Mobility measures to influence exchangeability of bicycle and car commutes

A case study at MST, Enschede

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August, 2020

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Preface

While writing this thesis I have learnt a lot. Among others, setting up a survey, which was harder than I expected, that the political sensitivity of mobility measures as increasing parking cost make research even more challenging and many other things.

I am delighted that I have been able to contribute to research for MST to try and persuade (occasional) car commuters towards commuting by bike and learning more on the variables that influence that transition.

I would like to thank dr. Tom Thomas and prof. dr. ing. Karst Geurs for their support and feedback during my thesis. I appreciate the valuable discussions, particularly during the set-up of the survey and towards the tough end of this research.

The discussions helped me to improve the survey set-up, which was the most challenging part of the research for me. Special thanks to Fons Overkamp and Drs. Herman Krabbenbos of MST for the opportunity to do my thesis research at MST, for the discussions we had throughout the research and the pleasant cooperation.

Vincent van Oversteeg

Abstract

In literature, not much knowledge is available about parking problems and persuading specific groups of employees away from car commuting from an employer perspective. Despite the consensus, being policymakers must tailor their policies to be valuable and productive. Therefore, this cross-sectional study aims at contributing knowledge to the effect of employees mobility measures on the exchangeability of car and bike commutes for specific populations in order to be able to implement effective policies to guide our mobility towards a more sustainable one. In order to do so, this study answered the following research question:

How can mobility measures influence the exchangeability of car and bike commutes at the MST, Enschede?

At the MST, a hospital in Enschede, parking problems were present for employees. Analysis of parking and bicycle commute data, both temporal and spatial, showed that employees switched their commuting mode from active in the summer towards car commuting in the winter. It also confirmed that parking problems only occurred during active hours for office personnel and healthcare staff on weekdays.

To persuade employees towards commuting by bike, MST tested a carrot-and-stick approach through stated choice experiments in cross-sectional a survey. The attributes were: increasing the parking cost and making the parking cost distance-dependent during peak hours (entering the parking garage Monday to Friday 6:00-14:00), increasing bicycle subsidy and decreasing parking cost outside peak hours. Parking problems not being present outside peak hours led to the latter attribute, also to accommodate employees working night shifts.

Cross-sectional mixed logit models estimated the stated choice experiments in order to research their different opinions. Among others, car users were more sensitive to an increase of initial parking cost, whereas non-car users were more sensitive to an increase in bicycle subsidy. As expected employees living < from MST were more prone to increased bicycle subsidy, whereas employees >20km away find the increase in initial parking cost most important. Most passenger groups were indeed maximising their utility and chose the package of measures most convenient to them.

Analyses of the discrete choice experiments found that increasing parking cost was exper-

ienced more negatively by car users, trip chains, live more than 20km away, mode choice variation, and lower-income employees. An increase of distance-dependent parking cost was disliked more by employees living close to MST, employees with the lowest incomes and employees with intrapersonal mode choice variation. Increased bicycle subsidy was preferred more by non-car users and employees living close. Decreasing outside peak parking cost is preferred by employees without set departure times, living far away, single commute mode users and employees with lower incomes.

The effects were small, but the introduction of distance-dependent parking cost decreased the number of car commutes. Combined with increasing the bicycle subsidy, a decent acceptance and effect of the packages were achieved. Therefore, it is recommended to implement a distance-dependent parking cost in combination with an increase in bicycle subsidy.

Management Summary

The parking places of MST are insufficient for their employees despite measures that are already in place. Therefore, this research aims to both alleviate the pressure on the parking places of MST and tackle the high parking costs for MST. To do so, it investigates the temporal and spatial dimensions of the exchangeability of the car and bike as a commute mode. To understand which employees are persuadable through mobility measures to sustainable transport modes, besides the employees who already commute by sustainable transport modes at the hand of policies and projects of MST.

In literature, not much knowledge is available about parking problems and persuading specific groups of employees away from car commuting from an employer perspective. Despite the consensus, being policymakers must tailor their policies to be valuable and productive. Therefore, this cross-sectional study aims at contributing knowledge to the effect of employees mobility measures on the exchangeability of car and bike commutes for specific populations in order to be able to implement effective policies to guide our mobility towards a more sustainable one. In order to do so, this study answered the following research question:

How can mobility measures influence the exchangeability of car and bike commutes at the MST, Enschede?

In order to answer the research question, a conceptual model was derived, see Figure 1. The model starts with a mobility goal, in this case, influencing the exchangeability of commuters towards commuting by bike. To persuade employees towards commuting by bike, MST tested a carrot-and-stick approach through stated choice experiments in cross-sectional a survey. The mobility measures elected for this research to accomplish that goal are an increase in parking cost and distance-dependent parking cost during peak hours, decreasing the parking cost outside peak hours en increasing the distance-dependent bicycle subsidy.

The mobility measures are a product of the mode choice of employees and its variables since measures are tailored to a specific population. The mobility measures adjust some variables of the mode choice process and based on the altered variables, the deliberation phase starts. In the deliberation phase variables that influence mode choice, but are not influenced by mobility measures, play a role. The result of the deliberation phase is the

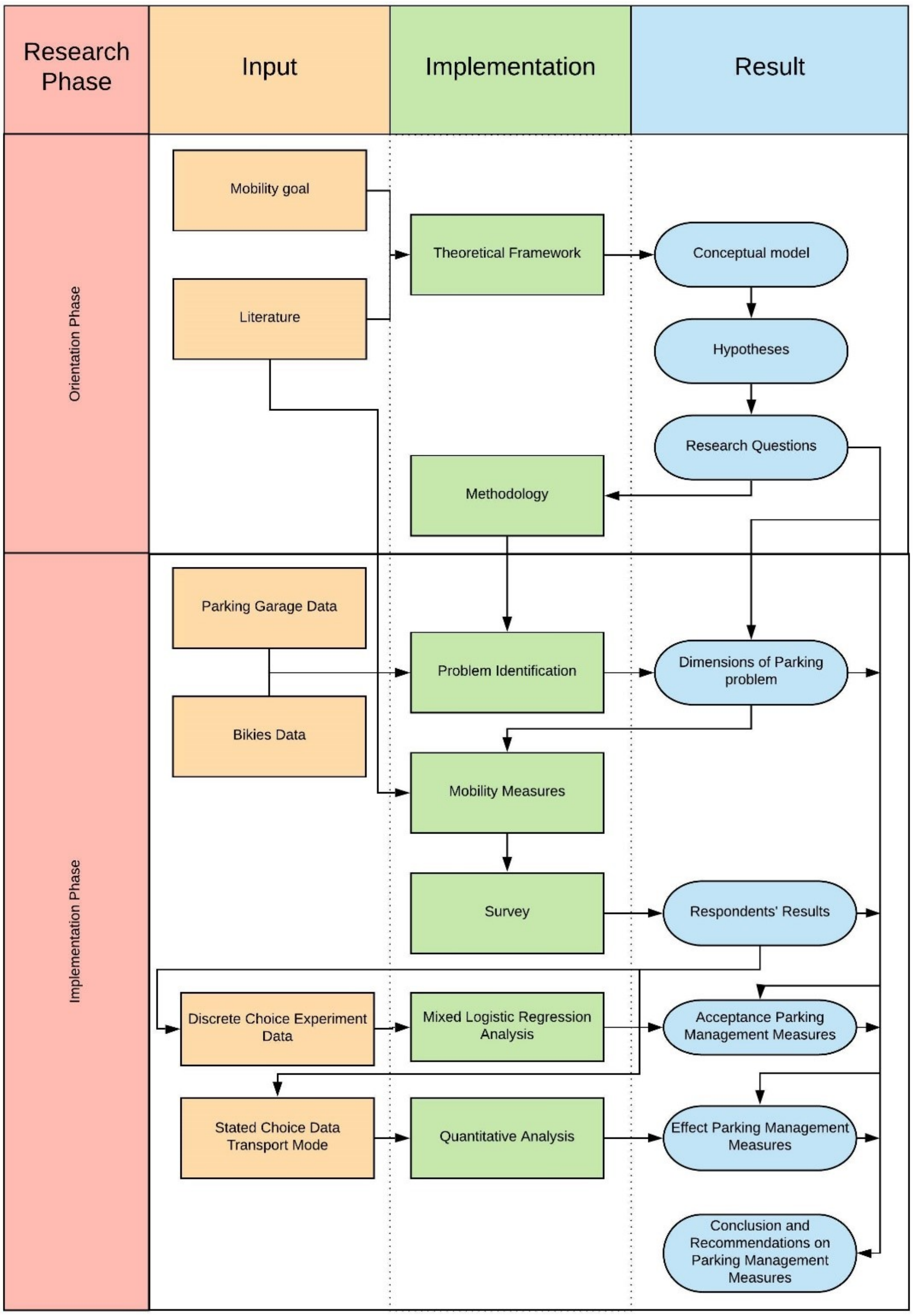


Figure 1: Research approach

changed or same commuting behaviour. The deliberation phase is an essential part of this research, as it represents the trade-off between acceptance and effect. As everyone accepts measures that do not harm them, but those measures will generally also be less effective.

First, the temporal and spatial dimensions of the exchangeability of car and bike commuters are investigated. The temporal analyses showed that employees switched their commuting mode from active in the summer towards car commuting in the winter, see Figure 2. It also confirmed that parking problems only occurred during active hours for office personnel and healthcare staff on weekdays.

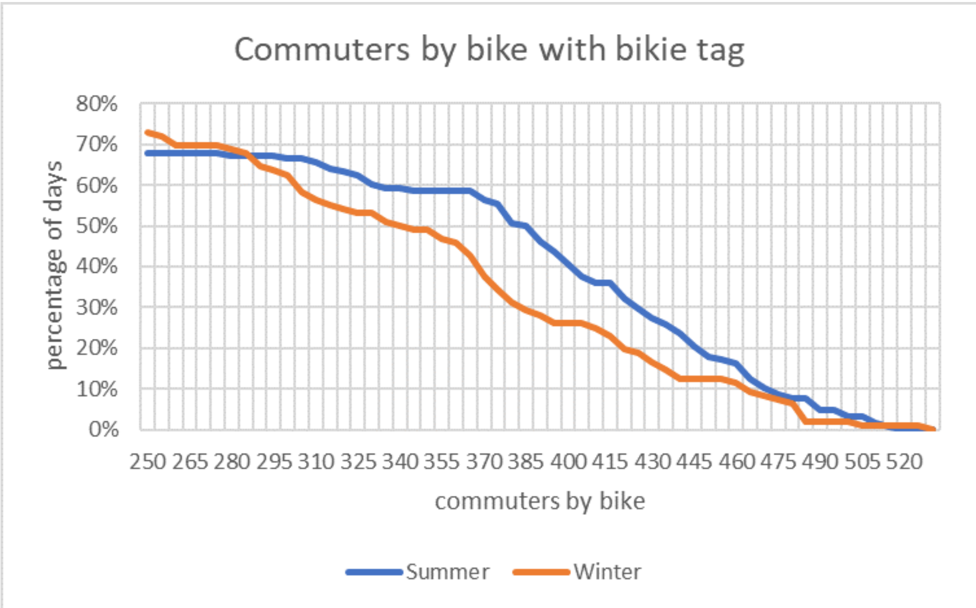


Figure 2: Cumulative distribution for the number of bicycle commuters

The spatial analysis confirmed employees switch from commuting by bike in the summer towards commuting by car in the winter. The amount of bikies commuters is approximately half to one-third of the total amount of car commuters since not all employees have a bikie tag and park their bike in the parking garage. Figure 3 confirms the exchangeability of transport modes.

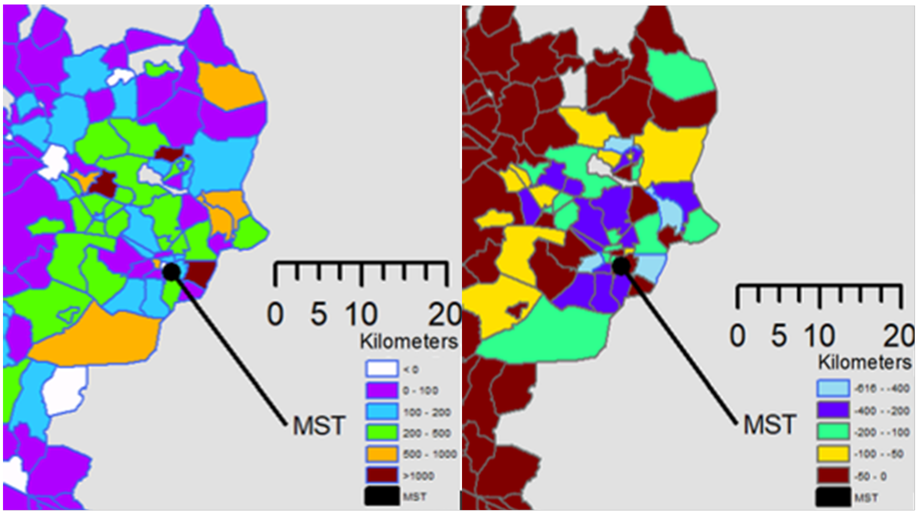


Figure 3: Resulting number of commutes (winter-summer) for the car (left) and bike (right)

The acceptance was estimated through cross-sectional mixed logit models for attributes, see Figure 4, from the stated choice experiments regarding mobility measures. Among others, car users were more sensitive to an increase of initial parking cost, whereas non-car users were more sensitive to an increase in bicycle subsidy. As expected employees living $<$ from MST were more prone to increased bicycle subsidy, whereas employees >20km away find the increase in initial parking cost most important. Most passenger groups were indeed maximising their utility and chose the package of measures most convenient to them.

Table 1 all attributes set to 0's for the choice experiment

Woon-werkafstand	**Parkeertarieven (ma-vrij 6:00-14:00)**	**Fietsersbeloning (altijd)**
<4km	€ 1,75	5 Bikies (ter waarde van € 0,20)
4-9km	€ 1,50	10 Bikies (ter waarde van € 0,40)
9-15km	€ 1,25	15 Bikies (ter waarde van € 0,60)
>15km	€ 1,-	20 Bikies (ter waarde van € 0,80)
Woon-werkafstand	**Parkeertarief buiten de spitsuren**	
Alle	€ 0,75	

Table 2 all attributes set to 1's for the choice experiment

Woon-werkafstand	**Parkeertarieven (ma-vrij 6:00-14:00)**	**Fietsersbeloning (altijd)**
<4km	€ 2,75	10 Bikies (ter waarde van € 0,40)
4-9km	€ 2,25	20 Bikies (ter waarde van € 0,80)
9-15km	€ 1,75	30 Bikies (ter waarde van € 1,20)
>15km	€ 1,25	40 Bikies (ter waarde van € 1,60)
Woon-werkafstand	**Parkeertarief buiten de spitsuren**	
Alle	€ 1,-	

Figure 4: Attributes for the stated choice experiments

Analyses of the discrete choice experiments found that increasing parking cost was experienced more negatively by car users, trip chains, live more than 20km away, mode choice variation, and lower-income employees. An increase of distance-dependent parking cost was disliked more by employees living close to MST, employees with the lowest incomes and employees with intrapersonal mode choice variation. Increased bicycle subsidy was preferred more by non-car users and employees living close. Decreasing outside peak parking cost is preferred by employees without set departure times, living far away, single commute mode users and employees with lower incomes.

The analyses of effects was performed through plotting the utility with the effect, see Figure 5. The most significant decreases occur for commuters with intrapersonal mode choice. Also, car users, single-car, 30-50k, and 4-9km employees decrease car use. Package G and C have the most significant effects, followed by H. Furthermore, has the lowest income category low utility (<-1.5) for all four elected packages. The trade-off between C and G, more precise, between a distance-dependent parking cost increase of €0,50 or €0,25 is only more productive and employees who trip chain, whereas for car commuters it is the other way around. The effects were small, but the introduction of distance-dependent parking cost decreased the number of car commutes. Combined with increasing the bicycle subsidy, a decent acceptance and effect of the packages were achieved. Therefore, it is recommended to implement a distance-dependent parking cost in combination with an increase in bicycle subsidy.

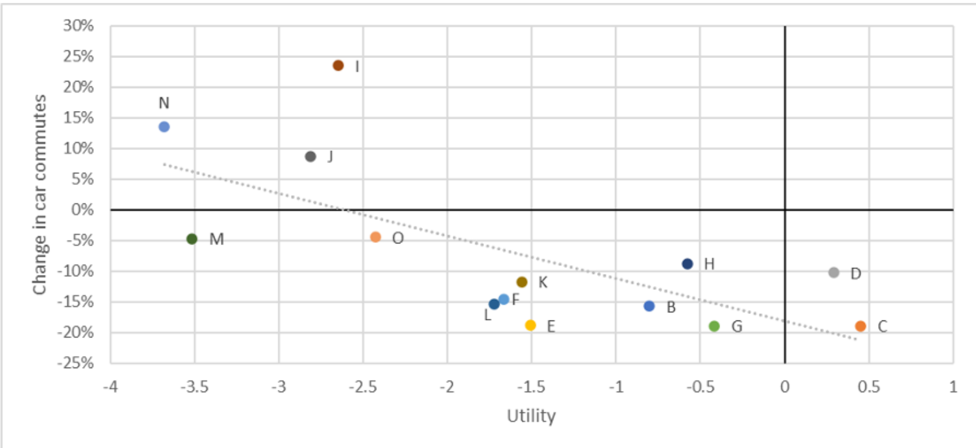


Figure 5: Overview of the utility vs effect

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Problem statement

Car commuting has many negative impacts upon society and the environment, among others road casualties, depletion of energy, noise and air pollution, congestion or daily delays, and extensive land use for the road network and parking facilities (Bergström & Magnusson, 2003; Habibian & Kermanshah, 2013). Still, car ownership is growing, while urban space becomes scarcer (Mingardo, van Wee & Rye, 2015). Therefore, parking gained importance in urban planning. Recently, in mobility management, the conventional supply-management approach is being replaced with a parking management approach (Mingardo et al., 2015). That means that instead of providing enough asphalt for parking places, other aspects are gaining attention: management of the price, supply, duration and location of parking to enhance the urban environment (Young & Miles, 2015). For example, paid street parking for non-residents.

It stimulates people to use their car when they are guaranteed a (free) parking place at work (de Vasconcellos, 2005; Fallon, Sullivan & Hensher, 2006; Kenworthy & Laube, 1996; Ye, Pendyala & Gottardi, 2007). Therefore, parking fees can potentially have a substantial effect on the commuting mode choice (Christiansen, 2015). Nonetheless, employee-paid parking is rare, except for one industry: hospitals (de Groote et al., 2019). Therefore, little research regarding paid workplace parking and a lack of knowledge about the acceptance of parking fees exists (de Groote et al., 2019).

Paid parking is not the only concept to move employees away from commuting by car. Other ways of persuading employees away from commuting by car are pushing for alternatives. Promoting walking, cycling and using public transport is also researched, but often in a piecemeal way. The literature strongly advises coordinating measures to be mutually reinforced (Antonson, Hrelja & Henriksson, 2017; Fioreze, Thomas, Huang & van Berkum, 2019; Pitsiava–Latinopoulou, Basbas, Papoutsis & Sdoukopoulos, 2012; Young & Miles,

Figure 1.1: Location of the MST in Enschede

2015).

At MST, a hospital in the city centre of Enschede, the capacity of the employee-paid parking is insufficient. Therefore, this research focusses on reducing the number of employees commuting by and parking their car through mobility measures. The location of the hospital, illustrated in Figure 1, is both an advantage and a disadvantage. On the one hand, the hospital is well accessible through walking, cycling, public transport, or a combination of these three for many people living in (the suburbs of) Enschede. On the other hand, new parking places are not available nearby and relocating is costly.

At MST, many initiatives regarding mobility management to reduce parking problems are already in place. However, no effects or participants of mobility programs are known. Increasing the supply has been attempted, as the in-house availability is insufficient during the winter, through renting parking places from the municipality — subsequently, the costs for the MST rise. Since the budget of a hospital is not destined to supply a parking spot, but to deliver health care, the hospital has to decrease these costs. Therefore, this research answers the following question:

How can mobility measures influence the exchangeability of car and bike commutes at the MST, Enschede?

Carpooling, promoting (e-)bicycles, public transport arrangements are a few of the other initiatives MST has. Despite the success of some initiatives, the result is not yet sufficient. However, already a, 80% share of commuters by bike exists, according to (Fioreze et al., 2019), complemented with 18% car commuters and 2% other. They also stated that it might be lower as they might not have attracted a representative subset. These measures are not synergised but implemented in a piecemeal way without an overview. For instance, many employees already carpool and commute by bike; however, the potential just as the exact number of employees carpooling is unknown due to unclear administration. Measures become truly valuable and useful if integrated into a transport development plan aiming to achieve the long-term targets of sustainable mobility (Pitsiava–Latinopoulou et al., 2012).

Potentially, both the parking pressure can be alleviated, and the new policies could assist in sustainability and vitality goals of MST.

In summary, the parking places of the MST are insufficient for their employees despite measures that are already in place. Therefore, this research aims to both alleviate the pressure on the parking places of MST and tackle the high parking costs for MST. To do so, it investigates the temporal and spatial dimensions of the exchangeability of the car and bike as a commute mode. To understand which employees can are persuadable through mobility measures to sustainable transport modes, besides the employees who already commute by sustainable transport modes at the hand of policies and projects of MST. However, not only the effects but this research also considers the acceptance of these measures for different transport groups (i.e. car user vs non-car user). This research will contribute knowledge to the acceptance and effect of mobility measures on specific populations to add knowledge on the substitutability of the car and bike for commutes, in order to be able to implement effective policies resulting in practical recommendations for the MST.

1.2 Reading guide

In section 2, a conceptual model is developed with influencing factors on the exchangeability of car and bike commutes using relevant literature from longitudinal studies investigating mode choice change and the mode choice process. Based on the conceptual model, hypotheses were derived followed by research questions in chapter 3 on both the temporal and spatial variance, and acceptance and effect of mobility measures.The Methodology, section 4, describes the path of this research starting with the approach. The set-up of the survey is elaborated and both the stated choice experiments and its analysis methods (Mixed are described. Section 6 describes the variation in parking demand due to seasonal variation and work hours and section 7 dives into the spatial exchangeability of car and bike commutes. After that the cross-sectional acceptance of mobility measures is modelled through mixed logit models in chapter 8. The effect of the mobility measures is described in the section after that with diagrams showing the utility and effects. This study then concludes in chapter 10, before it discusses the results, recommendations and limitations of this research in the final chapter.

Chapter 2

Theoretical Framework

This part establishes a framework regarding the interchangeability of commuting by car and bike. To the author's knowledge, no such framework for the change of mode choice exists. Therefore, the first part explains the mobility measures implemented to persuade away from car commuting found in hospital policies and literature. After that, it is investigated which variables influence mobility measures to try to influence. Furthermore, which variables, combined with the mode choice literature, can influence mode choice change is looked into. Based on those findings, the part after that elaborates determinants that influence the change of the commuting mode and drafts the conceptual model used for this research.

2.1 Mobility management

Mobility management may affect travel frequency, mode of transportation, trip destination, or travel time, and a rather comprehensive set of measures have been emerged so far (Litman, 2003). These measures can be encouraging or discouraging different transport modes, called push and pull policies (Steg & Vlek, 1997). For instance, pull policies encourage the use of non-car modes by making them attractive to car users. Push policies intend to push users towards another mode than car usage by making the car less attractive.

Habibian and Kermanshah (2013) investigated two pull policies: transit time reduction, and transit access improvement; and three push policies for commuters in the city of Teheran: increasing parking cost, increasing fuel cost, and cordon pricing. They concluded that push policies play a leading role in the mode choice process, while pull policies only slightly affect mode change decisions. Consequently, Habibian and Kermanshah (2013) argue that policymakers should focus mainly on push policies to change peoples' travel behaviour, though, they must be aware of the constraints their (car driving) population faces. However, implementing measures to promote the use of alternative modes, e.g. public transport or cycling, without complementary measures to deter car use might not have the desired effect on traffic growth and congestion(Fallon et al., 2006).

Most mobility management measures to reduce car use focus on car-parking policies, since almost all car trips start and end on a parking place (Christiansen, Engebretsen, Fearnley & Usterud Hanssen, 2017). For instance, the probability of commuting by car decreases with an increasing distance between the home parking place and home (Christiansen et al., 2017). Most studies, however, addressed how parking at the destination influences (commuting) mode choice. Christiansen (2015), showed that a moderate parking fee for employees of the Norwegian Public Roads Administration in Oslo already led to a significant reduction in car use for work trips. Employees became even more positive towards parking charges once implemented, since employees were able to arrive later and still park their car (Christiansen, 2015).

Different types of organisations use mobility management for different reasons. For example, municipalities implement P+R terrains to reduce congestion in the inner city (Hounsell, Shrestha & Piao, 2011). As parking is significant in influencing transport mode, the facilities offered by the employer play a significant part in the commuting mode choice. Heinen et al. (2010) state that the availability of facilities related to the car, for example (free) parking options, are negatively related to cycling, whereas facilities beneficial for cyclings, such as lockers or showers, are positively correlated to commuting by bike (Ton, Duives, Cats, Hoogendoorn-Lanser & Hoogendoorn, 2019). For this research, emphasis lays on mobility measures for companies and the next part analyses these more in-depth.

2.1.1 Employers mobility management measures

This part discusses mobility management measures from the perspective of a company more in-depth. First, two pull policies towards bike commuting and, second, different push policies focused around parking.

Encourage bike commuting
Erasmus medical centre, Rotterdam, struggled with parking problems, but also the public transport lines were overcrowded (Adviesdienst Verkeer en Vervoer, 2004). The hospital drafted a mobility management plan and implemented the following measures to increase bike commuting:

- Improving the changing rooms and shower facilities
- Secured bicycle parking
- Improved lighting in the bicycle parking
- Unobstructed sight at the bicycle parking
- Bicycle repair shop at the hospital for small maintenance and rental bikes

No data is available on the effects of the measures from the hospital itself, but literature has already investigated some measures. Ton et al. (2019) conclude that the availability of lockers, showers or changing rooms is essential for bicycle commuters. However, the presence of such facilities does not always have a significant effect and does not seem to result in higher frequencies of bike commuters (Stinson & Bhat, 2004). Moreover, people prefer safe bicycle parking over showers and lockers (Hunt & Abraham, 2007; Dickinson, Kingham, Copsey & Pearlman, 2003), and cyclists consider safe bicycle parking necessary (Abraham, McMillany, Brownlee & Hunt, 2002; Hunt & Abraham, 2007; Stinson & Bhat, 2004; Dickinson et al., 2003). That is even more true for younger people and individuals with expensive bicycles (Hunt & Abraham, 2007; Dickinson et al., 2003). The effect of improved lighting, unobstructed sight, and a bicycle repair shop is unknown.

Subsidising bike commuting
A bicycle subsidy increases the relative price of commuting by any other mode. Subsidising commuting by bike might also help to alleviate the pressure on parking places, despite the overall thought that push policies are more effective than pull policies (Habibian & Kermanshah, 2013). Ding, Cao, and Wang (2018) argue the contrary, namely that transit/vanpooling subsidies are more effective than limiting free parking. For instance, employees are more likely to use public transport when their company provides (or partially reimburse) transit passes (De Witte et al., 2013). Maastricht hospital implemented bicycle subsidies dependent on the commuting distance between early October and the end of March, see (the column on the right) Table 2.1 for the bicycle subsidy. The bicycle subsidy decreased parking demand. However, the effect was small and only present for employees with small commuting distances (Grotenhuis, Wiegmans & Rietveld, 2007; de Groote et al., 2019) conclude that generally, parking demand is higher during the winter, but with the bicycle subsidy, parking demand was steady. The authors do not mention any numbers on the bicycle subsidy. Wardman, Tight, and Page (2007) discovered that rewarding cyclists would increase the number of bike commuters and decrease the number of car users. However, these effects were in Great Britain, with cyclists share of only 6% in the analysed data.

Table 2.1: Parking tariffs (de Groote, van Ommeren, & Koster (2019))

Parking tariffs (Monday to Thursday).

	Old regime	New regime			
Commuting distance	All hours	Non-peak hours	Peak hours	Subscription	Bicycle subsidy
<2 km	€ 0,75	€ 0,75	€ 3,00	€ 5,00	€ 0,50
2-5 km	€ 0,75	€ 0,75	€ 2,00	€ 3,00	€ 0,75
5-7 km	€ 0,75	€ 0,75	€ 1,50	€ 2,00	€ 1,00
>7 km	€ 0,75	€ 0,75	€ 1,00	€ 1,00	€ 1,00
Weighted average tariff	€ 0,75	€ 0,75	€ 1,31	€ 1,61	€ 0,94

Park and Ride (P+R)

P+R is widely implemented in the UK as a form of 'access control', especially in historic towns and cities with limited road and parking space in the centre (Hounsell et al., 2011). Access control means that a measure focuses on reducing traffic, on decreasing congestion or pollution in, most often, central areas. However, hospitals use this measure to increase parking capacity, but no data on the acceptance or effect is known.

Academical Hospital Rotterdam is looking to increase the parking capacity outside their current parking possibilities through a P+R facility. Their parking capacity is insufficient, and they chose to increase the parking capacity through a P+R facility with a public transport line towards the hospital. The academic hospital in Groningen uses two P+R facilities (Adviesdienst Verkeer en Vervoer, 2004). One is only available for employees living further away than 10km, and the other is accessible for all employees. Upon presentation of the employee badge, the bus towards the hospital is free of charge.

Hounsell et al. (2011) analysed a P+R with one busy street and express buses to the city centre, to cut travel time and congestion on the road towards the city centre. Precisely what "P+R Zuiderval" could provide to the MST. From "P+R Zuiderval" an unimpeded bus journey is facilitated towards one of the entrances of the MST, which could make it more attractive than commuting the last part by car in congestion. One of the remarks of the research is that a P+R might not be successful if there are ample and affordable car parking spaces available in the city centre. Hounsell et al. (2011) suggest to restrict city parking or increase their costs to discourage people from driving to that city and encourage the use of the P+R. He also concludes to include park and ride in a consistent policy framework with complementary measures.

Pricing workplace parking

Employers often provide employees with subsidised or free parking at work. That distorts relative prices of alternative commuting modes and produces inefficiencies in the transport market (Evangelinos, Tscharaktschiew, Marcucci & Gatta, 2018). In an attempt to make commuters aware of the real cost of employer-provided parking space, the literature suggests pricing workplace parking, as a potentially effective policy. Empirical findings show that when firms introduced parking fees ($4.15) in downtown Los Angeles, this induces a 25% decrease of car use towards other transport modes, compared to free parking (Wilson, 1992). In the Netherlands, an increase in parking cost with 10% decreases commuting by car with 3% (en Vervoer, 2005).

Congestion pricing has usually proven to be more effective since it is better at affecting the time aspect of travel behaviour (Evangelinos et al., 2018). Nevertheless, parking charges seem superior to congestion pricing when it comes to acceptance. The reason seems to be that bigger (inner) cities charge parking for a long time (Evangelinos et al., 2018). Additionally, increasing parking costs is not only a fundamental variable for reducing travelling demand by private car, but also to finance more sustainable alternatives (Dell'Olio et al., 2019).

Workplace parking cash-out
Recently, also parking cash-out has been suggested as an effective and efficient policy to reduce (single occupancy) car commuting trips. Results in Dresden, Germany, indicated that parking cash-out has a significant negative effect on private car as a commuting choice (Evangelinos et al., 2018). Rewarding the abandonment of using a parking spot, rather than penalising continued parking has several advantages, of which the most important is probably making commuters sensitive to the opportunity cost of workplace parking (Evangelinos et al., 2018).

Commuting-distance dependent priced workplace parking (and subsidising commuting by bike)
Both congestion- and workplace pricing are longstanding measures to decrease the pressure on parking places. In the research of De Groote, van Ommeren, and Koster (2019), they tested distance-dependent congestion parking tariffs during peak hours (6:00-14:00 on Monday till Thursday). The parking costs increased, depending on the commuting distance, from €0,75 to €1 - €3 per hour. Additionally, monthly subscription costs were introduced in the parking garage but, only if employees parked their car in the parking garage during that month. For the complete parking tariffs and bicycle subsidy scheme, see Table 2.1. The new parking tariff reduced parking demand by 5 per cent, and the subscription fee an additional 2 per cent (de Groote et al., 2019). Moreover, the subscription fee reduced parking, especially on days with bad weather, when parking demand is usually higher (de Groote et al., 2019).

2.2 Mobility measures and mode choice indicators

Consensus exists in the literature on tailoring mobility measures to the specific population (Antonson et al., 2017; Fioreze et al., 2019; Pitsiava–Latinopoulou et al., 2012; Young & Miles, 2015) Most mobility measures adjust variables that influence the mode choice; for instance, parking management influences travel cost and car ownership (Guo, 2013).

Although most measures adjust some variables, limited cross-sectional mode choice studies are available. Studies often report the effects of the whole population, whereas it is crucial to know if the policy works as intended. Additionally, less knowledge exists on variables that do play a role, but what can not be adjusted by policies — for example, commuting distance or weather conditions. For example, Fioreze, Thomas, Huang, and Van Berkum (2019) found that avid car users are reluctant to engage with positive incentives to cycle to work. Alternatively, Peng, Dueker, and Strathman (1996) showed that parking charges had a different impact depending on public transport services from their residential location.

The next section briefly describes the mode choice before highlighting indicators included in the research to see if they influence the effect and acceptance.

2.2.1 Mode choice

Every employee travels with a particular travel mode towards their work. For people to determine their travel mode, there is a decision process between different transport alternatives; the mode choice. As illustrated in Figure 2.1, different perspectives of different disciplines determine this decision process; psychology, economy, and geography (Dijst, Rietveld & Steg, 2009). These perspectives are interrelated to a larger or smaller extent (Santos, Maoh, Potoglou & von Brunn, 2013). Objective or subjective circumstances, for instance, not owning a car, or a habit of commuting by car, limits this mode choice. For example, the perception that work is too far away, or people who habituated their commute by car to work are less likely to start commuting by bike. These people will probably not easily change that opinion and thus, their transport mode (Gatersleben & Appleton, 2007).

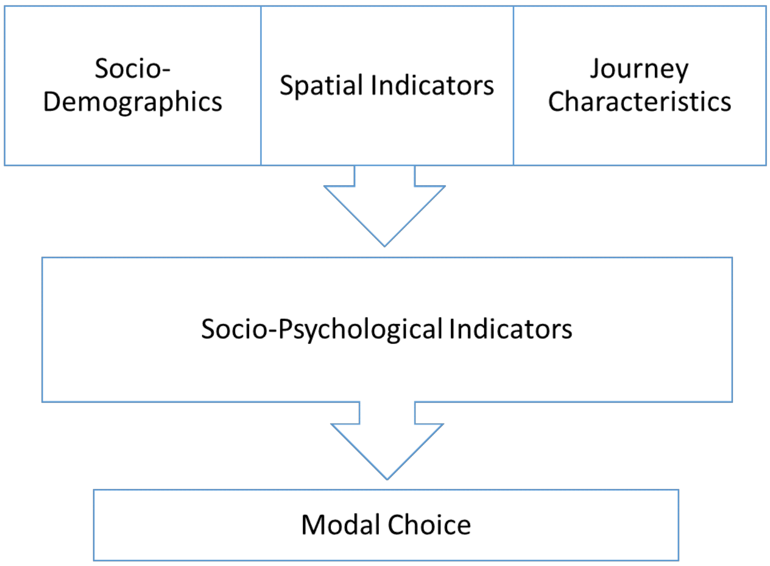


Figure 2.1: Framework of De Witte et al. (2013) for structuring mode choice

The factors and indicators illustrated in Figure 2.2 exist of different determinants. (De Witte et al., 2013) ordered 76 analysed papers in a figure to see how many times determinants are studied, and found significant regarding the mode choice, illustrated in Figure 2.2. Not all determinants are always significant, which stresses the importance of addressing the right indicators suited for the study, and that the decision process is not fully understood yet. Consequently, how to influence and select the right determinants for the decision process is also challenging.

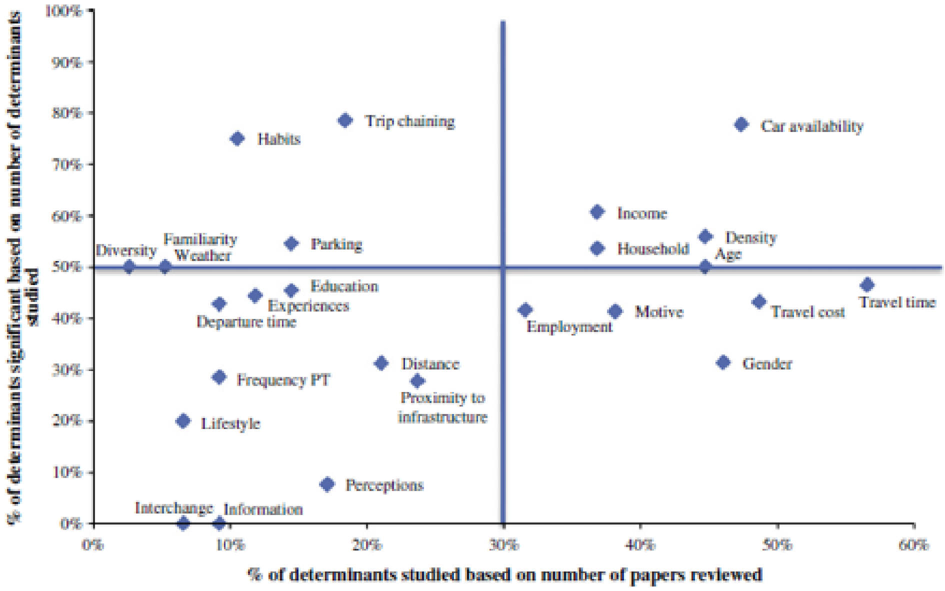


Figure 2.2: Overview of determinants studied and found significant in the 76 papers studied by De Witte et al. (2013)

2.2.2 Influential factors in changing the commute mode

Most research regarding mode choice change investigated the effect on the long term: longitudinal studies. That occurred since literature suggested that travel and commuting behaviours became habitual and that changes to commuting mode are far more likely at the time of significant life events (Clark et al., 2016). Overall, as is illustrated in Figure 2.3, life events, spatial context, and environmental attitude strongly influence changes in travel behaviour (Clark et al., 2016). For instance, employment changes and residential location relocations that alter the commute distance are associated the most with commute mode changes (Clark et al., 2016).

However, as argued before, travel behaviour change also occurs when other variables that play a role in the mode choice alter. This part shows determinants information of the relation with commuting mode choice change, following the structure of the framework of De Witte et al. (2013). Inclusion of unresearched factors regarding mode choice change is inevitable, as research is not abundantly available. Therefore, exploration of factors from other research areas as the mode choice is necessary, since these factors might also play a role in changing commute behaviour.

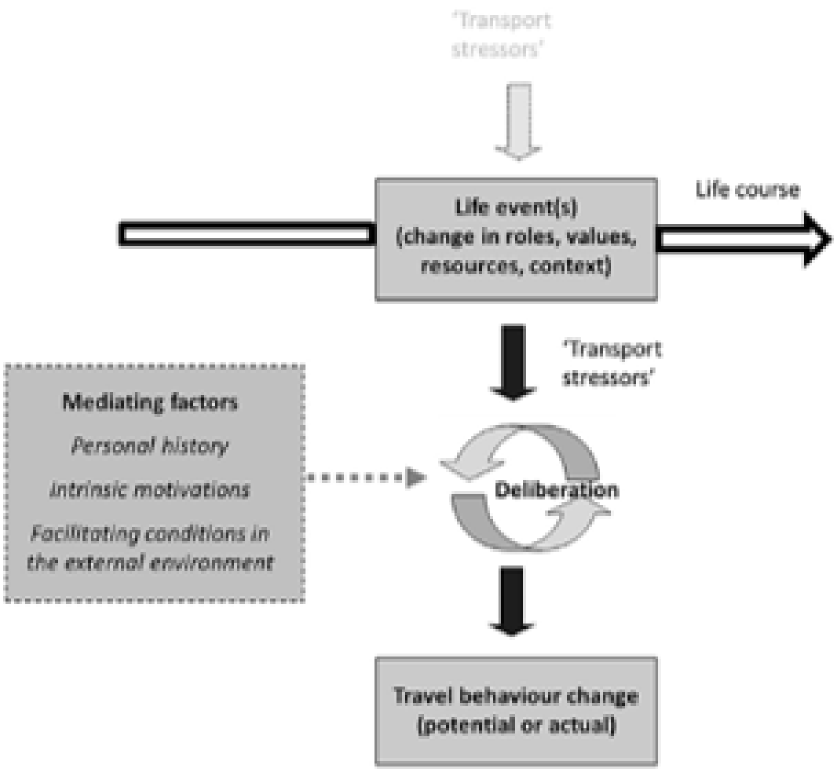


Figure 2.3: General conceptual model for travel behaviour change from Clark et al. (2016)

Socio-demographic indicators
Socio-demographic indicators shape the individual situation of the commuter, such as age, education, income, household composition, and household car ownership. This research includes the following indicators to capture their effect on mode choice change:

Function

According to Pickery (2005), higher educated people in Vlaanderen, Belgium, are more likely to have higher income levels, and as a result, they are more prone to use the car to go to work. Whereas Limtanakool et al. (2006) state that in the Netherlands, higher educated people use public transport, rather than the car, more frequently for commuting trips longer than 50km. Education sometimes interrelates with income and car ownership (De Witte et al., 2013). Higher educated people often cycle less because they have to travel more considerable distances to reach their jobs (Wardman et al., 2007). More importantly, those working in higher categories of employment (e.g. management roles), and those working for small employers or in self-employment, are less likely to (switch to) commute by active travel (e.g. walking or (e-)bike) (Clark et al., 2016).

Income

Overall, income entertains a positive relationship with car use and an inverse relationship with public transport use (De Witte et al., 2013). Hensher and Rose (2007) found this to be true in Sydney, but some research suggests that in the Netherlands income does not seem to affect the mode choice for business journeys (Limtanakool et al., 2006). For cycling, both positive (Dill & Voros, 2007; Stinson & Bhat, 2005) and contrary connections (Schwanen & Mokhtarian, 2005) between income and commuting by bicycle exist. The differences lay in some wealthier people spending more money on transport in general to buy a car (car ownership negatively affects cycling to work). In contrast, other wealthier people pay more attention to their health and therefore, cycle more (Heinen et al., 2010), which could synergise with working in a hospital and caring more about health in general. Different incomes might also have a different effect on mobility measures. Fioreze et al. (2019) already found that the richer one is, the bigger the chance that one is not interested in any kind of reward. Additionally, at a hospital, many doctors are present with high incomes, but also many domestic workers with lower incomes.

Spatial indicators

Spatial indicators characterise the spatial environment in which the journey, and thus mode choice, takes place. Density, public transport availability, and parking are examples.

Availability of infrastructure and services

Poor public transport services result in lower public transport use (de Vasconcellos, 2005), e.g. high travel times through bad connections and bus stops being far away from residential housing. However, it is not always a significant indicator of mode choice (De Witte et al., 2013). Phithakkitnukoon, Sukhvibul, Demissie, and Smoreda (2017) suggest that when the distance to public transport stops increases, the portion of transit users decreases. Rietveld (2000) even showed that in the Netherlands public transport stops need to be of a certain quality level (e.g. adequate (bicycle) parking facilities and good accessibility) not negatively to influence public transport use. Van de Walle and Steenberghen (2006) emphasise that travellers have a negative perception towards walking times, waiting times, and transfers. According to their research if there is no, or insufficient, public transport available, it generally results in car commutes. According to (Limtanakool et al., 2006), the availability of a public transport stop at the destination side is of greater importance than at the origin side. Higher frequencies of, e.g. busses, increase the comparative efficiency of public transport for other modes, and therefore, the share of public transport (Camagni, Gibelli & Rigamonti, 2002). The relative performance of other transport modes is essential to consider since employees will not take the bus if the travel time is an hour longer.

Parking

Especially in dense areas, the availability of parking has a high impact on mode choice (Kajita, Toi, Chisyaki & Matsuoka, 2004). Irrespective of the car being quicker than public transport, it stimulates employees to commute by car if there is a (free) parking place available at work (de Vasconcellos, 2005; Fallon et al., 2006; Kenworthy & Laube, 1996; Ye et al., 2007). The in-depth discussion of parking scenarios is available in the previous section, 2.2.

Journey characteristics
These characteristics are particular elements of the considered commute. The journey characteristics embody distance, travel time, travel cost, departure time, trip chaining, weather circumstances, information and interchange.

Distance

Distance, travel time and travel costs are directly related to each other (a longer distance often results in longer travel times and higher travel costs). Therefore, distance influences mode choice, and for longer distances, people prefer faster travel modes (De Witte et al., 2013). For instance, in Brussels, where the car is the dominant transport mode for commuting distances <30km (Pickery, 2005). Beyond this distance, train use becomes more likely for home-work commutes because the train becomes relatively better performing for longer distances (De Witte, Macharis & Mairesse, 2008). In the Netherlands, the trip length is the most discriminating factor in mode choice, since active modes and public transport are not always available for longer trips (Thomas, La, Puello & Geurs, 2019) Even car users prefer active modes when trips are very short (<2km), whereas car users also use the car twice as often as non-car users (Thomas et al., 2019).

Distance is also often identified as a significant factor for cycling (Heinen et al., 2010). Clark et al. (2016) found that active commuting is more likely for those living within five miles of work (approximately eight kilometres). Life events altering the commute distance are associated the most with commute mode changes, indicating that the distance, and thus possibilities, are indeed critical. These studies, however, are executed before the e-bike became a standard transport mode (in the Netherlands) and therefore, probably mentioned distances are obsolete. Albeit, a considerable distance has a negative influence on whether individuals can commute by bike at all.

Travel time

This indicator is also intertwined with travel distance since more considerable distances ask a more substantial travel time. Travel time is an essential determinant for mode choice (Vande Walle & Steenberghen, 2006). In general, with increasing travel times public transport and car are more preferred, with the car generally being far more favoured because of comfort, accessibility and quality of service (De Palma & Rochat, 2000). For instance involve public transport journeys in Sao Paolo often longer walking distances which results in higher travel times with public transport which in turn reduces the use of it (de Vasconcellos, 2005). Travellers also seem to be more sensitive to out-of-vehicle travel time than in-vehicle travel time (Bhat, 1998). Travel time for cyclists is also linked to effort needed. People perceive more effort as unfavourable, and longer cycling times result in less positive attitudes towards cycling, which would logically lead to less cycling for longer distances (Gatersleben & Appleton, 2007).

(travel) Cost

The costs of a journey play a role in mode choice (Kajita et al., 2004). Mainly public transport use is sensitive to increases in public transport fares (de Vasconcellos, 2005; Vega & Reynolds-Feighan, 2009). According to Cervero (2002), people are more likely to solo-commute if the costs of transit are higher relative to driving alone. However, only a limited share of car drivers would use public transport if it was made less expensive (De Witte et al., 2008; Mackett, 2003). Public transport shares are negatively associated with the cost of a monthly ticket (Santos et al., 2013). Subsequently, reducing fares is likely to increase the share of public transport in commuting trips (Santos et al., 2013), but cyclists will probably use public transport instead of car users (2005).

Cycling is relatively cheap (for both employer and employee) and therefore, one of the reasons why commuters cycle (Bergström & Magnusson, 2003). Since costs are reasons for people to choose their transport mode, it is highly likely that a change in costs will be able to persuade people towards other transport modes. As mentioned earlier does an increase in parking cost with 10% decreases commuting by car with 3% (en Vervoer, 2005).

Departure time

Public transport is unattractive during off-peak hours (especially in the night) due to lower service (Pritchard, Tomasiello, Giannotti & Geurs, 2019). In contrast, the car is more attractive during off-peak hours due to less congestion (Nurul Habib, Day & Miller, 2009). Therefore, departure time determines access to specific transport modes. Nevertheless, it is also related to the necessity of the trip. For home-work and home-school trips, operating hours oblige people to travel during peak hours.

Stinson and Bhat (2004) found that darkness harmed commuting by bicycle and, because of safety aspects, women generally care more about the presence of daylight than men. At a hospital also night work is performed and with safety as a reason to not travel with public transport or cycle (Hine & Scott, 2000) this could hamper commute mode change.

Trip chaining

Larger families have a higher probability of using private cars to go to work (De Palma & Rochat, 2000) since the presence of children increases car use (Fallon et al., 2006), which also has a significant negative impact on public transport use(Limtanakool et al., 2006) . In line with the previously mentioned research, having a family reduces the propensity to cycle (Moudon et al., 2005; Ryley, 2006). Having children as such is not the problem, but Fallon et al. (2006) mention that car use increases when having to drop off children.

Krygsman, Arentze and Timmermans (2007) state that the choice of trip chaining on a work tour often adjusts the mode choice (of car and public transport). Currie and Delbosc (2011) highlight that public transport chains are generally more complex than by car, which is why the car is favoured when trip chaining. Additionally, is trip-chaining also hard to combine with cycling to work (Dickinson et al., 2003). However, according to Nurul Habib et al. (2009) is a mode choice determined by all trips in the chain except if the first trip is a work trip, then the work trip is determining for mode choice. Witte et al. (2013) investigated trip chaining in mode choice studies and found it was rarely studied (18% of the 76 papers), but it was found significant in 80% of the papers. Women, in particular, mention that picking up children or shopping is hard to combine with commuting by bike (Dickinson et al., 2003). Therefore, employees who trip chain might be adamant about changing their commute mode.

Intrapersonal mode choice change

Less frequent car users have the highest transition probabilities to other transport modes. That suggests that once people use the car more frequently, changes in attitudes become less likely (Olde Kalter, La Paix Puello & Geurs, 2020). In contrast, the more multimodal individuals were, the more likely they are to switch from one behavioural profile to another (Kroesen, 2014) and the more likely they intend to decrease their car use (Heinen, 2018).

A higher level of variability may indicate that an individual is in an experimental phase, has a high level of self-efficacy to use different transport modes and thereby increases the responsiveness to a subsequent intervention. A third explanation might be that some of the measured change over time represents actual variability, possibly as a result of accessibility needs (Heinen & Ogilvie, 2016).

Weather conditions

Intrapersonal mode choice variation also occurs for work trips because of variation in weather circumstances (Thomas et al., 2019). Naturally, the effect of the weather varies among countries, as regions with low winter temperatures have sharper decreases than regions with milder winters. For instance, in Sweden, not only people cycle less in winter, but also the maximum distance cycled decreased from 20km in summer to 10km in winter. In this case, harmful maintenance service levels on cycleways (Bergström & Magnusson, 2003) and the limited hours of daylight (Stinson & Bhat, 2004) affect the mode choice. Generally, in adverse weather conditions cycling may not be perceived as a good alternative (Kim & Ulfarsson, 2008). Specifically, the chance of rain is the most negative weather aspect as a reason not to cycle (Brandenburg, Matzarakis & Arnberger, 2004). Despite this, it only half of the papers highlighted its significance (De Witte et al., 2013).

Socio-psychological indicators
These indicators are the subjective components, and these influence how an individual acts upon the option created by the previous groups of indicators. As stated earlier, has research included factors stemming from psychology just recently (De Witte et al., 2013). As a result, we have still limited understanding of perceived and attitudinal barriers of (sustainable) modes and motives of personal car use (Masoumi, 2019).

Therefore, it is crucial to take the subjective component into account when studying mode choice decisions (De Witte et al., 2013).Masoumi (2019) goes further in saying that for instance, according to literature, lack of comfort is one of the barriers to using public transport. In contrast, people like driving the car are the reason. Unsurprisingly, in every situation, socio-psychological indicators might affect mobility measures differently.

Habits

The existence of habits puts the validity of the assumption that we make decisions based on rational evaluation into question (Heinen et al., 2010). Consequently, base habit travellers their travel decision on a fraction of the information that is available since they investigate less information about alternatives (Verplanken, Aarts & Van Knippenberg, 1997) . Verplanken et al. (1997) suggest that habitual behaviour for other transport modes negatively influences bicycle use, which might hamper the effect of mobility measures.

To start working at approximately the same time implies a high level of habituation for the commute (Thomas et al., 2019). Additionally, intrapersonal mode choice variation for trips longer than 10km is relatively small (Thomas et al., 2019).

2.3 Conceptual model

From the analysed literature follows the conceptual model for this research in Figure 2.4, developed while keeping in mind the framework of De Witte et al. (2013) for mode choice and the model from Clark et al. (2016) for travel behaviour change. This model forms the basis of the research regarding mobility management measures at companies and its influence on mode choice.

The model starts with a mobility goal, which can be a result of different things, e.g. resolving parking place shortage or sustainable development goals. Mobility measures try to accomplish that mobility goal. The mobility measures are a product of the mode choice of employees and its variables since measures are designed for a specific population. The mobility measures adjust some variables of the mode choice process and based on the altered variables, the deliberation phase starts. In the deliberation phase variables that influence mode choice, but are not influenced by mobility measures, play a role. The result of the deliberation phase is the changed or same commuting behaviour. The deliberation phase is an essential part of this research, as it represents the trade-off between acceptance and effect. As everyone accepts measures that do not harm them, but those measures will generally also be less effective.

In this case, the mobility goal is to reduce the number of commuters who sometimes switch to commuting by car and reduce the number of car commuters in general. To do so, the investigated mobility measures, in this case, are a distance-dependent parking cost during peak hours and an increase in bicycle subsidy, based on de Groote et al. (2019). A decrease in parking costs outside the peak hours wraps up the measures tested for this research. The decrease responds to employees with night shifts who might commute by car due to safety concerns and other aspects mentioned earlier.

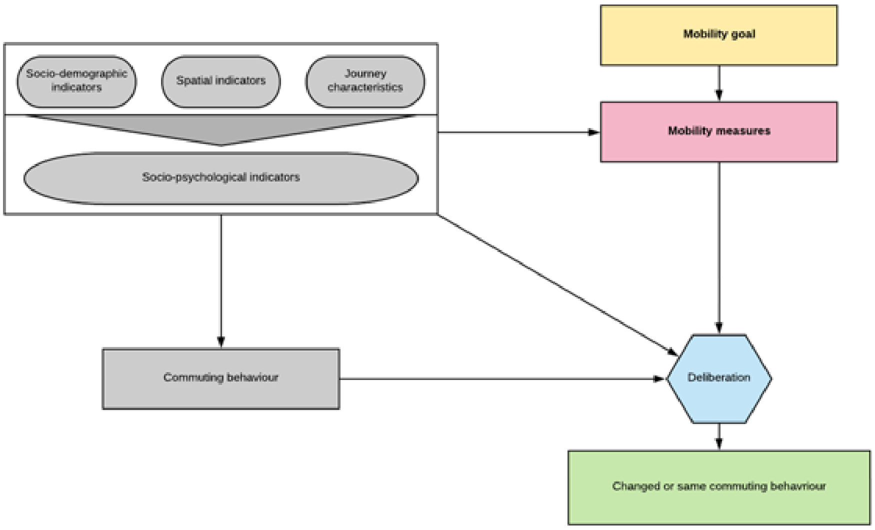


Figure 2.4: Conceptual model

2.4 Hypotheses

Based on the measures, literature, and conceptual model (Figure 2.4) this part drafts hypotheses for further guidance of this research. The first three hypotheses focus on the temporal and spatial aspects of the interchangeability of the bike and car for commutes for MST; the other hypotheses concern the cross-sectional effect and acceptance.

1. Temporal variation exists in parking demand and bicycle commutes due to the seasons and working hours

Parking demand for cars is generally higher in winter because people cycle less due to weather conditions (de Groote et al., 2019). Additionally, when both office personnel and health care workers work at MST, parking demand is higher than during weekends and during working hours when only healthcare workers are present.

2. The exchangeability of car and bike varies over different distances

For vast distances (>30km), the bike is not a suitable alternative, but only the car and public transport are (De Witte et al., 2008). For very short distances, even car users prefer active modes when trips are under two kilometres (Thomas et al., 2019). Consequently, somewhere between too long (>30km) and very short (<2km) distances, the car and bike will substitute each other.

3. Areas with public transport hubs have less exchangeability of car and bike commutes

The accessibility of the destination side is essential to use public transport for commutes

(Limtanakool et al., 2006). Also, higher frequencies of public transport increase the share of public transport (Camagni et al., 2002). Since MST is very well accessible through both the bus and the train, employees living close to public transport hubs are less likely to travel by bike or car. Consequently, they are also less likely to switch between those two modes.

4. An increase in the standard parking costs will:

1. Have a more substantial effect on influencing car commuters to commute by bike than increasing bike subsidy;
2. Yield more acceptance among:
   (a) Non-car commuters than employees with intrapersonal mode choice variation and car-commuters;
   (b) Employees with higher incomes;

Habibian & Kermanshah (2013) concluded that push policies play a leading role in the mode choice process, while pull policies only slightly affect mode change decisions; therefore, increasing parking costs is probably more useful. The measure does not affect employees who do not commute by car. The ones who occasionally commute by car will yield lower acceptance, but employees depending on their car to commute will yield the lowest acceptance. Additionally, employees with the highest incomes will probably care less about a cost increase. I Employees living further than fifteen kilometres from MST and employees trip chaining their commute will yield lower acceptance.

5. The introduction of the distance-dependent parking cost will:

1. Result in the most substantial decrease in parking demand for employees living close to MST;
2. Yield lower acceptance and have more effect among employees who live close to MST;

The distance-dependent parking costs are likely to have substantial effects for each distance category closer to MST, as for each distance category the parking cost increase (more information in the research approach section). As de Groote et al. (2019) already showed that increasing distance-dependent parking cost has more effect on employees living closer to the hospital. As a result, the acceptance will probably be lower for employees in each distance category that has to pay more in a package of measures.

6. A higher bicycle subsidy will:

1. Result in employees with mode choice variation to commute more by bike;
2. Receive acceptance among employees:
   (a) With intrapersonal mode choice variation;
   (b) Who live close to MST;

The bicycle subsidy increase will receive more acceptance among employees who cycle. As a result of an increase in bicycle subsidy, it is assumed that employees who cycle occasionally, increase the number of times they commute by bike. Subsequently, employees who live closer are probably more inclined with an increased bicycle subsidy as they are more likely to cycle more often.

7. Lower daily parking costs outside peak hours will:

1. Lead to more employees commuting by car who have working hours outside office hours;
2. Increase employees' acceptance of increasing parking costs;

Decreasing the outside peak parking cost intends to increase the acceptance of a package of measures and satisfy employees working night shifts. Especially employees who work night shifts and live far away will elect a package of measures with decreased outside peak parking cost.

Chapter 3

Research questions and scope

This chapter encompasses the sub-questions of the research that, together, answer the main research question and describes the scope that gives guidance to this research.

3.1 Main research question

This research aims at contributing knowledge to the effect of mobility measures on specific populations in order to be able to implement effective policies and to add knowledge on the substitutability of the car and bike for commutes. Consequently, this research answers the following research question:

How can mobility measures influence the exchangeability of car and bike commutes at the MST, Enschede?

3.2 Sub-questions of this research

The main research question is divided into governable sub-questions. The first part performs research regarding temporal and spatial exchangeability. This part gains more insight on available alternatives and the variables that determine the exchange of commute modes. Both the acceptance and the effect of different mobility measures are analysed. The focus lays on finding measures that both yield acceptance and effectively persuade employees to change their commuting mode. To do so, focus lays on increasing the chance of employees changing their travel mode after each sub-question follows a little justification and purpose of the question.

1. *What temporal variations are present in the parking problem?*

The first sub-question exposes the dimensions of the parking problem in order to find suitable parking management measures. At what moments, and how often parking problems occur, is vital to know to adjust measures to those moments. Possibly the switch towards car commuting is not even causing the parking problem. If the dimensions of the problem are understood, the measures can be tailored to those dimensions to try and find the most effective and suitable parking management measures for MST.

2. *What spatial variables influence the exchangeability of car and bike for commutes to MST?*

The second sub-question explores which spatial indicators are essential for employees to change their commute behaviour. As elaborated in the hypotheses, distance to MST and public transport availability probably play a role. The discovered spatial indicators that play a role in switching to car commuting, also have an essential part in the acceptance and effect since those employees have alternatives available.

3. *What is the acceptance of mobility measures among different segments of employees?*

Mixed logit models analyse the relative acceptance of attributes for subpopulations since the effect of mobility measures is likely not identical for all employees. Therefore, this question concentrates on different factors that play a role in the mode choice, and test their opinion about different attributes of the mobility measures. For example, it is assumed that distance has a significant influence on how easily employees are to persuade them towards commuting by bike. Alternatively, the opinion of car commuters and non-car commuters are likely to differ about parking costs. The outcome will, with the effects, contribute to the main research question to find a combination of mobility measures with both acceptance and an effect.

4. *What is the effect of mobility measures on the commuting mode of MST employees?*

The effect of the increase in parking costs will probably differ between different employees. As mentioned before, measures with higher acceptance among employees with the same variables probably have a lower effect. This question focuses on the effect of parking measures. Not the overall effect, but the effect on different transport groups is fascinating. The effect of factors, e.g. distance and income, to see which employee groups are more affected by the parking management measures.

This question also focusses on the effect of different combinations of mobility measures. Ding, Cao and Wang (2018) found that subsidising other transport modes is more effective than penalising car commuting. Their findings contradict the outcome of Habibian and Kermanshah (2013) that push policies are generally more effective than pull policies. The result of this research question can also be used to both penalise and subsidise different commuting modes in the future, since combining push and pull policies should be the most effective. This finding will also contribute to the main research question on how to persuade employees towards commuting by bike.

Ding, Cao and Wang (2018) found that subsidising other transport modes is more effective than penalising car commuting. Their findings contradict the outcome of Habibian and Kermanshah (2013) that push policies are generally more effective than pull policies. The result of this research question can also be used to both penalise and subsidise different commuting modes in the future, since combining push and pull policies is expected to be the most effective. This will also contribute to the main research question on how to persuade employees towards more sustainable transport modes, as it provides insights on how to persuade those employees

Finally, the findings of the research questions will be combined to answer the main research question and create (a collection of) mobility measures that reduce the number of cars parked at the MST and increase the number of active commuters.

3.3 Scope

According to Young and Miles (2015), parking management measures relating to the management of the price, supply, duration and location of parking to enhance the urban environment. In this case, the measures mentioned in the literature review will be examined. The modal split and effect on commuting modes only consider effects on car and active mode, as the focus lays on the interchangeability between commuting by car and by bike.

This study uses a cross-sectional survey with stated choice experiments to gather data. The focus is on finding a combination of mobility measures that persuade employees towards commuting by bike and yields acceptance among MST employees. Possibly, the most exciting part is what employees find important in mobility measures, as those insights will help mould the right mix of measures to change the commuting behaviour of employees.

The emphasis lays on employees commuting by the car that parks on the terrain of MST: P2 or Mooienhof. Synagoge, another parking terrain, is excluded because there is no data is available. The emergency parking places are not taken into account as well, since these are work-related and sufficiently available. To gather information about the opinions of employees, a survey is developed with stated choice experiments about mobility measures. Also, other factors that are found relevant in literature are included (see Literature section 2). Additionally, the weather is taken into account, but with 3 days of rain versus 11 dry days a causal connection is hard to make.

Chapter 4

Methodology

4.1 Research approach

The research approach is visualised in Figure **??** to create a manageable overview of the steps taken for this thesis. This section described the methods. First, the data collection - survey and stated choice experiments - are clarified. The final part elaborated on the technical details of the mixed logistic regression analyses.

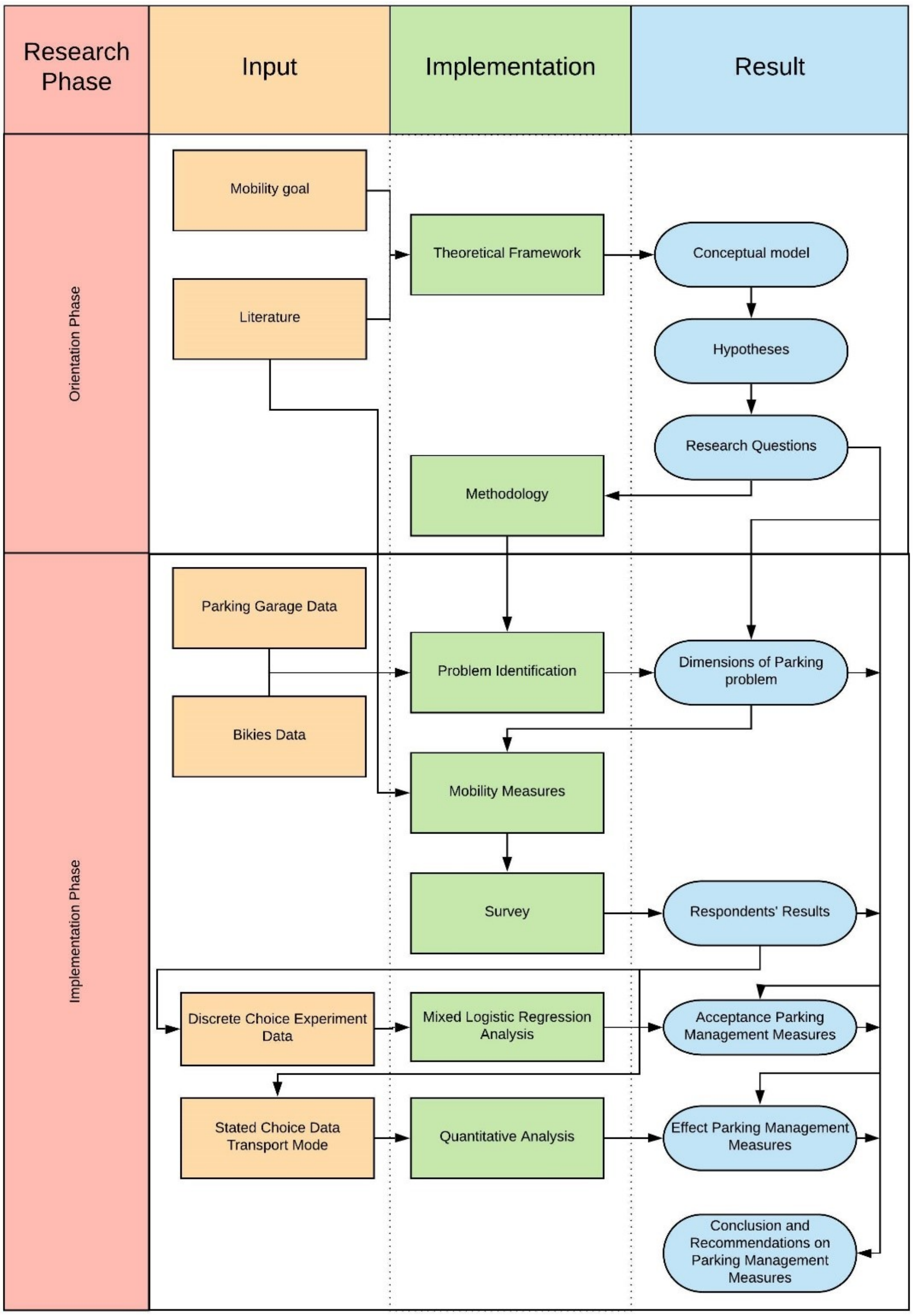


Figure 4.1: Research approach

4.2 Data collection

Every research requires data regarding the subject. This research uses data from the parking garage and bikies program of MST for the temporal and spatial aspects of employees switching from commuting to car or bike. These aspects use only simple data analyses will be explained further in the section about the dimensions of the parking problem. The survey, and in particular the discrete choice experiments, gather data for this research.

4.2.1 Survey

The primary data source for this research is the survey to gain information about the acceptance of employees for the proposed parking management measures. The survey included questions in different sections, some depending on the answers of previous questions. The survey has the following structure:

1. Small introduction
2. Questions about organisation, function, working hours, departure- and travel time
3. Questions about the motives for chosen transport mode(s), possible alternatives and parking place
4. Discrete choice experiments
5. Open questions about measures and general comments
6. General questions (socio-economics, household characteristics, and more determinants identified in the literature section)
7. End of the survey with a word of thanks

Questions about the organisation, departure- and travel time are for the cross-sectional analysis to see if the acceptance and effects between these segments differ for mobility measures. Motives for transport modes, their possible alternatives and parking place are used as an indication of employees' perception of alternatives. The discrete choice experiments play a vital role in this research for the acceptance and effect of different attributes, which the next section discusses. The general questions are used to compare the sample with MST personnel and for comparison of this research with other (future) research about acceptance and effect of mobility measures.

4.2.2 Stated choice experiments

The use of conjoint analysis is commonly used to measure the preferences of stakeholders (Hauber et al., 2016). The conjoint analysis describes a range of stated-preference methods that make respondents rate, rank or choose from a set of experimentally controlled profiles consisting of multiple attributes with different levels. Discrete choice experiment (DCE) is the most common type of conjoint analysis. DCE ask the respondents to make choices among sets of profiles in a series of choice questions. Therefore, it offers the opportunity to establish the preferences of MST employees for parking management measures (Hensher & Rose, 2007). The DCE uses, in coordination with MST (justification follows in the next subsection), the following attributes:

Parking tariff during peak hours (Monday to Friday 6:00-14:00 entering the parking garage)

- Parking costs for all employees living further away than 15km:
  - €1,- or €1,25
- Increase in parking cost with every distance category closer to MST:
  - €0,25 or €0,50

Parking tariff outside peak hours:

- €0,75 or €1,-

Bicycle subsidy (always applies):

- Current bicycle subsidy or double

Using simultaneous choice sets creation (creating alternatives and choice sets at the same time) has the advantage of considering full factorial design (all combinations) and orthogonality is preserved (Sanko, 2001). The number of games (or choice sets), however, using full factorial design, becomes 256 (L^{MN}, L is the number of levels, M the number of attributes and N the number of alternatives: 2^{4*2}). However, there is a strong likelihood that respondents will experience fatigue in carrying out too many choice exercises, increasing the response error. Likewise, too many attributes or levels may lead to some items being ignored by the respondents (Pearmain, Kroes & Davies, 1990).

To reduce the number of games this study removes trivial games (dominant scenarios). If all attributes for the choice set are the same, but one choice has €1 parking cost, and the other has €1,25, (almost) all respondents will choose the package with €1. Therefore, these games can be excluded to reduce the num ber of scenarios. In total 146 of the 256

Table 4.1: Cars parked in P2 and Mooienhof

	Cars parked	% of total	Average per day	Mo-Th (6:00-14:00)	% of winter/summer
Winter	131841	55%	690	74263	56%
Summer	107983	45%	631	58030	54%

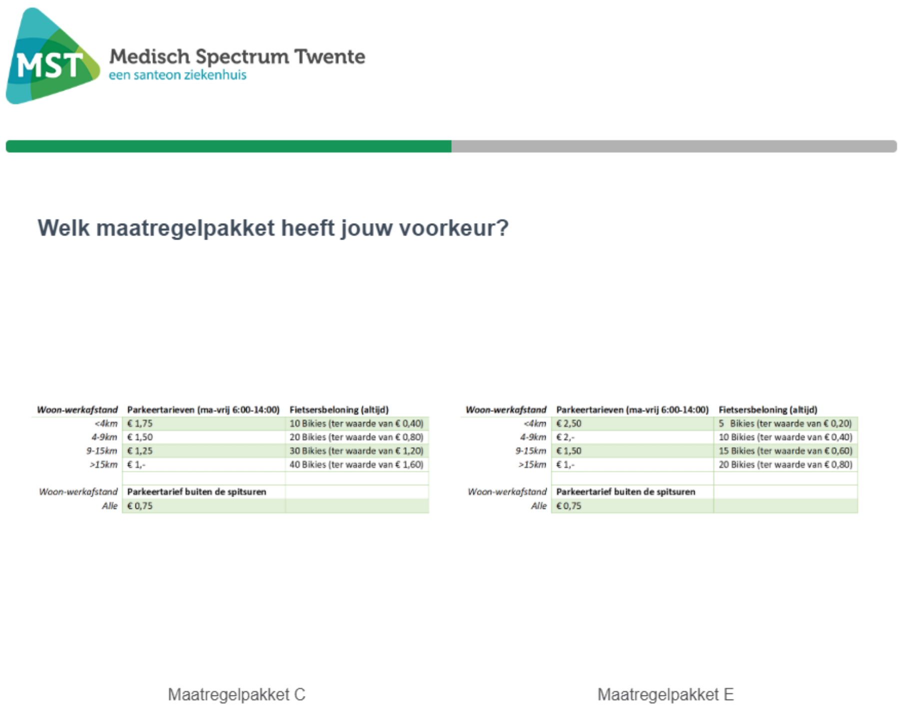
games are trivial, meaning a total of 110 games remains. The survey randomly assigns games to respondents to reduce biases. Figure 4.2 gives an example of a game.

A minimum of six respondents per game is required to satisfy large sample statistical properties (Bunch & Batsell, 1989). Additionally, Pearmain et al. (1990) recommend limiting the number of questions for each individual to 9 – 16 games per respondent. Since MST usually provides surveys of around 5 minutes, employees probably do not appreciate long surveys. Subsequently, only five choice sets are presented with the follow-up question of which transport mode the respondent would use given the scenario. Given the total of 110 games, every game requires six respondents, and that the survey presents five games to every respondent, the study requires a minimum of 132 respondents.

The first discrete choice experiment
The goal of the first experiment is to discover the relative importance of parking management measures among MST employees. The next part second describes the second discrete choice experiment, which focusses on the effectivity of the measures. To do such different packages of measures, are constructed from the attributes. Figure 4.2 gives an example (Appendix E shows all options).

The number of car commuters varies from winter to summer, see Table 4.1. During the summer, approximately every day 630 cars park versus 690 cars during the winter. A more in-depth elaboration follows in the Temporal analysis. Additionally, from Monday to Thursday 6:00-14:00 more than half of the parking transactions occur in only 24% of the time (40 hours/168 hours in a week). Therefore, this research increases the initial parking cost only for peak hours. So employees working at night are not penalised with higher parking tariffs. Additionally, since there is no objective to earn extra money and employees work night shifts, acceptance and effect for a decrease in the outside peak parking cost are investigated.

Cyclists use their bike for almost all shortest trips, but after five kilometres, the car becomes a serious alternative to them (Thomas et al., 2019). In order to investigate the opportunities of encouraging employees to commute more by bike for distances after 5km, the bicycle subsidies and parking costs are increased for different distance categories (for clarification purposes as the bicycle subsidy already is distance-dependent). De Groote et al. (de Groote et al., 2019) investigated that bicycle subsidy does increase bicycle commuters. However, they compared winter with summer; this experiment uses DCE for the same week.



Woon-werkafstand	Parkeertarieven (ma-vrij 6:00-14:00)	Fietsersbeloning (altijd)
<4km	€ 1,75	10 Bikies (ter waarde van € 0,40)
4-9km	€ 1,50	20 Bikies (ter waarde van € 0,80)
9-15km	€ 1,25	30 Bikies (ter waarde van € 1,20)
>15km	€ 1,-	40 Bikies (ter waarde van € 1,60)
Woon-werkafstand	**Parkeertarief buiten de spitsuren**	
Alle	€ 0,75	

Maatregelpakket C

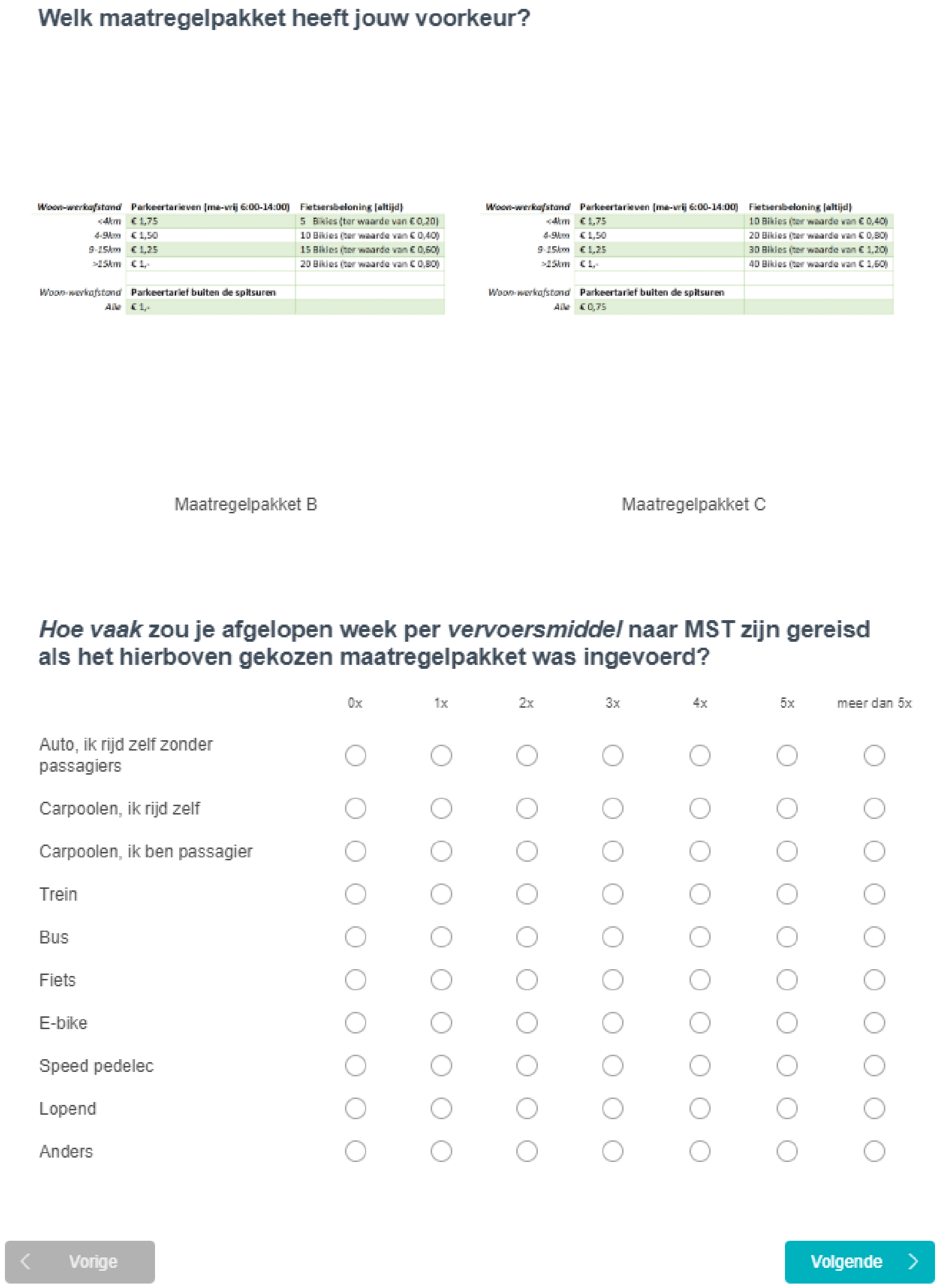
Woon-werkafstand	Parkeertarieven (ma-vrij 6:00-14:00)	Fietsersbeloning (altijd)
<4km	€ 2,50	5 Bikies (ter waarde van € 0,20)
4-9km	€ 2,-	10 Bikies (ter waarde van € 0,40)
9-15km	€ 1,50	15 Bikies (ter waarde van € 0,60)
>15km	€ 1,-	20 Bikies (ter waarde van € 0,80)
Woon-werkafstand	**Parkeertarief buiten de spitsuren**	
Alle	€ 0,75	

Maatregelpakket E

Figure 4.2: Example of a stated choice experiment regarding parking management measures

The second discrete choice experiment

The goal of the second experiment is to estimate the effects of mobility measures. Respondents state how many times they would have travelled to MST, with which transport mode if the package of measures they selected in experiment 1 was active. At the beginning of the survey, respondents also stated how many times they used which transport modes to commute to MST. Both answers are compared and analysed with simple statistics as the mean of the difference and its standard deviation. Figure 4.3 shows an example of the question regarding transport modes given their chosen package of measures.



Welk maatregelpakket heeft jouw voorkeur?

Woon-werkafstand	Parkeertarieven (ma-vrij 6:00-14:00)	Fietsersbeloning (altijd)
<4km	€ 1,75	5 Bikies (ter waarde van € 0,20)
4-9km	€ 1,50	10 Bikies (ter waarde van € 0,40)
9-15km	€ 1,25	15 Bikies (ter waarde van € 0,60)
>15km	€ 1,-	20 Bikies (ter waarde van € 0,80)
Woon-werkafstand	**Parkeertarief buiten de spitsuren**	
Alle	€ 1,-	

Maatregelpakket B

Woon-werkafstand	Parkeertarieven (ma-vrij 6:00-14:00)	Fietsersbeloning (altijd)
<4km	€ 1,75	10 Bikies (ter waarde van € 0,40)
4-9km	€ 1,50	20 Bikies (ter waarde van € 0,80)
9-15km	€ 1,25	30 Bikies (ter waarde van € 1,20)
>15km	€ 1,-	40 Bikies (ter waarde van € 1,60)
Woon-werkafstand	**Parkeertarief buiten de spitsuren**	
Alle	€ 0,75	

Maatregelpakket C

Hoe vaak **zou je afgelopen week per** ***vervoersmiddel*** **naar MST zijn gereisd als het hierboven gekozen maatregelpakket was ingevoerd?**

	0x	1x	2x	3x	4x	5x	meer dan 5x
Auto, ik rijd zelf zonder passagiers							
Carpoolen, ik rijd zelf							
Carpoolen, ik ben passagier							
Trein							
Bus							
Fiets							
E-bike							
Speed pedelec							
Lopend							
Anders							

Vorige

Volgende

Figure 4.3: Example of the stated choice experiment considering transport mode choices given specific parking management measures

4.3 Analysis methods

The first part introduces the model made in PandasBiogeme (Bierlaire, 2020), followed by a description of that model. The second part gives information on the results, goodness of fit, and assessment of the estimation. For more information on (mixed) logit models, the reader is referred to Modelling Transport from Ortúzar and Willumsen (2011) or Discrete Choice Methods with Simulation from Train (2002).

As a consequence of multiple observations by each individual, in the results, both inter-respondent heterogeneity and intra-respondent heterogeneity exist. Mixed logit models can handle this correctly (2011). Consequently, this research uses a mixed logit model for parameter estimation. Mixed logit models use the random utility theorem, which is elaborated first.

Random utility theory
Discrete choice models, in general, assume that everyone rationally chooses the alternative with the highest utility and can be decomposed in systematic utility (V_i) and random utility (ε_i) (Train, 2002). The systematic utility is the part the researcher tries to statistically estimate. The random utility is a vector of disturbances which explains the difference between the perceived utility and the true utility. The utility of alternative i is defined as: $U_i = v_i + \varepsilon_i$ The systematic utility is the part that can be statistically estimated and exists of an alternative specific constant (ASC), which captures the impact of factors not included in the model, and the attributes included in the model ($x_{i,j}$) (Train, 2002). The systematic utility of alternative I is expressed as follows: $V_i = ASC_i + \sum_{j=1} \beta i, j * xi, j$

Only differences in utility matter; therefore, the ASC of one of the alternatives is always fixed to zero. In this case, it only matters when employees chose a certain package of measures and the ASC of unelected is always fixed to zero (Train, 2002). The value of β shows the effect of the attribute on the utility. A larger value corresponds with a more substantial effect on the specific alternative, and the sign shows if it has a positive or negative contribution to the utility.

Logit model
The parameters of the utility function (V_i) are statistically estimated through a logit model. Different logit models exist, but as elaborated in the beginning of this subsection does this research use a mixed logit model. In this research, the mixed logit model uses a binary logit (two alternatives) and the probability of choosing one alternative over the other is defined as:

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{j} e^{V_i}}$$

This model assumes that the random variable is independent and identically distributed (IIA assumption), but that assumption is violated as we ask multiple questions to the same respondent. Because we do so, the answers of one respondent are not independent from each other. The mixed logit model solves this problem with including either a random coefficient or an error component, which are mathematically entirely equivalent (Department for Transport UK, 2014). In this case we use a random coefficient using Halton draws with base 2, skipping the first 10 as recommended by Train (2002). The utility functions look as follows:

$$V_{elected} = ASC_{elected} \cdot ASC_{sigma} + \beta_{Initial} \cdot x_{Initial_1} + \beta_{Increase} \cdot x_{Increase_1} + \beta_{Subsidy} \cdot x_{Subsidy_1} + \beta_{Outsidepeak} \cdot x_{Outsidepeak_1}$$

$$V_{unelected} = ASC_{elected} \cdot ASC_{sigma} + \beta_{Initial} \cdot x_{Initial_2} + \beta_{Increase} \cdot x_{Increase_2} + \beta_{Subsidy} \cdot x_{Subsidy_2} + \beta_{Outsidepeak} \cdot x_{Outsidepeak_2}$$

The 1 corresponds to the first choice and the 2 to the second choice presented to respondents. The attribute levels for the parameters are displayed in Appendix E. Appendix H shows the full model.

Model assessment
The mixed logit with the random coefficient for the alternative specific constant model fit is assessed through the rho-squared as it is often used how well a model fits the data in comparison with the basic model.

Log likelihood: $L = \sum_n logP(i_n| \{1,2\} ; x_n, \beta)$

The initial log-likelihood is the log-likelihood L^i of the sample for the model defined with the default values of the parameters.

The final log-likelihood is the log-likelihood L^* of the sample for the estimated model.

The likelihood ratio test for the initial model is: $-2(L^i - L^*)$

The likelihood ratio test analyses if the model improved with including more parameters.

The rho squared for the initial model is: $\rho^2 = 1 - \frac{L^*}{L^i}$

The rho-squared is often used to measure how well a model fits data. In this case the rho-squared is also used as the most important indicator. The rho-squared compares the fitted model with the model when all parameters are zero, and has a value between 0 and 1. 1 means the model fits the data perfectly and a value between 0.2 and 0.4 is considered as a good fit (Hauber et al., 2016).

Chapter 5

Descriptive statistics

This section presents the descriptive statistics resulting from the survey. In March 2020, 3517, employees of MST, Enschede, received the survey. After deleting incomplete data, data of 856 respondents remained, which brings the response rate to 24%. Table 5.3 shows the socio-economic variables of employees and 5.2 their trip characteristics, both in comparison with available data from MST and CBS for a frame of reference. From these tables, the considerable differences are highlighted at the end of this section.

Employees also filled out how many times they commuted with which commuting mode towards MST. These results are separated into three transport mode groups:

- Car: driver, travelling alone, car-pooling, as a driver and car-pooling as a passenger;
- Public transport: train and bus;
- Active mode: bike, e-bike, speed pedelec and walking.

As is presented in Figure'5.1 and Figure 5.2 for shorter distances, an active mode is preferred. Single-mode users prefer active modes more than employees with intrapersonal mode choice variation. For both single-mode users and intrapersonal mode choice variation, in the category 8-14km, employees commute more by car than by bike. According to the data few employees commute by public transport to MST for all distances. The average modal share is almost equal to the modal share for single-mode employees since that amount is much higher than the number of intrapersonal mode choice employees, see Table 5.1.

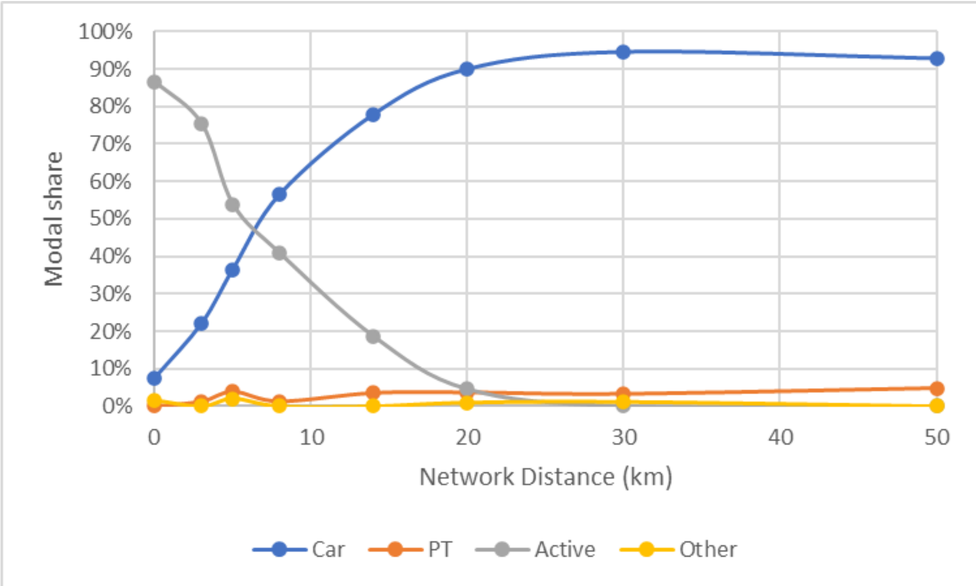


Figure 5.1: Modal share for single-mode employees

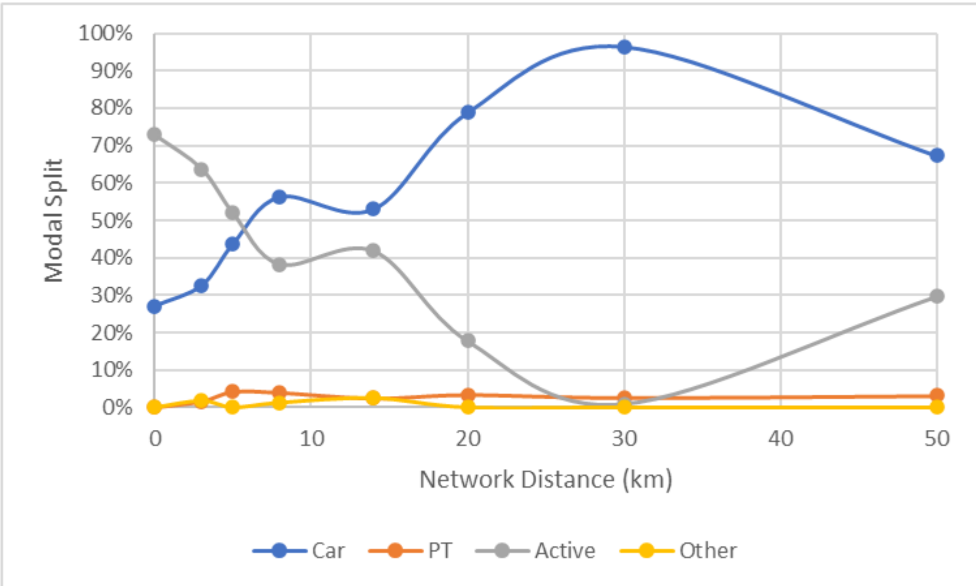


Figure 5.2: Modal share for employees with intrapersonal mode choice

Table 5.3 shows that compared with CBS data (CBS, 2020) from the Netherlands, the data sample is a bit older. The household size is much larger than average, especially for the lowest and highest category. The number of children in the household does not coincide with the average in the Netherlands. Many more respondents have no children, whereas the average Dutchman is more likely to have one child, which in turn is underrepresented

Table 5.1: Share of car, PT, Active mode

	Car	Public Transport	Active Mode	Other	Employees
All trips	61%	2%	36%	1%	856
Single mode	62%	3%	35%	1%	602
Mode choice variation	59%	2%	38%	1%	254

in the data sample, just as having two children. The level of education of the data sample is much higher since no one with primary education or lower, more employees from the MBO category and much more employees from the HBO category. Additionally, are all higher income categories over represented and have the respondents more cars in their household, except for the highest category, in the data sample compared to the average in the Netherlands and have MST.

Table 5.2 shows that MST employees generally have their residential location more 4-9km from MST and less 20-30km and >30km from MST.

Table 5.2: Trip characteristics of MST employees

	Sample	MST	CBS
Travel distance			
0-4km	17%	18%	
4-9km	16%	29%	
9-15km	15%	13%	
15-20km	12%	14%	
20-30km	20%	12%	
>30km	21%	15%	
Set arrival and departure times			(2001)
Yes	49%		55%
No	51%		45%

Table 5.3: Socio-demographic variables

	Sample	MST	CBS
Age - average	49		42 (2020)
Working hours - average	30	31	31
Household size			(2019)
1	9%		38%
2	30%		33%
3	17%		12%
4 or more	44%		17%
Number of children in the household			(2019)
0	40%		26%
1	17%		45%
2	31%		20%
3	10%		9%
4 or more	2%		-
Level of Education			(2019)
Primary Education or Lower	0%		9%
Lower secondary education, upper secondary education	9%		20%
MBO (Vocational school), HAVO, VWO (upper secondary education)	29%		37%
HBO or University propedeuse or bachelor university	62%		32%
Other	1%		2%
Personal yearly income before taxed			(2018)
<€10.000	3%		15%
€10.000 - €30.000	34%		43%
€30.000 - €50.000	44%		25%
€50.000 - €75.000	11%		11%
€75.000 - €100.000	2%		4%
€100.000 - €200.000	4%		2%
>€200.000	2%		0%
Number of cars in the household			(2012)
0	2%		28%
1	45%		50%
2	48%		19%
More than 2	5%		4%

Chapter 6

Temporal Analysis

This part researches the following hypothesis: there exists temporal variation in parking demand and bicycle commutes due to seasons and working hours. The first part researches seasonal variation, followed by brief analyses of smaller time units: months, weeks and days, and compares it with the variation in commutes by bike. Before this section concludes, it presents a small analysis of the impact weather has on the number of cars in the parking garage and the number of commutes by bike.

Car commutes
The temporal analysis analyses car use with the help of parking data. Figure 6.1 gives an oversight of the available parking places for MST employees (all parking locations and their capacity are available in Appendix B, Table 13). P2 is the parking garage of MST next to the hospital exclusive to employees with 870 parking places. The municipality owns Mooienhof, and MST rents 80 parking places at this location from 1-10-2018 until 12-4-2019. Synagoge, also owned by MST, is a large parking area (79 places) but left out of the analysis since there is no data available.

Bicycle commutes
The temporal analysis uses bikies data from January until August 2019. Bikies are registered when employees park their bike in the bicycle parking garage, which not all employees do since they also park their bike on the street next to MST. Additionally, not all commuters have a tag, which is confirmed by the count of parked bikes (Table 6.1) in comparison with the number of bike commuters with bikies tag (Figure 6.2) shown in the next section.

Figure 6.1: Location of MST's parking places

6.1 Seasonal variation

This section addresses for every point the variation in car commutes first, and then it addresses the variation in bicycle commutes. It compares the winter period (1 October – 12 April) and the summer period (13 April – 30 September). The winter period coincides with the time MST rents additional parking places at Mooienhof for analysis purposes.

The car analysis uses parking gate data from entries and exits of commuters to determine the number of parked cars. Appendix A shows an overview of the number of cars in P2 and Mooienhof, and only P2. From this figures follow that holidays are less crowded and that there are moments more than 900 people and at its maximum, even 927 cars are in P2 (25 march 2019 14:51), whereas the capacity is 870 cars. Also, employees seem to park their car more often during the winter period than the summer.

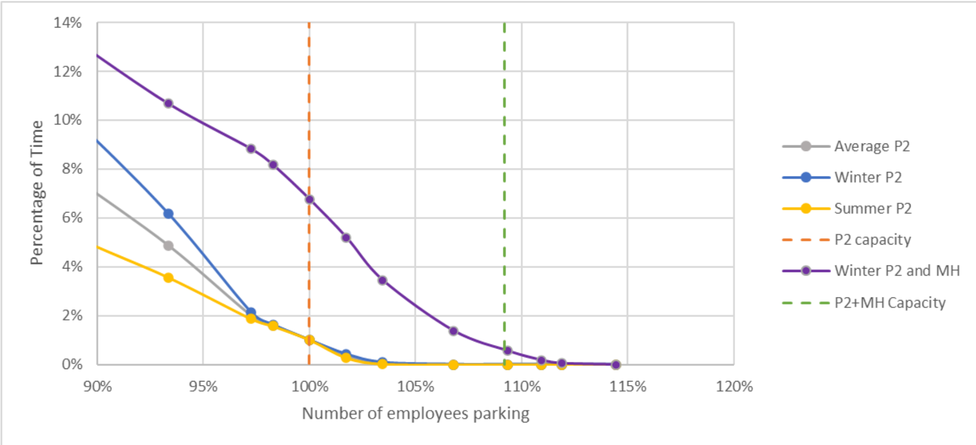


Figure 6.2: Cumulative distribution of employees parking starting at 90% of the capacity of P2

From Figure 6.2 follows that during the winter period, more employees commute by car. However, for P2 the number of cars parked between 97% to 101% of the capacity occurs just as often. Below 97% of the capacity, no parking problems occur, and more cars parked than 100% of the capacity occurs approximately just as frequently during winter and summer. During the winter period, MST also rents the Mooienhof to increase parking capacity. As a result, more employees commute by car, as is also displayed in Figure 6.2. Not only the maximum amount of employees parking increases in the winter period but continuously more employees commute by and park their car. On average, an extra 75 employees commute by car during the winter.

For the commuters by bike with a bikie tag Appendix A gives an overview. Figure6.3 shows that for commuters by bike, it is the other way around. Almost continuously more employees commute by bike during the summer than the winter. The maximum number of commuters by bike is approximately the same, but as mentioned earlier, is not the total amount of bicycle commuters. Table 6.1, shows the total number of bicycles parked in the bicycle parking garage for a week in march of the bikie data, which confirms not all employees have a bikie tag since the maximum is approximately 800 bicycles in contrast to the maximum of 526 commuters with bikie tag.

Aditionally, discussion with focus groups resulted in knowing that employees also park their bike close to MST (but not in the parking garage) because that is more convenient to reach their workplace. It is essential to consider that the available data probably covers half (or even less) of the bike commuters.

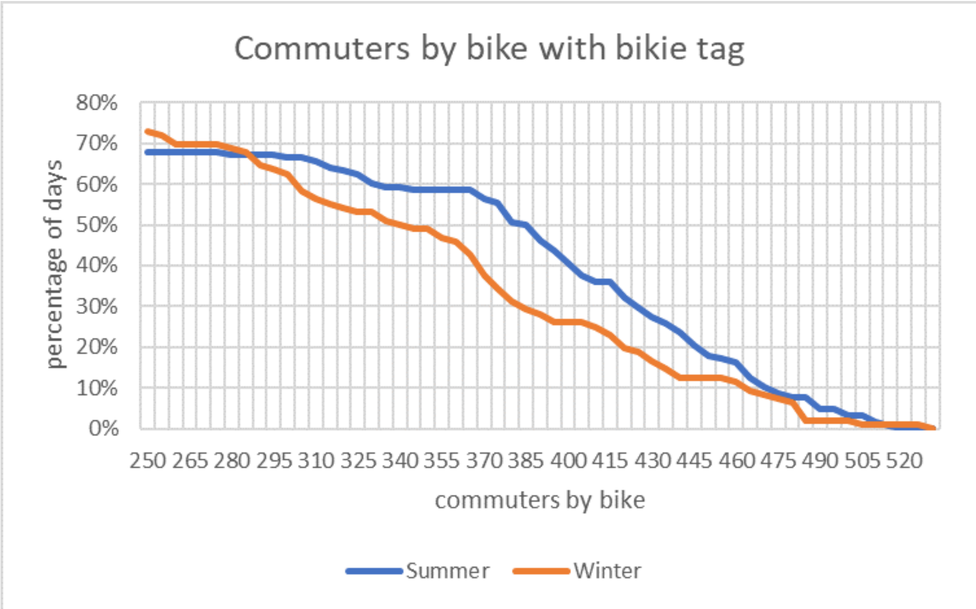


Figure 6.3: Cumulative distribution for the number of bicycle commuters

Table 6.1: Bicycles parked in the parking garage

	0:00-6:00			10:00-12:00		
	Regular bikes	E-bikes	Total	Regular bikes	E-bikes	Total
Tuesday	38	2	40	389	332	
Wednesday	33	3	36	410	310	720
Thursday	34	3	37	578	220	798
Friday	35	4	39	560	Unknown	560
Saturday	49	2	51	77	18	95
Sunday	38	5	43	70	17	87

From Table 6.2 follows that for an average weekday employees commute more by car in the winter and more by bicycle in the summer. As approximately half of the bicycle commuters have a bikie tag, the difference in bicycle commuters is much higher. Accordingly, employees switch from commuting by bike towards commuting by bike in the winter.

Table 6.2: Average number of commuters with bikies tag and by car

	Bicycle Commutes		Car Commutes	
	Daily	Weekday	Daily	Weekday
Winter period	295	376	661	776
Summer period	312	404	585	648
Difference	16	27	75	129

6.1.1 Monthly variation

The average of the summer and winter period differs, but the month to month difference might give other insights. In Figure 6.4, the data of P2 and Mooienhof together, confirm that the winter is more crowded than the summer. In June, July, August, the amount of car commuters does not exceed the capacity of P2, which makes sense since Mooienhof is not available, which limits the supply of parking space. In May and September, both in the transition period, the capacity of P2 is exceeded, like in all winter months. In February, June, July, August and October Dutch people usually have holidays, which could be a reason these months are less crowded.

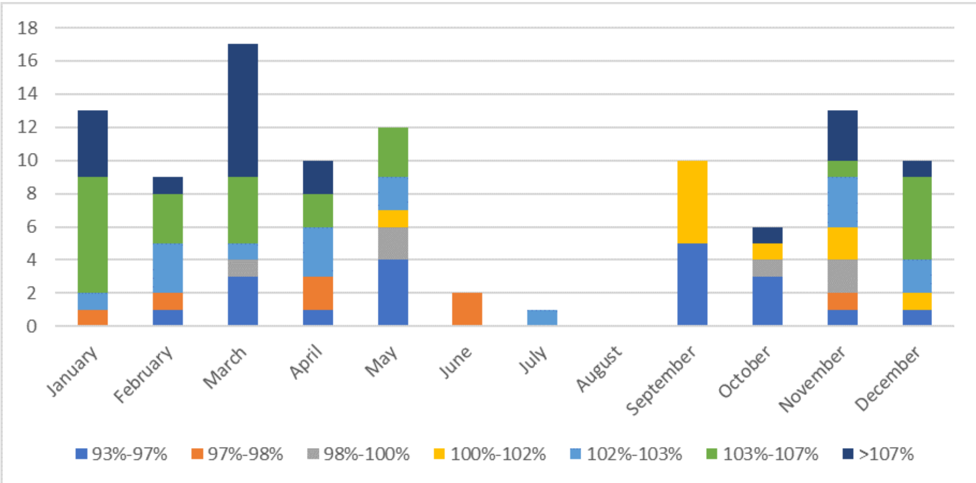


Figure 6.4: visualisation of the percentages of parking capacity exceeded for each month

Of all summer months, only May has capacity problems (>100%), which confirms the hypothesis that employees travel more by car during the winter period resulting in capacity problems during the winter period.

6.2 Weekly variation

The differences in months confirm that employees consequently commute more by car during the winter than in the summer. However, in February and October, parking demand seems lower in comparison with other winter months. The parking data per week, see Figure 6.5, shows the holiday periods. In week 1, 17, 24, 30-34, 42, 43 and 52 parking demand is lower than the average week minus one standard deviation.

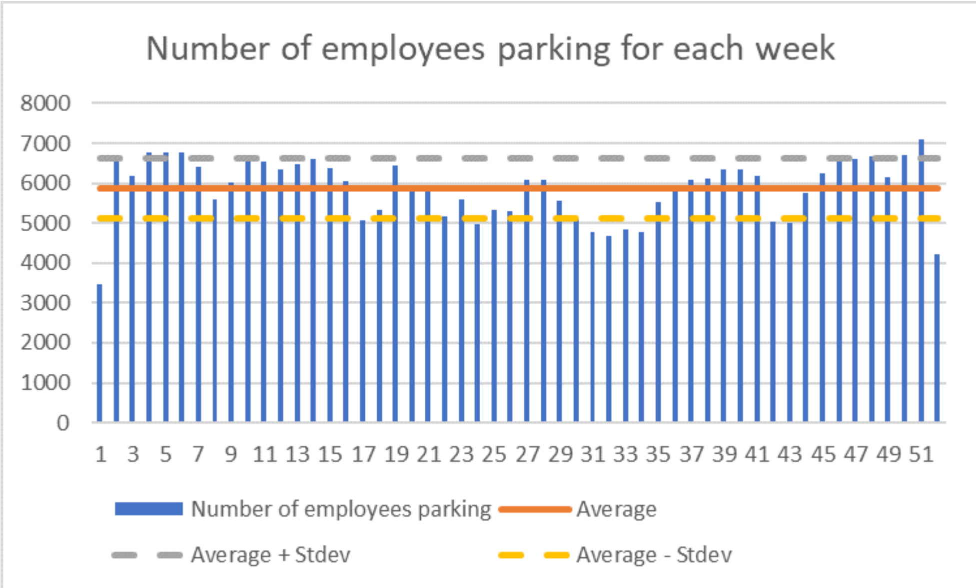


Figure 6.5: Number of cars parked per week with line for the average and the standard deviation added and subtracted from that average

During week 1 and 52 the occupation is below the average minus two standard deviations (see Appendix B), because of the Christmas holiday. Therefore, these weeks are excluded from further analysis. Except for the holiday weeks, almost every week during the winter, more than average employees park their car. These weeks, the capacity of solely P2 would not have been sufficient, and the Mooienhof is needed to supply extra parking places. Table 3 confirms that no parking problems are occurring during the holidays.

Table 6.3: Weeks with lower parking demand

Week(s)	Month (year)	Holiday?
1	January (2019)	Christmas holiday
8, 9	February (2019)	Spring holiday
17	April (2019)	Some schools had Whitsuntide holiday
24	June (2019)	No
30, 31	July (2018)	Summer holiday
31, 32, 33, 34	August (2018)	Summer holiday
42, 43	October (2018)	Autumn break
52	December (2018)	Christmas holiday

The data for bike commuters is specified for weeks in Figure 6.6 (the winter period lasts until week 16). Overall the lower frequencies correspond with the weeks fewer employees commute by car and holidays (Table 6.3). Week 4, 5, 10 and 11; however, frequencies of bikies commuters are much lower. Week 11 could also be due to spring holiday (different parts of the Netherlands can have different holiday weeks) It could also be the result of fewer employees commuting by bike because of the weather conditions, which is the case for week 4 and 5.

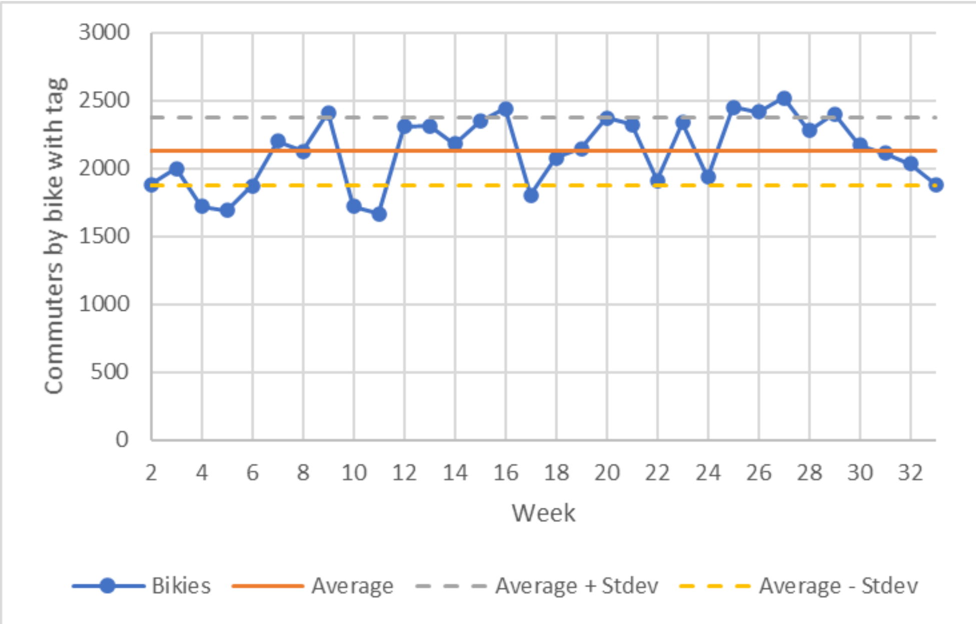


Figure 6.6: Commuters by bike with bikie tag specified per week

6.3 Inter-daily variation

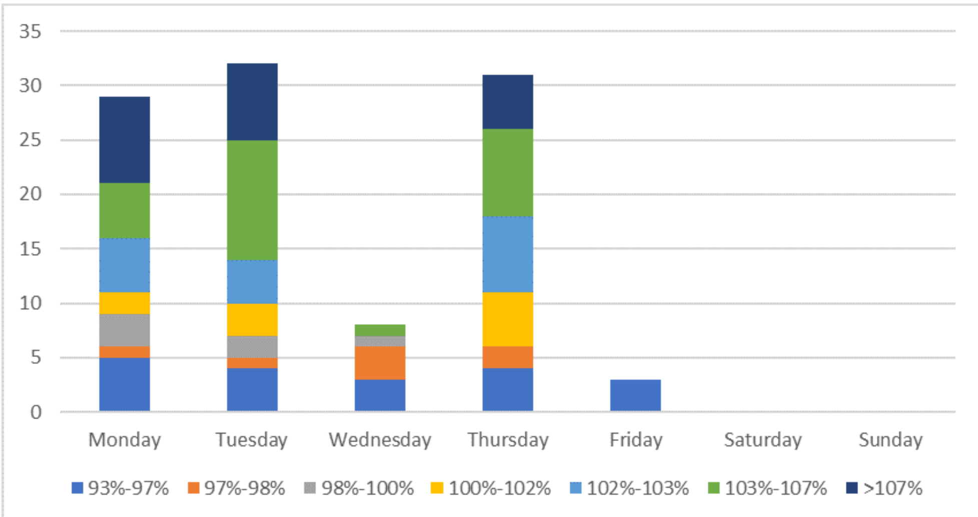


Figure 6.7: Visualisation of the percentages of parking capacity exceeded for each day

The amount of surgeries is constant during the week, but office personnel is also working on weekdays. Therefore, parking problems probably only occur on weekdays. The data confirm that hypothesis. Figure 6.7 illustrates the frequency of capacity bins for each day. It shows that Monday, Tuesday and Thursday are the busiest days, whereas Wednesday and Friday almost no capacity problems occur (Wednesday 1 time 103-107%). Not even in the winter. On Friday three times, 93%-97% of parking capacity was reached, whereas that often happened on Monday, Tuesday and Thursday. For the exact numbers, see Appendix A. The number of commuters by bike seems more stable during the week than car commutes, see Table 6.2 1 and Appendix A.

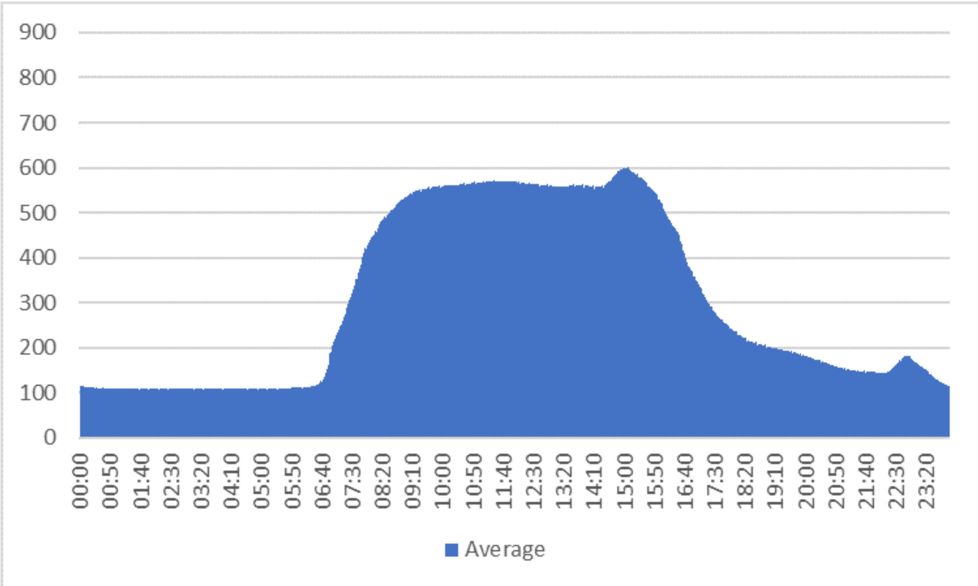


Figure 6.8: Distribution of the average daily parking place occupation

6.4 Conclusion

This analysis confirmed that there exists temporal variation in parking demand due to the seasons and working hours and employees exchange their commuting modes from car and bike, as illustrated in Table 6.2. Parking capacity problems occur mainly during the winter period and only during workdays in non-school holiday weeks. Since working hours are similar throughout the year, it is, because more employees commute by car and park their car in the parking garages of MST. Because parking problems only occur during weekdays, that indicates that parking problems mainly occur due to office personnel. Around that time two main alternatives exist for commuting by car: public transport and the bicycle.

As mentioned for the monthly variation, parking problems occur in the transition months September and May. Table 6.4 shows workdays, when it was raining, outside the holidays for September and October for comparison. The combination of rain and temperature influences the number of cars most, following 6 and 24 September and especially 30 October. Unfortunately, no bikies data was available for these days.

Table 6.4: Number of parked cars in the transition period

Temperature (°C)	Duration of Rain (h)	Sum of rain (mm)	Date	P2+MH	P2
14.4	1	11.4	03/09/2018	765	765
11.4	4.9	3.8	06/09/2018	879	879
11.1	2.6	2.6	07/09/2018	671	671
12.1	2	0.9	12/09/2018	756	756
9.6	0.2	0.1	21/09/2018	770	770
3	5.7	8.7	24/09/2018	875	875
3.5	6.4	8.4	01/10/2018	862	826
5.6	8.7	9.7	02/10/2018	956	896
10	0.5	1.1	04/10/2018	871	813
3.9	0.2	0.9	30/10/2018	733	655

Chapter 7

Spatial Analysis

First, a map with the residential location and full-time equivalent (FTE, 1= 40 working hours) of MST employees, train and bus lines gives the first check to both access to public transport and the employees' commuting distances can be performed. Then the residential location of car commuting employees in winter and summer is compared to investigate the exchangeability.

7.1 esidential location

Since the focus of this research lies in the commute mode of employees, their residential location and access to different transport modes are essential since not for all employees all transport modes are accessible. An overview of employees' residential location (if in the Netherlands) is shown in Appendix B with an enhanced view on the surrounding of Enschede. Not only the residential location but precisely the number of hours worked per employee is important, as that should be a better indicator of how many times an employee travels towards MST. Therefore Figure 1 shows the FTE's per PC4 area. Most FTE's live in Enschede and surroundings also close to public transport lines, providing access to public transport, car and (e-)bike commutes.

Figure 2 displays employees' distance from home to MST. The bicycle is most used for distances between 0.5km and 3.5km (Martens, 2004; Rietveld, 2000), whereas in Sweden people commute 20km during the summer and 10km during the winter (Bergström & Magnusson, 2003). That is supported by Fioreze et al. (2019), who found that one-way distances up to 20km are feasible by bicycle for most employees (64% in their research) in Enschede. A significant share of employees lives within those distances, providing opportunities for policies to increase bicycle commuting. Depending on which employees already commute by bike there might be opportunities to increase the number of commuters by bike and decrease the number of commuters by car.

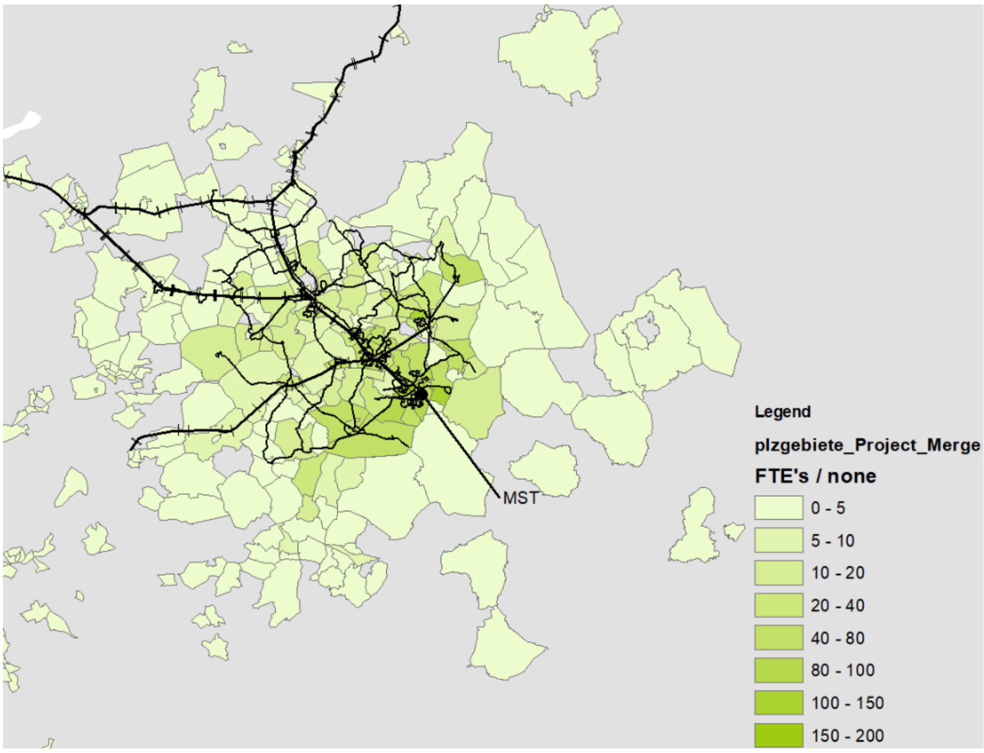


Figure 7.1: FTE per PC4 location

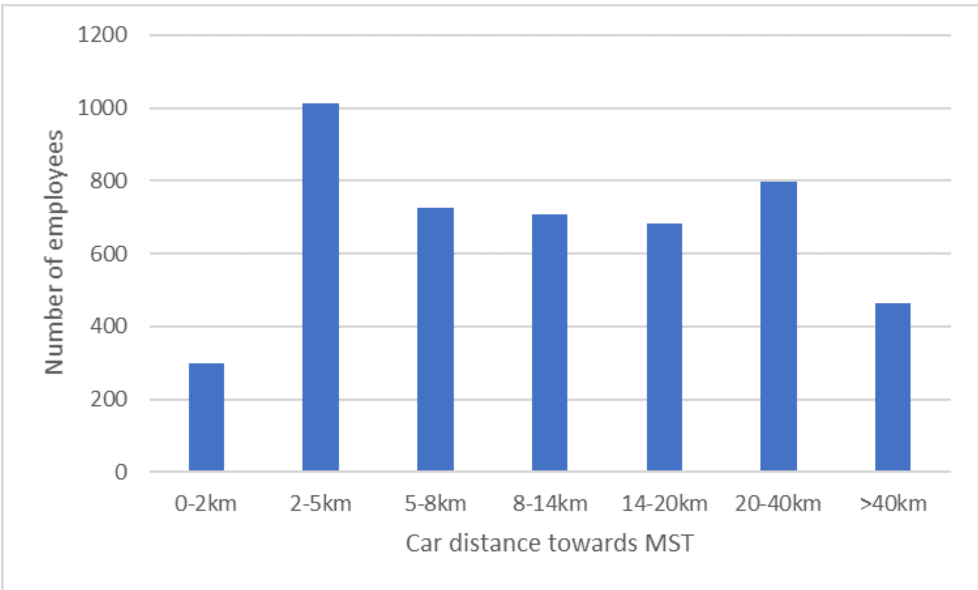


Figure 7.2: Distance categories for all MST employees

There is some insight in which MST employees travel with public transport from the survey. Based on the numbers from the national bureau of statistics of the Netherlands and Fioreze et al. (2019) the percentage of commuters by public transport is deficient. Therefore, it is highly unlikely that public transport hubs influence the exchangeability of car and bike commuting.

The share of active modes represents a larger group of commuters. The modal split of Table 1 suggests it is more likely that employees switch between commuting by car and commuting by bike. In general intrapersonal mode choice variation tends to be low for commuting trips, possibly because of the habitual character of these trips (Thomas et al., 2019). On the other hand, commuters that occasionally cycle to work are more likely to be encouraged to cycle more often than commuters that never cycle (Fioreze et al., 2019). Having multiple transport options, particularly for short distances, increases intrapersonal mode choice variation (Thomas et al., 2019). Additionally, commuting by bicycle has advantages over other modes of transport, both for the commuter and society (Heinen et al., 2010).

Table 7.1: Modal split data for active mode, car and public transport

	CBS data				Fioreze et al. (2019)	Survey
Transport mode	Netherlands	High Urban	East-Netherlands	Overijssel	MST	MST
Active Mode	28%	29%	32%	34%	80%	36%
Car	59%	56%	61%	60%	18%	61%
Public Transport	10%	11%	4%	4%	?	2%
Total	97%	96%	97%	98%	98%	±99%

7.2 Car and bike commuters origins

In the previous section, the model split showed that public transport is unlikely to play a role in exchangeability of car commutes, despite the convenient location of MST. To confirm that, origins can be compared for car and bicycle commutes both in the summer and the winter. For each PC4 area for both the summer and the winter period, the total amount of car commutes per day is illustrated in Appendix B. The number of times employees scanned their badge at the parking garage for entering is used as the number of times an employee parked his car.

Figure 3 shows the difference in the number of car and bike commutes. The legend shows the number of commutes during the summer subtracted from the number of commutes during the winter. Most regions seem to commute more by car and less by bike during the winter. The bicycle commutes are based on the bikies data and, therefore, should be multiplied by at least two. In that case, the delta's are roughly the same for most areas.

Remarkably, many regions very close to MST exchange car and bicycle commuting. Despite, MST has a policy in place that employees are not allowed to park their car from October until April when living closer than 8km. Naturally, exceptions are made for employees (i.e. bad health).

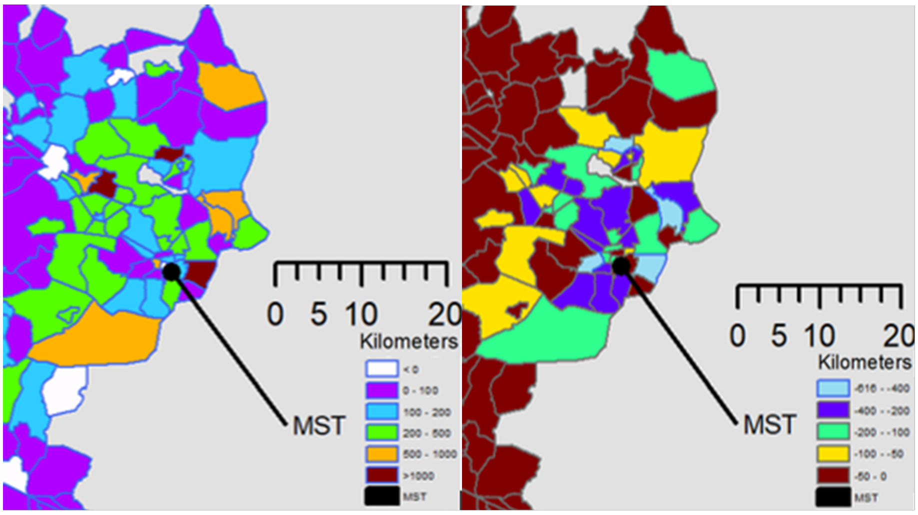


Figure 7.3: Resulting number of commutes (winter-summer) for the car (left) and bike (right)

7.3 Conclusion

In summary, this analysis denies the hypothesis that the exchangeability of car and bike commutes is less in areas with a convenient public transport connection. However, that is because a tiny part of the MST employees commutes by public transport and that the biggest public transport hubs in Haaksbergen, Oldenzaal and Hengelo show high exchangeability rates.

The analysis also confirms the hypothesis that employees exchange their commute by bike for a convenient commute by car during the winter. The delta from the car commutes roughly coincides with the delta on the right.

As a result, employees commute more by car during the winter than they do during the summer and the other way around for bike commutes. Additionally, it also shows that many employees from Enschede and surroundings who exchange their commute mode live within cycling distances. The exchangeability does vary for different distances, but, remarkably, many employees living close to MST also commute by car during the winter.

Chapter 8

Acceptance of Mobility Measures

In this section, the mixed logit models, discussed in section 4, determine the relative value of the attributes used in the stated choice experiments of the survey. Each mixed logit model is equivalent, but uses a subset of the data. For instance, in the models for car users, only employees who stated they commuted at least once by car are present in the subset. Conversely, employees who stated they did not commute by car are the non-car user's. The first part briefly discusses the coefficients of the logit functions per segment, and the second part concludes based on the analysis.

8.1 Car users

Table 8.1 shows that car users experience high initial parking cost (-2.75) much more harmful than non-car users (-0.7). Conversely, a high increase of distance-dependent parking cost is experienced equally harmful among both segments (-0.93 and -0.87). Non-car users (1.59) perceive doubling the bicycle subsidy more positive than car users (0.96). The increase of outside peak parking cost (€0.75 to €1,-) has a small negative effect on car users (-0.38) but does not significantly affect non-car users. Increasing the initial parking cost determines mainly the choice for a package of measures for car users. For non-car users, this is the case for the bicycle subsidy; however, it is much smaller than the effect of the initial parking cost on car users.

Table 8.1: Results for the mixed logit model for (non-)car-users

Car User		Yes	No
		B (SE)	B (SE)
Elected	ASC	-0.45 (0.17)**	-0.45 (0.24)**
	ASC_Sigma	1.76 (0.14)***	1.46 (0.17)***
	Initial Parking Cost	-2.75 (0.22)***	-0.7 (0.26)**
	Distance Dependent Parking cost	-0.93 (0.13)***	-0.87 (0.16)***
	Bicycle Subsidy	0.96 (0.11)***	1.59 (0.18)***
	Outside Peak Hour Parking Cost	-0.38 (0.11)***	0.32 (0.15)
	R^2	0.322	0.233

*p<0.05, **p<0.01, ***p<0.001.

8.2 Trip chaining (for children)

The model presented in Table 8.2 shows no significant differences between employees who do and employees who do not trip chain. Both segments experience an increase in parking cost, distance-dependent parking cost and outside peak parking cost negatively, and the bicycle subsidy positively. The differences between the coefficients of the two groups are not substantial, and there might be a difference in how both segments experience an increase in the initial parking cost. The results of the mixed logit model regarding employees who trip chain for dropping off and picking up their children, and the ones who do not, coincide with the previous paragraph. Table 8.3 shows almost the same results, except for the increase of the initial parking cost.

Table 8.2: Results for the mixed logit model segmented for trip chaining employees

Trip Chaining		Yes	No
		B (SE)	B (SE)
Elected	ASC	-0.57 (0.19)**	-0.17 (0.2)**
	ASC_Sigma	1.57 (0.14)***	1.78 (0.16)***
	Initial Parking Cost	-2.22 (0.23)***	-1.77 (0.24)***
	Distance Dependent Parking cost	-0.96 (0.14)***	-0.76 (0.15)***
	Bicycle Subsidy	0.96 (0.12)***	1.25 (0.14)***
	Outside Peak Hour Parking Cost	-0.23 (0.11)**	-0.07 (0.13)**
	R^2	0.269	0.273

*p<0.05, **p<0.01, ***p<0.001.

Table 8.3: Results mixed logit model segmented by employees who trip chain for their children and those who do not

Trip Chain for Children		Yes	No
		B (SE)	B (SE)
Elected	ASC	-0.81 (0.31)**	-0.27 (0.16)**
	ASC_Sigma	-1.7 (0.26)***	1.67 (0.12)***
	Initial Parking Cost	-2.77 (0.4)***	-1.82 (0.18)***
	Distance Dependent Parking cost	-1.07 (0.24)***	-0.81 (0.11)***
	Bicycle Subsidy	0.98 (0.2)***	1.13 (0.1)***
	Outside Peak Hour Parking Cost	-0.33 (0.19)**	-0.13 (0.09)**
	R^2	0.297	0.265

*p<0.05, **p<0.01, ***p<0.001.

8.3 Set departure times

Table 8.4 shows the results for employees with set departure times. Like the previous model, there is not much difference between most coefficients of the attributes. However, increasing the parking cost outside the peak hours decreases the chance significantly of employees without set departure times to choose the package of measures. This effect is absent for employees who do have a set departure time.

Table 8.4: Mixed logit model distinguished for employees who have set departure times

		Yes	No
		B (SE)	B (SE)
Elected	ASC	-0.48 (0.2)**	-0.31 (0.19)**
	ASC_Sigma	1.8 (0.16)***	1.56 (0.14)***
	Initial Parking Cost	-2.05 (0.24)***	-2 (0.23)***
	Distance Dependent Parking cost	-0.9 (0.14)***	-0.84 (0.14)***
	Bicycle Subsidy	1.22 (0.13)***	0.98 (0.12)***
	Outside Peak Hour Parking Cost	0.03 (0.12)	-0.34 (0.12)**
	R^2	0.282	0.261

*p<0.05, **p<0.01, ***p<0.001.

8.4 Distance categories

As shown in Table 8.5, a clear difference exists between distance groups regarding initial parking cost. Employees living <4km and 9-15km are less adverse towards an increase in initial parking costs , than employees living 4-9km or >15km from MST.

The increase of distance-dependent parking cost is experienced the most negatively by employees living 4-9km from MST. Secondly, employees who live <4km and 9-15km perceive increasing the distance-dependent parking costs negatively. The distance-dependent parking costs also negatively influences employees living >15km from MST, but the effect is minimal.

The bicycle subsidy affects all distance categories positively. However, no clear distinction is visible on the difference in the effects. Only for employees living >15km from MST the outside peak parking cost increase negatively influences the choice for a package of measures (so a decrease is favoured).

Table 8.5: Mixed logit model for different distance categories

Distance	<4km	4-9km	9-15km	>15km
Elected	B (SE)	B (SE)	B (SE)	B (SE)
ASC	-0.62 (0.32)**	-1.14 (0.38)**	0.73 (0.42)	-0.26 (0.2)**
ASC_Sigma	-1.26 (0.23)***	1.5 (0.26)***	1.73 (0.28)***	1.87 (0.17)***
Initial Parking Cost	-0.67 (0.34)**	-1.99 (0.46)***	-0.49 (0.46)**	-2.92 (0.26)***
Distance Dependent Parking cost	-1.28 (0.22)***	-2.31 (0.33)***	-0.77 (0.27)**	-0.29 (0.14)**
Bicycle Subsidy	1.56 (0.23)***	1.12 (0.24)***	1.52 (0.25)***	1.06 (0.14)***
Outside Peak Hour Parking Cost	0.41 (0.21)	0.28 (0.24)	0.24 (0.24)	-0.58 (0.13)***
R^2	0.261	0.303	0.29	0.377

*p <0.05, **p<0.01, ***p<0.001

8.5 Intrapersonal mode choice variation or single-mode commuters

As illustrated in Table 8.6, employees with intrapersonal mode choice variation (IPMCV) and single-mode car commuters find an increase in initial parking cost significantly more unpleasant, than employees who commute only by an active mode. The same acceptance is present for the outside peak parking cost.

IPMCV employees are negatively affected through an increase in distance-dependent parking cost. Only car and only active commuters are both affected less.

Employees who only commute actively are more prone to bicycle subsidy than car commuters and employees with IPMCV.

Table 8.6: Results for mixed logit model distinguishing for mode choice

Mode choices		Only Car	Only Active	IPMCV
		B (SE)	B (SE)	B (SE)
	ASC	-0.21 (0.21)**	-0.45 (0.26)**	-0.7 (0.28)**
	ASC_Sigma	1.69 (0.17)***	1.48 (0.18)***	1.88 (0.21)***
Elected	Initial Parking Cost	-2.53 (0.27)***	-0.63 (0.27)**	-2.91 (0.36)***
	Distance Dependent			
Parking cost	-0.57 (0.15)***	-0.9 (0.18)***	-1.51 (0.21)***	
	Bicycle Subsidy	0.85 (0.14)***	1.71 (0.19)***	1.07 (0.17)***
	Outside Peak Hour			
Parking Cost	-0.53 (0.13)***	0.32 (0.17)	-0.16 (0.17)**	
	R^2	0.331	0.246	0.314

*p<0.05, **p<0.01, ***p<0.001.

8.6 Income groups

For different income groups, the coefficient of the increase ininitial parking cost is almost equally negative for all income groups. The distance-dependent parking cost holds lower acceptance among lower-income groups (30k-50k and <30k) than the higher income groups (>75k and 50k-75k). Bicycle subsidy is welcomed equally by all income groups, except for the highest incomes (>75k) and an increase in outside peak hour parking costs negatively influences lower incomes (30k-50k and <30k).

Table 8.7: Mixed logit models for different income categories

Income	>75k	50k-75k	30k-50k	<30k
Elected	B (SE)	B (SE)	B (SE)	B (SE)
ASC	-0.8 (0.59)**	-0.07 (0.4)**	-0.24 (0.22)**	-0.77 (0.24)**
ASC_Sigma	-1.17 (0.43)**	-1.59 (0.31)***	-1.74 (0.17)***	1.67 (0.18)***
Initial Parking Cost	-1.83 (0.71)**	-1.5 (0.45)***	-1.95 (0.26)***	-2.5 (0.3)***
Distance Dependent Parking cost	-0.17 (0.41)**	0.27 (0.3)	-0.99 (0.15)***	-1 (0.18)***
Bicycle Subsidy	0.83 (0.36)	1.34 (0.28)***	1.27 (0.14)***	0.89 (0.16)***
Outside Peak Hour Parking Cost	0.12 (0.34)	0.4 (0.24)	-0.29 (0.14)**	-0.3 (0.15)**
R^2	0.19	0.28	0.292	0.263

*p<0.05, **p<0.01 ***p<0.001

8.7 Conclusion

Car users experience an increase in parking costs (both distance-dependent and initial) more negatively and bicycle subsidy less positively than non-car users. Car users also find a decrease in the outside peak parking cost attractive, whereas non-car users are unaffected. Non-car users are primarily cyclists, since there are almost no public transport users, which clarifies the difference in opinion between these groups. The decrease in outside peak parking costs is attractive for employees (partially) working night shifts and commuting by car. Therefore, car users are significantly affected by the decrease in outside peak parking cost.

The mixed logit model differentiated for employees who trip chain and the ones who do not, does not provide evidence that a difference between these groups exists. However, employees trip chaining for their children and the ones who do not do provide such evidence. Reasons stated for trip chaining, as illustrated in Figure **??**, are most frequently for household errands, but also activities for children, such as bringing them to school. The difference between employees who trip chain and the ones who trip chain for their children, could be explained by the fact that errands are more flexible than dropping children off at school. For example, household errands or leisure are both possible during the weekend, whereas daycare, school or sport of children are fixed moments. Additionally, leisure and small errands are possible by bike.

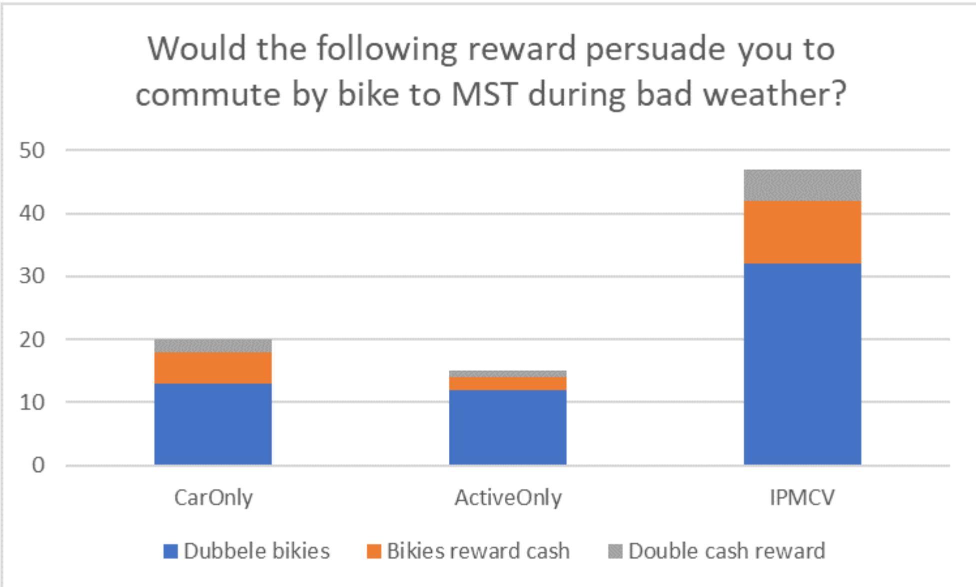


Figure 8.1: Causes of trip chaining for different transport modes.

Employees who do not have set departure times are, contrary to employees who do, more likely to accept a package of measures with decreased outside peak parking cost (€0,75 vs

€1,-). Employees without set departure times (also) work night shifts, which explains the relation with outside peak parking cost.

Generally, employees living close by are more affected by the increase of the distance-dependent parking cost than the initial parking cost (and vice versa), and favour an increase in bicycle subsidy the most from all distance categories. That makes sense, since most of the employees living close to MST frequently cycle to work and the distance-dependent parking costs affect employees who live closer to MST more (just as an increase in initial parking costs affects employees living >15km from MST more). An exception to this rule are employees from the 4-9km category. These employees experience both an increase in initial parking costs and distance-dependent parking cost negative. This effect is odd, since most employees in this category commute frequently by bike. An explanation could be that employees perceive the bicycle subsidy as not good enough, whereas the consequences of new parking tariffs are present to them, as commuting by car might be a good alternative to them.

Employees living farthest from MST (>15km) react positively to a decrease in parking cost outside the peak hours. These employees are most dependent on commuting by car and employees with night shifts; therefore, probably appreciate a decrease in outside peak parking costs.

Employees with IPMCV and only car commuters experience an increase in initial parking costs very adverse. Most IPMCV employees also commute by car, which means the increase in initial parking costs affects these two groups and explains their negative attitude against increasing the initial parking costs.

IPMCV employees also experience an increase in distance-dependent parking costs the most negative from all groups. These employees live at distances from MST, Enschede and surroundings, so they can both commute by bike and by car, but do not want to be penalised when they choose to commute by car. In general, only active employees care less about the parking costs, since they commute by an active mode and employees who only commute by car live too far away for the distance-dependent parking cost to affect them.

Surprisingly, employees who only commute by car and with IPMCV appraise bicycle subsidy roughly the same. Unsurprisingly, active commuters appreciate bicycle subsidy significantly more. The outside peak parking costs are more relevant to car commuters than employees with IPMCV. Partially, because employees who commute only by car mainly live far away from the MST so that car commutes are more convenient. However, also employees with IPMCV appreciate the decrease in outside peak parking cost. These employees live at a distance that the choice for active commuting or by car is a competitive one, but when they work night shifts, they probably prefer the car for e.g. safety reasons.

All income groups prefer lower initial parking cost. However, the higher incomes (>75k and 50k-75k) are more complacent to distance-dependent parking cost than lower incomes (30k-50k and <30k), which confirms the hypothesis, higher-income employees travel further and are, therefore, unaffected by the distance-dependent parking cost. Consequently, the bicycle subsidy does not affect the highest income group, whereas other income groups prefer an increase in subsidy. Additionally, lower outside peak parking cost are preferred by lower-income groups, whereas higher income groups are indifferent. Lower-income groups are working more night shifts (e.g. security), and if duty calls for a doctor during the night, he or she can park at the emergency parking places.

Employees who stated extra bikies would encourage them to cycle in bad weather and those who did not, value all attributes approximately the same, apart from the bicycle subsidy. The subsidy is much more crucial to them than other employees. Most employees within this group already commute by an active mode, see Figure 8.2, but also employees who commute by car stated they would be more encouraged with increased bikies.

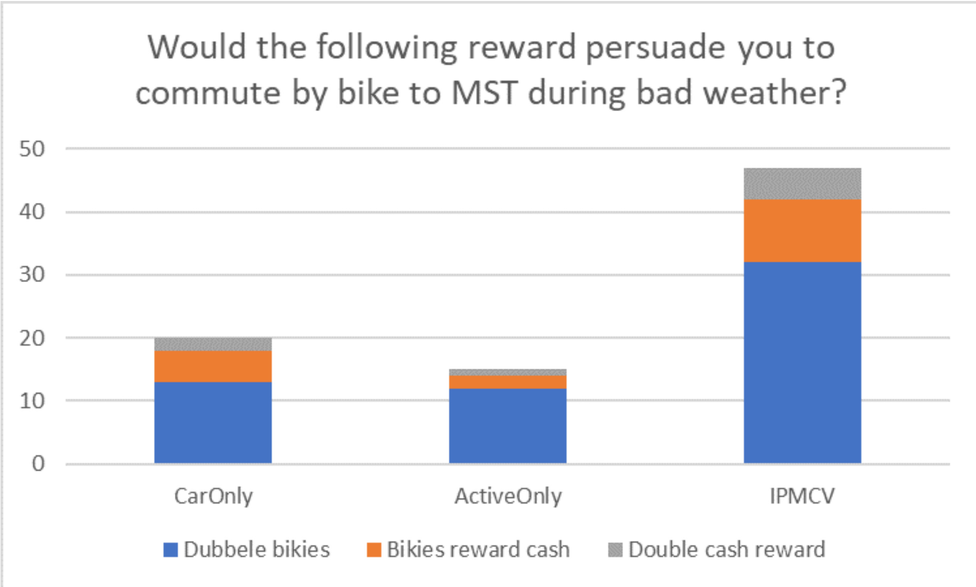


Figure 8.2: Breakdown of employees who stated they would commute by bike for different rewards.

Chapter 9

Effect of Mobility Measures

Eventually, the effect of the mobility measures is an essential aspect to consider, since the goal is to reduce the number of employees commuting by car. The stated choice experiments regarding the number of commutes per mode, described in the research approach, are the starting point for the analyses in this chapter. The first part creates an overview of the overall effects and utility of the different packages of measures. From that analysis, follows four selected packages to investigate the effects for different segments more in-depth.

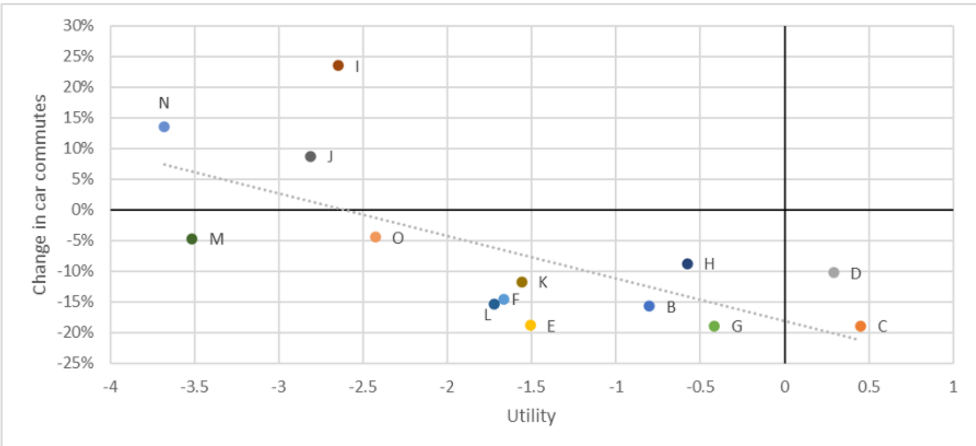


Figure 9.1: Overview of the utility vs effect

Figure 9.1 shows that most packages reduce the number of car commutes. The only exceptions are package I, J, and N, but these are not often elected, just as packages F, M, N, O are not often elected, see Table 9.1. The change in the number of car commutes is steadily around 10-20%. Unexpectedly, a negative utility does not correspond with a decrease in car commutes. The expectation was that packages without acceptance would generate the most significant decrease in car commutes since employees do not want those measures implemented. In other words, a negative utility does not coincide with a more significant decrease in car commutes, whereas the expectation was the other way around. For instance, package C and D have a positive utility, but also cause a decrease in car commutes. The most remarkable from Figure 9.1 is the increase in car use for packages with a very negative utility.

Table 9.1: Percentage elected and attributes visualised per package

	Elected (%)	Elected	Initial Cost	Increase in Cost	Bicycle Subsidy	Outside peak Cost
B	52%	275	€1,-	€0,25	Normal	€1,-
C	85%	365	€1,-	€0,25	Double	€0,75
D	78%	431	€1,-	€0,25	Double	€1,-
E	45%	181	€1,-	€0,50	Normal	€0,75
F	38%	324	€1,-	€0,50	Normal	€1,-
G	70%	328	€1,-	€0,50	Double	€0,75
H	76%	435	€1,-	€0,50	Double	€1,-
I	26%	119	€1,25	€0,25	Normal	€0,75
J	35%	148	€1,25	€0,25	Normal	€1,-
K	68%	300	€1,25	€0,25	Double	€0,75
L	56%	137	€1,25	€0,25	Double	€1,-
M	16%	86	€1,25	€0,50	Normal	€0,75
N	14%	37	€1,25	€0,50	Normal	€1,-
O	42%	68	€1,25	€0,50	Double	€0,75

However, the specific effects on different segments within the respondents are essential to consider, which the next chapter discusses. For a more in-depth analysis, the elected packages are C, G, H, and K, for these seem to affect mode choice (Figure 9.1), and both have enough respondents and have different attributes (Table 9.1).

Disaggregated analyses on effects

From the Table in Appendix E follows that overall the effect of the package of measures C, G, H and K led to a decrease of employees using the car. To ensure a significant effect for a package of measures, two times the standard deviation in the mean of the difference (95% interval) added or subtracted to the average difference must not contain zero. Otherwise, the effect can also still be zero, and no significant effect occurs. The distinguish between employees who wanted extra bikies to cycle in bad weather and the ones who did not lead to no results worth mentioning (see Appendix E), just as for employees trip chaining for their children. The following figures display the cross-sectional effects of the measures. Figure 1 shows the effects and utilities for different distances. Employees living >15km from MST experience K very harmful, whereas all other distance categories value G more negative than K. Employees living 4-9km are the only ones with lower utility for package H than C, meaning that they are more against €0,50 distance-dependent increase and outside peak cost of €1 than the other distance categories.

The packages with a significant effect are C and G for employees living >15km from MST and K for employees living 9-15km from MST. If C and G were implemented employees living >15km from MST would keep the same parking cost during peak hours, with decreased parking cost outside peak hours and an increased bicycle subsidy resulting in a small decrease in car commuters. Employees living 9-15km from MST reduce their car commute if parking cost increase with €0,50, combined with an increased bicycle subsidy and decreased parking cost outside peak hours.

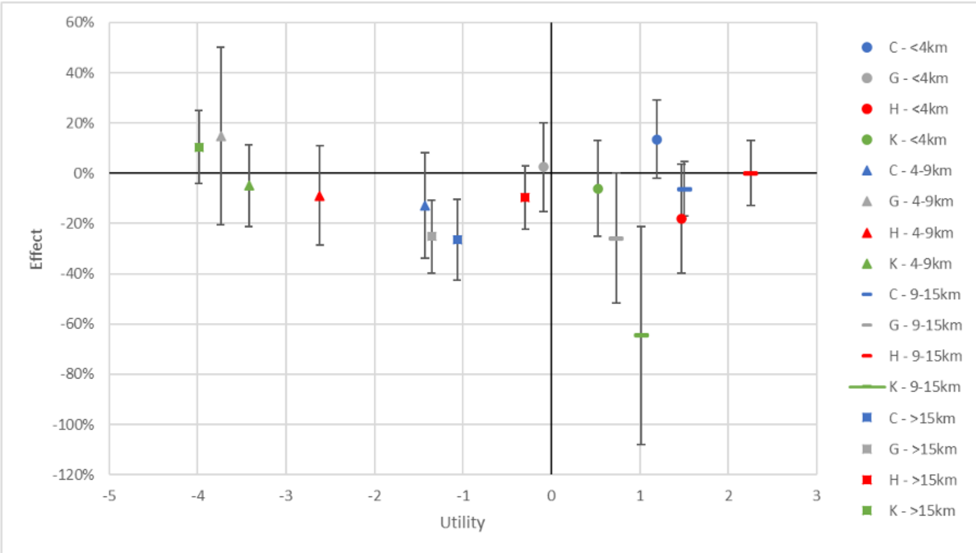


Figure 9.2: Effect of measures for different distance categories

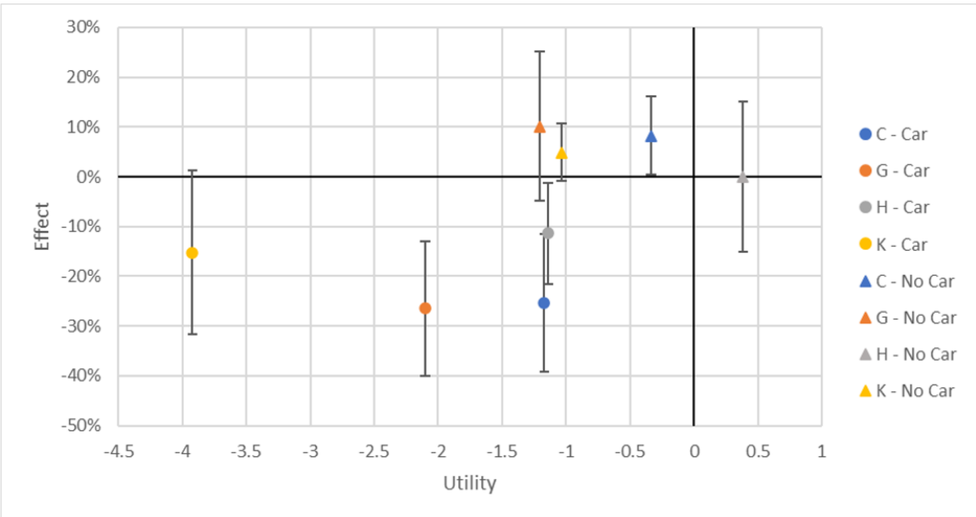


Figure 9.3: Effects of measures for car users and no- car users

Figure 9.3 shows that car users value K (high initial parking cost) worse than G (high distance-dependent parking cost) and non-car users the other way around. The packages C and G have significant effects on car users, and no effects are observed for non-car users. Both C and G increase the bicycle subsidy, resulting in fewer car commuters. Additionally, G increases the distance-dependent parking cost with €0,50 instead of €0,25.

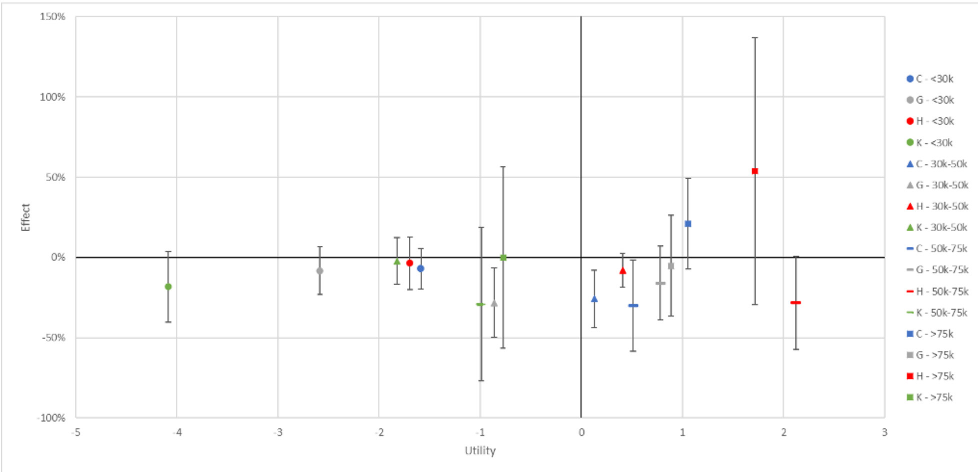


Figure 9.4: Effects of packages for income groups

Figure 9.4 shows the effect of the packages on different income groups. The utility varies a lot for different income groups. K unanimously has the lowest utility, G has the second-lowest utility for all income groups except for 50-75k, who choose C as second worst. The best utility for most income groups is for package H, only <30k chooses package C as the best. However, all utilities are low for the lowest income category. Only the income group 30-50k significantly decrease their car commutes as a consequence of package C and G, with an increase in bicycle subsidy and for G an increase of €0,50 for the parking cost.

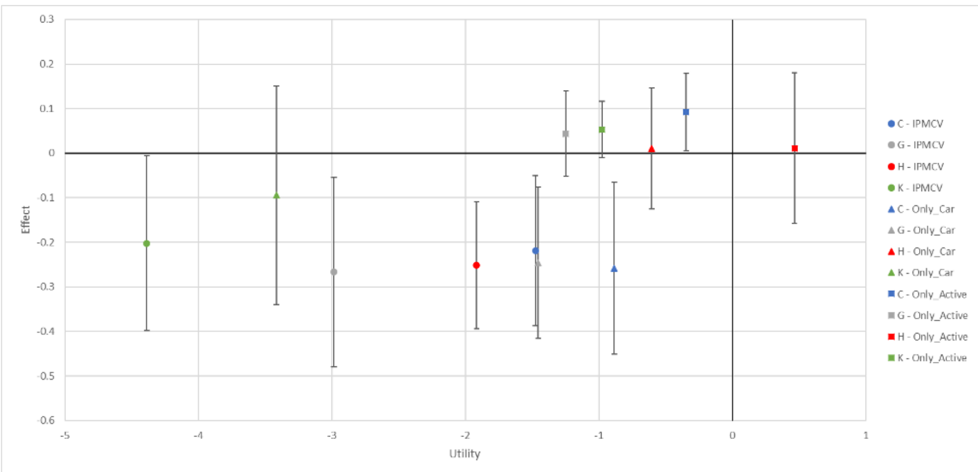


Figure 9.5: Effects for employees only commuting by car, only by bike and with intrapersonal mode choice variation

In Figure 9.5, the most negative utility corresponds to package K; however, single-bike users value G worse than K. single-bike users find €0,50 distance-dependent increase in parking cost more harmful than an initial increase of €0,25. Both single-car and single-active commuters appreciate H the most. Single-car users probably because the initial parking cost maintain and single-bike users because the bicycle subsidy increases.

The most significant effects occur for the intrapersonal mode choice variation group. For all packages, except for K, a decrease in car use occurs. Again, for G and C, also a decrease occurs for single-car users.

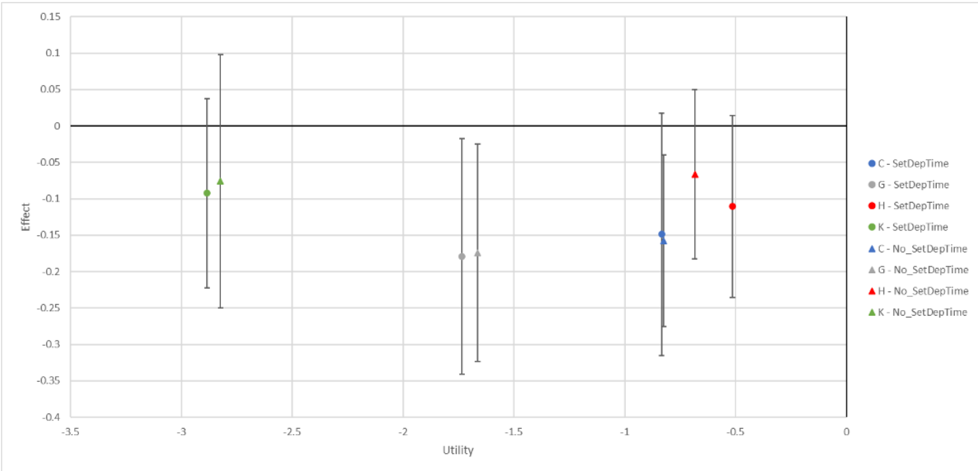


Figure 9.6: Effects for employees with regular and irregular working hours

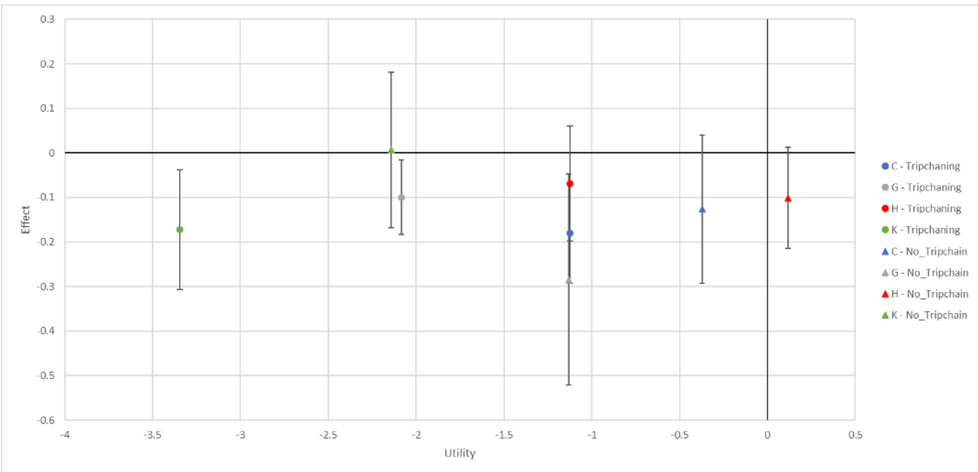


Figure 9.7: Effects for employees who trip chain their work trip and the ones who do not

The differences for employees with irregular working hours, Figure 9.6, and trip chaining employees, Figure 9.7, are small. Figure 9.6 shows that both groups decrease car use with package G and employees with set departure times also decrease car use in case of package C. In Figure 9.7, both segments decrease car use with package G.

Conclusion

The most significant decreases occur for commuters with intrapersonal mode choice. Also, car users, single-car, 30-50k, and 4-9km employees decrease car use. Package G and C have the most significant effects, followed by H. Furthermore, has the lowest income category low utility (<-1.5) for all four elected packages. The trade-off between C and G, more precise, between a distance-dependent parking cost increase of €0,50 or €0,25 is only more productive and employees who trip chain, whereas for car commuters it is the other way around.

Chapter 10

Conclusion

This research aims at contributing knowledge to the effect of mobility measures on specific populations in order to be able to implement effective policies to increase the number of commuters by bike and to add knowledge on the substitutability of the car and bike for commutes. This part provides the answer to the research question. For an overview, first, it shows the sub-questions and its answers followed by an answer to the main research question.

What temporal variations are present in the parking problem?

The analysis confirmed that there exists temporal variation in parking demand due to seasonal conditions and working hours and employees exchange their commuting modes from car and bike. Parking capacity problems occur mainly during the winter period and only during workdays in non-school holiday weeks.

As mentioned for the monthly variation, parking problems occur in the transition months September and May. Table 3 shows workdays, when it was raining, outside the holidays for September and October for comparison. The combination of rain and temperature influences the number of commuters by car the most.

Since working hours are similar throughout the year, it is, because more employees commute by car and park their car in the parking garages of MST. Because parking problems only occur during weekdays, working hours play a huge role. Additionally, it makes finding alternatives easier as around that time, and two main alternatives exist for commuting by car: public transport and the bicycle.

What spatial variables influence the exchangeability of car and bike for commutes to MST?

In summary, this analysis denies the hypothesis that the exchangeability of car and bike commutes is less in areas with a convenient public transport connection. However, that is because a tiny part of the MST employees commutes by public transport and might not be accurate for other cases.

The analysis does confirm the hypothesis that employees exchange their commute by bike for a convenient commute by car during the winter. The delta from the car commutes roughly coincides with the delta for the bicycle commutes (if multiplied, since not all bicycle commuters have a bikie tag).

As a result, employees commute more by car during the winter than they do during the summer and the other way around for bike commutes. Additionally, it also shows that many employees from Enschede and surroundings who exchange their commute mode live within cycling distances. The exchangeability does vary for different distances, but, remarkably, many employees living close to MST also commute by car during the winter.

What is the acceptance of mobility measures among different segments of employees?

Car users experience an increase in parking costs (both distance-dependent and initial) more negatively and bicycle subsidy less positively than non-car users. Car users also find a decrease in the outside peak parking cost attractive, whereas non-car users are unaffected. Non-car users are primarily cyclists since there are almost no public transport users, which clarifies the difference in opinion between these groups. The decrease in outside peak parking costs is attractive for employees (partially) working night shifts and wanting to commute by car for safety reasons.

The mixed logit models for employees who trip chain and the ones who do not, provide evidence there exists no difference between these groups. However, for employees trip chaining for their children, there is a difference in how attributes are perceived.

Reasons stated for trip chaining, as illustrated in Figure 10.1, are most frequently for household errands, but also activities for children, such as bringing them to school. The difference between employees who trip chain and the ones who trip chain for their children probably is a result of errands being more flexible than dropping children at school. For example, household errands or leisure are both possible during the weekend, whereas day-care, school or sport of children are fixed moments at the beginning or end of a workday. Additionally, leisure and small errands are possible by bike.

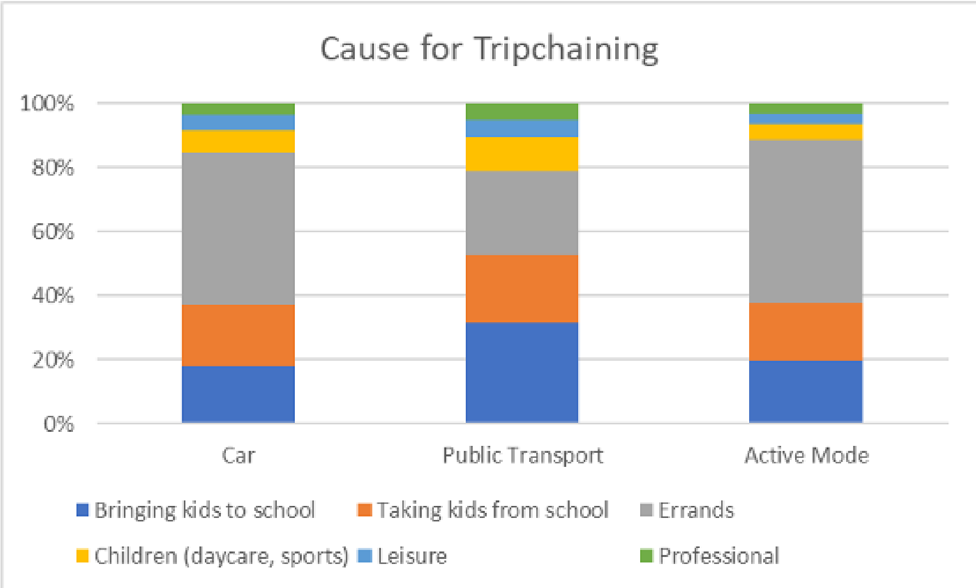


Figure 10.1: Causes of trip chaining for different transport modes

Employees who do not have set departure times are, contrary to employees who do, more likely to accept a package of measures with decreased outside peak parking cost (€0,75 vs €1,-). Employees without set departure times (also) work night shifts which explain the relation with outside peak parking cost.

Generally, employees living close are more affected by the increase of the distance-dependent parking cost than the initial parking cost (and vice versa) and favour an increase in bicycle subsidy the most from all distance categories. That makes sense since most of the employees living close to MST frequently cycle to work and the distance-dependent parking costs affect employees who live closer to MST more (just as an increase in initial parking costs affects employees living >15km from MST more). Though, oddly, employees living <4km feel they (sometimes) need to commute by car. An exception to this rule are employees from the 4-9km category. These employees experience both an increase in initial parking costs and distance-dependent parking cost very negative. This effect is odd, since most employees in this category commute frequently by bike. An explanation could be that employees perceive the bicycle subsidy as not good enough, whereas the consequences of new parking tariffs are very present to them.

Employees living >15kmfrom MST react positively to a decrease in parking cost outside the peak hours. These employees are most dependent on commuting by car and employees with night shifts; therefore, probably appreciate a decrease in outside peak parking costs.

Employees with IPMCV and single-car commuters experience an increase in initial parking costs very adverse. Most IPMCV employees also commute by car, which means the increase in initial parking costs affects these two groups and explains there negative attitude against increasing the initial parking costs.

IPMCV employees also experience an increase in distance-dependent parking costs the most negative. These employees live at a distance from MST so they can both commute by bike and by car, but do not want to be punished when they choose to commute by car. In general, only active employees care less about the parking costs since they commute by an active mode and employees who only commute by car live to far away for the distance-dependent parking cost to affect them.

Surprisingly, employees who only commute by car and with IPMCV appraise bicycle subsidy roughly the same. Unsurprisingly, active commuters appreciate an increased bicycle subsidy significantly more. The outside peak parking costs are more relevant to car commuters than employees with IPMCV. Partially, because employees who commute only by car mainly live in a distance car commutes are more convenient. However, also employees with IPMCV appreciate the decrease in outside peak parking cost. These employees live at a distance that the choice for active commuting or by car is a competitive one, the use of both modes acknowledges that but when they work night shifts probably prefer the car for, e.g. safety reasons.

All income groups prefer lower initial parking cost. However, the higher incomes (¿75k and 50k-75k) are more complacent to distance-dependent parking cost than lower incomes (30k-50k and ¡30k), which confirms the hypothesis, higher-income employees travel further and are, therefore, unaffected by the distance-dependent parking cost. Consequently, the bicycle subsidy does not affect the highest income group, whereas other income groups prefer an increase in subsidy. Additionally, lower outside peak parking cost are preferred by lower-income groups, whereas higher income groups are indifferent. Lower-income groups are working more night shifts (e.g. security), and if duty calls for a doctor during the night, he or she can park at the emergency parking places.

Employees who stated extra bikies would encourage them to cycle in bad weather and those who did not, value all attributes approximately the same, apart from the bicycle subsidy. The subsidy is much more crucial to them than other employees. Most employees within this group already commute by an active mode, but also employees who commute by car stated they would be more encouraged with increased bikies.

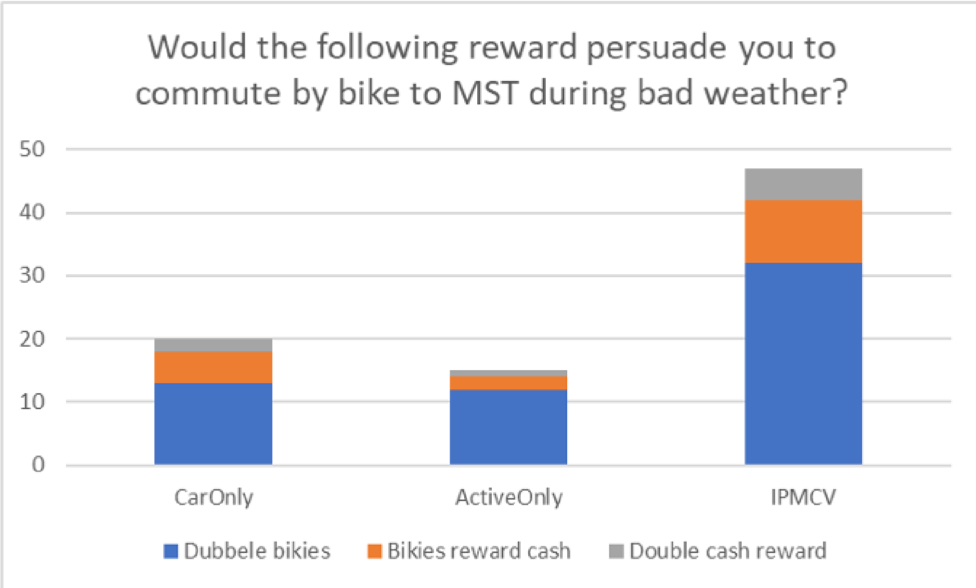


Figure 10.2: Rewards convincing employees to commute by bike

What is the effect of mobility measures on the commuting mode of MST employees?

The effects of the package of measures are small, and therefore caution with implementing is vital. The most significant decreases occur for commuters with intrapersonal mode choice. Also, car users, single-car, 30-50k, and 4-9km employees decrease car use. Package G and C have the most significant effects, followed by H. Furthermore, has the lowest income category low utility (<-1.5) for all four elected packages. The trade-off between C and G, more precise, between a distance-dependent parking cost increase of €0,50 or €0,25 is only more productive and employees who trip chain, whereas for car commuters it is the other way around.

This report aimed at reducing the number of car commuters to overcome parking problems at MST, which resulted in the following research question:

How can mobility measures influence the exchangeability of car and bike commutes at the MST, Enschede?

The effects of the measures seem small; however, package C and G, both with increased bicycle subsidy, had the most significant effect. Figure 10.2 confirms that employees are willing to commute by bike, even with bad weather. Package C and G both increase the parking cost for employees living close to MST, C with €0,25 and G with €0,50, but are more or less equally accepted among different categories.

The groups where the effect of package C and G occurs is among single-car users and also employees with intrapersonal mode choice. Therefore, car users decrease their car use in scenario C and G. Employees who trip chain or have no set departure time decrease the number of car commutes in case of scenario G, due to the extra €0,25 per distance category. Employees with a set departure time only decrease their commutes in scenario C. Remarkably, only effects occur for employees in the income category 30-50k.

The effects of C and G do not seem to outrun each other much; therefore, package C is probably enough to solve the parking problem. Figure 10.2 shows many employees are already prepared to cycle during bad weather, which is a reason for employees to switch towards car use. The distance dependent-parking cost increases the effect, resulting in a practical carrot-and-stick approach. The amount of increase per distance category (€0,50 or €0,25) does not increase that effect.

Chapter 11

Discussion

This chapter reflects on the chosen methodology and outcome of this research. Additionally, it discusses practical and theoretical recommendations and the limitations of this research.

For the analyses of the parking problem, the conclusion drawn was in line with earlier research: more employees commute by car in the winter. Parking problems occurring only on weekdays when office personnel is also working was also in line with the hypothesis. Bike and car being substitutes for one another also coheres with literature and comparing origins confirm that exchange. Nevertheless, a small share of commuters by bike have a bikie tag and park their bike in the parking garage. The origins of the employees commuting by bike, therefore, might differ from what the data of our share of bike commuters indicated. Additionally, the commuters by public transport are unknown and conclusion on bike and car being substitutes instead of bike and bus might have been drawn to fast based on the sample. The employee database also had some flaws in it regarding residential areas of employees. For instance, employees who cycle almost every day, but living in Groningen (commute distance ¿100km). The amount of incorrect residential areas is probably limited, but still necessary to note. For both the bikies data and the parking garage data the origins are not

Many employees filled in the survey, but the respondents might not have been a representative subset of MST employees since very few public transport users were attracted. Also, the amount of doctors and domestic employees seems to low. Their opinion could have been underrepresented. Among others, this could have affected the results on acceptance for different incomes.

The capacity of P2 varied during the analysis period. In 2018 the limit of the gates in the parking garage was 900, which could partially explain why more employees were able to enter the parking garage. Redevelopment of the surrounding (car) roads of the MST was ongoing during the time of the data; therefore, employees could have already switched to another transport mode. Additionally, the analyses of the parking data, excluded parking capacity of Synagoge parking terrain (80 parking places) since there was no data available.

Employees who finished the survey could have misunderstood the questions with filling in the number of commutes after the choice experiments. For instance, respondents stated that they travelled four times per week alone in their car, four times carpooling as a driver and four times carpooling as a passenger. Because of survey fatigue, respondents might have misunderstood more questions that were not filtered. The findings might also be biased since it is possible that the survey did not attract a representative subset. The invitation to the survey mentioned parking problems and mobility measures, which might have led to more car commuters and less public transport or even bike commuters.

For the effects on the commuting mode, it is essential to consider this research was performed in Enschede, where public transport use is generally lower. The mobility measures might have a more significant effect on the long run.Introducing a rewarding scheme, for instance, does not make an employee sell the car immediately, but that might occur when employees keep paying the increased parking costs for a longer time. On the other hand, employees may state they will start commuting by bike but prove unable to maintain their new commuting mode.

For a generalisation of the results, a few critical aspects need consideration. This case study was done at only one hospital, which means many irregular working hours, many high incomes and highly educated employees. The health sector could also be more inclined to being healthy, which has been linked to more commuting by bike (Fioreze, Thomas, Huang, '—&' van Berkum, 2019). Furthermore was employee paid parking already present, which is not common in the Netherlands. Implementing it from scratch probably raises much more resistance.

According to the stated preference data, MST should increase the bicycle subsidy and possibly converting the reward for cycling towards cash in case of bad weather. This research does confirm that a carrot-and-stick approach might be valuable in exchanging employees car commuting for commuting by bike. Not only employees with intrapersonal mode choice variation stated they would start commuting by bike, but also single-car commuters did so. MST should also consider investigating which departments in the hospital can alter their shifts. This way, both the curve is flattened for peak parking demand, but in the future might also realtime updates on the parking capacity to employees working in specific shifts be possible.

For further research moving commuters away from their car might not be the solution for employees who love the flexibility of their car. This reluctance of car users might be less present when more emphasis is put on carpooling. Also carpooling in a multi-model system might be interesting. Further investigation is needed to solve the problem of less cycling under unpleasant weather conditions, although de Groote et al. (2019) argues that increasing parking cost decreases the peaks of car commutes. Future research in temporary rewards for days with (very) bad weather, for either carpooling or commuting by bike, might prove to be valuable in decreasing peak demand in car commutes. A longitudinal (smartphone-based) study on the effects of measures and variation will prove itself valuable to gain more insight into the actual effects. In such a study, it would be easier to implement weather conditions as data is available per day.

Nonetheless, this study shows that even single-mode car users are willing to engage with the use of positive incentives if also negative incentives are present. Finally, the results presented here might help to formulate better sustainable transport strategies for MST and others, increasing the use of active modes as sustainable commuting becomes more and more valuable.

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Appendix A

Temporal variation

Table 1 overview of parking place location, sort, and capacity

Parkeerterrein	Aantal plaatsen	Personeel/bezoekers	Beschikbaar	Tarieven	Bezetting (20-12-2017)
Spoedpost	19	- Bezoekers spoedpost - Grote rolstoelbussen (kunnen niet in de garage i.v.m. de hoogte)	24/7	Van Heek tenzij kortingskaart.	< 50%
Radiotherapie	9	- Bezoekers radiotherapie	Overdag	€2,- per bezoek Taxi gratis	>100%
Diagnostisch Centrum Twente	15	- Bezoekers DCT	Overdag (In principe < 30 min)	Van Heek	Nog niet gestart.
Parkeergarage MST (P2)	870 (885)	- Personeel - Bezoekers - Extern (+/- 31 bewoners o.a. Getfertweg)	Personeel: 24/7 Bezoekers: zat- en zondag	Personeel: €1, - Bezoek: van Heek tenzij kortingskaart. Extern: gratis?*	90-100%, afhankelijk van weer.
Terrein nabij ambulance hal (VKC)	7	- Verloskundigen en (hoog)zwangere - Evt. ouders opgenomen baby's	24/7	Gratis	Zeer wisselend
	7	- Spoedoproepen MST - Dienstdoende huisartsen HAP	24/7	Gratis	Zeer wisselend
Synagoge	79	- Personeel	24/7	€1,-	20-30%
Mooienhof (huur)	80	- Personeel	Maandag 00.00 t/m donderdag 24.00 uur (oktober t/m maart)	€1,-	100%
Terrein Gebouwbeheer	15	- Spoed - Bussen e.d. aannemers/ leveranciers op aangeven gebouwbeheer.	- Spoed: avond en weekend - Aannemers: doordeweeks	Gratis	100%

Bezoekers
Medewerkers
Bezoekers en medewerkers

Figure 1 number of cars parked per week with two standard deviations

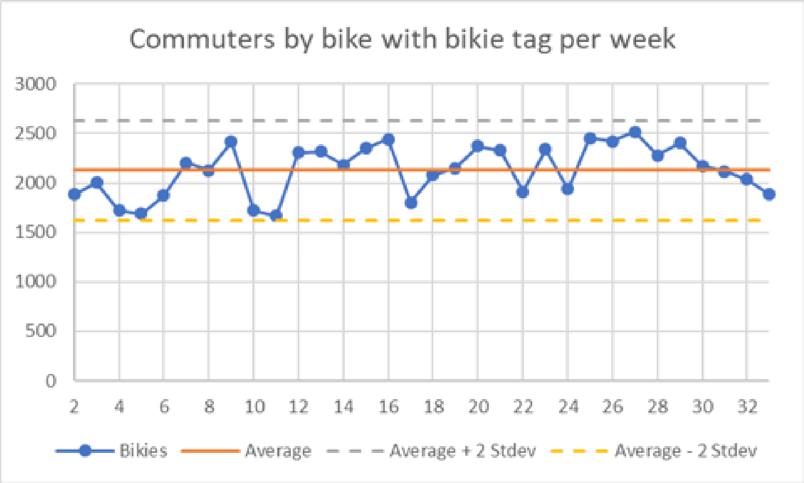

Figure 2 number of bikie tag commuters per week with two standard deviations

Table 2 cars parked in P2 and Mooienhof per day with two standard deviations

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Average	794	811	712	815	675	288	258
Maximum	991	969	902	991	836.5	478	338

Table 36 maximum and average commuters by bike with bikies tag for each day

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Average	381	423	382	382	311	90	76
Maximum	500	526	481	495	417	113	108

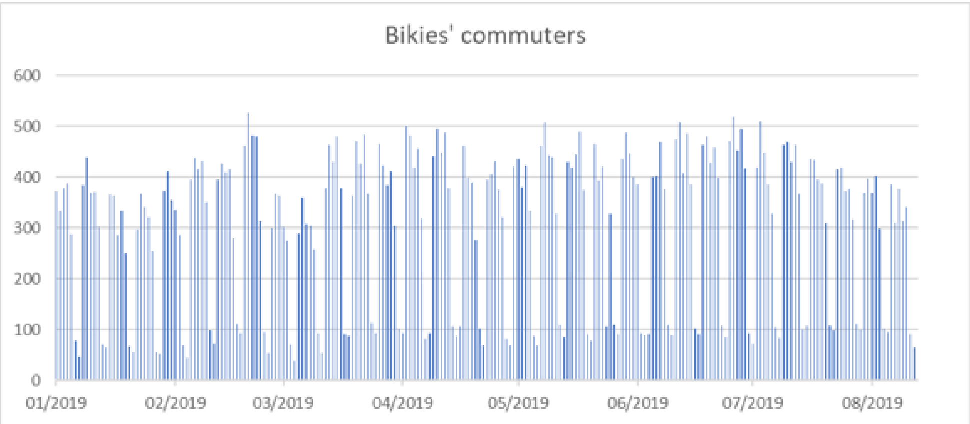

Figure 3 commuters by bike with bikies tag

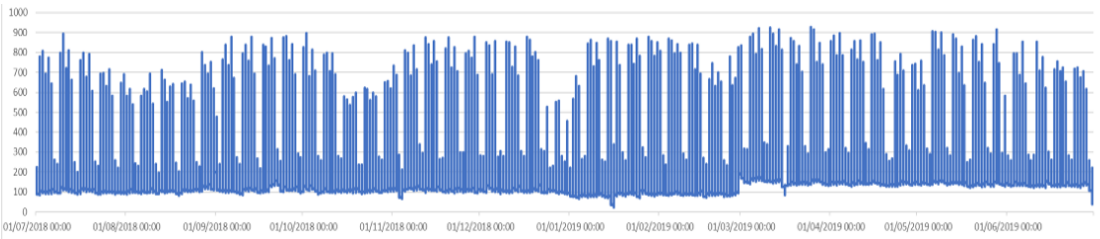

Figure 5 the number of cars in P2 throughout the year

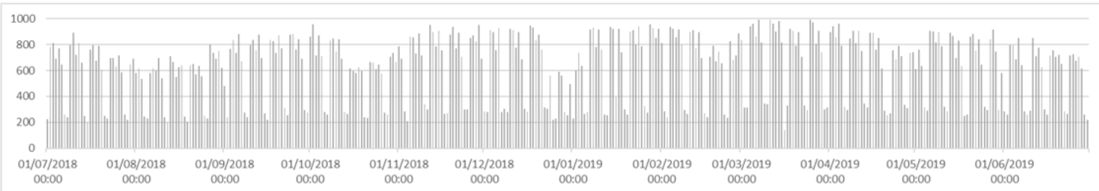

Figure 6 the number of cars parked in P2 and Mooienhof throughout the year

Appendix B

Spatial variation

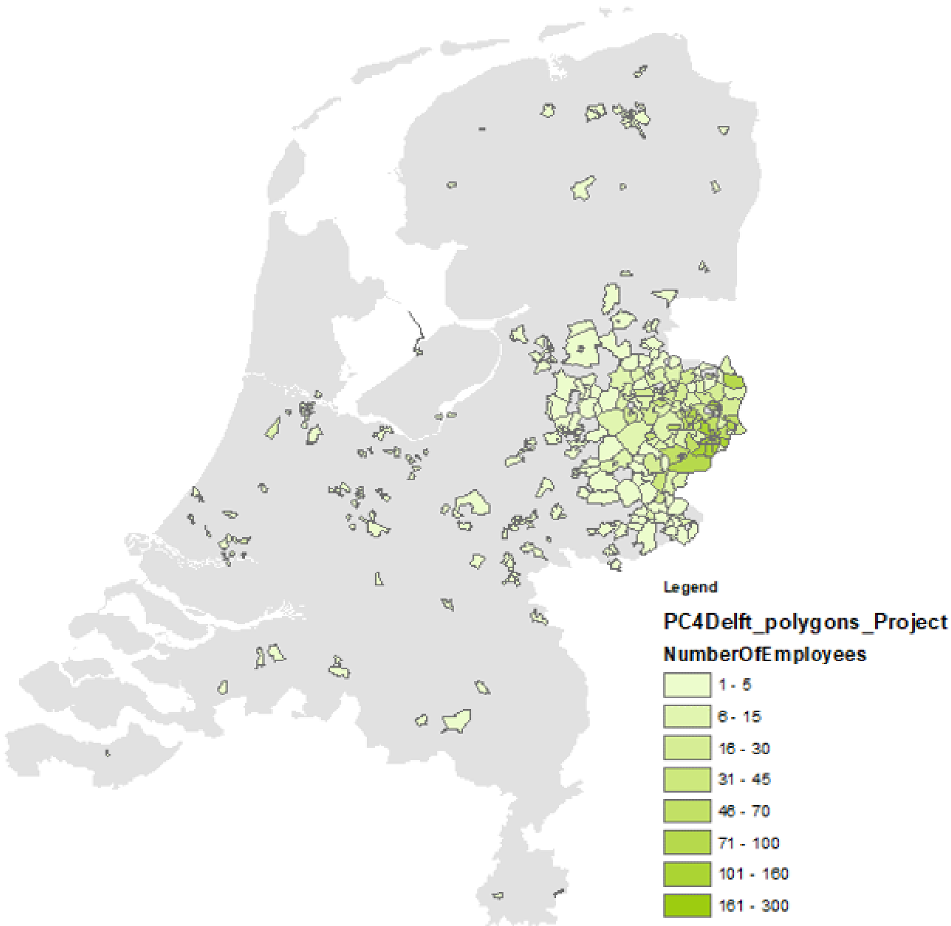

Figure 4 visualisation of the residential location of MST employees throughout the Netherlands
Note: 49 German employees are excluded

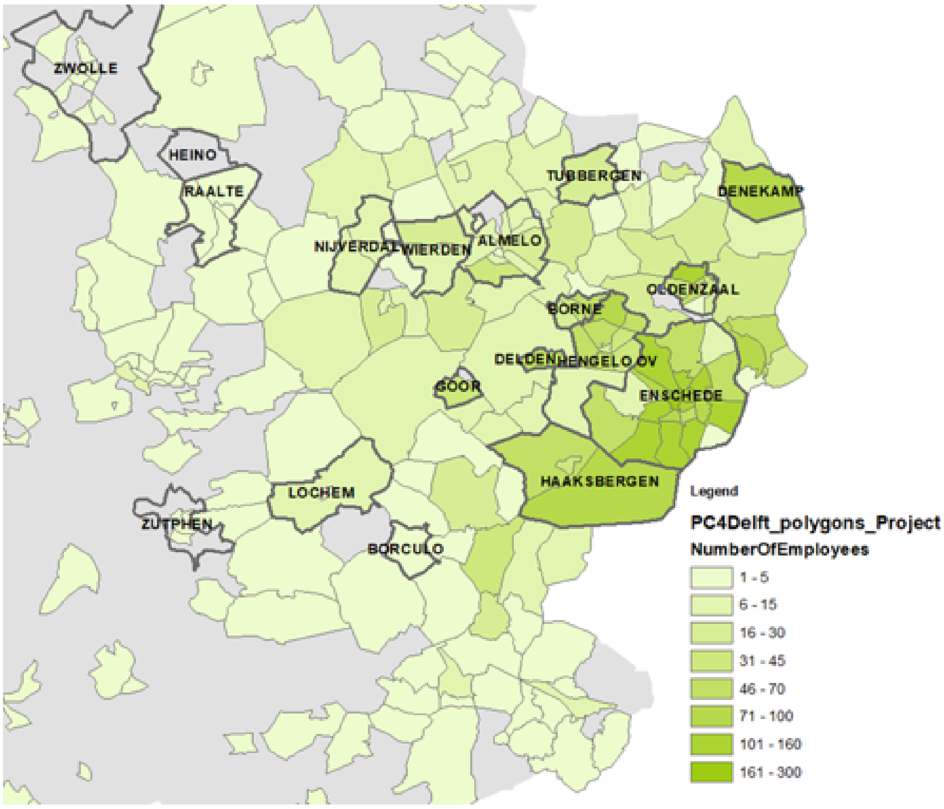

Figure 5 Overview of residential areas (PC4) of the employees of the MST in (the surrounding of) Enschede

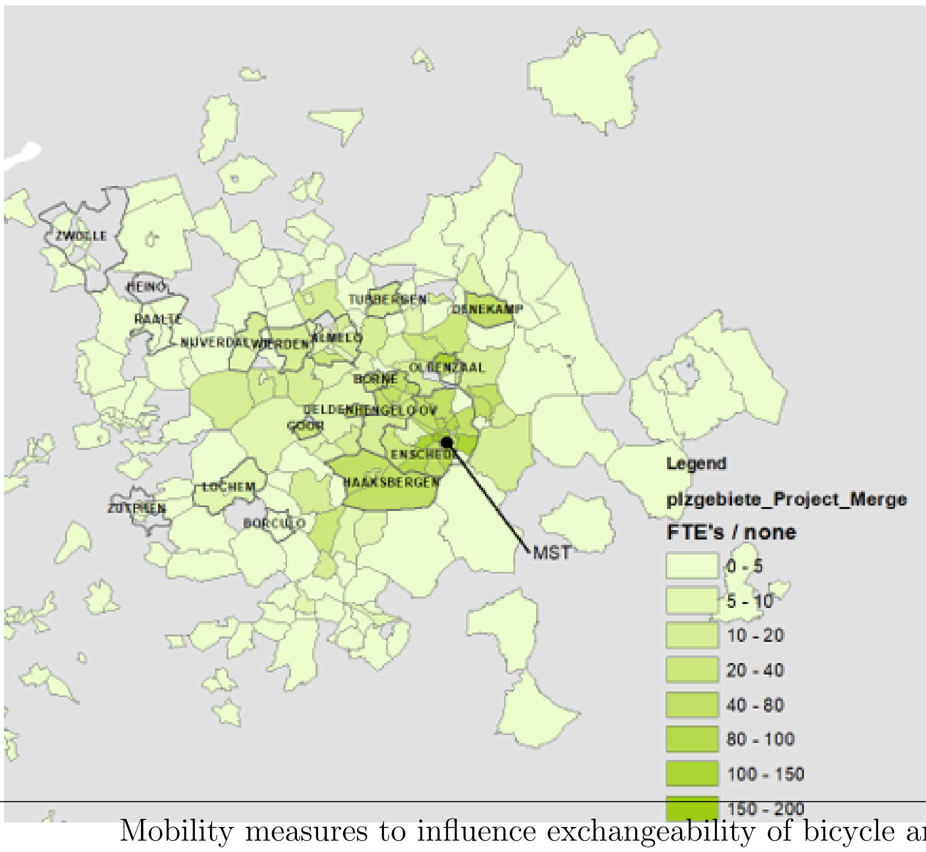

Figure 6 Overview of PC4 codes with the corresponding FTE's in (the surrounding of) Enschede

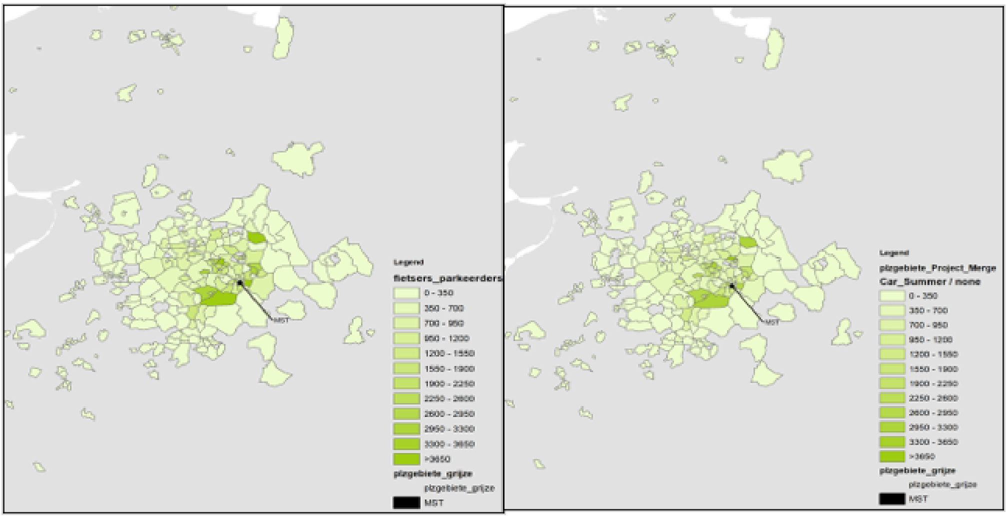

Figure 7 PC4 areas amount of commutes by car for the winter period (left) and the summer period (right)

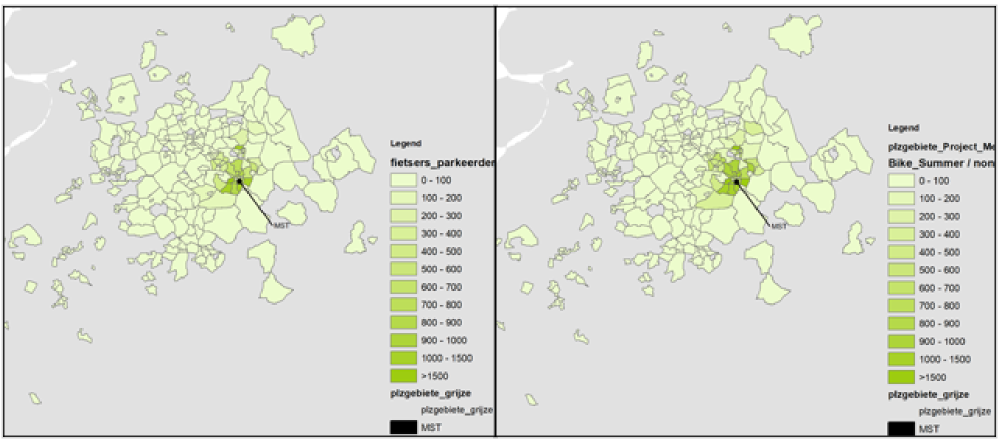

Figure 8 PC4 areas with amount of commutes by bike with bikie tag for the winter period (left) and the summer period (right)

Appendix C

Stated choice experiments

Table 1 all attributes set to 0's for the choice experiment

Woon-werkafstand	**Parkeertarieven (ma-vrij 6:00-14:00)**	**Fietsersbeloning (altijd)**
<4km	€ 1,75	5 Bikies (ter waarde van € 0,20)
4-9km	€ 1,50	10 Bikies (ter waarde van € 0,40)
9-15km	€ 1,25	15 Bikies (ter waarde van € 0,60)
>15km	€ 1,-	20 Bikies (ter waarde van € 0,80)
Woon-werkafstand	**Parkeertarief buiten de spitsuren**	
Alle	€ 0,75	

Table 2 all attributes set to 1's for the choice experiment

Woon-werkafstand	**Parkeertarieven (ma-vrij 6:00-14:00)**	**Fietsersbeloning (altijd)**
<4km	€ 2,75	10 Bikies (ter waarde van € 0,40)
4-9km	€ 2,25	20 Bikies (ter waarde van € 0,80)
9-15km	€ 1,75	30 Bikies (ter waarde van € 1,20)
>15km	€ 1,25	40 Bikies (ter waarde van € 1,60)
Woon-werkafstand	**Parkeertarief buiten de spitsuren**	
Alle	€ 1,-	

Table 3 Goodness of fit for the Mixed Logit models

Models	**Car_user**	**Non_Car_User**	**Only_Active**	**Only_Car**	**IPMCV**	**Tripchaning**	**No_Tripchain**
Rho squared	0.32	0.23	0.25	0.33	0.31	0.27	0.27
Log-likelihood test for the initial model	-1583.84	-657.80	-585.71	-937.14	-707.01	-1120.13	-1121.51
Log-likelihood	-1074.17	-504.79	-441.40	-626.96	-484.66	-818.77	-815.55
Likelihood ratio test for the initial model	1019.35	306.01	288.62	620.35	444.69	602.71	611.93
Sample size	528	212	188	315	232	373	367
Models (continued)	<4km	4-9km	9-15km	>15km	<30.000	50.000-30.000	75.000-50.000
Rho squared	0.26	0.30	0.29	0.38	0.26	0.29	0.28
Log-likelihood test for the initial model	-349.35	-325.09	-337.56	-1229.64	-734.04	-973.87	-239.83
Log-likelihood	-258.10	-226.65	-239.59	-765.66	-540.80	-689.88	-172.67
Likelihood ratio test for the initial model	182.50	196.88	195.95	927.97	386.49	567.99	134.32
Sample size	112	109	110	409	244	318	79
Models (continued)	>75.000	TripChainKids	No_TripChainKids	SetDepTime	No_SetDep Time	Extra bikies bad weather	No_Extra bikies bad weather
Rho squared	0.19	0.30	0.27	0.28	0.26	0.37	0.27
Log-likelihood test for the initial model	-90.80	-397.87	-1843.77	-1105.57	-1136.07	-257.85	-1983.79
Log-likelihood	-73.58	-279.69	-1354.35	-794.14	-839.58	-162.03	-1455.96
Likelihood ratio test for the initial model	34.44	236.35	978.84	622.87	592.98	191.63	1055.65
Sample size	30	141	599	360	380	82	658

Table 4 resulting car commute changes given a specific package of measures is elected

Package of measures	Elected	Average Car commutes	Absolute difference Car commuters	Average difference Car commuters	Standard Deviation of the difference	Standard Deviation in the mean of the difference	Percentage Change
B	275	2.30	-43	-0.16	0.91	0.05	2.4%
C	365	2.38	-69	-0.19	0.98	0.05	2.2%
D	431	2.48	-44	-0.10	0.85	0.04	1.7%
E	181	3.07	-34	-0.19	0.99	0.07	2.4%
F	324	2.89	-47	-0.15	0.97	0.05	1.9%
G	328	2.72	-62	-0.19	1.08	0.06	2.2%
H	435	2.46	-38	-0.09	0.88	0.04	1.7%
I	119	1.73	28	0.24	0.79	0.07	4.2%
J	148	1.82	13	0.09	1.16	0.10	5.2%
K	300	2.30	-35	-0.12	0.90	0.05	2.3%
L	137	1.76	-21	-0.15	0.90	0.08	4.3%
M	86	1.79	-4	-0.05	0.95	0.10	5.7%
N	37	1.22	5	0.14	0.84	0.14	11.4%
O	68	1.82	-3	-0.04	0.81	0.10	5.4%

Appendix D

Effects of mobility measures

Table 1 resulting car commute changes given a specific package of measures is elected

Package of measures	Elected	Average Car commutes	Absolute difference Car commuters	Average difference Car commuters	Standard deviation in the mean of the difference
B	275	2.30	-43	-0.16	0.05
C	365	2.38	-69	-0.19	0.05
D	431	2.48	-44	-0.10	0.04
E	181	3.07	-34	-0.19	0.07
F	324	2.89	-47	-0.15	0.05
G	328	2.72	-62	-0.19	0.06
H	435	2.46	-38	-0.09	0.04
I	119	1.73	28	0.24	0.07
J	148	1.82	13	0.09	0.10
K	300	2.30	-35	-0.12	0.05
L	137	1.76	-21	-0.15	0.08
M	86	1.79	-4	-0.05	0.10
N	37	1.22	5	0.14	0.14
O	68	1.82	-3	-0.04	0.10

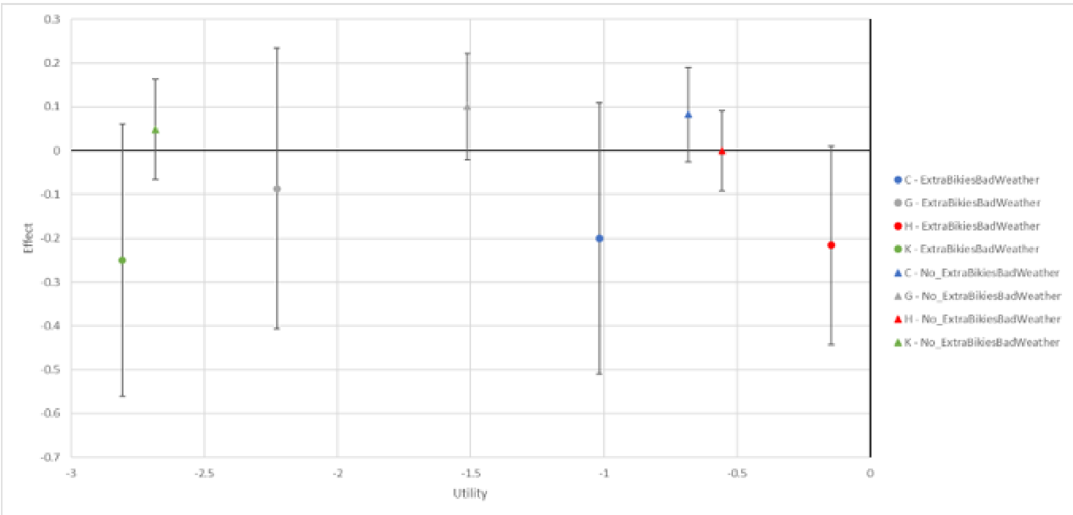

Figure 1 effects for different categories of employees

Appendix E

Javascript PT and car travel times

```
function TRAVELTIMES(){
  //pak de actieve spreadsheet
  var ss = SpreadsheetApp.getActiveSpreadsheet().getActiveSheet();
  //neem alle waarden uit een kolom (startrij,startkolom,aantal rijen, aantal kolommen)
  //aanpassen welke rij het invullen van waardes moet beginnen
  var Origins = ss.getRange(2,1,161,1).getValues();
  //ss.getRange(row, column, numRows, numColumns)

 // programma's uitvoeren
 var Car = Origins.map(DRIVING);
 var Car_PT = Car.map(TRANSIT);

  // zet de arrays terug in de spreadsheet
 ss.getRange(2, 2,Car_PT.length, Car_PT[0].length).setValues(All_Modes);

}
function DRIVING(row){
  //bepaal de bestemming
  var Destination = ["Medisch Spectrum Twente Netherlands"]
  //stel herkomst (origin) en bestemming (destination) in
  var mapObj = Maps.newDirectionFinder();
   //stel ook de aankomsstijd in
  var arrive = new Date(2019, 12, 16, 8);

  mapObj.setOrigin(row[0,0]);
  mapObj.setDestination(Destination);
  mapObj.setArrive(arrive);
  //haal de routebeschrijving erbij
  var directions = mapObj.getDirections();
  switch (directions["routes"][0]){//bij geen ov route invullen dat de route niet gevonden i:
    case undefined:
      var distance = "No route found";
      var triptime = "No route found";
      break;
    default:
  var getTheLegs = directions["routes"][0]["legs"][0];
  //haal de afstand en reistijd op
  var distance = getTheLegs["distance"]["value"]/1000;
  var triptime = getTheLegs["duration"]["value"]/60;
  }
  return [row[0],distance,triptime];
}
```

```
  return [row[0],distance,triptime];
}
function TRANSIT(row){
  //stel ook de aankomsstijd in voor de dienstregeling
  var arrive = new Date(2019, 10, 21, 8);
  var Destination = ["Medisch Spectrum Twente Netherlands"]
  var mapObj = Maps.newDirectionFinder();

  mapObj.setOrigin(row[0,0]);
  mapObj.setDestination(Destination);
  //bepaal de vervoerswijze (mode) en stel de aankomsstijd in
  mapObj.setMode(Maps.DirectionFinder.Mode["TRANSIT"]);
  mapObj.setArrive(arrive);

  var directions = mapObj.getDirections();

  switch (directions["routes"][0]){//bij geen ov route invullen dat de route niet gevonden i
    case undefined:
      var distanceT = "No route found";
      var triptimeT = "No route found";
      var stops = "No route found";
      break;
    default:
  var getTheLegs = directions["routes"][0]["legs"][0];

  //vraag ook het aantal stops op (-2 want herkomst en bestemming rekent hij mee)
  var distanceT = getTheLegs["distance"]["value"]/1000;
  var triptimeT = getTheLegs["duration"]["value"]/60;
  var stops = getTheLegs["steps"].length;
  }
  return [row[0],row[1],row[2],distanceT,triptimeT,stops];

}
```