 12:00 hours. This may be partly due to higher speed levels because of lower densities of traffic on roads, and partly because of poor visibility and alcohol consumption by drivers (Shefer and Rietveld 1997). Interestingly, the share of fatalities drops together with the share of serious injury accidents at around 07:00 and stays lower until the evening peak hours. Also, the share of minor and other injury accidents in general is falling after the morning peak hours. This may be because more vehicles are travelling during this whole period, leading to higher densities of road traffic and fewer accidents (Shefer and Rietveld 1997). This also mitigates accident severity by reducing the fatal and serious injury accidents and increasing the minor injury and material-damage accidents.

Table 7.5: Percentage changes in shares of different types of accidents[1,2]

	Fatal	Injury crashes				Material
		Serious	*Minor*	*other*	*Total*	
Wind speed (m/s)	3.33	-1.61	-0.76	-0.67	**-1.00**	**0.19**
Wind speed square (m/s)	-0.33	-0.03	-0.03	-0.08	-0.05	**0.01**
Temp 0° C and 10° C	**26.33**	**31.42**	**12.73**	**17.28**	**20.17**	**-4.34**
Temp 10°C to 20° C	**43.00**	**51.23**	**28.85**	**37.06**	**38.73**	**-8.29**
Temp 20° C and 25° C	**70.00**	**76.58**	**49.82**	**62.53**	**62.68**	**-13.41**
Temp > 25° C	**109.00**	**75.23**	**57.76**	**72.56**	**68.50**	**-14.86**
Sunshine (in minutes)	-0.13	**0.26**	**0.21**	**0.14**	**0.20**	**-0.04**
Precipitation (in minutes)	**-0.67**	-0.32	**-0.03**	-0.03	**-0.13**	**0.03**
Precipitation mm	-1.00	0.06	-0.24	-1.56	-0.61	**0.13**
Snow	-39.33	**-18.84**	**-29.39**	**-32.92**	**-27.39**	**5.91**
Clouds	-3.33	**-1.71**	**-1.30**	**-1.00**	**-1.32**	**0.29**
Fog	-24.67	-3.45	-5.55	1.69	-2.29	0.63
Thunder	6.00	-10.32	-4.88	8.86	-1.62	0.30
Hourly dummies (23)			included			
Regional Dummies (31)			included			
Yearly dummies (9)			included			

Note:

(1) Bold coefficients are statistically significant at the 5 % level.

(2) Reference categories for temperature, snow, fog, thunder, seasonal variables are, respectively, temperature lower than 0° C, no snow, no fog, no thunder, and spring.

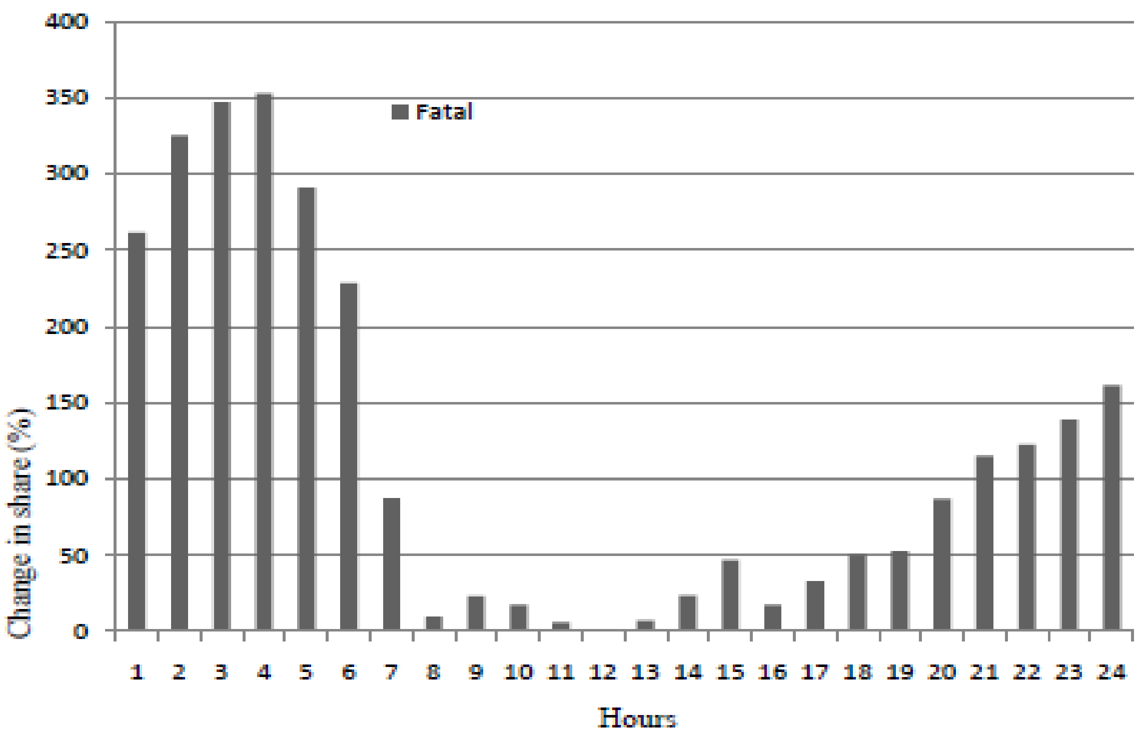

Figure 7.3: Percentage change in share of fatal accidents (reference period: 12:00-13:00)

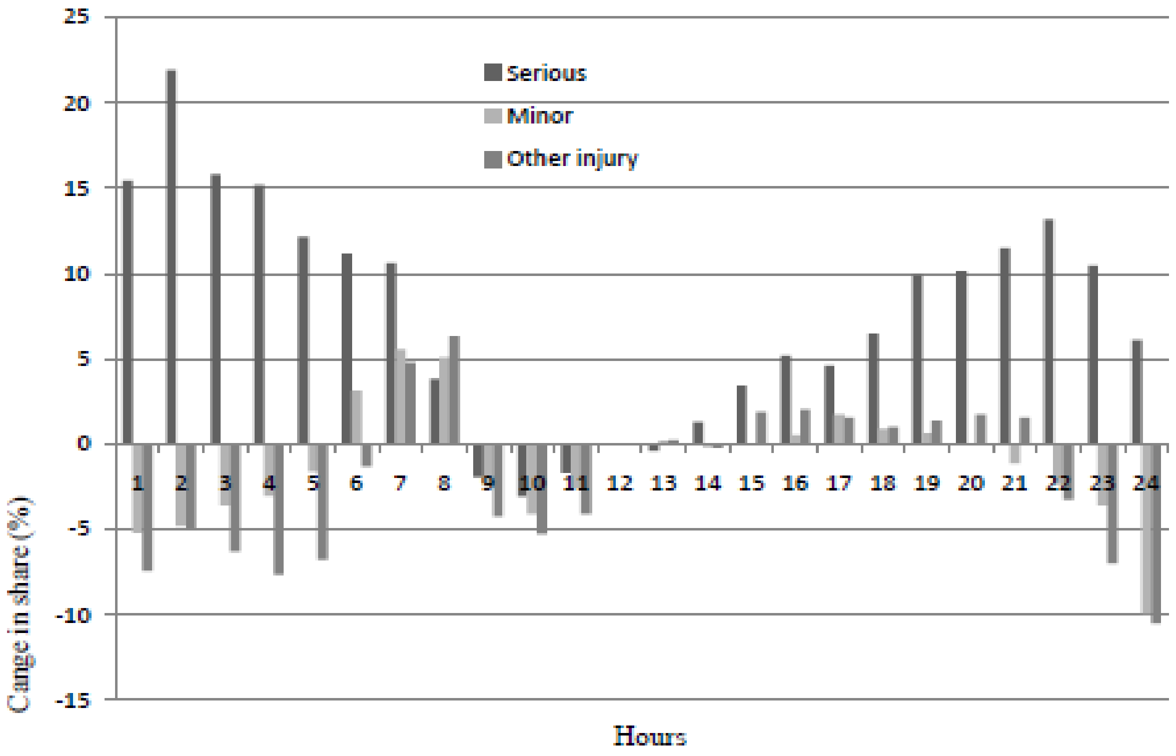

Figure 7.4: Percentage change in share of injury crashes (accidents) (reference period: 12:00-13:00)

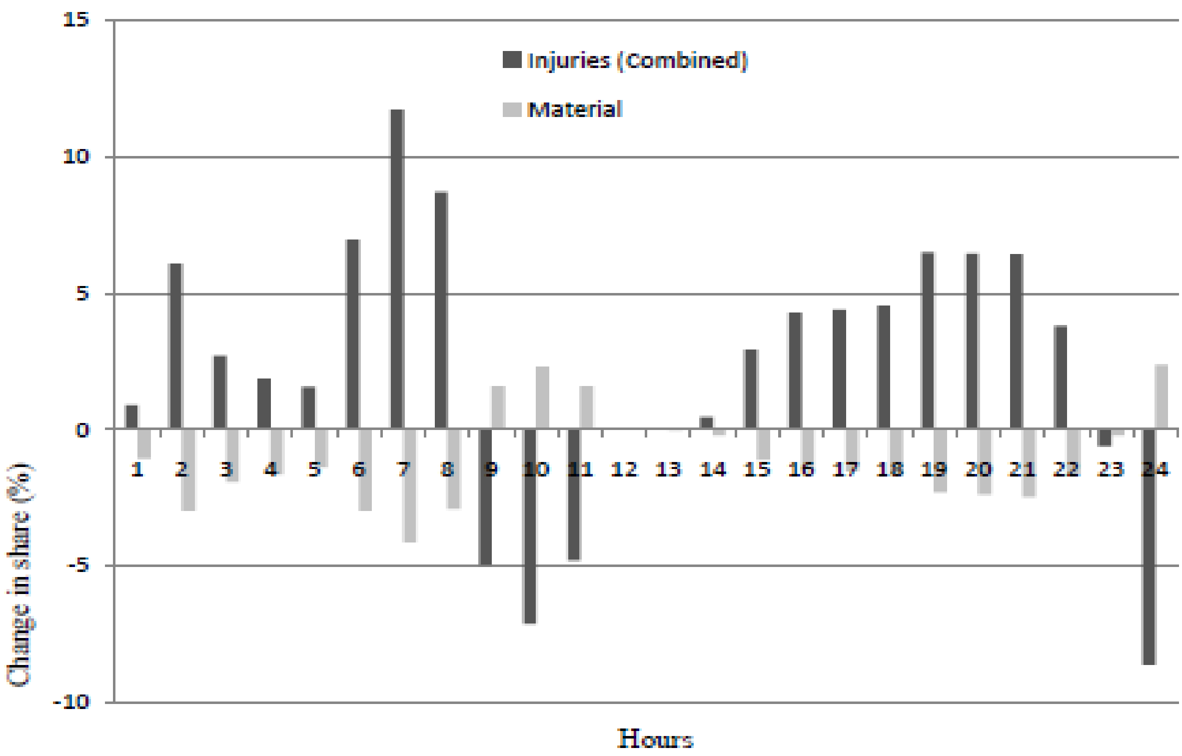

Fig 7.5: Percentage change in share of injury crashes (combined) and material damage accidents (reference period: 12:00-13:00)

7.7 Summary and conclusions

This chapter has investigated the effects of hourly variations in weather on the number of road accidents on all Dutch roads. We make a distinction between different types of accidents (fatal, injury, and exclusively material damage).

The impacts of weather on traffic accidents are the result of changes in exposure (for example, more cyclists on the roads during warm weather), changes in the probability of risks (for example, snow makes roads slippery), and changes in driving styles (people may slow down during adverse weather conditions). Our data unfortunately do not allow us to decompose these three factors. But combining the findings in this chapter with the results in preceding chapters, we find that all three mechanisms play a role, but their weights vary according to the specific type of weather. For example, in the case of high temperatures, the exposure effect dominates, whereas in the case of precipitation the direct risk effect dominates. The decrease in the severity of accidents during snow may be the result of changes in driving behavior.

The major results can be summarized as follows: *precipitation* has a strong adverse influence on the number of all types of accidents. Both the *number* of road accidents and also severity of accidents strongly increase with temperature. The number of road accidents also increases with *snow, clouds* and the presence of *fog*. However, the severity of accidents decreases with snow. A side result of our analysis is that we find strong variations in the number of accidents per hour. For example, the number of accidents during the evening peak is much higher than during the morning peak. This is a striking result that cannot be explained by differences in weather conditions, and that we suggest as a subject for further research.

Appendix 7A

Table 7A: Descriptives

Variable	Mean	Std. Deviation
Weather Variables		
Wind speed (m/s)	4.517	2.75
Wind speed squared (m/s)	27.98	35.48
Temperature < 0^{o}C	0.056	0.230
Temperature between 0^{o}C to 10^{o}C	0.419	0.493
Temperature between 10^{o}C to 20^{o}C	0.452	0.498
Temperature between 20^{o}C to 25^{o}C	0.058	0.234
Temperature > 25^{o}C	0.015	0.121
Duration of sunlight (minutes per hour)	12.001	20.905
Precipitation duration (minutes per hour)	4.366	13.462
Precipitation (mm)	0.097	0.508
Clouds (0 to 9 scale. 9 full cloudy)	5.244	2.626
Fog	0.020	0.139
Snow	0.007	0.082
Thunder	0.006	0.074
Other variables		
Weekend	0.286	0.452
Spring	0.252	0.434
Summer	0.255	0.436
Autumn	0.249	0.433
Winter	0.247	0.431
Total number of observations	2805504	

Appendix 7B

Table 7B: Results of negative binomial models on number of hourly accidents[1,2]

Variables	Fatal	Accidents with Injury				Material	Total Accidents
		Serious	Minor	Remaining	Total injuries		
Wind speed (m/s)	0.0187	-0.00725	-0.00244	-0.00183	-0.00407	0.00183	0.00107
	(0.015)	(0.004)	(0.004)	(0.004)	(0.002)	(0.001)	(0.001)
Wind speed squared (m/s)	-0.002	-0.00011	0.00001	-0.00053	-0.00018	0.00020*	0.00011
	(0.001)	0.0004	(0.00001)	(0.0002)	(0.0001)	(0.00001)	(0.0001)
Temp 0^o C and 10^o C	0.0803	0.12576**	0.06665**	0.06356**	0.08436**	-0.08042**	-0.05399**
	(0.060)	(0.019)	(0.019)	(0.018)	(0.011)	(0.005)	(0.004)
Temp 10^oC to 20^oC	0.1487*	0.21242**	0.13123**	0.15326**	0.16503**	-0.12167**	-0.07351**
	(0.065)	(0.021)	(0.021)	(0.020)	(0.012)	(0.005)	(0.005)
Temp 20^o C and 25^o C	0.2819**	0.29769**	0.20650**	0.23094**	0.24423**	-0.20070**	-0.12134**
	(0.076)	(0.024)	(0.024)	(0.022)	(0.014)	(0.006)	(0.006)
Temp > 25^o C	0.4003**	0.29025**	0.26594**	0.24097**	0.26440**	-0.22604**	-0.13735**
	(0.096)	(0.030)	(0.029)	(0.028)	(0.017)	(0.008)	(0.008)
Sunshine (minutes/hour)	0.0019**	0.00371**	0.00343**	0.00301**	0.00334**	0.00188**	0.00213**
	(0.001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.00006)	(0.00005)
Precipitation (minutes/hour)	0.0025*	0.00544**	0.00683**	0.00677**	0.00637**	0.00704**	0.00692**
	(0.001)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0008)	(0.00007)
Precipitation (mm)	0.0138	-0.00383	-0.00141	-0.00142	-0.00183	0.00351	0.00255
	(0.028)	(0.008)	(0.008)	(0.007)	(0.005)	(0.002)	(0.002)
Snow	-0.0796	-0.10524*	-0.14988**	-0.18877**	-0.14784**	0.16166**	0.12357**
	(0.143)	(0.043)	(0.039)	(0.039)	(0.023)	(0.009)	(0.009)
Clouds	-0.0209**	-0.01147**	-0.00882**	-0.00987**	-0.00995**	-0.00199**	-0.00377**
	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.0004)	(0.0004)
Fog	-0.0464	0.07165*	0.08063**	0.09457**	0.08176**	0.08833**	0.08672**
	(0.093)	(0.029)	(0.028)	(0.027)	(0.016)	(0.008)	(0.007)
Thunder	0.0586	0.03296	0.04150	0.11945**	0.06706**	0.06262**	0.06314**
	(0.141)	(0.041)	(0.038)	(0.036)	(0.022)	(0.011)	(0.010)
Weekend	0.0153	-0.17884**	-0.33043**	-0.38361**	-0.29868**	-0.32301**	-0.31259**
	(0.025)	(0.008)	(0.008)	(0.008)	(0.005)	(0.002)	(0.002)
Autumn	0.1291**	0.05537**	0.08725**	0.07978**	0.07463**	0.04346**	0.04915**
	(0.029)	(0.009)	(0.009)	(0.008)	(0.005)	(0.002)	(0.002)
Winter	0.0524	0.01270	0.01412	-0.00422	0.00682	0.03017**	0.02735**
	(0.037)	(0.011)	(0.011)	(0.010)	(0.006)	(0.003)	(0.003)
Summer	-0.0453	-0.11007**	-0.10422**	-0.12084**	-0.11141**	-0.06981**	-0.07619**
	(0.029)	(0.009)	(0.009)	(0.008)	(0.005)	(0.002)	(0.002)
Hourly dummies	Included	Included	Included	Included	Included	Included	Included
Yearly dummies	Included	Included	Included	Included	Included	Included	Included
Regional Dummies	Included	Included	Included	Included	Included	Included	Included
Constant	-6.5372** (0.128)	-4.79254** (0.043)	-5.67533** (0.052)	-5.20317** (0.047)	-4.06733** (0.027)	-1.70567** (0.012)	-1.63073** (0.011)
Ln α		-1.48554** (0.096)	-1.82637** (0.094)	-1.71007** (0.083)	-1.95787** (0.042)	-1.87543** (0.010)	-1.94285** (0.009)
Model chi-square	4657	72346	129873	134096	298805	1140000	1285000
Log likelihood	-51472	-349506	-340317	-372202	-783455	-2018000	-2246000
Pseudo R^2	0.04	0.09	0.16	0.15	0.16	0.22	0.22

(1) Standard errors are in parentheses, **p<0.01, * p<0.05* + p<0.1.

(2) Dependent variables are number of hourly accidents (of different types) . The number of observations is 2, 805, 504 with 80 degree of freedom.

Appendix 7C

Table 7C: Direct influence of weather on road accidents
(Results of Poisson hourly-fixed-effects models)[1,2]

	Material	**Total Accidents**
Wind speed (m/s)	-0.015**	-0.012**
	(0.002)	(0.002)
Wind speed squared (m/s)	0.0003*	0.00001
	(0.00015)	(0.0001)
Temp 0^o C and 10^o C	-0.045**	-0.043**
	(0.01)	(0.009)
Temp 10^oC to 20^o C	-0.050**	-0.041**
	(0.012)	(0.011)
Temp 20^o C and 25^o C	-0.097**	-0.078**
	(0.014)	(0.013)
Temp > 25^o C	-0.123**	-0.108**
	(0.020)	(0.018)
Sunshine (minutes/hour)	0.002**	0.002**
	(0.0001)	(0.00001)
Precipitation (minutes/hour)	0.003**	0.003**
	(0.0003)	(0.0001)
Precipitation mm	-0.0003	-0.002
	(0.003)	(0.002)
Snow	0.132**	0.120**
	(0.012)	(0.011)
Clouds	-0.005**	-0.005**
	(0.001)	(0.001)
Fog	0.039**	0.034**
	(0.009)	(0.008)
Thunder	-0.022+	-0.019
	(0.013)	(0.012)
Regional Dummies	Included	Included
Hourly -fixed effects	Included	Included
Observations	1,386,170	1,410,139
Number of hour-specific effects	82,131	83,486
Log likelihood	-981480	-1099000
Model chi-square	305072	389880
Degrees of freedom	39	39

Notes:
(1): Standard errors are in parentheses, **p<0.01, * p<0.05* + p<0.1.
(2): Dependent variables are the number of hourly accidents (of different types).

Appendix 7D

Table 7D: Results of OLS[1,2]

VARIABLES	Fatal	Accidents with Injury				Material
		Serious	Minor	Remaining	Total injuries	
Wind speed (m/s)	0.00010	-0.00050+	-0.00025	-0.00024	-0.00100*	0.00090*
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Wind speed square (m/s)	-0.00001	-0.00001	-0.00001	-0.00003	-0.00005	0.00006
	(0.000001)	(0.00002)	(0.00002)	(0.00002)	(0.00003)	(0.00003)
Temp 0^o C and 10^o C	0.00079*	0.00974**	0.00420**	0.00622**	0.02017**	-0.02096**
	(0.0003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Temp 10^oC to 20^oC	0.00129**	0.01588**	0.00952**	0.01334**	0.03873**	-0.04002**
	(0.0004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Temp 20^o C and 25^o C	0.00210**	0.02374**	0.01644**	0.02251**	0.06268**	-0.06479**
	(0.0004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Temp > 25^o C	0.00327**	0.02332**	0.01906**	0.02612**	0.06850**	-0.07177**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Sunshine (minutes/hour)	-0.000004	0.00008**	0.00007**	0.00005**	0.00020**	-0.00020**
	(0.000004)	(0.00001)	(0.00001)	(0.00001)	(0.0001)	(0.00002)
Precipitation (minutes/hour)	-0.00002**	-0.00010**	-0.00001	-0.00001	-0.00013**	0.00015**
	(0.000006)	(0.00001)	(0.00001)	(0.00001)	(0.0001)	(0.00003)
Precipitation mm	-0.00003	0.00002	-0.00008	-0.00056	-0.00061	0.00064
	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Snow	-0.00118	-0.00584*	-0.00970**	-0.01185**	-0.02739**	0.02856**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Clouds	-0.00010**	-0.00053**	-0.00043**	-0.00036**	-0.00132**	0.00142**
	(0.00003)	(0.0001)	(0.00001)	(0.0001)	(0.0001)	(0.0001)
Fog	-0.00074	-0.00107	-0.00183	0.00061	-0.00229	0.00303
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Thunder	0.00018	-0.00320	-0.00161	0.00319	-0.00162	0.00144
	(0.001)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Weekend	0.00134**	0.00885**	0.00257**	-0.000002	0.01143**	-0.01276**
	(0.0001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Autumn	0.00035*	0.00062	0.00273**	0.00151**	0.00486**	-0.00521**
	(0.0001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Winter	0.00011	-0.00122	-0.00093	-0.00158*	-0.00373**	0.00363**
	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Summer	0.00012	-0.00147**	-0.00017	-0.00167**	-0.00331**	0.00319**
	(0.0001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hourly dummies	Included	Included	Included	Included	Included	Included
Yearly dummies	Included	Included	Included	Included	Included	Included
Regional dummies	Included	Included	Included	Included	Included	Included
Constant	0.00871**	0.04624**	-0.00041	0.01739**	0.06322**	0.92807**
	(0.001)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)
R-squared	0.002	0.012	0.019	0.008	0.023	0.024
Parameters	80	80	80	80	80	80
N of observations	907480	907480	907480	907480	907480	907480

Notes:
(1): Standard errors are in parentheses, **p<0.01, * p<0.05* + p<0.1.
(2): The dependent variables are different types of accidents as share of total hourly accidents.

PART IV

SUMMARY AND POLICY IMPLICATIONS

Chapter 8

Summary and Policy Implications

8.1 Concluding Remarks

Does weather influence transportation and travel behaviour? The current literature focuses on different aspects of the effects of weather on transportation, ranging from road safety to travel demand. A review of the literature was presented in Chapter 1. The value added of this thesis to previous research is that it uses micro-data for travellers together with a bigger geographic coverage, longer time period, and hourly measured weather conditions. Further, this thesis improves on some methodologies, as will be explained in Section 8.5. The main objective of this thesis is to quantify the influence of weather on travel behaviour, and provide policy recommendations in the context of the possible impacts of climate change on travel behaviour.

The results of the thesis can be summarized in few main points, as follows: temperature is the most important weather variable as far as travel behaviour is concerned, followed by precipitation and wind. Cycling is the mode of transportation which is most sensitive to weather conditions. Higher temperatures lead to modal shifts from car and public transport towards cycling. Public transport demand decreases with temperature, but the demand for public transport may increase to certain destinations. Finally, higher temperatures, precipitation and snow are potential hazards for road safety.

This thesis was divided into three parts. Part I consisted of three chapters (Chapter 2, 3 and 4). These parts mainly focused on the role of weather in choice decisions regarding mode and destination. Part II consisted of Chapters 5 and 6. This part focused on the role of weather in the travel time of commuting trips. Finally, Part III consisted of Chapter 7 which focuses on the role of weather in road accidents. Parts I, II and III are summarized in Sections 8.2, 8.3 and 8.4. Section 8.5 then describes the policy implications of the findings. Finally, Section 8.6 makes suggestions for future research.

8.2 Part I

Part I consisted of three empirical studies based on travel surveys and KNMI weather reports for the years 1996 to 2005. In Chapter 2, we examined the impacts of weather on the decision to travel to the beach and the travel modes for Dutch travellers during the period 1996 to 2005. The important contribution of this chapter is that we were able to combine three choice decisions: destination choice, the distance of the trip, and the mode choice decision, while including local and hourly-measured weather conditions. We used data on leisure trips (made during the summer) and examined discrete choice models. The results indicated that weather has a strong influence on both beach and mode choice. Wind and precipitation both have a negative influence, whereas higher temperatures encourage beach trips.

Chapter 3 focused on the influence of weather on travel demand (using the OVG/MON survey from 1996 to 2005), while considering different trip purposes and different modes of transportation. Two measures were employed to measure individual travel demand: *daily number of trips per person* and *daily travelled distance per person*. We use hourly weighted averages of weather, where the weights are based on the number of trips made during various hours of the day. Finally, count models were estimated to observe the effects of varying weather conditions on travel demand. Overall, we found that travel demand is not strongly influenced by weather conditions. Strong wind, extremly warm weather, and more precipitation negatively affect total daily travel demand.

We also investigated the role of weather in the demand for different modes of transportation. The demand for cycling is most sensitive to weather conditions, followed by public transport. The results indicate that there is strong substitution of travel modes for individuals at extreme temperatures. During extremely high temperatures (temperatures higher than 25^o C) the total travel demand is reduced by around 5 per cent compared with temperatures between 0^o C to 10^o C. However, for these higher temperatures, the demand for walking, car and public transport reduces by about 10, 15, and 20 per cent, respectively, whereas the demand for cycling increases by around 22 per cent. This clearly shows a modal shift from car, public transport and walking to cycling during extremely warm temperatures. On the other hand, precipitation leads to a modal shift from bicycle to public transport and car. The results further indicate that demand for recreational trips is more sensitive to weather conditions, followed by demand for trips to visit family and friends. The demand for commuting trips is not affected by weather conditions.

Mode choice is an important travel decision for individuals. Chapter 4 focused on the role of weather in individual mode choice decisions. We use OVG/MON data sets for the period 1996 till 2005. We estimated separate MNL models for different trip purposes and one combined MNL model for all trips to obtain overall picture of weather and mode choice decisions. It may be noted, that in Chapter 4, hourly trips and weather data are used. The results indicated that the mode-choice decision is strongly influenced by weather conditions. However, to what extent weather influences the mode choice decision depends on the purpose of the trips. Strong wind negatively influences the probability of cycling; precipitation reduces the probability of cycling but increases the probability of using the car. With lower temperatures, people switch from cycling to car and public transport, whereas people prefer walking and cycling as temperatures increase. The intensity of substitution between cycling and car trips during varying temperatures depends on trip purpose.

It is interesting to compare the findings of Chapter 3 and Chapter 4. Even though both chapters use two different methodologies and focus on different research questions, the findings of both chapters are comparable.

8.3 Part II

Part II focused on commuting trips conditional on distance, and hence on speed. Chapter 5 uses commuting-trip data (for the year 1996 only). We focus on commuting trips for several reasons. First, commuting is hardly influenced by weather conditions (see also Part I). Second, most individuals make two commuting trips per day, and thus we were able to estimate panel models to control for unobserved heterogeneity. The individual-fixed effects results indicate that snow is the only weather component that reduces trip speed (by about 7 per cent). However, since snowfall is rare, the welfare loss is limited in the Netherlands. One other interesting finding is that the speed reduction in the morning and evening peaks on congested routes is around 7 per cent. The associated welfare loss through increases in travel time is around € 0.23 per commuting trip. These effects are exacerbated by rain, which has a strong negative effect on trip speed on congested routes, especially during the evening peak. The welfare effect of rain for these trips ranges between 9 and 12 per cent of total commuting costs and amounts to (at least) € 0.50 per commuting trip.

Chapter 6 focused on commuting trips by public transport using a similar econometric model to the one used in Chapter 5. However, the focus of Chapter 6 was different. Here, the objective was to focus on the role of public transport in an integrated transportation system (we use MON data for the years 2004 and 2005). The data covers commuting trips made by bus, tram, metro (BTM) and train during this period. The results show that wind strength has a small but negative effect on the speed of bus, tram and metro commuting trips. Snow has a substantial negative effect on the speed of public transport trips. The associated welfare loss is 53 eurocents per commuting train trip per person, and 76 eurocents per commuting trip per person for trips by BTM. Rain strongly affects the speed of commuting trips by bus on congested routes. The associated welfare loss is € 1.15 per commuting trip per person.

8.4 Part III

Part III of the thesis consisted of only one chapter and focused on road safety analysis. The objective was to investigate the role of weather in hourly road accidents using BRON data sets from 2000 to 2009. We were able to distinguish between different types of road accidents using negative binomial and Poisson models which were estimated to investigate the effects of weather on the number of fatal, injury and material-damage accidents.

The results are consistent with the earlier literature. Fatal accidents and injury-related accidents increase with temperature, whereas material-damage road accidents (and therefore the total number of accidents) decrease with temperature. A similar pattern can be observed for snow which reduces the severity of accidents, despite the increase in the number of road accidents, as material-damage accidents increase.

8.5 Relevance of findings

The most important contribution of this study is the quantification of the influence of weather on individual travellers. This thesis confirms that weather does have a strong influence on *modal shift* (for Dutch travellers). People switch from cycling to car and public transport during extremely cold weather, and also in the presence of rain (see Chapter 4). This has practical implications for public transport planners and future transport investment as public transport demand increases during extremely cold weather, and the capacity of public transport may need to be adjusted accordingly (to meet additional demand). Given that, during snow the management of public transport and trains, in particular, is already a challenge for Prorail and NS, coping with additional demand brings yet another challenge for their future policies. However, it is important to consider the welfare effects of such policies. The current thesis only considers the additional demand (the traveller side), while ignoring the costs involved (the supply side).

Second, a modal shift also takes place at higher temperatures. This has implications for short-run and long-run transportation investment and traffic management. In the short run, during the summer period, there will be less demand for public transport. However, there may be additional demand for some specific destinations such as beaches (see Chapter 2).

In the long run this has implications for policy to accommodate the effects of climate change. It implies that Dutch travellers are hardly vulnerable to warmer weather conditions because people still prefer to cycle even in temperature higher than 25^{o} C (see Chapter 4). This implies that no revision of investments in the cycling routes is required now, or even in the long run as an adaptation measure for possible future climate change. However, there may be some threshold level of temperature, where cyclists may switch to other modes of transportation. Although this is not very likely in the near future or in the long run, nevertheless, such a possibility cannot be ruled out completely.

Another contribution is that this thesis has presented several methodological improvements. For example, Chapter 2 combined three individual choice decisions: namely, destination choice, mode choice, and distance of travel, in a simple nested logit model with an empirical application. Distance was included in the analysis by taking average distances from a municipality to all beaches and then used as an exogenous variable. Similarly, Part II which focused on the travel time of commuting trips also uses an improved methodology for commuting trips analysis by using panel-fixed effects models with individual-specific fixed effects to control for unobserved heterogeneity.

Some policy recommendations can be made to improve road safety in various weather conditions based on the current findings. As explained in Chapter 7, the severity of accidents increases with temperature, and decreases with snow. As this is most likely because of the high number of pedestrians and cyclists on roads, this suggests that Dutch traffic safety authorities should tighten safety measures to protect non-motorized travellers in general and during the summer in particular. The total number of accidents also increases with snow, although the severity of accidents falls during snow. This is mainly due to the reduced number of cyclists during snow, as was found in Chapter 3, which further supports the recommendation for additional cyclist safety measures. These can be realized in two ways. first: by making cycling safer by introducing additional safety measures, such as, use of helmets, restricting using cell phone during cycling etc; and second: introducing more strict rules for motorized travellers to protect cyclists.

8.6 Future research

The main focus of this thesis was to quantify the influence of weather on travel behaviour. This was done in this thesis for the Netherlands for various travel decisions. However, there are still many aspects which could be explored as an extension to the current analysis, or as possible new directions based on this analysis.

First, the results could be used to undertake a study on possible climate-change impacts for Dutch travellers. In that respect, this analysis can provide a basis for more advanced studies. We know now how weather influences travel demand, destination choice, and mode choice decision. An analysis could be made on the results from this thesis, in order to portray the expected future picture of travel behaviour in a changed climate scenario. And hence, appropriate policy could then be designed for transport in order to cope with future climate change.

Second, the findings of this thesis could be used as a starting point for a study on weather alerts for road users and for public transport managers. For example, NS could be informed about an expected increase in demand for trains during colder weather in general, or an increased demand for the trains to beach destinations during warmer weather conditions. Similarly, road users could be warned about traffic safety risks in various weather conditions.

Third, safety research is focused on hourly accidents. Several extensions and improvements are possible. The data is aggregated on an hourly basis, and has the advantage that we can see all accidents in varying weather conditions. However, we cannot say something about an individual accident. An extension is possible to focus on individual accidents rather than on hourly aggregations.

Another improvement could be made by using improved weather data for road safety research. The current thesis uses weather data that is measured locally, but the analysis could have been improved considerably if even more-local weather data had been available for precipitation, in particular. One possible extension is the use of radar data for precipitation measurements. This data is collected by KNMI at a 2 square kilometre spatial resolution. The use of this data will not only provide very local weather influences, but would also provide a much better regional analysis of road safety.

References

Aaheim, H. A. and Hauge, E. K. 2005, Impacts of Climate Changes on Travel Habits, A National Assessment Based on Individual Choices 2005:07 Center for International Climate and Environmental Research, Blindern, Oslo

Adams, R. L. 1973, Uncertainty in Nature, Cognitive Dissonance, and the Perceptual Distortion of Environmental Information: Weather Forecasts and New England Beach Trip Decisions *Economic Geography*, vol. (49), no. 4, pp. 287-297

Andreescu, M., P. and Frost, D. B. 1998, Weather and Traffic Accidents in Montreal, Canada *Climate Research*, vol. (9), no. 3, pp. 225-230

Andrey, J. 2010, Long-term trends in weather-related crash risks *Journal of Transport Geography*, vol. (18), no. 2, pp. 247-258

Andrey, J. and Yagar, S. 1993, A Temporal Analysis of Rain-Related Crash Risk *Accident Analysis and Prevention*, vol. (25), no. 4, pp. 465-472

Andrey, J., Suggett, J., Mills, B. and Leahy, M. 2001, Weather-Related Road Accident Risks in Mid-Sized Canadian Cities *Canadian Multidisciplinary Road Safety Conference XII Proceedings, June 11-13, London*

Arnott, R., De Palma, A. and Lindsey, R. 1991, Does Providing Information to Drivers Reduce Traffic Congestion? *Transport Research Part A*, vol. (25), pp. 309-318

Arnott, R., De Palma, A. and Lindsey, R. 1999, Information and Time-of-usage Decisions in the Bottleneck Model with Stochastic Capacity and Demand *European Economic Review*, vol. (43), no. 3, pp. 525-548

Baker, C. J. and Reynolds, S. 1992, Wind-Induced Accidents of Road Vehicles *Accident Analysis and Prevention*, vol. (24), no. 6, pp. 559-575

Becken, S. 2010, The Importance of Climate and Weather for Tourism *Faculty of Environment, Society and Design, Lincoln University, New Zealand*

Bergström, A. and Magnusson, R. 2003, Potential of Transferring Car Trips to Bicycle during Winter *Transportation Research Part A: Policy and Practice*, vol. (37), no. 8, pp. 649-666

Bertness, J. 1980, Rain-Related Impacts on Selected Transportation Activities and Utility Services in the Chicago Area *Journal of Applied Meteorology*, vol. (19), no. 5, pp. 545-556

Bigano, A., Jacqueline, M. H. and Richard, S. J. T. 2006, The Impact of Climate on Holiday Destination Choice *Climate Change*, vol. (76), pp. 389-406

Bijleveld, F. and Churchill, T. 2009, The Influence of Weather Conditions on Road Safety SWOV Institute for Road Safety Research, Report No. R-2009-9, The Netherlands

Brandenburg, C., Matzarakis, A. and Arnberger, A. 2004, The effects of weather on frequencies of use by commuting and recreation bicyclists. Berichte des Meteorologischen Instituts der Universitt Freiburg, Freiburg 12: pp.189-197

Braun, O. L., Lohmann, M., Maksimovic, O. and Meyer, M. 1999, Potential impact of climate change effects on preferences for tourism destinations: A psychological pilot study *Climate Research*, vol. (11), pp. 247-254

Brijs, T., Dimitris, K. and Greet, W. 2008, Studying the Effect of Weather Conditions on Daily Crash Counts Using a Discrete Time-Series Model *Accident Analysis and Prevention*, vol. (40), no. 3, pp. 1180-1190

Brilon, W. and Ponzlet, M. 1996, Variability of Speed-Flow Relationships on German Autobahns *Transport Research Record*, vol. (1555), pp. 91-98

Brodsky, H. and Hakkert, A. S. 1988, Risk of a Road Accident in Rainy Weather *Accident Analysis and Prevention*, vol. (3), pp. 161-176

Cameron, A. C. and Trivedi, P. K. 1986, Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests *Journal of Applied Econometrics*, vol. (1), no. 1, pp. 29-53

Cameron, A. C. and Trivedi, P. K. 2005, *Microeconometrics Methods and Applications*, Cambridge University Press New York, USA

Chapman, R. 1973, The Concept of Exposure *Accident Analysis and Prevention*, vol. (5), pp. 95-110

Chung, E., Ohtani, O., Warita, H., Kuwahara, M. and Morita, H. 2005, Effects of Rain on Travel Demand and Traffic Accidents *IEEE Intelligent Transportation Systems Conference Proceedings, 13-15 September, Lausanne*, Switzerland

Chung, E., Ohtani,O., Warita, H., Kuwahara, M. and Morita, H. 2005, Effect of Rain on Travel Demand and Traffic Accidents *IEEE Conference Proceedings, Japan*

Cools, M., Moons, E. and Wets, G. 2010, Assessing the Impact of Weather on Traffic Intensity *Weather, Climate and Society*, vol. (2), no. 1, pp. 60-68

De Freitas, C. R. 2006, Recreation Climate Assessment *International Journal of Climatology*, vol. (10), no. 1, pp. 89-103

De Palma, A. and Lindsey, R. 1998, Information and Usage of Congestible Facilities Under Different Pricing Regimes *Canadian Journal of Economics*, vol. (31), no. 3, pp. 666-692

De Palma, A. and Rochat, D. 1999, Understanding Individual Travel Decision: Results from Commuters Survey in Geneva *Transportation*, vol. (26), pp. 263-281

Edwards, J. B. 1996, Weather-Related Road Accidents in England and Wales: A Spatial Analysis *Transport Geography*, vol. (4), pp. 201-212

Edwards, J. B. 1998, The Relationship Between Road Accident Severity and Recorded Weather *Journal of Safety Research*, vol. (29), no. 4, pp. 249-262

Eisenberg, D. 2004, The Mixed Effects of Precipitation on Traffic Crashes *Accident Analysis and Prevention*, vol. (36), pp. 637-647

FHWA 2006, Empirical Studies on Traffic Flow in Inclement Weather FHWA-HOP-07-073. Road Weather Management Program, Office of Operations, *Federal Highway Administration*, 400 Seventh Street, S.W., Washington, D.C. 20590

Fomunung, I., Washington, S. and Guensler, R. 1999, Statistical Model for Estimating Oxides of Nitrogen Emissions from Light Duty Motor Vehicles *Transport Research Part D*, vol. (4), pp. 333-352

Fosgerau, M. 2005, Speed and Income *Journal of Transport Economics and Policy*, vol. (39), pp. 225-240

Fridstrøm, F., Ifver, J., Ingebrigtsen, S., Kulmala, R. and Thomsen, L. K. 1995, Measuring the contribution of randomness, exposure, weather, and daylight to the variation in road accident counts *Accident Analysis and Prevention*, vol. (27), no. 1, pp. 1-20

Goetzke, F. and Rave, T. 2006, Bicycle Use in Germany: Explaining Differences between Municipalities through Network Effects *University of West-Virginia*, Morgantown, USA

Greene, W. H. 2007, *Econometric Modelling Guide*, LIMDEP Version 9.0, Econometric Software, Inc, 15 Gloria Place , Plainview, NY 11803 USA

Gurmu, S. and P. K. Trivedi 1996, Excess Zeros in Count Models for Recreational Trips *Journal of Business and Economic Statistics*, vol. (14), pp. 469-477

Hall, F. L. and Barrow, D. 1988, Effect of Weather on the Relationship Between Flow and Occupancy on Freeways *Transport Research Record* no. 1457, pp. 184-191

Hamilton, J. M. 2004, Climate and the Destination Choice of German Tourists, DINAS-COAST, Centre for Marine and Climate Research, Hamburg University, Germany

Hamilton, J. M. and Maren, A. L. 2004, The Role of Climate Information in Tourist Destination Choice, Working Paper FNU-56, *Centre for Marine and Climate Research*, Hamburg University, Germany

Haranc, R., Sterzin, E., Krechmer, D., Rakha, H, and Farzaneh, M. 2006, Empirical Studies on Traffic Flow in Inclement Weather *Publication No. FHWA-HOP-07-073*, Federal Highway Administration, Washington, D.C. USA.

Hassan, A. Y. and Barker, J. D. 1999, The Impact of Unseasonable or Extreme Weather on Traffic activities within Lothian region, Scotland *Transportation Research*, vol. (7), pp. 209-213

Hatzopoulou, M. A. and Miller, E. J. 2010, Linking an Activity-Based Travel Demand Model with Traffic Emission and Dispersion Models: Transports' Contribution to Air Pollution in Toronto *Transport Research Part D*, vol. (15), pp. 315-325

Hensher, D. A., Rose, M. J., and Greene, W. H. 2005, *Applied Choice Analysis: A primer*, Cambridge University Press

Hermans, E., Brijs, T., Stiers, T., and Offermans, Q. 2006, The Impact of Weather Conditions on Road Safety Investigated on an Hourly Basis Transportation Research Board Annual Meeting 2006, CD-Rom Paper

Hofman, M. and O' Mahony, M. 2005, The Impact of Adverse Weather Conditions on Urban Bus Performance Measures Intelligent Transport System, The Proceedings of the 8th International IEEE Conference on Intelligent Transport Systems , 13-15 Sept, Dublin, Ireland

Hogema, J. H. 1996, Effects of Rain on Daily Traffic Volume and on Driving Behaviour TM-96-B019 TNO Human Factor Research Institute, The Netherlands

Holmen B. A. and Niemeier D. A. 1998, Characterizing the Effects of Driver Variability on Real-World Vehicles Emissions *Transportation Research Part D*, vol. (3), no. 2, pp. 117-128

Ibarra, E. M. 2010, The Use of Webcam Images to Determine Tourist-Climate Aptitude: Favourable Weather Types for Sun and Beach Tourism on the Alicante Coast (Spain) *International Journal of Biometeorol*, vol. (Published online DOI 10.1007/s00484-010-0347-8),

Ibrahim, A. T. and Hall, F. L. 1994, Effect of Adverse Weather Conditions on Speed-Flow-Occupancy Relationships *Transport Research Record*, vol. (1457), pp. 184-191

IPCC 2007, IPCC Fourth Assessment Report: Climate Change. The Intergovernmental Panel on Climate Change *The Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jean, A., Brian, M., Mike, L. and Jeff, S. 2003, Weather as a Chronic Hazard for Road Transportation in Canadian Cities *Natural Hazards*, vol. (28), pp. 319-343

Keay, K. and Simmonds, I. 2006, Road accidents and rainfall in a large Australian city *Accident Analysis and Prevention*, vol. (38), pp. 445-454

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 *Transport Resources*, vol. (31), pp. 181-203

KNMI 2006, KNMI Climate Change Scenarios 2006 for the Netherlands, Retrieved 16 June 2010, from http://www.knmi.nl/klimaatscenarios/knmi06/WR23mei2006.pdfKNMI

Koetse, J. M. and Rietveld, P. 2009, The impact of climate change and weather on transport: An overview of empirical findings *Transportation Research Part D: Transport and Environment*, vol. (14), no. 3, pp. 205-221

Lancaster, T. 1990, *The Econometric Analysis of Transition Data*, Cambridge University Press, Cambridge.

Lenzen, M. 1999, Total Requirements of Energy and Green House Gases for Australian Transport *Transport Research Part D*, vol. (4), pp. 265-290

Lise, W. and Tol, R. S. J. 2002, Impact of Climate on Tourist Demand *Climate Change*, vol. (55), pp. 429-449

Maddison, D. 2001, In Search of Warmer Climates? The Impact of Climate Change on Flows of British Tourists *Climate Change*, vol. (49), pp. 193-208

Mandel, B., Gaudry, M. and Rothengatter, W. 1997, A Disaggregate Box-Cox Logit Mode Choice Model of Intercity Passenger Travel in Germany and its Implications for High-Speed Rail Demand Forecasts *The Annals of Regional Science*, vol. (31), pp. 99-120

Martin, P. T., Hansen, J. P. and Quintana, I. 2000, Inclement Weather Signal Timings Research Report MPC01-120, UTL University of Utah, Salt Lake City.

Maze, T. H. and Agarwal, M. B. G. 2006, Whether Weather matters to Traffic Demand, Traffic Safety and Traffic Operations and Flow *Transport Research Record*, vol. (1948), pp. 170-176

Miller, Ted R. 1989, Impacts of global climate change on metropolitan infrastructure In: John C. Topping Jr (ed.), With Climate Change, Climate Institute Washington, DC, USA.

Moreno, A. and Amelung, B. 2009, Climate Change and Coastal & Marine Tourism: Review and Analysis *Journal of Coastal Research* Special Issue 56, pp. 1140-1144

Moreno, A., Amelung, B. and Santamarta, L. 2008, Linking Beach Recreation to Weather Conditions: A Case Study in Zandvoort, Netherlands *Tourism in Marine Environments*, vol. (5), no. 2-3, pp. 111-119

Nankervis, M. 1999, The Effect of Weather and Climate on Bicycle Commuting *Transportation Research*, vol. (33), Part A, pp. 417-431

Ndreescu, M. P. and Frost, B. D. 1998, Weather and traffic accidents in Montreal, Canada *Climate Research* no. 9, pp. 225-230

Nofal F. H. and Saeed, A. 1997, Seasonal variation and weather effects on road traffic accidents in Riyadh City *Public Health*, vol. (111), pp. 51-55

Nookala, L. S. 2006, *Weather Impact on Traffic Conditions and Travel Time Prediction*, Master's Thesis Department of Computer Science, University of Minnesota, Duluth, Minnesota 55812 U.S.A.

Perry, A. and Symons, L. 1994, The Wind Hazard in the British Isles and its Effects on Transportation *Journal of Transport Geography*, vol. (2), no. 2, pp. 122-130

Richardson, A. J. 2000, Seasonal and Weather Impacts on Urban Cycling Trips TUTI Report 1-2000 The Urban Transport Institute, Victoria, Australia.

Rietveld, P., Bruinsma, F. R. and Van Vuuren, D. 2001, Coping with Unreliability in Public Transport Chains: A Case Study for The Netherlands *Transportation Research*, vol. (35), pp. 539-559

Rietveld, P., Zwart, B., Van Wee, B. and Van der, H. T. 1999, On The Relationship Between Travel Time and Travel Distance of Commuters: Reported Versus Network Data in the Netherlands *Annual of Regional Science*, vol. (33), pp. 269-287

Sabir, M., Van Ommeren, J., Koetse, J. M. and Rietveld, P. 2010a, Adverse Weather and Commuting Speed *Networks and Spatial Economics (forthcoming)*

Sabir, M. Van Ommeren, J., Koetse, M. and Rietveld, P. 2010b, The Effects of Weather and Individual Characteristics on the Speed of Public Transport Trips: An Empirical Study for the Netherlands. In M. Givoni, and D. Banister, Editors, *Integrated Transport: From Policy to Practice*, Routledge, (pp: 275-288), USA

Satterthwaite, S. P. 1976, An Assessment of Seasonal and Weather Effects on the Frequency of Road Accidents in California Accident *Analysis and Prevention*, vol. (8), pp. 87-96

Shefer, D. and Rietveld, P. 1997, Congestion and Safety on Highways: Towards an Analytical Model *Urban Studies*, vol. (34), no. 4, pp. 679-692

Small, A. K. 1982, The Scheduling of Consumer Activities: Work Trips *American Economic Review*, vol. (72), pp. 467-479

Small, A. K. and Verhoef, E. T. 2007, *The Economics of Urban Transportation*, 2nd Edition, Routledge, London.

Snowden, R. J., Stimpson, N. and Ruddle, R. A. 1998, Speed Perception Fog up as Visibility drops *Nature*, vol. (392), p. 450

Statistics Netherlands 2008, Commuter Cyclists Prefer Short Distances, CBS Web Magazine (16th September 2008), The Netherlands

Stern, E. and Zehavi, Y. 1990, Road Safety and Hot Weather: A Study in Applied Transport Geography *Transactions of the Institute of British Geographers*, vol. (15), no. 1, pp. 102-111

Stern, S. N. 2006, *Economics of Climate Change*, Cambridge University Press Cambridge

SWOV 2009, Fact sheet: Influence of Weather on Road Safety, Institute for Road Safety Research, The Netherlands

Talab, D. H. 1973, An Investigation into the Relationship between Rainfall and Road Accident Frequencies in Two Cities *Accident Analysis and Prevention*, vol. (5), pp. 343-349

Thomas, T., Weijermars, W. and Van Berkum, E. 2008, Variations in Urban Traffic Volumes *European Journal of Transport and Infrastructure Research*, vol. (8), no. 3, pp. 251-263

TRB 2008, Potential Impacts of Climate Change on U.S. Transportation, *Transportation Research Board* Special Report 290. Transport Research Board, Washington, D.C. USA.

Van Berkum E. C., Hagens, A. and Weijemars, W., E, (2006) Impact of Weather on Urban Travel Demand in the Netherlands, retrieved on 1 February 2011 from http://www.atmo.tudelft.nl/images/atmo/publications_results/project_4c/2006_ewgt_bari.pdf

Van Oldenborgh, G. and Van Ulden, A. 2003, On the Relationship Between Global Warming, Local Warming in the Netherlands and Changes in Circulation in the 20th Century *International Journal of Climatology*, vol. (23), pp. 1711-1724

Van Ommeren, J. and Dargay, J. 2006, The Optimal Choice of Commuting Speed: Consequences for Commuting Time, Distance and Costs *Journal of Transport Economics and Policy*, vol. (40), pp. 279-296

Van der Waerden, P., and H. Timmermans. 2003, Key Events and Critical Incidents Influencing Transport Mode Choice Switching Behavior: Exploratory Study. Presented at *82nd Annual Meeting of the Transportation Research Board*, Washington, D.C., USA

Waalkes, S. M. 2003, Cold Weather and Concrete Pavements: Troubleshooting and Tips to Assure a Long-Life Pavement *Annual Conference of the Transportation Association of Canada St. John's, Newfoundland and Labrador.* Illinois, USA.

Wardman, M. 1998, The Value of Travel Time: A Review of British Evidence *Journal of Transport Economics and Policy*, vol. (32), pp. 285-316

Waters, W. G. I. 1996, Values of Travel Time Savings in Road Transport Project Evaluation World Transport Research, Proceedings of 7th World Conference on Transport Research. Vol 3. Pergamon, Oxford.

Whiffen, B., Delannoy, P., and Siok, S. 2002, Fog: Impact on Road Transportation and Mitigation Options *National Highway Visibility Conference, Australia.*

Winters, M., Friesen C. and Teschke, K. 2007, Utilitarian Bicycling: A Multilevel Analysis of Climate and Personal Influences *American Journal of Preventive Medicine*, vol. (32), no. 1, pp. 52-58

Wooldridge, J. M. 2003, *Introductory Econometrics: A Modern Approach*, 2nd Edition, South-Western College

Wyon, D. P., Wyon, I. and Norin, F. 1996, Effects of moderate heat stress on driver vigilance in a moving vehicle *Ergonomics*, vol. (39), no. 1, pp. 61-75

Young, R. K. and Liesman, J. 2007, Estimating the relationship between measured wind speed and overturning truck crashes using a binary logit model *Accident Analysis and Prevention*, vol. (39), pp. 574-580

Samenvatting (Summary in Dutch)

Samenvatting (Nederlands)

Wordt het reisgedrag van individuen beïnvloed door het weer? Recent onderzoek bestudeert de effecten van het weer op transport gerelateerde aspecten, van verkeersveiligheid tot aan de daadwerkelijke vraag naar transport. In Hoofdstuk 1 van dit proefschrift wordt een overzicht gegeven van dit onderzoek. Deze dissertatie draagt bij aan een verdere ontwikkeling van de literatuur door het expliciet gebruik van individuele reizigersgegevens (micro-data) in combinatie met bestudering van een groter geografisch gebied, langere tijdsperioden en per uur gemeten weersomstandigheden. Verder worden in deze dissertatie enige methodologische verbeteringen aangereikt. De belangrijkste bijdrage van dit proefschrift is het kwantificeren van het effect van weersinvloeden op het reisgedrag. Aan de hand van deze kwantitatieve analyse wordt beleidsadvies opgesteld om mogelijke invloeden van klimaatsverandering op het reisgedrag te ondervangen.

De belangrijkste resultaten van dit onderzoek laten zien dat het weer een meetbare invloed heeft op reisgedrag; hierbij is temperatuur de meest belangrijke variabele, gevolgd door neerslag en wind. Fietsen is als transportmiddel het meest gevoelig voor weersomstandigheden. Hogere temperaturen leiden tot een verschuiving van het gebruik van de auto en het openbaar vervoer naar de fiets. De vraag naar openbaar vervoer neemt voor de meeste maar niet alle bestemmingen af als de temperatuur daalt. Hogere temperaturen, neerslag en sneeuw vormen een mogelijk risico voor verkeersveiligheid.

Deze dissertatie omvat uit drie delen. Deel I bestaat uit de Hoofdstukken 2, 3 en 4. Deze hoofdstukken richten zich vooral op de rol van het weer in de keuze van transportmiddel en bestemming. Deel II bestaat uit de Hoofdstukken 5 en 6. In dit deel wordt de relatie tussen weer en de reistijd van woon-werkverkeer geanalyseerd. Tenslotte wordt in Deel III (Hoofdstuk 7) het effect van weersomstandigheden op verkeersveiligheid onderzocht. Een samenvatting van de delen I, II en III wordt gegeven in Sectie 8.2, 8.3 en 8.4. Sectie 8.5 geeft vervolgens beleidsimplicaties weer voortkomend uit de resultaten van dit proefschrift. In Sectie 8.6 worden enkele suggesties gegeven voor toekomstig onderzoek.

Samenvatting Deel I

Deel I bestaat uit drie empirische studies, elk van deze drie studies is gebaseerd op enquêtes betreffende reisgedrag en weerrapportages van het KNMI over de jaren 1996 tot en met 2005. In Hoofdstuk 2 onderzoeken we de effecten van het weer op de keuze om naar het strand te gaan en de daarbij gekozen manier van reizen voor Nederlandse reizigers in de periode 1996 tot en met 2005. In dit hoofdstuk bestuderen we alle niet-zakelijke verplaatsingen in de zomerperiodes. We analyseren in een discreet keuze analyse model het gecombineerde effect van drie keuzes: de bestemmings-, afstands- en transportmiddelkeuze. In het model zijn ook de lokale en per uur gemeten weersomstandigheden opgenomen. De resultaten geven aan dat het weer een grote invloed heeft op de bestemmings- en transportmiddelkeuze. Wind en neerslag hebben een negatief effect op strandbezoek en hogere temperaturen bevorderen juist strandbezoek.

Hoofdstuk 3 bestudeert de invloed van het weer op de vraag naar verplaatsingen door te kijken naar de verschillende doelen per trip en de gebruikte transportmiddelen. In dit hoofdstuk maken we gebruik van de OVG/MON enquêtes van 1996 tot en met 2005. We definiëren gewogen gemiddelde weersomstandigheden per dag waarbij de uurlijks gemeten weersomstandigheden worden gewogen met het aantal tijdens dat specifieke uur. Twee maatstaven worden gebruikt om de individuele vraag naar verplaatsingen te meten: *dagelijks aantal verplaatsingen per persoon* en *dagelijks afgelegde afstand per persoon*. We schatten count modellen om het effect van verschillende weersomstandigheden op de vraag naar verplaatsingen te meten. We concluderen dat de vraag naar verplaatsingen niet sterk wordt beïnvloed door de weersomstandigheden. Harde wind, extreem hoge temperaturen en meer neerslag doet de vraag naar verplaatsingen afnemen.

We kijken ook naar de rol van het weer op de keuze tussen verschillende transportmiddelen om op de plaats van bestemming te komen. Het fietsgebruik is het meesrt gevoelig voor weersomstandigheden, gevolgd door openbaar vervoer. De resultaten geven aan dat er een sterke substitutie tussen transportmiddelen plaatsvindt bij extreme temperaturen. In het geval van extreem hoge temperaturen (hoger dan 25^{o} C) vermindert de totale vraag naar verplaatsingen met ongeveer 5 procent vergeleken met temperaturen tussen de 0^{o} C en 10^{o} C. De hoeveelheid verplaatsingen per openbaar vervoer, per auto of lopend daalt bij deze temperaturen respectievelijk met 20, 15 en 10 procent. Dit is in tegenstelling tot het gebruik van de fiets, dat stijgt bij extreem hoge temperaturen met ongeveer 22 procent. Met andere woorden, er treedt een verschuiving op in het gebruik van transportmiddelen bij extreem hoge temperaturen; van auto, openbaar vervoer en lopen naar fietsen. Op een vergelijkbare manier leidt neerslag tot een verschuiving van fietsen naar het openbaar vervoer en de auto. De resultaten laten verder zien dat de vraag naar recreatieve verplaatsingen het meest gevoelig is voor weersomstandigheden, gevolgd door de vraag naar verplaatsingen voor het bezoeken van familie en vrienden. De hoeveelheid woon-werk verplaatsingen wordt niet beïnvloed door weersomstandigheden.

De keuze van het transportmiddel is een belangrijke keuze binnen het individuele reisgedrag. Hoofdstuk 4 bestudeert het effect van weer op de keuze van het transportmiddel. We gebruiken wederom de OVG/MON enquêtes over de jaren 1996 tot en met 2005. We schatten verschillende multinomiale logit modellen voor elk reismotief en een gecombineerd model voor alle reismotieven samen. Het aantal verplaatsingen en de weersomstandigheden zijn gemeten per uur. Met behulp van de resultaten concluderen we dat de keuze van het transportmiddel sterk wordt beïnvloed door weersomstandigheden. De mate waarin het weer de keuze van het transportmiddel beinvloedt, hangt af van het doel van de verplaatsing. Harde wind verkleint de kans dat de fiets wordt gekozen en neerslag verkleint deze kans ook, maar vergroot de kans dat men de auto kiest. Met lagere temperaturen verkiest men de auto en het openbaar vervoer boven de fiets, en met hogere temperaturen kiest men eerder om te gaan fietsen of lopen. De mate waarin mensen schakelen tussen het gebruik van de fiets en de auto bij varierende temperaturen hangt af van het doel van de verplaatsing.

Bij het vergelijken van de resultaten uit Hoofdstuk 3 en Hoofdstuk 4 blijkt dat ondanks het gebruik van een verschillende methodologie voor de verschillende onderzoeksvragen, de resultaten uit beide hoofdstukken vergelijkbaar zijn.

Samenvatting Deel II

In Deel II wordt woon-werkverkeer geanalyseerd gegeven de afstand, en dus de snelheid. Hoofdstuk 5 gebruikt data over woon-werkverkeer uit 1996. We concentreren onze analyse op woon-werkverkeer vanwege twee specifieke redenen. Ten eerste, de vraag naar woon-werkverkeer wordt nauwelijks beïnvloed door weersomstandigheden (zie Deel I). Ten tweede, de meeste individuen maken twee woon-werkverkeer verplaatsingen per dag. Dit laatste stelt ons dus in staat om een paneldataset te construeren en via de bijbehorende methoden te controleren voor niet-geobserveerde heterogeniteit. De individuele fixed effects resultaten laten zien dat enkel sneeuw leidt tot een gereduceerde snelheid in de verplaatsing (rond 7 procent). Aangezien sneeuwval niet vaak voorkomt in Nederland is het welvaartsverlies beperkt. Een ander interessant resultaat is dat de reductie in snelheid in de ochtend- en avondspits op drukke routes ongeveer 7 procent is. Het bijbehorende welvaartsverlies veroorzaakt door de toename in reistijd is ongeveer €0.23 per woon-werk verplaatsing. Dit welvaartseffect wordt versterkt door neerslag. Neerslag heeft een sterk negatief effect op de gemiddelde snelheid, vooral in de avondspits op drukke routes. Het welvaartseffect van neerslag ligt tussen de 9 en 12 procent van de totale kosten van woon-werkverkeer en is geschat op minimaal €0.50 per woon-werkverkeer verplaatsing.

Hoofdstuk 6 analyseert verplaatsingen voor woon-werkverkeer middels het openbaar vervoer, gebruikmakend van dezelfde econometrische modellen als in hoofdstuk 5. De nadruk ligt in dit hoofdstuk op de rol van openbaar vervoer als schakel in de keten van een geïntegreerd vervoerssysteem. We gebruiken hiervoor de MON datasets voor de jaren 2004 en 2005; deze dataset verschaft informatie over de verplaatsingen voor woon-werkverkeer per bus tram, metro en trein. Uit de resultaten blijkt dat windkracht een klein maar significant effect heeft op de gemiddelde snelheid van bus, tram en metro per verplaatsing. Sneeuw heeft een substantieel negatief effect op de gemiddelde snelheid van al het openbaar vervoer. Het welvaartsverlies van sneeuwval bedraagt €0.53 voor een woon-werk verplaatsing per trein en

€0.76 voor een woon-werk verplaatsing per bus, tram en/of metro. Neerslag heeft een sterk negatief effect op de gemiddelde snelheid van woon-werk verplaatsing per bus op drukke routes. Dit resulteert in een welvaartsverlies van €1.15 per woon-werk verplaatsing.

Samenvatting Deel III

Deel III van deze dissertatie bestaat uit een hoofdstuk waarin verkeersveiligheid centraal staat. In dit hoofdstuk analyseren we het effect van weer op het aantal verkeersongelukken per uur. Hiervoor maken we gebruik van BRON datasets voor de jaren 2000 tot en met 2009. We maken onderscheid tussen verkeersongelukken met fatale afloop, verkeersongelukken met immateriële schade en verkeersongelukken met enkel materiële schade. Middels het schatten van negatief binomiale en Poisson modellen kunnen we de effecten van weer op deze verschillende soorten verkeersongelukken schatten.

Onze resultaten zijn consistent met de in de bestaande literatuur gerapporteerde resultaten. Verkeersongelukken met lichamelijk letstel en of een dodelijke afloop nemen toe naarmate de temperatuur stijgt, terwijl de verkeersongelukken met materiële schade toenemen als de temperatuur daalt. We hebben een gelijksoortig patroon gevonden voor sneeuwval; ondanks dat het aantal totale ongelukken (vooral met materiële schade) toeneemt, neemt het aantal ernstige ongelukken af.

Beleidsrelevantie

De belangrijkste bijdrage van dit proefschrift is het kwantificeren van weerseffecten op reizigers. Deze dissertatie bevestigt dat het weer sterke verschuivingen in de keuze tussen vervoersmiddelen veroorzaakt, althans voor Nederlandse reizigers. Men verkiest de auto en het openbaar vervoer boven de fiets tijdens extreem koud weer en als het regent (zie Hoofdstuk 4). Dit heeft praktische gevolgen voor het openbaar-vervoerbeleid en toekomstige investeringen; aangezien de vraag naar openbaar vervoer toeneemt bij extreem koud weer zou de capaciteit van het openbaar vervoer moeten worden aangepast om deze extra vraag te accommoderen. Naast het reeds bestaande probleem van het operationeel houden van openbaar vervoer tijdens sneeuwval, voornamelijk het verkeer per spoor waarvoor Prorail en de NS verantwoordelijk zijn, wijzen onze resultaten op de te accommoderen extra vraag. Het is echter belangrijk om bij het accommoderen van deze extra vraag de effecten voor de welvaart te bestuderen, oftewel een kosten-baten analyse uit te voeren. Het hier gepresenteerde onderzoek kijkt enkel naar de vraagzijde, zonder de kosten voor de accommodatie van deze extra vraag te kwantificeren.

Ten tweede, een verschuiving in het gebruik van transportmiddelen doet zich ook voor bij hogere temperaturen. Dit heeft gevolgen voor korte- en lange termijn transport gerelateerde investeringen en verkeersmanagement. Op de korte termijn, gedurende de zomerperiode, zal er minder vraag zijn naar openbaar vervoer. Voor sommige bestemmingen kan een extra vraag naar transport worden verwacht, zoals bijvoorbeeld stranden (zie Hoofdstuk 2).

Op de lange termijn moet transport beleid gericht zijn op het accommoderen van de effecten van de klimaatsverandering. Onze resultaten laten zien dat Nederlandse reizigers nauwelijks hinder ondervinden van hogere temperaturen omdat de preferentie voor fietsen ook nog bestaat bij temperaturen hoger dan 25^{o} C (zie Hoofdstuk 4). Dit houdt in dat er geen veranderingen in de investeringen aan fietsinfrastructuur noodzakelijk zijn op de korte- en lange termijn om de gevolgen van een mogelijke klimaatsverandering te accommoderen. Er kunnen grenswaarden zijn waarbij fietsers overstappen naar andere transportmiddelen. Dit is echter niet zeer waarschijnlijk op de korte- en lange termijn.

Ook presenteert dit proefschrift enkele methodologische verbeteringen. Zo is bijvoorbeeld in Hoofdstuk 2 een logit model geschat waarbij rekening wordt gehouden met drie individuele keuzes: bestemmings-, transportmiddel-, en afstandskeuze. Afstand is in eerste instantie als de gewogen gemiddelde afstand de gemeente naar alle stranden meegenomen, en vervolgens als een exogene variabele. Deel II presenteert ook een methodologische verbetering middels het schatten van panel modellen met constante individuele storingstermen om te controleren voor niet-geobserveerde heterogeniteit in het effect van weer op de individuele woon-werkverkeer verplaatsingen.

We geven ook enkele beleidsaanbevelingen betreffende verkeersveiligheid onder verschillende weeromstandigheden. Zoals wordt beschreven in Hoofdstuk 7, is er een positief verband tussen de mate van (immateriële en materiële) schade veroorzaakt door ongelukken en de temperatuur en een negatief verband met sneeuwval. Gegeven dat het aandeel van fietsers en wandelaars hoog is bij hogere temperaturen, moet beleid zich richten op veiligheidsmaatregelen om niet-gemotoriseerd verkeer, voornamelijk in de zomer, beter te beschermen. Het totaal aantal verkeersongelukken stijgt tijdens periodes met sneeuw, de mate van schade neemt dan echter af. Dit komt voornamelijk door het gereduceerde aantal fietsers tijdens periodes met sneeuw, zoals aangetoond in Hoofdstuk 3. Dit versterkt de aanbeveling voor verdere maatregelen om fietsers te beschermen. Er kan bijvoorbeeld worden gedacht aan het verplicht stellen van beschermende kleding tijdens het fietsen, een verbod op mobiel bellen op de fiets in te voeren en het verder ontvlechten van infrastructuur voor gemotoriseerd en niet-gemotoriseerd verkeer.

Onderzoeksagenda

Dit proefschrift richt zich op het kwantificeren van het effect van weer op individueel reisgedrag. In deze dissertatie is dit effect op verschillende aspecten van reisgedrag van

Nederlandse reizigers geanalyseerd. Echter, vele aspecten van dit reisgedrag moeten nog worden onderzocht, zowel als uitbreiding op de analyses van deze dissertatie en als nieuwe onderzoeksrichtingen.

Ten eerste, de resultaten kunnen worden gebruikt om de effecten van klimaatsveranderingen op Nederlandse reizigers te analyseren. In dit opzicht kan deze dissertatie een basis vormen voor meer geavanceerde studies. We hebben hier aangetoond hoe het weer de vraag naar verplaatsingen en de keuze van bestemming en transportmiddel beïnvloedt. De gerapporteerde resultaten kunnen worden gebruikt als input voor klimaatscenario's om zo een toekomstbeeld te verkrijgen van het reisgedrag in Nederland. Aan de hand van deze toekomstbeelden kan transportbeleid worden aangepast aan mogelijke toekomstige klimaatsveranderingen.

Verder kunnen de resultaten uit dit proefschrift worden gebruikt als een basis voor een studie naar weersgerelateerde verkeersmeldingen (mogelijk in de vorm van waarschuwingen) voor reizigers en openbaar vervoer bedrijven. Zo kan bijvoorbeeld de NS worden geïnformeerd over een verwachte stijging in het aantal passagiers tijdens periodes met kou en een stijging van het aantal passagiers richting de stranden tijdens warm weer. Op een vergelijkbare wijze kunnen weggebruikers worden gewaarschuwd voor de onveiligheid op de weg tijdens verschillende weersomstandigheden.

Ten derde kan het onderzoek naar verkeersveiligheid worden verbeterd. Op dit moment is dit onderzoek gebaseerd op de meting van het aantal ongelukken per uur. Dit heeft als voordeel dat we alle ongelukken waarnemen onder verschillende weersomstandigheden. We kunnen echter niets zeggen over de specifieke omstandigheden van een individueel ongeluk. Een mogelijk vervolgonderzoek zou zich kunnen richten op data van individuele ongelukken in plaats van een per uur geaggregeerd totaal aantal ongelukken.

Tenslotte kan er een verbetering tot stand komen in het onderzoek naar verkeersveiligheid door gebruik van verbeterde metingen van weersomstandigheden. Het onderzoek in dit proefschrift is gebaseerd op lokale weersomstandigheden. Een verdere verfijning in deze data, met name de gegevens over neerslag, zal de analyses verbeteren. Een mogelijke manier om deze verfijning te realiseren is het gebruik van radargegevens voor het meten van neerslag. Deze data wordt door het KNMI verzameld op een schaal van twee vierkante kilometer. Deze data geven niet alleen preciezer ruimtelijk beeld van weersomstandigheden, maar leveren ook een veel betere regionale anlyse van de verkeersveiligheid op.