Improving the cyclability in The Netherlands

How infrastructural investments can the increase the bicycle share

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Abstract

A contemporary issue in spatial planning is the car-orientated development. The focus on cars does not come without consequences and issues regarding this car-dependency consists of environmental, economic, and societal problems. Investing in bicycle infrastructure is on the agenda of many cities around the world and can be seen as a key factor in a new sustainable mobility paradigm. This thesis investigated the effect of bicycle highways on the probability of commuting by bicycle. Bicycle highways are a recent development in bicycle infrastructure. They provide high-quality cycling connections between cities with several principles that attract commuters, such as directness, safety, and comfort. There is a scientific gap in the effect of these routes and the aim of this research is to evaluate these bicycle highways with the following research question:

What is the impact of bicycle highways on the probability of commuters to cycle to work?

The impact of cycling infrastructure on travel mode choice behavior can be studied from various angles. The theoretical framework focuses on the mechanisms that can explain a change in travel mode choice by making use of the theory of planned behavior, the utility maximization theory, the time geography, and a socioecological perspective. These theories focus from their own point of view how cycling behavior can change by investing in bicycle infrastructure and what factors and explanations can encourage individuals to cycle to work.

The evaluation design in this study is known as an impact evaluation and uses a difference-in-difference design to assess the impact of the bicycle highway. The difference-in-difference design quantifies the effect of the intervention by comparing the outcome of the treatment group to the control group. This allows to make a causal claim. Data from OViN/ODiN and the bicycle highways built in the Netherlands until 2021 were merged into a dataset with trips that were made between 2010 and 2021. A logistic regression is used to estimate the effects as the dependent variable is binary of nature. An individual cycles to work or does not cycle to work.

The results present an increase in the probability of commuting by bicycle of 3.4 percentage points after the bicycle highway is completed with a significance of 99%. This model is controlled by year and month fixed effects. These results indicate that the investments

in bicycle highways lead to more commuters to cycle and, therefore, can reduce the car dependency. The outcomes of this research can lead to a better understanding of the phenomenon of bicycle highways and its effects. The effects are relevant for governments and municipalities that have policy goals such as reducing congestion and improving population health.

Key words: Sustainable mobility, Bicycle Highways, The Netherlands; Difference-in-Difference

Preface

Dear reader,

In the first lecture of the course Urban Networks, the objectives of the session were to get a better understanding of the concept's accessibility and mobility. Transport must be seen as a derived demand where users are consuming the service that results from the demand for another service. Most people have a destination where they need to be, and they travel in order to get there. The car-orientated mobility planning paradigm should shift to an accessibility-based planning paradigm. We got told that planning on accessibility is the driving force for sustainability and must needed to develop a better world around us.

This master thesis is based on that first lecture where the term bicycle highway came up as an alternative to car-orientated planning. This took my interest that I quickly became interested in the subject and the effects it might have on the modal split. Conducting my own research has been an educative and insightful period with ups and downs. It has been a rollercoaster ride but, in the end, I can say that I'm proud of the delivered product.

Thanks,

Ferry van der Haar
Nijmegen, 2023

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BEIC	Built Environmental Infrastructural Changes
CAPI	Computer Assisted Personal Interviewing
CATI	Computer Assisted Telephone Interviewing
CAWI	Computer Assisted Web Interviewing
CBS	Centraal Bureau voor de Statistiek
CHIPS	Cycle Highways Innovation for smarter People transport and Spatial planning
GIS	Geographical Information System
GPS	Global Positioning System
MON	Mobiliteitsonderzoek Nederland
NGO	Non-Governmental Organization
ODiN	Onderweg in Nederland
OViN	Onderzoek Verplaatsingen in Nederland
PC4	Postcodegebied numeriek
RCT	Randomized controlled trial
SPSS	Statistical Package for the Social Sciences
SQL	Structured Query Language
TBP	Theory of Planned Behavior
VIF	Variance Inflation Factor

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1 | Introduction

The topic of this master thesis will be proposed and elaborated in this chapter. The need for a more sustainable form of transportation is the starting point from where this research proceeds. The research problem, research aim, and research questions will be disclosed subsequently. The scientific and societal relevance will be explained through an extensive review. This chapter will point to the reader what is the research gap in evaluating cycling infrastructure and how this research adds to knowledge to that gap.

1.1 | Sustainable mobility

One of the most contemporary issues in spatial planning is the need for a more sustainable form of transportation. In urban development, a car-orientated system has been the standard for years (Banister, 2005; Chapman, 2007; Schiller, Bruun & Kenworthy, 2010). However, this car-orientated system does not come without consequences. Issues regarding the automobile dependency consists of diverse environmental, economic, and social problems, such as congestion, urban sprawl, global warming, smog, acid rain, loss of street life, access problems for those without cars and physical and mental health problems related to lack of physical activity (Banister, Anderton, Bonilla, Givoni, & Schwanen, 2011; Chapman, 2007). This automobile dependency evolved from the growing popularity of the car. According to Larsen (2017), cars began to colonize the streets after the second world war. They became popular due to their speed, the coolness, and the cheap oil. Cars were also needed, due to the urban sprawl caused by growing populations. The share of global population living in urban areas has surpassed 50% and it is predicted that this is likely to increase to 66% by 2050 (UN, 2014). This growth in the size of urban areas result in an increase in the demand for transport (Banister et al., 2011) and many urban areas are not designed to accommodate this growth in transport demand in terms of automobile infrastructure, which emphasizes the need for a different approach to urban transport. Cycling can be seen as a key factor and the solution in a new sustainable mobility paradigm (Parkin, 2012). Therefore, cycling is on the policy agenda of many cities around the world. A higher share of cycling in the modal transport split will among others contribute to a more attractive urban environment (Rietveld & Daniel, 2004; Law, Sakr & Martinez, 2014).

1.2 | Bicycle infrastructure

The investments in bicycle infrastructure seems to have an impact on the level of cycling with regard to the modal split (Buehler & Puchler, 2012; Dill & Carr, 2003; Handy et al., 2014; Heinen et al., 2010; Hunt & Abraham, 2007). It can be seen as an essential ingredient for improving bicycle use (VandenBulcke et al., 2011; Winters, Davidson, Kao, & Teschke, 2010). Bicycle infrastructure encompasses the whole of bicycle lanes, paths, intersections, roundabouts, bridges, tunnels, marking, signage, and lightning (Buehler, & Dill, 2016; Heinen et al., 2010). Hull and O'Holleran (2014) conclude in their study that cycle infrastructure can encourage more cycling and recommend, among other things, the following guidelines for a sufficient bicycle infrastructure:

- Wide cycle lanes;
- Direct routes connecting all land uses;
- Segregation where possible;
- Clear signage;
- No discontinuities of cycle lanes at hazardous locations.

Research shows that investments in cycling facilities and infrastructure can lead to more bicycle use (Barnes, Thompson, & Krizek, 2006; Hull & O'Holleran, 2014; Stinson & Bhat, 2003) and, especially, if this infrastructure is physically segregated from motorized traffic and pedestrian lanes, which increase the comfort and safety perception of the cyclists (Bai, Liu, Chan, & Li, 2017; Buehler, & Dill, 2016; Heinen et al., 2010; Dill, 2009; Hunt & Abraham, 2007; Stinson & Bhat, 2003; Wardman, Tight, & Page, 2007). Bicycle infrastructure is heavily interlinked with safety. An extensive body of cycling research, in Europe, the USA, Australia and Asia, shows that the perceived traffic danger of cycling is an important deterrent to higher cycling levels (Buehler & Puchler, 2012; Dill, 2009; Hull & O'Holleran, 2014; Parkin, Wardman, & Page, 2007; Pulugurtha, & Thakur, 2015; Reynolds, Harris, Tesche, Cripton, & Winters, 2009). As good bicycle infrastructure can reduce the risk of collision with motorized traffic it can encourage people to cycle (Hull & O'Holleran, 2014).

Intersections can be a source of conflict and a cause for delay for cyclists. Therefore, these should be kept at a minimum. Intersections are perceived as negative and as problematic parts of a cyclists 'route (Heinen et al., 2010). Caulfield, Brick & McCarthy (2012) found in a stated preference study that the number of intersections that a respondent encounters has a negative effect and that they choose a route with less interactions. This is in line with the research from Broach, Dill, & Gliebe (2012). They also found that cyclists try to avoid stops signs and traffic signals. However, traffic signals seem to be valued when cyclists needed to turn to left or cross at high-traffic streets. Given the fact that roadway intersections must appear somewhere, it seems virtually impossible to avoid all conflicts between motor vehicles and cyclists (Pucher & Buehler, 2008).

1.3 | Bicycle highways

One of the most recent initiatives in order to find an answer to sustainable transportation is the bicycle highway. The concept has its origin in the Netherlands, where pre-cycle highways have been established in Tilburg and in The Hague in the 1980s. These municipalities formulated policies to slow down the increase of motorized traffic and to strengthen the position of the bicycle (Van Goeverden, Sick Nielsen, Harder, & van Nes, 2015). In both cities, the number of cyclists increased and from surveys can be concluded that the perceived changes in quality improved (Van Goeverden & Godefrooij, 2011). However, modern designs have been used since 2006 with the initiative 'Fiets Filevrij!', which translates to 'cycle traffic jam free! The goal of the initiative was to stimulate commuters to take bicycle instead of the car for distances up to 15 kilometers (Ter Avest, 2015). The concept quickly spread across Europe and bicycle highways were introduced in The Netherlands, Germany, Denmark, the United Kingdom, and Belgium (Liu, te Brömmelstoet, Krishnamurthy, & van Wesemael, 2019; Pucher & Buehler, 2017; Rayaprolu, Llorca, & Moeckel, 2018; Skov-Petersen, Jacobsen, Vedel, Thomas, & Rask, 2017).

Nowadays, different countries are implementing these bicycle highways in order to facilitate longer distance cycling. Since each country has its own name for those types of bicycle infrastructure (Fietsostrades, Superhighway, Snelfietsroute, Doorfietsroute, Velobahn, or Radschenllwege), the European Cyclist Federation (ECF) formulated a common definition of a cycle highway:

"*A cycle highway is a mobility product that provides a high quality functional cycling connection. As backbone of a cycle network, it connects cities and / or suburbs, residential areas, and major (work) places* *and it satisfies its (potential) users."*

(Faber, 2016)

A bicycle highway has certain specific characteristics that should be considered in order to be perceived as a bicycle highway. However, these characteristics should be seen as guidelines and not as criteria. According to the European Cyclists' Federation (2014) bicycle highways should:

- Be at least 5km long;
- Have a minimum width of 3m, if one-directional and 4m, if bi-directional;
- Be separated from motorized traffic and pedestrians;
- Avoid steep climbs and afford mild gradients;
- Avoid frequent stops to enable high average speeds;
- Receive regular maintenance.

The CROW is a Dutch organization and publishes design manuals for traffic engineering. In 2014, they published a design manual related to bicycle highways. This manual is line with the guidelines provided by European Cyclists' Federation. The CROW described the following principles for bicycle highways in order to be successful:

- Coherence: planners need to make sure that cyclists can go where they want, and bicycle highways are the backbone of this cycle network;
- Directness: bicycle highways need to reduce journey time by providing a direct connection between the main origin and the main destination;
- Attractiveness: bicycle highways are integrated in their surroundings. Positive elements are green, open spaces, well maintained and negative elements are congestion, industry and dark.
- Safety: planners should minimize intersections and high traffic streets;
- Comfort: bicycle highways are comfortable. This means that there is room for safe overtaking, minimal stops, or vibrations from the pavement.

1.4 | Research problem statement

Making use of the bicycle as a primary form of transportation can help to overcome the environmental, economic, and social problems that are associated with car dependency.

However, even though governments and municipalities do acknowledge the potential of the bicycle in terms of being the solution to transportation problems, improving the modal split on cycling seems to be a bottleneck. As cycle highways are a new form of bicycle infrastructure, research needs to show the effect of these interventions. A longitudinal research design should address the net effects of a bicycle highway because cross-sectional research can't make causal claims (Buehler, & Dill, 2016; Mölenberg et al., 2019). There is a scientific gap in evaluation studies on travel mode behavior and the aim of this research is to evaluate the effectiveness of the bicycle highways. To be more specific, this research sets out to explain the influence of the cycle highway on the mode choice behavior of commuters. Understanding of this influence is vital in urban planning and city politics in order to support bicycle highways as a means of sustainable transport. Do new infrastructural investments in the bicycle network enhance the share of cycling in the modal split? The results of this research will contribute to a better understanding of commuters and can, therefore, be implemented to improve the policies concerning the bicycle highways. This leads to the following research question:

> *What is the impact of bicycle highways on the probability of commuters to cycle to work?*

1.5 | Societal Relevance

Pucher and Buehler (2008) argue that cycling can be seen as the most sustainable form of urban transport, which is not only feasible for short trips but also for trips at a medium distance. Transportation planners, policy makers and NGOs at different levels consider the improvement of levels of cycling and walking as a desirable objective. Besides the desire to reduce car use and its corresponding negative externalities, they are also concerned with the public health, livability, physical activity, and quality of life (Den Broeder, Scheepers, Wendel-Vos, & Schuit, 2015; Götschi, Garrard, & Giles-Corti, 2016). As more cycling means more societal benefits, this research has an extensive body of societal relevance. Cycling causes no environmental damage and has relatively low economic costs, both in direct user costs and public infrastructure costs (also see: Heinen, van Wee, & Maat, 2010; Paige-Willis, Manaugh, & El-Geneidy, 2012). Cycling for daily trips can provide physical activity and has significant effects on personal health. Research conducted by Fishman, Schepers & Kamphuis (2015) shows that 6500 deaths are prevented each year in the Netherlands and the life expectancy of residents is six months longer due to improved health. As motorized transport is associated with a higher risk of overweight and obesity (McCormack & Virk, 2014), active transportation, such as cycling, is associated with various health benefits by an extensive number of studies (Buekers, Dons, Elen, Int Panis, 2015; Crane, Rissel, Standen et al., 2017; Dill, 2009; Götschi, Garrard & Giles-Corti, 2016). Physical activity has beneficial effects on life expectancy, cardiovascular fitness, sleep quality, and a variety of chronic conditions. Physical activity reduces the risk of coronary heart disease, high blood pressure, a stroke, etc. (Götschi et al., 2016).

As an active and a low-carbon form of transportation, the bicycle plays a prominent role in the efforts to reduce the car dependency. These benefits have encouraged many cities to implement policies and invest in infrastructure to initiate more cycling. These policy initiatives aim to increase the modal share of cycling and are implemented in cities all around the world (Dextre, Hughes, & Bech, 2013), in small urban areas as well as megacities (Pucher & Buehler, 2012), in developing countries (Brussel & Zuidgeest, 2012) as well as in countries with, already, a high modal share of cycling (Pucher & Buehler, 2008).

1.6 | Scientific relevance

In this paragraph, the scientific relevance will be explained. First, there will be an elaboration on the academic literature on sustainable transportation. Secondly, research that covers the importance of bicycle infrastructure is discussed. Subsequently, the focus will be on the research gap that three systematic review studies uncover in the relationship between infrastructure and cycling. Finally, relevant research on the effect of bicycle highways on cycling is presented.

There is an extensive amount of academic literature elaborating on sustainable transportation and the necessity of a new mobility paradigm (Banister, 2008; Black, 2010; Chapman, 2007; Schiller et al., 2010). All agree on the necessity of reducing the pollutants caused by the contemporary transport system and come to the following conclusion: city planners need to invest in more sustainable transportation systems. The role of the bicycle in this sustainable mobility paradigm is being investigated by multiple scientists by various angles from urban planners to health-related scientists (Larsen, 2017; Parkin, 2012; Pucher & Buehler, 2017; Winters, Buehler, & Götschi, 2017). However, the current scientific knowledge has limited longitudinal study designs that evaluate bicycle highways.

Research have highlighted the importance of bicycle infrastructure on high cycling levels (Buehler & Puchler, 2012; Dill & Carr, 2003; Handy et al., 2014; Heinen et al., 2010;

Hull & O'Holleran, 2014; Hunt & Abraham, 2007; Wardman, Tight, & Page, 2007). However, numerous research incorporate a cross-sectional model which collects data from a specific population at one point in time and develops an understanding of the variables that are associated with cycling (Buehler & Puchler, 2012; Dill & Carr, 2003; Krizek, Handt, & Forsyth, 2009; Rietveld & Daniel, 2004). Aggregate cross-sectional studies often show that there is a positive correlation between infrastructure and cycling levels. Research that is conducted by Dill & Carr (2003) shows, in analyzing data from 35 large cities in the United States, that higher levels of bicycle infrastructure are positively and significantly correlated with higher rates of bicycle commuting. This is also shown in other studies. Buehler & Puchler (2012) found correlation between both striped bike lanes and separated paths with bicycle commuting in their study on 90 U.S. cities. Disaggregate individual-level studies show a preference of cyclists towards segregated bicycle infrastructure (Dill, 2009; Hunt & Abraham, 2007; Stinson & Bhat, 2003; Wardman, Tight, & Page, 2007). Cross-sectional designs are valuable to develop an understanding of the impact of an intervention, but more robust longitudinal designs are needed to make claims. Three studies have systematically reviewed other studies that evaluate infrastructural intervention. The reviews of Yang, Sahlqvist, McMinn, Griffin, & Ogilvie (2010), Stewart, Anokye, & Pokhrel (2015) and Mölenberg, Panters, Burdorf, & Van Lenthe (2019) will be elaborated. Interventions can be distinguished in individual, group, or environmental/physical interventions. Cases of individual or group interventions are media campaigns or incentives from the community or from work. Infrastructural intervention examples vary from the opening of cycling lanes, the installation of a city-wide cycling network, or the improvement of existing cycling infrastructure (Yang et al., 2010; Mölenberg et al., 2019).

Yang et al. (2010) tried to determine which interventions are effective in promoting cycling. In 2010, they only found six studies that focused on interventions to promote cycling. Besides physical interventions, the different studies mainly focused on social marketing campaigns and were built on behavior change. Where Yang et al. (2010) focused on cycling for any purpose, Stewart et al. (2015) shifted their view to only focus on commuter cycling. They wanted commuter cycling as the dependent variable in their review. Twelve studies were found from which seven evaluated individual- or group-based interventions. The other five evaluated environmental interventions.

Mölenberg, Panter, Burdorf, & van Lenthe (2019) reviewed the effects of infrastructural interventions which can be effective in promoting cycling. Twenty of those provide information on cycling behavior, and sixteen assessed the usage of the cycling infrastructure. Part of the studies did both. In sum, twenty-nine studies found an increase in cycling. The studies that investigated the usage of the infrastructure found larger changes after the intervention than the studies that reported cycling behavior. Another difference is seen for studies that tested on statistical significance and used subjective measurement methods (surveys and direct observation), compared to studies that did not perform statistics and used objective measurement methods (GPS and automatic counting stations), where the former shows larger changes in the amount of cycling than the latter. As Yang et al. (2010), Stewart et al. (2015) also conclude that interventions have the potential to stimulate bicycle use.

However, little agreement seems to exist on study designs and how effectively evaluate these interventions, where many forms of error or bias exist. Various studies on bicycle highways have used different designs and methodologies and focus on different outcomes. A quantitative study was carried out by Skov-Petersen et al. (2017). They analyzed bicycle highways in Copenhagen in a framework of induced travel demand and cyclist satisfaction. The study pursuits a modal share change after bicycle infrastructural improvements. Bicycle count data and three web-based questionnaire surveys in 2011, 2012 and 2013 were used as methods for their research. Skov-Petersen et al. (2017) do make use of pre- and a post intervention data with a control site. The study design shows data from the counting stations over a period 35 months before and after the intervention and questionnaires that were send to bicyclists before and one and two years after the intervention. The study showed that investments in the infrastructure led to an increase in the number of people using them, where most of the cyclists switched from alternative routes to the improved routes. They found that only 4-6% of the cyclists on the renewed routes switched to cycling from other modes. Besides, the findings deriving out of the questionnaires showed that bicyclists experienced a significant improvement, compared to the control group, in the surface, lightning conditions, the perceived safety and personal security. Heesch, James, Washington, Zuniga, & Burke (2016) also evaluated the opening of a segment of infrastructure with count data and questionnaires. However, they only provided evidence of a cyclists shifting their route to the city center. Their research provides little insight into the effect on the modal split.

Other scientific research papers on bicycle highways focus on the quantification of the expected changes in the mobility behavior and the modal split. The research of Agarwal, Ziemke, & Nagel (2019) identified the potential of increase in the bicycle share in Patna, India. Making use of an activity-based multi-agent transport simulation framework, they calculated that bicycle share can grow up to 48%. Rayaprolu, et al. (2018) quantified the potential influence of bicycle highways with a mode choice model, making use of individual commute data from a German Household travel survey. Results show that bicycle highways reduce motorized travel and increase cycling. However, they indicate that a bicycle highway alone will not be able to support major changes and that strong governmental support to prioritize cycling is needed. Furthermore, they found that the effect is stronger as proximity to the corridor increases. When commuters live in zones on the bicycle highway the effect is the strongest and it declines in the scenarios where commuters live within 1 km of the bicycle highway and 2 km within the bicycle highway.

To conclude, a lot of research has been carried out on bicycle infrastructure but still relatively few on bicycle highways and its effectiveness on changing travel mode behavior. Various methodologies have been performed with both positive and negative results. Many of the mentioned studies have a cross-sectional research design. However, cross-sectional research does not prove causality. They do contribute to a better understanding of the plausibility and coherence of the subject. There is a need for more consensus on how to evaluate the effectiveness of infrastructural investments and this research is set out on helping to achieve this matter and evidence is needed to support causality.

2 | Theoretical Framework

In this chapter, the theoretical basis for the research will be elaborated. At first, the knowledge about travel mode choice behavior will be explained. Three main theories with a different perspective are discussed. According to Gilbert (2015), a theory is an explanatory tool to understand and explain a phenomenon that may be difficult to comprehend without it. Theories and models provide a framework for understanding the underlying causes and mechanisms of a phenomenon. Subsequently, the scientific knowledge of evaluation designs that is relevant to this research is reviewed. In the third paragraph, the socioeconomic variables that may influence travel behavior are discussed.

2.1 | Travel mode choice behavior

People travel in order to participate in certain activities. Several functions or activities are dispersed within an area which means that people have to travel. This leads to a process where people have to make a choice which mode to take, which is based on a behavioral decision (Götschi, de Nazelle, Brand, Gerike, 2017). According to Van Acker, Van Wee & Witlox (2010) daily travel patterns are the result of a hierarchical decision structure, which ranges from short-term decisions on daily activities to long term lifestyle. Research on travel behavior has been largely conducted since the late 90s (Handy, 1996; Cervero & Radisch, 1996) and is conducted in order to understand how these travel decisions are being made. Such decisions include determining a transport route and mode. (Van Acker, van Wee & Witlox, 2000).

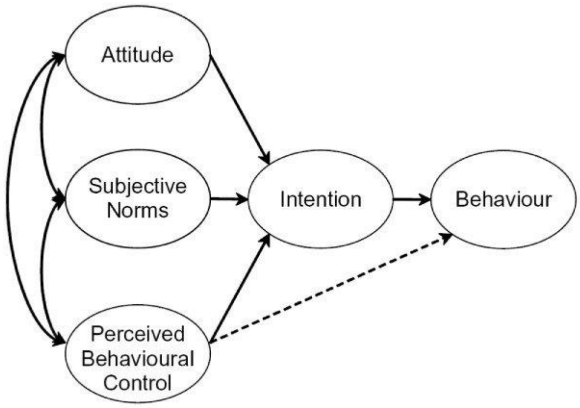
Travel behavior can be studied from various angles and disciplines such as geography, economy, and psychology. All disciplines try to explain travel-related decisions and behavior from their own context. According to Handy (2005), theoretical frameworks in transport geography refer to the mechanisms that are determining the travel behavior, whereas the theoretical frameworks in social psychology define specific factors influence travel behavior. Psychological theories seem to be used the most to explain travel behavior. These theories focus on attitudes, beliefs, and preferences. The most common theory is the Theory of Planned Behavior from Azjen (1991). Secondly, from the economic perspective, the utility maximization theory is the best-known theory to explain behavior change in transport. Another perspective, closely interlinked with utility theory, is the time geography (Hägerstrand, 1970). The upcoming paragraphs elaborate on these theories.

2.1.1 | Theory of Planned Behavior

The Theory of Planned Behavior (Ajzen, 1991) is a psychological model that is widely accepted to explain individual decision making. It emerged from the critique on the Theory of Reasoned Action (Fishbein & Ajzen, 1975; Nilsson & Küller, 2000). The Theory of Reasoned action explains behavioral intentions based on the influence of attitudes and subjective norms. In the Theory of Planned Behavior, Ajzen (1991) adds perceived behavioral control in order to have a stronger predictability on the behavior of individuals (figure 1).

Figure 1

The theory of Planned Behavior (Ajzen, 1991)



As presented in figure 1, the intention that leads to a behavior can be explained from three components. The first predictor is the attitude. The attitude towards the intention to perform a certain type of behavior can be favorable or non-favorable. The second factor influencing behavior is the subjective norm. This component refers to the perceived social pressure to execute or not execute this behavior, or how other people think about your behavior. The last component is the perceived behavioral control. This focuses on the perception of difficulty and efficacy to carry out the behavior (Ajzen, 1991).

Although the Theory of Planned behavior has been used extensively in various research contexts, it is also a theory that has undergone criticism. A critique often given is the fact that it only focuses on three behavioral predictors and excludes unconscious influences and emotions on behavior (Hardeman et al., 2002; Sniehotta, Presseau, & Araújo-Soares, 2014). Therefore, many scientists use 'extended' forms of the Theory of Planned behavior to improve their model. Components that are added in transport mode choice research are: moral norm, descriptive norm, environmental concern, visibility, and habit (Bamberg, Ajzen, & Schmidt, 2003; Bird, Panter, Baker, Jones, & Ogilvie, 2018; Donald, Cooper, & Conchie, 2014). Bird et al. (2018) stated in their model that the perceived behavioral control has a positive influence on cycling behavior and behavior change. This also accounts for the research by Donald et al. (2014), where the perceived behavioral control was the important variable for predicting the intention to cycle.

According to Bamberg (2012), there are four factors that have a potential influence on people's Perceived Behavioral Control: trip distance, bicycle availability, cycling infrastructure and personal circumstances. As the Perceived Behavioral Control is proven to be the strongest predictor by different travel behavior studies (Bird, et al., 2018; Donald, et al., 2014), these factors have a positive effect on the intention to commute by bicycle and, therefore, perform the behavior. Cycling infrastructure is one of the factors that influences the Perceived Behavioral Control (PCB) of individuals (Bamberg, 2012). This means that the implementation and investment of bicycle highways should encourage more people to commute to work as they can boost the Perceived Behavioral Control and, therefore, make more commuters cycle.

2.1.2 | Utility Maximization Theory

From an economic perspective, the most common theory to explain modal choice is the Utility Maximization theory. The theory assumes that an individual makes a decision as a rational economic consumer (homo economicus) and there makes a rational trade-off between various travel modes (McFadden, 1974). The Utility Theory provides a function to an individual as he or she selects a travel mode which maximizes his or her utility (Maat, Van Wee & Stead, 2005; McFadden, 1974; Minal & Sakhar, 2014). The utility is the trade-off between the benefits and the costs to get to a location. In its simplest form this can be equated as:

$$U(X_i,S_t) \geq U(X_j, S_t)$$

U ( ) is the mathematical utility function;

X_i, X_j are the mode choices describing *i* and *j*;

S_t are the socio-economic characteristics of individual *t*.

Which means that when the utility of alternative *i* is greater than the utility of the alternatives, *i* will be preferred as the chosen travel mode (Minal & Sekhar, 2014). The benefits and costs of each travel mode is not specifically the distance an individual needs to travel, but rather on the costs linked with bridging the distance. These costs include time. However, the costs considered important for trip utility have shifted beyond just monetary cost and travel time. Individuals also consider factors such as health impact, environmental impact, safety, the weather and comfort, when making transportation decisions (Krizek, Handy, & Forsyth, 2009; Maat, van Wee, & Stead, 2005; Rojas López & Wong, 2019). These costs are key factors that influence the decision-making process and determines the utility of each travel mode.

Research on bicycle highways have analyzed a variety of factors that can change the utility of cycling after the completion of a bicycle highway. Grigoropoulus et al. (2021) found that bicycle highways can lead to a reduction in travel time which can increase the perceived utility. Additionally, a study by Skov-Petersen et al. (2017) shows that cyclists experienced a significant higher level of safety and comfort. Those factors are also relevant as people are more likely to cycle if they feel safe and comfortable. Experienced health benefits are modeled in research by Buekers et al. (2015).

Thus, if the introduction of bicycle highways increases the perceived utility of cycling as a mode of transportation, it may lead to an increase in the number of individuals choosing the bicycle instead of the car. The Utility Theory can be useful in understanding the travel mode choice and provide a useful explanation of the mechanisms by which the introduction of bicycle highways might influence the mode choice due to the process of utility maximization.

2.1.3 | Time geography

In the Utility Theory, individuals are assumed to be rational economic consumers who make choices on the perceived utility. However, this assumption of economic rationality is based on an unrealistic view that individuals are free to choose the alternative they prefer without any constraints. Unfortunately, some resources are scarce. Advocates of the constraint approach argue that travel mode choices can not only be based on Utility Theory but that choices are also constrained by factors such as space, time, and the institutional context (Hägerstrand, 1970; Maat, van Wee, & Stead, 2005).

Torsten Hägerstrand introduced time geography in 1970 and formulated two concepts in a spatio-temporal framework: a space-time path and a space-time prism (Hägerstrand, 1970). A Space-Time path is the path that an individual can follow in each time frame, shaped by diverse constraints. The path (figure 2) differs from person to person due to a difference in speed and different locations where one needs to be. A Space-Time Prism indicates what an individual can reach in space at each moment and is an extension of the Space-Time Path. However, the space-time prism (figure 3) does not trace the unique path an individual take but shows where one might move with its time (Hägerstrand, 1970, Van Acker, Van Wee, & Witlox, 2010).

Figure 2

A Space-Time Path

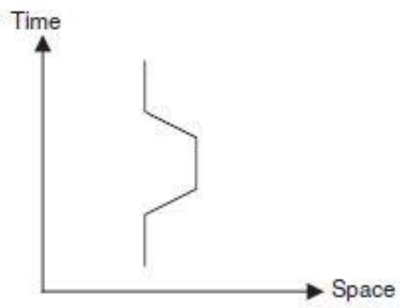
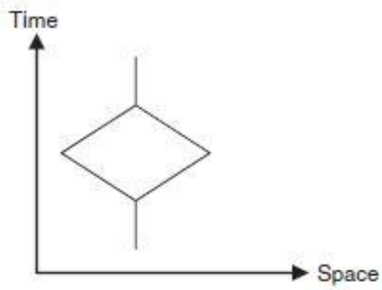


Figure 3

A Space-Time Prism



The constraints that Hägerstrand points out are capability constraints, coupling constraints and authority constraints. Capability constraints are limitations of the physical being such as eating, sleeping, and getting less physical when getting older. It affects the individual's ability to perform activities or mode of transport. Coupling constraints refer to the fact that people have to be some somewhere at a specific time for a specific duration with other individuals. This can be related to social, work or family obligations. Authority constraints are constraints that are set by someone else such as opening hours, the train schedule, maximum travel speed and, other regulations. Time geography can be used to study mobility patterns by taking the constraints that shape an individual's movement into account. The theory can provide valuable insights in the interactions between individuals, space, time, and constraints.

Bicycle highways are an upgrade of the bicycle infrastructure and their design takes speed, costs, and effort into account. While characteristics of the bicycle highway can vary from region to region, the core idea is that it provides direct, fast, and safe bicycle trips (Rayaprolu et al., 2018). People can enhance their space-time path because they can cycle to their destination on a direct route with minimal stoppage or intersections. Therefore, they can maximize their utility in their space-time prism, which can lead to more bicycle use.

2.1.4 | An ecological model

A social ecological model is a framework that recognizes that an individual's behavior is influenced by multiple factors such as individual, interpersonal, organizational, community, and policy levels. It emphasizes the environmental and policy context of behavior, while incorporating social and psychological influences (Sallis, Owen, & Fisher, 2015). Ogilvie et al. (2011) developed a framework for evaluating the effect of infrastructural interventions from a public health perspective. It emphasizes multiple factors that influences travel behavior. These factors demand for a more holistic model that is needed to understand the determinants of active commuting. Ogilvie et al. (2011) describe four factors: physical environmental factors, individual factors, social environmental factors and household and family factors. These factors are interrelated and can influence each other. This is in line with the core principles that is proposed by Sallis et al. (2015): influences on behaviors interact across these different levels. Götschi, Nazelle, Brand, & Gerike (2017) developed a comprehensive framework from a socioecological point of view. The Physical Activity through Sustainable Transport Approaches (PASTA) framework is a framework that serves as a cross-reference to include known determinants and confounders to travel choices. The PASTA framework distinguishes three domains: social context determinants, physical context determinants and individual level determinants. The first domain consists of the policy context where urban and transport planning, politics and advocacy are determinants that influence the built environment and the individual. Within the second domain, the physical context determinants, are the built environment and the natural environments. In the third domain, the determinants are at the individual level such as: socioeconomic characteristics, locations of work and home, opportunities and constraints, attitudes, and habit. All these determinants lead to a travel choice. An example is that bicycle highways affect the built environment with a more connected and safe bicycle infrastructure. This improvement in safety may help an individual to bike more, or the bicycle highway connects two cities with a high-quality direct bicycle path which means for an individual to commute by bicycle instead of the car.

2.2 | Evaluation research

Programs, policies, and interventions are often implemented to change an outcome, to reach certain goals or to get beneficiaries. In the past, policies and interventions were often implemented without evaluations to determine their effectiveness. The use of evaluations has grown in response to the need for evidence-based decision making (Rossi, Lipsey, & Freeman, 2004). The theory and application of an evaluation has been explored by scholars since the 1950s. In the 1970s, evaluation research emerged as a distinct field in the social sciences. This was driven by the understanding of the costs and benefits and therefore, by evidence-based decision making. These interventions can be examined with monitoring and evaluations, which are part of evidence-based policy making (Gertler, Martinez, Premand, Rawlings, & Vermeersch, 2011). Evidence-based policy making have become an increasingly important part of policymaking. Monitoring is a continuous process that tracks program implementation and day-to-day data. Evaluations are objective assessments of a planned, ongoing, or completed program, policy, or intervention. Rossi et al. (2004) divides these in process evaluation and impact evaluation. Evaluations are performed in a broad spectrum of sciences and therefore, has been defined in multiple ways (Guyadeen & Seasons, 2016). The scientific field ranges from health, economic studies, political studies, and spatial planning. With a structured process, information about the outcome should help reach an objective.

Evaluations are executed to answer specific questions that are related to the design, the implementation, and the results of specific investments. According to Rossi et al. (2004), there are four different purposes of performing an evaluation: program improvement, accountability, knowledge generation, and a hidden agenda. A program improvement intends to obtain more information on project, program and policy implementation and improvement. It can be seen as a process evaluation as it is often conducted during the implementation phase of a policy. It is the work of the evaluator to work closely stakeholders in designing, conducting, and reporting the evaluation. The second purpose of evaluating is accountability. These types of evaluations are known as summative evaluations, or as impact evaluations. These evaluations are conducted at the end of an intervention to determine the extent to which anticipated results were realized. It empirically measures the causal effects of an intervention on outcomes of interest. The findings of summative evaluations are intended for decision makers at a high er level with program oversight. Knowledge generation is the third purpose for conducting an evaluation. These evaluations are conducted to test new approaches to a problem or for a researcher to test whether a program, based on theory, is workable and effective. The outcomes of these type of evaluations are presented through journals or conference papers. A last purpose of conducting an evaluation has according to Rossi et al. (2004) has little to do with the effect of the intervention. These types of evaluations are often part of a decision that has already been and are a display of public relations.

Evaluations in infrastructural projects are often part of summative evaluations or impact evaluations. One of the main challenges in undertaking impact evaluations of interventions is establishing causality or demonstrating that the observed impact can be attributed to the intervention and not to external factors. Relevant external factors to infrastructural interventions are, among others, factors such as population growth, economic conditions, and an aging population. White (2006) suggests that impact evaluation can establish causality by using counterfactual analysis. This compares the actual outcomes with what would have happened without the intervention, allowing for the isolated net effect of the intervention's impact. These external factors are called the counterfactual. This is an estimate of what the outcome would have been if the intervention did not take place (Gertler et al., 2011; Khandker, Koolwal, & Samad, 2010). On a theoretical, conceptual level, solving the problem of the counterfactual requires an identical clone of the treatment group. A key challenge then, is to find a control group that has the same characteristics as the treatment group. According to Gertler et al. (2011), in an ideal situation, the treatment and control group should be the same in at least three ways: at first, the treatment group and control group should be identical in the absence of the program. Second, the treatment and control group should react to the intervention in the same way. They both should equally benefit from the intervention. The third similarity should be that both groups cannot be differentially exposed to other interventions. However, in practice, researchers try to find a control group that fits the treatment group the best way.

2.3 | Socioeconomic characteristics

Gender appears to have a minimal influence for an individual in the choice to cycle or not. However, the relationship with cycling and gender seems to be country specific. In countries with high rates of cycling, the differences between men and women are less substantial (Pucher & Buehler, 2008; Vandenbulcke et al., 2011). Research performed in the Netherlands by Engbers & Hendriksen (2010) and Harms, Bertolini, & te Brömmelstoet (2014) show a higher number of female cyclists than male. On the contrary, in countries with low cycling rates, such as the USA, UK and Australia these differences are more apprehensible. Women are more restrained to cycling and name traffic and aggression from motorists, which lowers their perceived safety, as the main constraints (Moudon et al., 2005; Heinen, Van Wee, & Maat, 2011; Garrard, Handy, & Dill, 2012; Heesch, et al., 2012).

Research shows that age has a negative impact on cycling levels as it is affected by the physical fitness of people. Therefore, younger people tend to cycle more than the elderly (Dill & Voros, 2007; Heinen et al., 2010; Moudon et al., 2005). As with gender, the differences in age are less substantial in countries with high rates of cycling than in countries with low cycling levels (Harms et al., 2014).

The effect of income on mode choice shows mixed results in research. Dill & Voros (2007) found that a higher income means higher cycling levels because people are more aware of their health and fitness. On the contrary, Witlox and Tindemans (2004), Plaut, (2005) and Schwanen and Mokhtarian (2005) state that there is a negative relationship between income and cycling levels, as a high income can indicate that people spend more money on buying a car. Research has found that the availability of a car in the household has a negative impact on the likelihood of individuals using a bicycle as the mode of transportation. Having multiple cars in a household does even further decrease the likelihood of cycling. (Dill & Voros, 2007; Gao et al., 2018 Stinson & Bhat, 2004; Scheepers et al., 2013; Stinson & Bhat, 2004).

The relationship between education level and cycling as mode of transport is ambiguous and can vary depending on the context. Some studies have found that highly educated individuals tend to cycle less (Heinen et al., 2010; Rodriquez-Valencia, Rosas-Satizábal, Gordo, & Ochoa, 2019), while others have fond that a higher level of education leads to more cycling (De Geus, De Bourdeauhuij, Jannes, & Meeusen, 2008; Engbers, & Hendriksen, 2010). Additionally, cities with a higher share of students may have higher levels of cycling due to students using bicycling to get to university and keep on using them for their work later as they created a habit. Factors such as job location and type also play a role in this relationship as high skilled jobs may not be available in every city and therefore requires a trip with the car.

Ethnicity also plays a role in mode choice. In The Netherlands, an individual with a non-western migrant background seem to make less use of a bicycle than an individual with native Dutch background (Harms et al., 2013). This is also supported by findings in Rietveld & Daniel (2004), Heinen et al. (2010), and Gao et al. (2018).

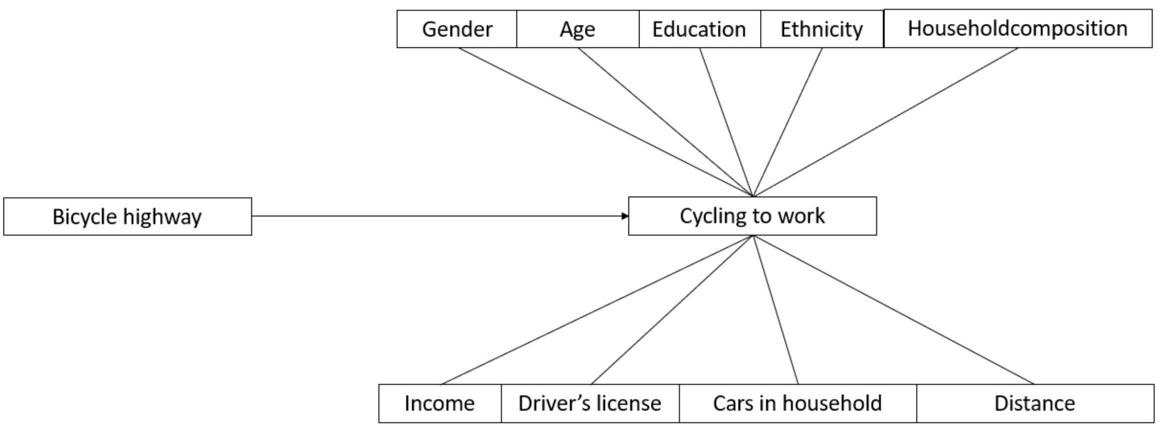
Travel distance is a key characteristic that can strongly influence an individual's mode choice. Research has found that as the distance of the trip increases, the likelihood of cycling decreases. Longer distances can require more travel time and effort. Various studies have found that longer trip distances are negatively associated with bicycle use (Buehler, 2012; Heinen et al., 2010; Muñoz et al., 2016, Winters et al., 2017).

2.4 | Conceptual Framework

The conceptual model of this thesis is shown in the figure below. It presents an overview of the dependent, independent and control variables. The dependent variable is 'Cycling to work'. The independent variable that will try to explain the dependent variable is 'Bicycle highway. The control variables are 'Gender', 'Age', 'Education', 'Ethnicity', 'Householdcomposition', 'Income', 'Driver's license', 'Cars in household', and 'Distance'.

Figure 4

The conceptual model



3 | Methodology

In this chapter, an elaboration on the methodological choices will be given and the methods used to conduct this research will be addressed. The first paragraph concerns the philosophical framework of the research from where this research proceeds. In the second paragraph, the focus is on the research methods and the research design. Different designs will be discussed, and the design used will be explained. Paragraph three informs on the data collection. Subsequently, paragraph four explains how the collected data is prepared for analysis. The construction of the variables used in this research are mentioned in paragraph five. The sixth paragraph explains the analytical methods of the research and the seventh paragraph convenes the validity and the reliability of the conducted research.

3.1 | Research philosophy

Evaluation research distinct itself from scientific research as it is the goal to generate information about the implementation and effectiveness of policies and interventions designed to develop change. Evaluation research employs a variety of social science methods to generate information. A research paradigm serves as a philosophical framework for the study and direct the researcher to the research methods appropriate for the phenomena under investigation (Clarke, 1999). According to Guba & Lincoln, a research paradigm is defined as (1994, p.107)

> "A *set of basic beliefs that deals with ultimates or first principles. It represents a worldview that defines, for its holder, the nature of the world".*

This worldview is based on ontological, epistemological, and methodological questions. Greene (1994) categorizes four philosophical frameworks in which program evaluation can take place: post positivism, pragmatism, interpretivism and critical normative science. In the post positivism framework, there is a strong emphasis on quantitative methods. The reality is something that is objective and that there is solely a single reality. It concentrates on measuring effectiveness and causal knowledge by focusing on rational methods of empirical inquiry as experiments and quasi-experimental designs. Pragmatism is a philosophical framework that emphasizes the use of methods that match the objective under study. It came up as a response to the difficulties associated with identifying clear objectives. It focuses on management, practicality, and quality control by making use of surveys, interviews, and observations. A third model is grounded in the interpretivism framework where there is a strong emphasis on pluralism and in understanding the diverse stakeholders involved. Qualitative methods are used to enhance the understanding of programs from the perspectives of the stakeholders. By making use of case studies, interviews, and document reviews. The task of a qualitative researcher is to acquire insight and understanding of the stakeholder's point of view. The last philosophical framework that Greene (1994) distinguishes has a critical and normative approach. It involves collaboration and negotiation with stakeholders during the evaluation process. By making use of stakeholder participation, the outcome of the evaluation contributes to emancipation, empowerment, or social change. This research is studied from a post positivism framework where quantitative methods are employed and there is an objective reality.

3.2 | Research design methods and design

A general distinction can be made between quantitative research and qualitative research. The former emphasizes the quantification in the collection and analysis of data with a deductive approach with the focus on testing of theory. This differs from qualitative research, which emphasizes words rather than quantification. Qualitative research accentuates on an inductive approach to the relationship between theory and research. (Bryman, 2012; Guba & Lincoln, 1994; van Thiel, 2014). In this research, quantitative methods will be adopted. This method is chosen because of its ability to analyze an extensive amount of data. Therefore, it is more useful than a qualitative approach hence the aim of the research is to assess the effectivity of the bicycle highways by making use of a large dataset over multiple years.

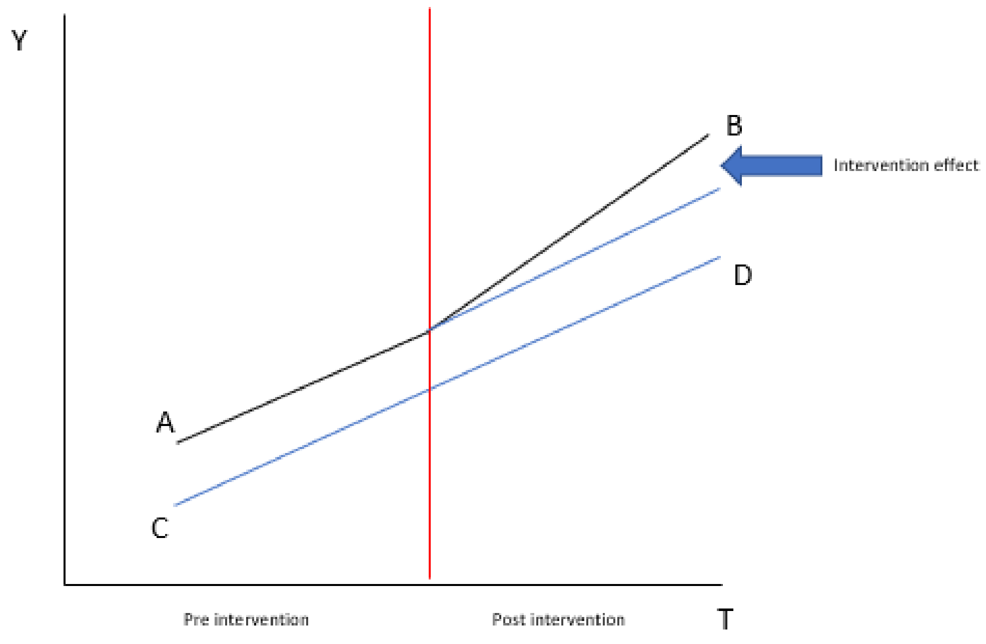
Evaluation research relies on the principles and methodologies of the social, behavioral, and statistical sciences (Clarke, 1999). Identifying causal relationships between variables is a fundamental goal of impact evaluation. Therefore, a robust research design is important. Multiple research designs are common in social sciences and variations within these designs exist. Four research designs can be distinguished: an experimental design, a cross-sectional design, a longitudinal research design, and a case study (Bryman, 2012; Van Thiel, 2014). Relevant within the framework of this study are the experimental and longitudinal research designs (Clarke, 1999; Rossi et al, 2004)

An experimental design can be seen as the benchmark for causal findings as it provides trustworthiness and robustness with a high internal validity. Rossi et al., (2004) see this as the 'gold standard' design for assessing causal effects. In social sciences is commonly used by researcher who assess the impact of new reforms or policies. For a study to be an experiment, it must control for the possible effects of other explanations of a causal finding. A classic experimental design is the randomized controlled trial (RCT) where participants are randomly assigned to a treatment or a control group. A quasi-experimental design, an alternative to randomizes controlled trials, has a lower internal validity because the participants are not randomly assigned to a group. They are called quasi-experimental because the researcher selects the criterions for assignment and thus, the condition to randomly assign participants is not met. A natural experiment is a another experimental design. These experiments are often recommended if the impact of population level policies is evaluated. Many variants are found in literature but common is that exposure to the intervention has not been manipulated by the researcher (Craig et al., 2012; Rossi et al., 2004). Clarke (1999) makes a distinction between weak and strong quasi experimental designs. Three weak designs are identified: the one-shot case study, the one group, pre-test and post-test design, and the static group comparison. The one-shot case study only observes one group after the implementation of the intervention. There is no control group and there is no data of the situation before the intervention. The one-group, pre-test and post-test design is also called a before-and-after study. The only population that is under observation is the treatment group. Therefore, it cannot measure the net effect of the intervention due to possible other factors that changed in the treatment group. The third design is the static-group comparison where a comparison is made between a treatment and a control group but only after the treatment. In this design, baseline data is not known which can imply that differences already existed before treatment.

Since it is important to include a control population when evaluating and to add the component of time, the Difference-in-Differences (DiD) design will be employed. The technique is widely used in evaluating outcomes of experiments with interventions and/or policies within econometrics, public policy, health research, management, and medicine sciences for impact evaluation (Frederiksson & Magalhàes de Oliveira, 2019; Greene & Liu, 2020; Wing, Simon, & Bello-Gomez, 2018). The DiD "compares the changes in outcomes over time between a population that is enrolled in a program (the treatment group) and a population that is not (the comparison group)" (Gertler et al., 2011, p95). More specifically, it quantifies the effect of an intervention on an outcome by comparing the average change over time in the outcome of the treatment group to that of the control group (Greene & Liu, 2020). Measuring the before-and-after situation of an intervention would not give the researcher the answer due to other factors that change over time. Likewise, comparing two areas at the same moment from which one did receive, and the other did not receive the intervention is also open to doubt because baseline data (pre-treatment) can differ. This means that it is difficult to derive a causal relationship, as there is no dimension of time. The difference-in-difference methodology combines insights from cross-sectional treatment and control comparison studies and before and after studies. This combination provides a robust framework with a higher internal validity. Figure 2 visualizes the difference-in-differences design. C and D represent the control group before and after the intervention. A stands for the treatment group before the intervention and B represents the treatment group after the intervention. The parallel trend assumption is also visible. If the intervention did not take place, A-B would have the same bar as C-D. This is also known as the counterfactual. The intervention effect is visualized between the black and blue line in the post intervention section.

Figure 2

A visual representation of the difference-in-difference model



In the basic, a two-group two-period design, difference-in-differences approach (Greene, & Liu, 2020), the outcome Y is formulated by the following equation:

$$Y = \beta 0 + \beta 1 * (Time\_period) + \beta 2 * intervention + \beta 3 * (time * intervention) + \beta 4 * Covariates + \epsilon$$

Where Y is the outcome of interest. $\beta 0$ is the intercept of the regression. *Time* is a dummy variable that takes the value 0 or 1, depending on whether the observation refers to the pre or post treatment period. *Intervention* is a dummy variable that takes the value 0 or 1, depending on whether the observation refers to an individual in the control or treatment group respectively. *Time*intervention* is the interaction term, which shows the interaction effect of the two dummy variables. ε is the error term which captures the effect of omitted factors. This means that the interaction term $\beta 3$ is the coefficient of interest. It shows the effect of treatment on the treated group in the post treatment period and can be rewritten as follows:

$$\beta 3 = (\bar{Y}_{T,1} - \bar{Y}_{T,0}) - (\bar{Y}0_{C,1} - \bar{Y}C_{,0})$$

$\bar{Y}_{T,1}$ represents the treatment group post treatment and $\bar{Y}_{T,0}$ represents the treatment group before treatment. Is shows the estimated average change in the outcome ($\bar{Y}$). This is the same for the control group ($C,1$; $C,0$). Thus, $\beta 3$ stands for the estimated average effect of the treatment on the treatment group (Greene, & Liu, 2020). However, a two-group two-period design is not applicable to more situation when interventions are implemented at different times. More common in the empirical application is a deviation from the two-group two-period design which is called a two-way fixed regression. This design involves multiple groups and time periods (Wing et al., 2018). This leads to the following equation:

$$Y_{gt} = A_g + B_t + \delta D_{gt} + \epsilon_{gt}$$

Where Y_{gt} represents the outcome of interest. The g and t represent the groups and time periods. A_g is a group-fixed effect and shows whether g falls within the intervention group or control group. B_t is a time-fixed effect and represents the effects of time-varying but group-invariant factors. D_{gt} has the value of 1 if the intervention is active in group g and in period t. If one of them is not, the value is 0. ϵ_{gt} is an error term. δ holds the value of the effect of the intervention (Wing et al., 2018).

As travel behavior may also affected by socioeconomic characteristics, X_{ij} is added to the equation and represents the relevant individual socioeconomic characteristics of the person per trip.

$$Y_{gt} = A_g + B_t + \delta D_{gt} + X_{ij} + \epsilon_{gt}$$

The parallel trend assumption is an important assumption for confirming the internal validity of DiD models (Greene, & Liu, 2020; Wing et al., 2018), which states that both treatment and control group must follow the same trend over time if no treatment is given. The parallel trend assumes that the unmeasured variables are either time-invariant group attributes or time-varying factors that are group invariant (Wing et al., 2018).

3.3 | Data collection

In this research, a secondary data analysis has been carried out. Three datasets have been used for this research. The dependent and independent variables can be found in a dataset that is a merge of multiple years of OViN and ODiN data. The second dataset is a shapefile with postal codes in The Netherlands on a PC4 level. A shapefile containing all bicycle highways in the Netherlands, completed in or before 2021 is the third dataset.

3.3.1 OViN/ODiN Data

The first dataset is a merge of the OViN and ODiN datasets from 2010 to 2021. This data is relevant for policymakers as they want to have a better understanding of the transportation activity. In the Netherlands, this data is collected by means of the Dutch national travel survey called OViN (Onderzoek verplaatsingen in Nederland). OViN surveys were carried out by the CBS (Centraal Bureau voor de Statistiek) and were held from to 2010 to 2017. From 2004 to 2009, the research was called 'MON' (Mobiliteitsonderzoek Nederland) and from 2018 until present, the research is called ODiN (Onderzoek verplaatsingen in Nederland).

The CBS gathers data in the Netherlands to provide sufficient information about the travel behavior of the inhabitants of the Netherlands. Citizens of the Netherlands, inhabitants of institutions and elderly facilities excluded, are approached with a letter to complete the OViN questionnaire online making use of Computer Assisted Web Interviewing (CAWI). If no response has been given, the people would get a call to complete the questionnaire by Computer Assisted Telephone Interviewing (CATI). If no phone number is known the questionnaire would take place at the respondents' home to obtain the data by Computer Assisted Personal Interviewing (CAPI). ODiN differs from OViN as children under six years old are not included and only CAWI is used to complete the ODiN questionnaire. People are asked about their trips in a day with questions regarding the place of departure and the place of arrival with corresponding postal codes at PC4 level, with what purpose, with which transport mode and how long it takes to get to their destination. Adjacent to these specific trip and legs questions, the CBS asks general information like personal and socioeconomic characteristics (sex, age, education, income, etc.).

This dataset is valuable to the research because it offers longitudinal data on people's movements with connected socioeconomic characteristics.

3.3.2 Bicycle highways

The dataset with bicycle highways is provided by thesis supervisor dhr. Ploegmakers. In order to be selected as a bicycle highway, the route needed to differ from regular a bicycle path and meet the criteria that corresponds with a bicycle highway. The organization Tour de Force updates this database yearly. All bicycle highways constructed in or before 2021 are visualized in figure 3 and presented in table 1. This data is relevant because connections between place of departure and place of arrival can be made that align with a bicycle highway. A shapefile with all postal codes in The Netherlands is used to analyze which postal code a bicycle highway cover.

Figure 3

A map of bicycle highways constructed in/or before 2021

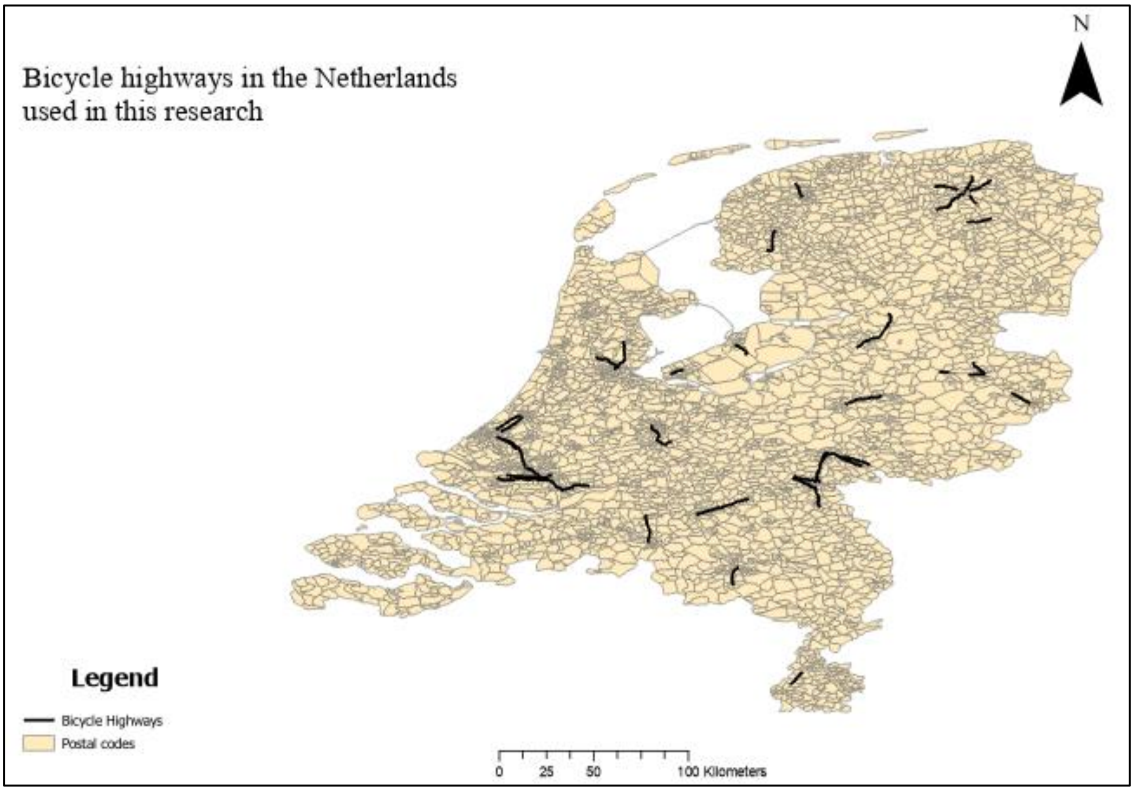


Table 1:

Bicycle highways used in this research

Name in research	Year announcement	Year start construction	Year realized
Almelo – Vriezenveen	2007	2018	2020
Amsterdam – Purmerend	2010	2014	2016
Amsterdam – Zaandam	2007	2008	2016
Apeldoorn – Deventer	2007	2008	2018
Arnhem – Nijmegen	2008	2011	2015
Arnhem – Zevenaar	2009	2012	2016
Cuijk – Mook – Nijmegen (MaasWaalpad Limburg)	2011	2015	2020
Cuijk – Mook – Nijmegen (MaasWaalpad Noord Brabant)	2011	2015	2020
Den Haag – Leiden	2008	2010	2015
Dordrecht – Papendrecht – Sliedrecht	2009	2013	2018
Eindhoven – Valkenswaard	2009	2015	2016
Groningen – Bedum (binnen bebouwde kom)	2007	2013	2015
Groningen – Bedum (buiten bebouwde kom)	2007	2013	2015
Groningen – Haren	2012	2016	2018
Groningen – Roden	2004	2013	2016
Groningen – Ten Boer	2007	2016	2018
Groningen – Zuidhorn	2003	2007	2011
Hengelo – Enschede	2007	2008	2011
Houten – Utrecht West	2009	2013	2015
Leeuwarden – Stiens	2013	2016	2016
Leiden – Voorburg	2008	2010	2015
Lelystad Waterwijk – Lelystad Airport	2017	2018	2021
Maastricht – Sittard	2011	2018	2019
Nijmegen – Beuningen	2009	2012	2017
Nijmegen – Mook – Cuijk	2011	2015	2020
Nijmegen Zuid – Beuningen	2009	2012	2017
Nijverdal – Wierden	2007	2013	2021
Pijnacker – Den Haag	2007	2008	2016
Pijnacker – Rotterdam	2007	2008	2016
Rotterdam – Dordrecht	2009	2013	2014
‘s-Hertogenbosch – Oss	2009	2014	2016
Sneek – Woudsend	2009	2013	2015
Stadsdeel Ijsselmonde Rotterdam	2011	2018	2021
Tilburg – Waalwijk	2014	2019	2021
Vries – Zuidlaren	2006	2017	2018
Wierden – Almelo	2007	2014	2021
Zwolle – Hattem	2007	2008	2021
Zwolle – Staphorst	2014	2017	2018
Zwolle – Hattem	2007	2008	2012

3.4 | Data Preparation

In this section, the preparation of the data is described. The various datasets needed to be combined and prepared in order to analyze and answer the research question. The first step consisted of determining which trips made by respondents benefitted from bicycle highways and which trips didn't. ArcGIS Pro is utilized in order to identify which postal codes are within 2.5 kilometers of a bicycle highway. This is done with the geoprocessing tools 'Buffer' and 'Intersect'. A geoprocessing tool is a command or a function that can perform an operation on GIS data. The 'Buffer' tool can create a buffer polygon around selected points, lines, or areas. Buffers of 2.5 kilometer were taken for each bicycle highway. The tool 'Intersect' computes an intersection of the input features, bicycle highways and postal codes, and produced a table with postal codes that can be reached within the buffer and align with the bicycle highway are combined as an arrival and destination combination. These arrival and destination combinations are merged with the OViN/ODiN dataset with trip data from 2010 to 2021. This generated a dataset where for each trip made by respondents the postal code combination is added as a variable. The data on the year of announcement, start of construction and year of completion are added as variables to the dataset in order to construct specific bicycle highway dummy variables.

3.5 | Variable construction

In this paragraph the construction of the variables will be discussed. First, the created dummy variables will be explained and subsequently the control variables are defined. The original OViN/ODiN dataset contains numerous variables. Not all these variables are relevant for the analysis performed in this research.

The dependent variable in this research is 'Bicycle Use'. This is a binary dummy variable and shows which trips are made with the bicycle as the main mode of transportation to commute and which trips are made with the car as the main mode of transportation. This implies that when a respondent uses his bicycle to travel to his work, he or she uses the bicycle as a main mode of transportation. However, if he or she cycles to the train station and continuous by train, the bicycle is not the main mode of transportation. The dummy is constructed by only selecting cases which are made by bicycle or car and then recoding the variable 'Hoofdverplaatsmiddel'. A second binary dummy variable is 'cyclehighway_2021'.

This variable divides the treatment and the control group, as it indicates whether a trip is made within the buffer zone and the departure and arrival align with the route of the bicycle highway. Three other dummy variables are created which divide the treatment group in ‘pre-treatment’, ‘during-treatment’, and ‘post-treatment’. A trip belongs to the ‘pre-treatment’ if the trip is made before the start of construction. Trips that fall into ‘during-treatment’ are trips that are made after the start of construction but before the completion of the bicycle highway. Trips that belong to the ‘post-treatment’ group are trips that are made one year or more after the completion of the bicycle highway.

The variable ‘geslacht’ is a dichotomous variable coded as ‘Male’ or ‘Female’. It is not recoded. The variable ‘leeftijd’ is recoded in seven age classes. These are ‘18 – 25’, ‘26 – 35’, ‘36 – 45’, ‘46 – 55’, ‘56 – 65’, ‘66 – 75’ and ‘76 and older’. The variable ‘herkomst’ refers to the ethnic group the respondent belongs to. It is not recoded. The CBS divided ‘herkomst’ in ‘Domestic, ‘Western immigrant’ and ‘Non-western immigrant’. Western immigrants are from countries within Europe (not Turkey), North America, Oceania, Indonesia, and Japan. Nonwestern immigrants are from countries within Africa, Latin-America, Asia (not Indonesia and Japan) and Turkey. The CBS also adds the category ‘Unknown’. The variable ‘Household composition’ is recoded into ‘Single household’, ‘Couple without children’, ‘Couple with children’, and ‘Other’. The category ‘Other’ refers to households that do not fit in the categories. This includes respondents living in student housing or co-living projects. The variable ‘education’ has been recoded to four categories. The first category, ‘Low’, consists of respondents with no finished education, finished elementary school or the lower secondary school (VMBO). The second category ‘Middle’ consists of respondents who finished the higher secondary school (HAVO, VWO) or obtained a degree at MBO level. Respondents within category ‘High’ are respondents who achieved a diploma at HBO or WO (university) level. ‘Other’ refers to education that does not fit in aforementioned categories or unknown education. Household income is measured by ‘hhgestinkg’. This is the standardized discretionary household income after taxes. The CBS has divided it in 10% groups. These groups are recoded to the following categories. The first category ‘Low Income’ consists of the first to third 10% group, the category ‘Middle Income’ refers to the fourth to seventh 10% group. The category ‘High Income’ refers to the eight to tenth 10% group. The CBS has added the category ‘Unknown’. The variable ‘OPRijbewijsAu’ contains information if the respondent has a driver’s license or not. It is not recoded. The variable ‘HHAuto’ consists information of the number of cars in the household. It is recoded to the following categories: ‘No Cars, ‘1 Car’ and ‘2 or more Cars’. The variable ‘Afstv’ is the distance of transportation measured by hectometers. It is measured at ratio scale and recoded to the following categories: '1,01 km – 2,5 km', '2,51 km – 5,00 km', '5,01 km – 7,50 km', '7,51 km – 10,00 km', '10,01 km – 15,00 km', '15,01 km – 20,00 km', '20,01 km – 25,00 km'.

3.6 | Analytical methodology

In order to find a relationship between the bicycle highway and the use of the bicycle, a regression analysis will be employed. There are different regression analyzes that can be performed to find a relationship between variables. The most extensively used regression is a linear regression. The dependent variable in a linear regression can be at interval or ratio level. A linear regression predicts the value of continuous variables, and the output is a continuous value. However, in this research, the dependent variable is dichotomous. Therefore, a linear regression is not suitable. A respondent commutes to work with his bicycle, or a respondent does not commute with his bicycle. If the outcomes are visualized in a graph, the values of the dependent variable would not be in a straight line but in a S-curve, as the outcome can only be 0 or 1 (de Vocht, 2014).

Figure 4

A linear regression line is not suitable for a dependent dichotomous variable

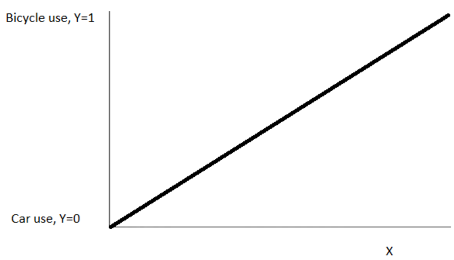
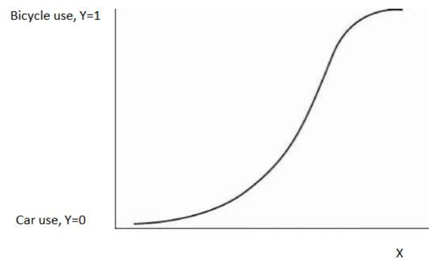


Figure 5

A logistic regression curve is suitable for a dependent dichotomous variable



A logistic regression allows to predict categorical outcomes from categorial and continuous variables. Thus, a logistic regression has been carried out to predict the chance that the outcome variable has a 0 or a 1. Instead of predicting the value of Y, we predict the probability of Y occurring. Regarding this research, it means whether we can predict the chance that someone makes use of a bicycle of not make use of a bicycle. The logistic regression equation can be expressed as:

$$\text{Logit} = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \ldots\ldots \beta_k * X_k$$

where β_0 is the intercept of the model (constant). The parameters β_k are the partial regression coefficients where the explanatory effect of X_k is expressed by β_k. The change of Y occurring can be equated as:

$$P(Y) = \frac{1}{1 + e^{-logit}}$$

Where *e* is the base of natural logarithms. The number *e* is a mathematical constant equal to 2,71828. This leads to the following equation for predicting the probability of Y occurring:

$$P(Y)\frac{1}{1 + e^{-(\beta 0 + \beta 1 * X1 + \beta 2 * X2 + \ldots\ldots \beta\, k * Xk)}}$$

According to De Vocht (2014) there are four assumptions that should be met if carrying out a logistic regression analysis. First, the dependent variable should be dichotomous, and the independent variables should be at least at interval or ratio level. However, it is possible that the independent variables are made of categorial dummies. Second, there should be a theoretical relation between the dependent and the independent variable(s). Third, the model should be linear, where the logit is a combination of the independent variables. Lastly, the model cannot have multicollinearity. This occurs when there is a strong correlation between two or more independent variables (Field, 2013). Multicollinearity can be identified by computing the variance inflation factor. The VIF indicates if an independent variable has a strong linear relationship with other independent variables. Bowerman & O'Connell (1990) provide guidelines in interpreting the VIF scores. A problem occurs when the largest VIF is greater than 10.

The sufficiency of the overall fit of the logistic model is shown by the -2LogLikelihood (-2LL), which is expressed by the chi-square statistic. If the significance of the chi-square is lower than 0.05, the model is significant to the data (Field, 2013). Next to the fit of the model overall, the contribution of the independent variables is also important. The z-statistic, also known as the Wald statistic, tells if the β-value for the independent variable is significantly different from zero. If there is a significant difference from zero, it means that the independent variable makes a significant contribution to the prediction of the outcome (Field, 2013). This means that the contribution of the independent variable is outcome of chance.

Other important characteristics are the R squared indices. The Cox & Snell R^2 is based on the deviance of the model, the deviance of the original model and the sample size. However, this statistic can't reach 1 (Field, 2013). Therefore Nagelkerke (1991) adjusted the formula, so it has a theoretical range between 0 and 1. This statistic indicates the quality of the model. A higher Nagelkerke R^2 indicates a strong relationship between the dependent and the independent variables (De Vocht, 2014; Field, 2013).

3.7 | Validity and reliability of the research

Research is conducted in order to answer a problem statement and the quality of the answer that is given depends on the validity and the reliability of the research. The following will elaborate on the importance of internal validity, external validity, and reliability in research and how this is applied within evaluation research.

3.7.1 | Internal validity

Validity can be seen as the most important quality criterion of social research. It is concerned with the integrity of the conclusions that can be drawn from the research. This also holds for evaluation research (Gertler et al., 2011). Does it measure what it intends to measure. (Bryman, 2012; van Thiel, 2014). The internal validity of a research focuses on the effectiveness of the study, which means that the estimated impact of the intervention is measuring the true impact of the invention without any potential confounders. The question is if the conclusion holds a causal relationship between two or more variables. According to Gertler et al., (2011) an evaluation design has internal validity if it uses a valid comparison group. The parallel trend assumption is an important feature for this comparison group. The internal validity of a different-in-difference design revolves around the parallel trend assumption where the assumption is made that in absence of the intervention the variables in the treatment and control group increase or decrease simultaneously. The internal validity of a research design can be enhanced by performing a robustness check to study the main assumptions of the research design. This is done by comparing the original model to a model with adjusted variables and cases to test the stability of the effect (Wing et al., 2018).

3.7.2 | External validity

External validity is concerned with the generalization of the research beyond the specific research context (Bryman, 2012; van Thiel, 2014). As it is important to produce evidence of the effectiveness of bicycle highways and enhance its usability to government officials and other stakeholders, having a high external validity is important. The external validity of a research is therefore key for policy makers as it determines whether the results from the evaluation can be replicated (Gertler et al., 2011). Having an external validity means that the effect of the bicycle highways in the study population can be generalized to populations with comparable populations. This means that the evaluation sample must be a representative sample of the whole population and can be done with several variations of random sampling. The 'Centraal Bureau voor Statistiek' uses a stratified two-stage sampling model to ensure a representative sample of the population. As this data is derived from individuals in The Netherlands, the effectiveness of bicycle highways can be generalized to other municipalities. Generalizing this research to other countries with a lower cycling share and no specific bicycle infrastructure might be difficult. However, the outcomes of this research can be generalized to countries with already high cycling volumes. Yet, complications with the external validity can always arise when working with questionnaires. If respondents who have been asked to participate eventually don't, the non-response will diminish the representativeness of the sample.

3.7.3 | Reliability

The reliability of a research raises the question whether the results of the study conducted are repeatable. Does a researcher measure the same results when repeatedly again. The variation between those results is called the measurement error (Rossi et al., 2004). To ensure a high reliability in research, the researcher needs to focus on the accuracy and the consistency with which the variables are measured (Bryman, 2012; van Thiel, 2014). A high accuracy can be achieved with a correct and precise focus on the variables. The consistency focuses on the repeatability of the research, which means that under similar circumstances, similar results will be found using the same measurements.

4 | Results

This chapter presents the results of the conducted research and analysis. In the first paragraph, the study population will be presented and the socioeconomic characteristics of the study population are described. In the second paragraph, the outcome of the logistic regression models is presented and discussed. Subsequently, the net effect of the interventions is calculated. Lastly, in the fourth paragraph, a robustness test is performed to indicate the stability of the effect using a different subset of the data.

4.1 | Study population

The data used in this research are the recorded trips made by respondents to the OViN/ODiN questionnaires, from the period 2010 to 2021. These accumulated datasets formed one dataset with 1.370.272 recorded trips. However, not all of these were eligible for this research. The study population is composed of individuals who are 18 years of age or older, who reported commuting as the motive for their trip, who used either a bicycle or a car as their main mode of transportation, and who traveled a distance between 1 and 25 kilometers. Trips that started and ended in the same postal code were also removed from the study population. These criteria are used to ensure that the study population is a representative set of individuals who are likely to be affected by the intervention, if a bicycle highway is constructed adjacent to their location.

The study population is divided into four groups: a control group, a pre-treatment group, a during-treatment group and a post-treatment groups. This groups are presented in table 2. The individuals who belong to the control group are individuals who live in a postal code that is not affected by a bicycle highway. This means that the individuals in the control group do not benefit before, during or after the realization of the intervention for their commute. The individuals in the pre-treatment group are individuals who made a trip that aligns with the route of a bicycle highway, but they made the trip before the start of construction. This means that the individuals in this group did not have any beneficiaries yet. The during-treatment group made a trip after the start of construction but before completion. The post-treatment group consists of individuals who commuted on a route that aligns with a bicycle highway after its completion. These four groups together make the study population for this research. Respondents who are not part of one of these three groups are removed from the dataset.

The study population, after the beforementioned criteria are applied, consists of a total of 124.320 trips. 53.1% of those trips are mad by male and 47.9% female. The study population includes respondents aged from 18 to 92 years, with most respondents being aged between 46-55 years (27.2%). 84.9% of the trips are made by domestic respondents, 8.1% by western foreigners and 6.9% by non-western foreigners. 48.2% of the reported trips are made by individuals who has a household with a partner and children. The study population slightly consists of more trips from which respondents have a high level of education (40.8%) compared to a medium level of education (40.7%). 16.8% has a lower level of education and it is unknown for 1.7%. The categories for income are divided between 41.8% for the high-income group, 41,2% for the medium income group, 16.4% for the lower income group and 0.6% is unknown. The majority owns a driver's license (93.9%). The number of cars is divided by having one car (46.4%) or two or more cars (45.5%). The other 8.1% do not own a car. Most respondents (23.4%) travel between 2.51km – 5.00 km to their job, followed by 1.00 km – 2.50 km. Only 9.4% of the respondents travel 20.01 km – 25.00 km to work.

Table 2

Socioeconomic statistics of study population

	Pre-treatment		**During - treatment**		**Post-treatment**		**Control**		**Total**	
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**
Gender										
Male	3580	50.3	2837	51.0	6698	51.9	53190	53.9	66305	53.3
Female	3539	49..7	2730	49.0	6216	48.1	45530	46.1	58015	46.7
Age										
18-25	789	11.1	586	10.5	1563	12.1	10537	10.7	13475	10.8
26-35	1498	21.0	1027	18.4	3141	24.3	18339	18.6	24005	19.3
36-45	1717	24.1	1278	23.0	2439	18.9	21705	22.0	27139	21.8
46-55	1803	25.3	1514	27.4	3093	24.0	27431	27.8	33841	27.2
56-65	1184	16.6	970	17.4	2140	16.6	173058	17.5	21599	17.4
66-75	104	1.5	164	2.9	450	16.6	2832	2.9	3550	2.9
75 and older	24	0.3	28	0.5	88	0.7	571	0.6	711	0.6
Ethnicity										
Domestic	6041	84.9	4587	82.4	10098	78.2	84871	86.0	105597	84.9
Western foreigner	584	8.2	480	8.6	1398	10.3	7698	7.8	10088	8.1
Non-western foreigner	494	6.9	500	9.0	1490	11.5	6151	6.2	8635	6.9
Householdcomposition										
Single household	1339	18.8	1050	18.9	2918	22.6	14237	14.4	19544	15.7

Couple without children	1954	27.4	1624	29.2	3842	29.8	28196	28.6	35616	28.6
Couple with children	3221	45.2	2429	43.6	5259	40.7	48954	49.6	59863	48.2
Other	605	8.5	464	8.3	895	6.9	7333	7.4	9297	7.5
Education level										
Low education	1264	17.8	826	14.8	1470	11.4	17309	17.5	20869	16.8
Medium education	2703	38.0	2201	39.5	4080	31.6	41609	42.1	50593	40.7
High education	3036	42.6	2488	44.7	7059	54.7	38197	38.7	50780	40.8
Unknown	116	1.6	52	0.9	305	2.4	1605	1.6	2078	1.7
Household income										
Low income	1548	21.7	1193	21.4	2273	17.6	15426	15.6	20440	16.4
Medium income	3003	42.2	2205	39.6	4624	35.8	41362	41.9	51194	41.2
High income	2550	35.8	2151	38.6	5857	45.4	41414	42.0	51972	41.8
Unknown	18	0.3	18	0.3	160	1.2	518	0.5	714	0.6
Driver's license										
No	586	8.2	443	80.0	1364	10.6	5228	5.3	7621	6.1
Yes	6533	9.8	5124	92.0	11550	89.4	93490	94.7	116697	93,.
Unknown	0	0	0	0	0	0	2	0.0	2	0.0
Cars in household										
No	884	12.4	714	12.8	2392	18.5	6064	6.1	10054	8.1
1 car	3665	51.5	2931	52.6	6383	49.4	44698	45.3	57677	46.4
2 or more cars	2570	36.1	1922	34.5	4139	32.1	47958	48.6	56589	45.5
Distance of trip										
1,00 km – 2,50 km	1353	19.0	1019	18.3	2704	20.9	10439	10.6	15515	12.5
2,51 km -5,00 km	2391	33.6	1951	35.0	4674	36.2	20127	20.4	29143	23.4
5,01 km -7,50 km	1193	16.8	911	16.4	2144	16.6	12250	12.4	16498	13.3
7,51 km – 10,00 km	929	13.0	746	13.4	1626	12.6	13787	14.0	17088	13.7
10,01 km -15,00 km	770	10.8	561	10.1	1130	8.8	17574	17.8	20035	16.1
15,01 km – 20,00 km	357	5.0	271	4.9	474	3.7	13241	13.4	14343	11.5
20,01 km – 25,00 km	126	1.8	108	1.9	162	1.3	11302	11.4	11698	9.4

4.2 | Binary logistic regression analysis

The results of this research are presented in this paragraph. First, the assumptions of a binary logistic regression will be tested. Second, the results of the logistic regression analysis will be presented. Subsequently, the models and the odds ratio's will be discussed, highlighting the relationship between the dependent variable and the independent variables.

4.2.1 | Assumptions of binary logistic regression

In this research, the dependent variable is binary as an individual cycles or uses the car to travel to work. The second assumption is that there should be theoretical relationship between the dependent variable and the independent variables, this is mentioned in chapter one and two. Multicollinearity can be an issue when performing a logistic regression analysis. As discussed, it occurs when an independent variable has a strong linear relationship with other independent variables and have a variance inflation factor of 10 or higher. The Variance inflation factor for the independent variables are calculated and are shown in table 3. It can be concluded that the independent variables do not have a strong linear relationship with each other. Therefore, the results of the logistic regression analysis can be considered reliable.

Table 3

Variance inflation factor analysis

Variable name	Collinearity tolerance	Variance Inflation Factor
Cyclehighway_2021	.305	3.281
During-treatment	.580	1.724
Post-treatment	.351	2.85
Year	.855	1.170
Month	1	1
Gender	.988	1.012
Age Classes	.931	1.074
Ethnicity	.962	1.039
Household composition	.858	1.166
Education	.920	1.087
Household income	.848	1.180
Driver's license	.871	1.148
Vehicles in household	.710	1.109
Distance of transportation	.872	1.147

4.2.2 | Results logistic regression analysis

Table 4 presents the results of the logistic regression. The outcomes are presented in the odds ratio (Exp(B)) with the standard error and the significance level. The odds ratio is the exponential of the coefficient (*b*) for the variable. An odds ratio greater than 1 represents an increase in the likelihood of commuting to work with a bicycle and stands for a decrease in taking the car. An odds ratio less than 1 means a decrease in the likelihood of commuting to work with a bicycle and an increase in taking the car. Categorical variables should be interpreted with care. The odds ratio for a category is the difference with the reference category. For example, if male is the reference category and the odds ratio for female is 1.5, it means that the odds of commuting by bicycle for females are 1.5 times higher than for men.

Table 4

Results of logistic regression models (1)

	Model 1		Model 2		Model 3	
	Exp(B)	S. E	Exp(B)	S. E	Exp(B)	S.E.
Cyclehighway_2021	2.357	.026***	1.316	.032***	1.147	.037***
During-treatment	1.044	.037	1.039	.046	1.055	.047
Post-treatment	1.255	,032***	1.121	.041***	1.172	.044***
Gender (reference category: Male)						
Female			.962	.016	.980	.022
Age (reference category: 18-25)						
26-35			.631	.032***	.654	.046***
36-45			.715	.031***	.719	.045***
46-55			1.060	.030*	1.041	.044
56-65			1.167	.033***	1.134	.048***
66-75			.596	.053***	.615	.074***
76 and older			.450	.102***	.357	.154***
Ethnicity (reference category: Domestic)						
Western foreigner			.755	.030***	.775	.041***
Non-western foreigner			.467	.034***	.466	.044***
Household composition (reference category: Single household)						
Couple without children			2.487	,027***	2.354	.037***
Couple with children			3.137	,027***	2.918	.036***
Other			1.483	,038***	1.383	.052***
Education (reference category: Low education)						
Medium education			1.181	,024***	1.279	.036***
High education			1.906	,024***	2.212	.036***
Unknown			1.046	,066	1.145	.095
Household income (reference category: Low income)						
Medium income			1.181	,024***	1.125	.034***

High income			1.492	,026***	1.506	.036***
Unknown			.557	,127***	.496	.166***
Driver's license (reference category: No)						
Yes			.050	,057***	.056	.080***
Unknown			.000	28420.7	.000	28420.7
Vehicles in household (reference category: No cars)						
1 car			.085	,042***	.079	.056***
2 or more cars			.020	,045***	.018	.061***
Distance of trip (reference 1.00 km – 2.50 km						
2.51 km – 5.00 km			.447	,025***	.489	.035***
5.01 km – 7.50 km			.249	,028***	.272	.039***
7.51 km – 10.0 km			.140	,029***	.146	.041***
10.01 km – 15.0 km			.073	,030***	.078	.044***
15.01 km – 20.0 km			.027	,043***	.024	.064***
20.01 km – 25.0 km			.011	,061***	.010	.096***
Controls	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Number of observations	124320		124320		60824	
Nagelkerke R^2	.061		.524		.546	
Chi Square	5588.962***		59574.822***		31527.047***	

Notes: Significance is shown with * for P < 0.10, ** for P < 0.05, and *** for P < 0.01.

In table 5, the odds ratios and standard error with significance level are given for the time effects in this research.

Table 5

Results of logistic regression models (2)

	Model 1		**Model 2**		**Model 3**	
	Exp(B)	S.E	Exp(B)	S.E	Exp(B)	S.E.
Cyclehighway_2021	2.357	.026***	1.316	.032***	1.147	.037***
During-treatment	1.044	.037	1.039	.046	1.055	.047
Post-treatment	1.255	,032***	1.121	.041***	1.172	.044***
Year (reference category: 2010)						
2011	1.063	.031*	1.139	.039***	1.135	.056**
2012	1.015	.031	1.126	.039***	1.076	.057
2013	1.021	.031	1.136	.040***	1.07	.059
2014	1.132	.031**	1.308	.040***	1.298	.059***
2015	1.065	.033	1.172	.042***	1.115	.061*
2016	1.117	.033***	1.270	.042***	1.148	.061*
2017	1.050	.033	1.159	.042***	1.069	.061
2018	1.29	.028***	1.339	.037***	1.154	.054***
2019	1.364	.029***	1.529	.038***	1.371	.055***
2020	1.268	.030***	1.345	.039***	1.314	.057***
2021	1.242	.030***	1.256	.039***	1.119	.057**
Year (reference category: January)						
February	1.081	.030***	1.096	.038**	1.110	.054**
March	1.190	.029***	1.256	.037***	1.161	.052***
April	1.293	.030***	1.482	.038***	1.292	.054***

May	1.310	.030***	1.468	.038***	1.330	.054***
June	1.338	.030***	1.526	.038***	1.529	.054***
Juli	1.382	.030***	1.643	.038***	1.637	.053***
August	1.420	.030***	1.687	.039***	1.608	.053***
September	1.352	.029***	1.535	.037***	1.521	.054***
October	1.254	.029***	1.411	.037***	1.338	.052***
November	1.220	.029***	1.360	.037***	1.299	.052***
December	1.066	.031***	1.101	.039**	1.030	.056
Controls	Yes		Yes		Yes.	
Year fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Number of observations	124320		124320		60824	
Nagelkerke R^2	.061		.524		.546	
Chi Square	5588.962***		59574.822***		31527.047***	

Notes: Significance is shown with * for P < 0.10, ** for P < 0.05, and *** for P < 0.01.

Regression model 1

The first model in table 4 shows a logistic regression analysis where only the bicycle highways dummy variables are being regressed with fixed effects for years and months. The percentage of correctly predicted outcomes slightly improves from 64.9% (block 0) to 66.7% (block 1). This is an increase of 1.8% correctly predicted outcomes by the model. The Chi-squared test has a value of 5588,962 (p < .001) indicating a good model fit. The odds ratio for the dummy variable 'Cyclehighway_2021' is 2.357, indicating that individuals who live in areas near bicycle highways have a higher likelihood in commuting by bicycle than individuals who don't live in an area that is close to a bicycle highway. This model, however, does not find a significant impact for the variable 'During-treatment'. This indicates that the start of construction of bicycle highways does not statistically improve the likelihood of individuals taking the bicycle to commute to work. On the other hand, the variable 'Post-treatment' shows a significant and positive effect on the likelihood of cycling to work as the odds ratio is 1.255. This means that individuals who live in an area where a bicycle highway is completed have a higher likelihood of commuting by bicycle compared to individuals who don't live in area with a completed bicycle highway. A Nagelkerke R Squared of .061 means that only a minimal part (6.1%) of the model is predicted by the variables that are in the model. This suggests that other factors, not included in this model, may play a role in determining the mode of transportation for commuting.

Regression model 2

In model 2, the bicycle highways are regressed in combination with the socioeconomic characteristics and fixed effects for years and months. Where the percentage of correctly predicted outcomes in model 1 improved only 1.8%, in model 2 it improves from 64.9% to

80.9%. This indicates a positive change of 16.0%. The Chi-squared test has a value of 59574,822 ($p < .001$). The odds ratio for the dummy variable ‘Cyclehighway_2021’ is 1.316 and has a significance of 99%. The variable ‘During-treatment’ is not significant. The variable ‘Post-treatment’ is significant at a 99% level and has an odds ratio of 1.121. This indicates that individuals who live in an area close to a completed bicycle highway have a higher likelihood of commuting by bicycle. The second model has a Nagelkerke R Squared of .524 which is considerably higher than the R^2 of model 1. This model explains 52.4% of the difference in mode choices, which indicates that the inclusion of socioeconomic characteristics in the model improves the explanatory power of the model. The second model provides a more comprehensive understanding of how a bicycle highway in combination with socioeconomic characteristics are related to the likelihood of commuting by bicycle.

The socioeconomic characteristics have an important role in regression model 2 as the correctly predicted outcomes and the Nagelkerke R Squared are both higher in the second model. The sex of the person commuting to work on a bicycle is significant for this study population. This variable is not significant ($p=0.140$) with a Wald-statistic of 6.019. The variable age is significant with a Wald-statistic 957.891 ($p < 0.001$). The reference category is the age group ‘18-25’. The likelihood of commuting to work on the bicycle is the highest in the age group ‘56-65’ with an odds ratio of 1.167. The likelihood of commuting on a bicycle is the lowest in the age group ‘76 and older’ with an odds ratio of .450. The category ‘Domestic’ is the reference category for the variable ‘Ethnicity’. This variable is significant ($p<0.001$) with a Wald-statistic of 541,579. Being a western foreigner in The Netherlands lowers the chance of taking a bicycle to work by 24.5% as the odds ratio for western foreigners is 0.755 in reference to domestic people. Being a non-western foreigner lowers the chance by 53.6% in relation to being a domestic person. The odds ratio for non-western foreigners is 0.467 in reference to domestic people. For the variable ‘Household composition’, ‘single household’ is the reference category. The variable is significant ($p<0.001$) with a Wald-statistic of 2034.216. The likelihood that an individual who has a different household composition commutes on bicycle is higher in reference to ‘single household’. If an individual’s lives with a partner and children, the odds of that individual commuting to work is 3.137 in reference to an individual from a single household. The variable ‘Education’ is significant with a Wald-statistic of 1031.281. The odds ratio for the category ‘High Education’ is 1.906 in reference to ‘Low Education’, which indicates that the likelihood for commuting by bicycle is higher for an individual who received a high degree. The income of a household is significant ($P<0.001$) with a Wald-statistic of 326.599. The odds ratio for high income households is 1.492 in reference to low-income households. This means that individuals from a high-income household are more likely to commute by bicycle than individuals from lower-income households. The variable ‘Driver’s License’ is significant ($p<0.001$) with a Wald-statistic of 2785.900. Not having a driver’s license is the reference category. The data shows that having a driver’s license lowers the likelihood of commuting by bicycle with 95.0% as the odds ratio is 0.050. As with having a driver’s license, having the ability to use a car for commuting, significantly decreases the likelihood of commuting by bicycle. As not having a car in the household is the reference category, the odds ratio for the category ‘1 car’ is 0.085 and for the category ‘2 or more cars’ is 0.020. The variable ‘Distance of transportation’ is significant ($p<0.001$) with a Wald-statistic of 15638.316. The reference category is ‘1.01 km – 2.50 km’. Commuting for a longer distance decreases the likelihood of commuting by bicycle.

Regression model 3

In the third regression model, the bicycle highways are also regressed in combination with the socioeconomic characteristics and fixed effects for years and months. However, it differs from model 2 as the control group is different. Individuals belong to this control group if they live in a postal code that is adjacent to a bicycle highway, but the trip did not align with the route of the bicycle highway. This lowers the number of observations to 60824. The percentage of correctly predicted outcomes improves from 59.2% (block 0) to 80.3% (block 1). This is an improvement of 21.2%. The Chi-squared test values 31527.047 ($p < 0.01$). The odds ratio for the dummy variables are higher than 1, indicating that the probability of cycling to work still increases after being exposed to the treatment.

4.3 | Average treatment effect

The average treatment effect is needed to address the net effect of the intervention. The treatment effect of the bicycle highways is found by subtracting the probability that an individual cycles to work of the pre-treatment group on the post-treatment group. These probabilities are calculated for the average respondent in the study population with the following equation:

$$P\,(Y)\ \frac{1}{1+e^{-(\beta 0\,+\,\beta 1\,*\,X1\,+\,\beta 2\,*\,X2\,+\,\ldots\ldots\beta\,k\,*\,Xk)}}$$

Table 6

The outcomes of the logit and probability calculations.

	Logit	Probability	Difference
Control group	-1.003	.268	
Pre-treatment	-0.728	.325	5.7%
During-treatment	-0.690	.333	0.8%
Post-treatment	-0.614	.351	2.6%

Table 6 shows the average treatment effect of bicycle highways on the probability of commuting using the bicycle in respect to the car. An individual who lives in area that belongs to the control group has a probability of 26.8% in taking the bicycle to work. This probability increases by 5.7 percentage points to 32.5% if an individual lives in an area where there is not a bicycle highway yet, who belong to the pre-treatment group. The probability of cycling to work for an individual who is exposed to the treatment but before the intervention is completed is 33.4%. This is an increase of 0.8 percentage points compared to the pre-treatment group. For the post-treatment group, the probability of commuting by bicycle increases to 35.1%. This is an increase of 2.6 percentage points compared to the during-treatment group and 3.4 percentage points compared to the pre-treatment group.

4.4 | Robustness of results

A robustness test is performed to analyze the model uncertainty by comparing baseline data to plausible alternative model specifications by adjusting variables to test the stability of the effect. In this robustness test, only the first journey of the respondents is taken into account (table 7). As this is only the first journey of the day, the models in table 7 show less observations than the models in table 5. The results slightly differ compared to the original models. Model 1 with only the bicycle highway dummy variables has higher odds ratios in the robustness test than in the original model and the significance does not change. The Nagelkerke R Squared changes from 0.061 to 0.062. In model 2, the socioeconomic characteristics of the respondents are added to the regression. The odds ratios for this model in table 7 differ from the original model in table 5. However, these odds ratios are still indicating that an individual's likelihood of commuting by bicycle is still improving after the construction of bicycle highways. These variables 'cyclehighway_2021' and 'Post-treatment' are still significant at a level of respectively 99% and 95%. For this model, the Nagelkerke R Squared also slightly improves from 0.524 to 0.530. Model 3 shows comparable odds ratios and the same results regarding significance in the original model (table 5) as in the robustness model (table 7). The Nagelkerke R Squared improves from 0.546 to 0.551, indicating that this model in the robustness test increases the explanatory power by 0.5 percentage points.

Table 7

Results of robustness analysis only using first trip of respondent.

	Model 1		Model 2		Model 3	
	Exp(B)	S.E	Exp(B)	S.E	Exp(B)	S.E.
Cyclehighway_2021	2.374	.034***	1.301	.044***	1.143	.050***
During-treatment	1.057	.049	1.030	.062	1.041	.064
Post-treatment	1.283	.043***	1.126	.055**	1.162	.060***
Controls	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Number of observations	68783		68783		33973	
Nagelkerke R^2	.062		.530		.551	
Chi Square	3192.711***		33434.284***		17841.649***	

Notes: Significance is shown with * for P < 0.10, ** for P < 0.05, and *** for P < 0.01

5 | Conclusion and discussion

This thesis attempted to assess the effect of bicycle highways on travel mode behavior by commuters. Bicycle highways are a new form of infrastructural investments to support a change in the modal shift towards higher cycling levels. In their design there is focus on coherence, directness, attractivess, safety and comfort in order to persuade commuters to rethink their modal choice. A great number of studies has indicated an effect of interventions on a change in travel mode choice. However, a vast amount of them failed to make a causal claim due to their cross-sectional design or stated preference studies. Other scientific work focused on modelling the possible future effects instead of measuring them. A scientific gap remained, and this research sets out to explain the influence of bicycle highways by making use of a natural experimental and longitudinal design. In order to fill that gap, the following research question was phrased:

What is the impact of bicycle highways on the probability of commuters to cycle to work?

An answer was sought by applying a difference-in-difference design to a database with eleven years of Dutch national travel surveys and information on forty-three bicycle highways. The start and the completion of these bicycle highways differed in years, which led to a multiple group and time period design. The findings in this research indicate that the investments in bicycle highways can lead to an increase in the likelihood of cycling to work compared to taking the car, as odds ratios were above 1. The odds ratios give an understanding of the size of the effect of the independent variable on the dependent variable. Three models are used to indicate the strength of these increasing probabilities. In model 1, only the bicycle highway dummy variables are regressed. Model 2 regressed these dummy variables with socioeconomic characteristics. Model 3 differs from model 2 as a sample of control group is taken. This sample consists of individuals who live adjacent to a bicycle highway but make a trip in another direction. The odds ratios for the variable 'Bicyclehighway_2021' vary from 1.147 in model 3 to 2.537 in model 1, indicating that living in an area with bicycle highways improves the probability of cycling to work. The odds ratios for the variable 'during treatment' vary from 1.039 in model 2 to 1.055 in model 3. This indicates that after the start of construction there is a modest improvement on the probability of cycling to work. The variable 'Post-treatment' varies from 1.121 in model 2 to 1.255 in model 1, indicating that exposure to the bicycle highway leads to higher probabilities of cycling. An estimation of the marginal treatment effect shows that the probability of commuters to cycle to work increases to 3.4 percentage points after the completion of a bicycle highway (model 2). This effect is calculated with the logit of the variables and is estimated for the average respondent in the study population. The interventions show a significant effect on the probability of commuting by bicycle or car. However, the model with socioeconomic characteristics improved strongly with respect to the model without the characteristics. In the robustness test, only the first trip of respondents is used which means that the amount of observations is lower than in the original models. The outcomes estimate that the odds ratio for 'Post-treatment' slightly increases in model 1 and model 2 but decreases in model 3. The robustness test shows that an adjustment to the study population does not alter the outcomes of this research.

The findings in this research indicate that the construction of bicycle highways can increase the probability of cycling to work. This supports international research that bicycle infrastructure can lead to more cycling. In their review, Mölenberg et al. (2019) identified thirty-one studies that assessed the effect of infrastructural interventions on cycling. They found that most evaluations found positive effects for the interventions but highlight the fact that different methodologies provide different results. The methodological choices made in this research allow for causal claims due to its difference-in-difference design. Various other studies with a difference-in-difference design found a positive result (Aldred et al., 2019; Goodman et al., 2014; Hirsch et al., 2017 & Rodriquez-Valencia et al., 2019). However, the found effects of these studies differ. These studies all focus on interventions that can improve cycling and all find that living near new bicycle infrastructure can predict changes in commuting by bicycle. This leads to a better understanding of the phenomenon. This research differs from them in size as it is a nationwide study using more than ten years of data. This research concludes that improvements to the bicycle infrastructure in the form of bicycle highways led to an increase in the probability of commuting by bicycle. Bicycle highways can have a significant impact on changing travel mode behavior and reduce the car dependency. This can lead to reaching policy goals, such as improving personal health, reducing congestion, and therefore, environmental problems.

5.2 | Limitations of research

The aim of this research was to provide an insight on the evaluation on bicycle highways with its effect on cycle usage for commuters. Obtaining more knowledge on this subject is constructive in reaching a new sustainable mobility paradigm. However, while the current research made contributions to the scientific knowledge on the effect, it also faces limitations. This chapter provides information on these limitations and outlines how further research can use these limitations into potential strengths.

The output that a model produce is only as powerful as the input. In order to have a longitudinal research design, secondary data of the Dutch national travel survey was used. This means that the data collected was collected for other purposes than this research. This questionnaire does not cover concepts such as attitude towards cycling, moral norm, environmental concern and perceived perceptions of safety, comfort, and convenience. These concepts can be important at a personal level in decision making regarding commuting (Donald et al., 2014, & Heinen et al., 2010). This data was not available in the OViN/ODiN dataset and requires a different research design and methodology. An interview or an extended version of a questionnaire can indicate those concepts more sufficiently. Other variables that could have been complementary to the conclusion are not in the OViN/OdiN dataset. An example are weather variables such as rain, wind, and temperature. These variables can be important in choosing for the bicycle or car when commuting to work (Heinen et al, 2010). These variables can be added to a logistic regression model if they are known for each observation. The month effects used in this research partly cover this issue as the odds ratios for summer months are higher than winter months (Table 5). The odds ratios in December and January are significantly lower than in July or August.

This study made use of the four-digit postal code as this information was available in the data from the OViN/ODiN dataset. For a more accurate measurement further research can expand the focus on using six-digit postal code information. Four digital postal codes are larger areas and holds more respondents. The buffer used in this research was 2.5 km around the bicycle highway. This means that in a larger postal code, the buffer does not completely entail the postal code and not all individuals live within those 2.5 km. However, the postal code was taken into account in this research. It might happen that not all individuals in a postal code benefit as much as someone else living in that postal code. By making use of six digital postal codes, the chances of these areal unit problems decrease. Besides, postal codes in The Netherlands are subject to change over time. This can have an impact on the analysis of the data. As this study has a longitudinal study design, postal codes that were used in 2010 may have changed in 2020.

This research did not distinguish regular bicycles from electric bicycles such as the speed pedelec. An electric bicycle gives a user the ability to cycle longer distances at a lower cost for energy input. This makes electric bicycles an option for commuting longer distances. It might be an interesting approach to further analyze the role of the electric bicycle in combination with the bicycle highway and if they synergize each other. Research suggest that electric bicycles have a strong influence on the changing modal split (Heinen et al., 2010)

To strengthen the conclusion of a research, triangulation of methodology can enhance the analysis and the interpretation of the findings. It broadens the insights from different perspectives of the subject being studied. As mentioned, enlarged questionnaires can help understand the attitude and norms towards commuting. For instance, Skov-Petersen et al. (2017) combined data from counting stations and a questionnaire in order to investigate the effects of two large cycle highways. Both methodologies showed a positive result in favor of the cycle highways.

Another point that needs to be mentioned is that this study does not take the effect of other interventions into account. This includes interventions that may have been implemented simultaneously with the bicycle highway that likewise is implemented to enhance cycling volume. Such interventions can be traffic regulations but also the construction of new roads.

In conclusion, this study provides valuable insights into the effects of bicycle highways on bicycle usage among commuters. However, it is important to consider the limitations and potential sources of bias. Overall, continued research on bicycle highways and their impact on cycling behavior can expand on this research and consider other factors that may influence mode choice.

5.3 | Recommendations for praxis

The conclusions that are drawn in this study can help strategists and governments, among others, overcome the knowledge gap of the net effect that bicycle highways have. As cycling is an active and a low-carbon form of transportation, it is beneficial over the car in many ways. It improves personal health, reduces congestion, and produces zero pollution, thus, cities want to implement policies and invest in infrastructure, such as bicycle highways, to initiate more cycling.

In The Netherlands a national policy program (Nationaal Toekomstbeeld Fiets, 2021) stated that the government wants to make The Netherlands more bicycle friendly, which is good for the health of people and for the environment. The document has the following focus points: main routes, bicycle parking, and bicycle stimulation. The Dutch State Secretary for Infrastructure and Water Management would like to see an extra 100,000 people commuting by bicycle by the end of 2024. The government would also like contribute to a nationwide network of bicycle highways.

Most bicycle highways that are constructed in the last years are built started with argumentation that is based on estimations on potential. The conclusions that are drawn in this research helps provincial authorities and municipalities in building a better case against opposition parties, as their argumentation will be based on causal facts.

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