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Cycle highway effects: Assessing modal choice to cycling in the Netherlands

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A R T I C L E I N F O

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A B S T R A C T

Cycle highways are regarded as a promising new type of infrastructure because they promote longer-distance cycling between (sub)urban residential areas and work and study centers. This study examines whether the emerging network of regional cycle highways in the Netherlands has contributed to a modal shift from car to bicycle. More specifically, we investigate the effect of these routes on commuting bicycle mode choice. Our main data sources are a national travel survey covering commuting journeys that were made between 2010 and 2021 and a comprehensive dataset we have compiled to document the exact timing and status of all cycle highways in the Netherlands. We employ a difference-in-differences approach with a binary logit model, comparing bicycle mode choice versus the car for trips that benefited from a new cycle highway, before and after the introduction of the new infrastructure, with a control group of trips that were not affected by the construction of a new route. We present results from a novel routing-based approach to measuring exposure to this new cycling facility, which allows us to establish the extent to which the fastest route to work traverses a newly constructed cycle highway. After controlling for relevant covariates, our main results indicate that the introduction of cycle highways has contributed to a shift in commuting behavior toward cycling, with an increase of approximately 10 % in cycling probability post-intervention for trips highly exposed to cycle highways. The results also indicate some heterogeneity in the effects of cycle highways across different groups of individuals. The findings of this study are especially important in the context of the Netherlands (or similar biking countries, such as Denmark). Although these countries have well-established cycling infrastructure, they can still derive benefits from new cycling routes and can support decision-makers in other countries who want to invest in cycling in the near future.

1. Introduction

The emergence of cycling as a promising alternative to driving has attracted considerable policy attention, largely due to the potential for active travel to bring about transformative health benefits through increased physical activity (Pucher and Buehler, 2008;

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Krizek et al., 2009; Handy et al., 2014). This is particularly notable when integrated into daily commuting travel (Heinen et al., 2010). Globally, cities have implemented various policy initiatives and actions aimed at increasing the role of cycling in urban transportation. Among the most important are investments in the expansion and improvement of cycling infrastructure. Literature suggests that infrastructural interventions have varying degrees of attractiveness and impact on cycling uptake, with users apparently preferring to cycle on physically separated, protected cycling paths with ample space and clear signalling (Buehler and Dill, 2016; Furth, 2021).

In light of this evidence, cycle highways or express bikeways are frequently identified as a promising development (see e.g. Buehler and Pucher, 2021). These types of routes facilitate safe, comfortable and continuous (uninterrupted) travel by providing separate bike paths with minimal road crossings. Consequently, cycle highways serve longer-distance bike commuters traveling between (sub)urban residential areas and nodes of work and study. By enabling increased cycling speeds, they not only accommodate conventional bicycles but also cater to faster e-bikes, which are witnessing a substantial rise in their market share. The concept, introduced by the Dutch about 15 years ago, has sparked the development of similar initiatives across the world, particularly in Europe (Liu et al., 2019; Cabral Dias and Gomes Ribeiro, 2021). While cycle highways show promise in comparison to conventional bike route facilities, they can be financially demanding, especially if robust features like tunnels or bridges compose their final design. Therefore, gaining a better understanding of their success in promoting cycling is crucial for the development of future cycling programs and investments.

The aim of this study is to assess whether the emerging network of regional cycle highways in the Netherlands has contributed to a shift in travel behavior from driving to cycling. To achieve this, a difference-in-difference (DiD) research design is employed, comparing the choice of bicycle versus car for commute trips that benefited from a new cycle highway, before and after the introduction of the new infrastructure, with a control group of trips that were not affected by the construction of a new route. We focus on commute trips, as cycle highways are primarily designed to facilitate this type of travel.[1] Our analysis exploits a comprehensive dataset that we have compiled to document the exact timing and status of all cycle highways in the Netherlands. We employ annual data from a cross-sectional origin–destination travel survey for the period 2010–2021 to investigate mode choice for trips that potentially benefitted from the construction of these routes. Trips are assigned to the control and intervention groups using a routing-based approach, which allows us to establish the extent to which the fastest route to work traverses a newly constructed cycle highway. We perform several sensitivity analyses to examine the robustness of our findings to different ways of defining exposure, and to using a different outcome variable, where we compare commuting bicycle choice to *all* other modes. In addition, we investigate heterogeneity in the effects of cycle highways across different groups of individuals to assess the value these groups attach to such interventions.

The article makes three main contributions to the existing literature. It represents one of the first systematic evaluations of how the construction of cycle highways might affect cycling behavior. Existing studies have evaluated the effectiveness of cycle highways and other routes of similar scale and design in terms of infrastructure usage. This typically involves the use of automated counting stations or mobile app data to measure the number of bikes on the new or improved route (Heesch et al., 2016; Skov-Petersen et al., 2017; Hong et al., 2020). While this type of research yields valuable insights regarding how many people are using the new infrastructure, it is important to note that due to the inherent nature of count data, it is not possible to discern whether observed changes can be attributed to an increase in the overall number of cyclists or simply to existing riders shifting to the new routes. Nevertheless, cycle highways are, at least in the Netherlands, designed to encourage people who primarily use cars to switch to cycling. This study seeks to establish the extent to which they are successful in doing so.

Second, we make a methodological contribution to the growing body of literature evaluating the effectiveness of cycling infrastructure using so-called ‘natural experiments’ where variation in accessibility to new cycling facilities is exploited to assign intervention and control groups. Existing studies have typically relied on ‘distance-based measures’ that define exposure in terms of the proximity of an individual’s home address to the intervention (see, for example, Dill et al., 2014; Goodman et al., 2014; Aldred et al., 2019; Rodriguez-Valencia et al., 2019). However, such measures of exposure may not necessarily yield valid estimates of intervention effects, because the impact of proximity to new cycling facilities will be strongly dependent on individual behavior and habits. As Aldred (2019) previously noted, travel is typically to ‘somewhere’ and that ‘somewhere’ can potentially change for many types of trip (also see Humphreys et al. (2016) for an extensive treatment of this challenge in the context of built environment interventions). In this context, we propose a routing-based approach that addresses this challenge by utilizing information on both the home and work locations of individuals in determining the degree to which they are exposed to new cycling facilities.

Finally, this article presents evidence on the effectiveness of new cycling facilities in a context where a mature and complete bikeway network already exists. The majority of studies evaluating the impact of cycling infrastructure are from the United Kingdom, North America and Australia, where cycling levels are low and cycling networks fragmented (see Mölenberg et al. (2019) and Xiao et al. (2022) for an overview of existing studies). Buehler and Dill (2016) have previously proposed that more evaluations should be conducted in cities and regions with robust cycling networks. This is because they assumed that the benefits of providing additional infrastructure may diminish once a basic level of cycling facility provision is reached.

The paper starts with a literature review of the cycling interventions literature, including underexplored gaps that have been highlighted in past reviews. This is followed by the explanation of the data, variables and modeling approaches adopted for the research. Then, the results are presented, and the effects of new cycle highways on mode choice are estimated, including the use of heterogeneous effect analyses. Finally, the paper discusses its main strengths and limitations, practical implications and conclusions.

[1] Another reason for limiting the analysis to commute trips is that they are relatively stable over time, which reduces the potential for biases to arise from the generation of new trips (Wardman, Tight, & Page, 2007; Zahabi et al., 2016).

2. Literature review

Our research builds on a growing body of literature that examines the impact of cycling infrastructure on travel behavior. Most studies have revealed a positive empirical association between the availability of bicycle infrastructure and cycling levels, either in terms of infrastructure usage or cycling behavior.[2]

A first strand of literature has investigated individual-level preferences for different bicycle facility types. The majority of these studies have relied on stated-preference surveys to examine how the likelihood to cycle changes under various bicycle infrastructure scenarios (see e.g. Tilahu,et al., 2007; Winters and Teschke, 2010; Griswold et al., 2018; Clark et al., 2019). Increasingly, revealed-preference techniques, such as GPS units to track cyclists' routes, have been employed to examine the relative attractiveness of different types of facilities on route choice (Menghini et al., 2010; Broac et al., 2012; Ton et al., 2017). Within this body of research, a discernible hierarchy of preferences has emerged depending on the specific type of infrastructure under analysis, with cyclists favoring separate paths over sharing lanes with motorized traffic. Studies have also found a preference specifically for infrastructure that facilitates continuous travel without the need to dismount at each intersection (Caulfield et al., 2012; Ton et al., 2017).

A second line of research has relied on travel surveys or censuses to establish a relationship between bicycle ridership and the availability of bikeway facilities. Most of the work in this area has examined levels of cycling at a more aggregated level, such as individual cities (see e.g. Dill and Carr, 2003; Buehler and Pucher, 2012; Schoner and Levinson, 2014; Yang et al., 2021). However, some studies have exploited these data sources to conduct individual-level analyses, examining the influence of bikeway facilities and other built environment characteristics on bicycle mode choice. Examples of such studies include Cervero and Duncan (2003), Winters et al. (2010), Braun et al. (2016) and Zahabi et al. (2016). Both aggregate- and individual-level studies have examined the influence of individual network components, such as bicycle lanes, tracks and paths or some combined measure of their total provision. Consequently, there is limited evidence on the impact of overall network connectivity, which encompasses factors such as directness, and accessibility (exceptions are Schoner and Levinson, 2014; Zahabi et al., 2016). Moreover, as these studies are primarily cross-sectional in nature, analyzing correlations between bike infrastructure and cycling behavior at a single point in time, they provide only limited evidence to support causal inference.

The challenge of establishing a stronger causal link between bikeway infrastructure and cycling levels has been addressed in a third stream of literature, which includes research that compares cycling behavior before and after the installation of new bikeway facilities (reviewed in Mölenberg et al., 2019). However, important challenges remain in this strand of literature, which we seek to address in this paper. A first challenge arises from the necessity of ensuring that observed effects do not solely reflect underlying time trends in cycling in the wider area. In order to capture the effect of these broader cycling trends, the use of controlled designs is recommended. Indeed, there is a growing body of natural experimental studies that exploit variation in accessibility to new cycling facilities to establish which members of the study population potentially benefit from the new infrastructure and which do not (see, for example, the evaluations included in the systematic review by Xiao et al. (2022) that consider the effectiveness of cycling infrastructure).

Secondly, the majority of these studies tend to focus on singular or a limited number of infrastructural interventions, whereas stated and revealed preference studies have found a preference specifically for continuous and connected bicycle facilities. This limitation is partially mitigated in more recent investigations, which have assessed the expansion of bicycle networks at the neighborhood or city-level (e.g. Aldred et al., 2019; Rodriguez-Valencia et al., 2019; Félix et al., 2020; Piras et al., 2022). However, these expansions frequently only involve investments in small-scale cycling links, like (segregated) cycle paths or tracks. In contrast, research that has examined major bike routes, such as cycle highways, specifically designed to facilitate continuous and long-distance travel has primarily assessed usage of the new or improved infrastructure.[3] As we already indicated, this type of analysis provides a less credible research design to assess actual behavioral change. Indeed, intercept surveys suggest that the proportion of users who would not have engaged in cycling had these improvements not occurred, was much smaller than the increase in bike counts (Heesch et al., 2016; Skov-Petersen et al., 2017).

A third methodological challenge in the use of natural experimental studies to evaluate cycling infrastructure, and indeed many other interventions that alter the physical environment, is the identification of the exposed population. A comparison is typically made within the study population between people who live closer to an intervention and those who live further away (see Mölenberg et al., 2019). Such approaches for characterizing exposure must rely on the rather strong assumption that exposure to cycling infrastructure is solely dependent on the proximity of the home location to the intervention site. However, the extent to which individuals living close to a new cycling facility actually benefit from this infrastructure will depend in large part on their (pre-existing) behavior and habits (see Humphreys et al., 2016; Aldred, 2019). For example, some individuals may reside in close proximity to a new bicycle route, yet rarely utilize it due to their daily routines and activities (e.g., commuting origins and destinations) taking them to other areas. Conversely, other individuals may reside far from the new infrastructure, yet their regular activities (such as commute route) may

[2] Buehler and Dill (2016) and Mölenberg et al. (2019) provide extensive reviews.

[3] Exceptions are studies by Merom et al. (2003) and Hirsch et al. (2017), which evaluated changes in cycling behavior rather than infrastructure usage for the 16.5 km long Rail Trail cycleway in Sydney and two off-road paths with a combined length of 16.4 km in the city of Minneapolis, respectively. In addition, several studies have examined how the 25 km long Cambridgeshire guided busway, which involved the construction of an adjacent parallel walking and cycling path, changed travel behavior (see e.g. Heinen et al., 2015b; Panter et al., 2016). The current study extends this research by providing an estimate of the *average* treatment effect of major bicycle routes, as we consider the effect of multiple routes of similar design across different regions. This may be important because the impact of new cycling facilities may vary across locations (see Mölenberg et al., 2019).

bring them close to it, increasing the likelihood of its use. Humphreys et al. (2016) therefore recommend the use of more 'dynamic' measures of exposure that take into consideration routine mobility and activity spaces. While such measures may require greater technical sophistication, they require less restrictive assumptions about who may be exposed to an intervention.

Some work has already been done in this direction. In their evaluation of an area-based program to create pedestrian and cycling-friendly street environments in London, Aldred et al. (2019) combine distance thresholds with context-based knowledge from officials involved in the implementation process to define exposure. This knowledge pertained to the visibility of the interventions and the key destinations they might serve. Hirsch et al. (2017) identify commuting trips that could potentially benefit from the cycling infrastructure under consideration by establishing whether the straight-line connection between the origin and destination tract centroids intersects the new infrastructure. The measure that arguably best approximates the dynamic exposure measure proposed by Humphreys et al. (2016), and which is most similar to our own, was developed for the evaluation of a new busway in the Cambridge area, which also entailed the construction of a parallel pathway for walking and cycling (reported in Heinen et al., 2015a; Heinen et al., 2015b). As one of the exposure measures, this study calculated the change in cycling (and walking) distance to work induced by this new transport infrastructure using a routing analysis.

3. Cycle highways in the Netherlands

Due to the expansion of urban living spaces in the Netherlands, transport networks of different metropolitan areas (notably in the Randstad) are beginning to overlap. It is precisely in these "corridors" that an important task for the further development of more efficient infrastructures can be found. With more people cycling longer distances, robust and efficient cycling infrastructures are important to encourage motorists to cycle to work, school, and/or other regional destinations. Cycle highways are specifically designed to promote regional cycling. It is difficult to pinpoint the first cycle highway in the Netherlands,[4] but the "cycle highway" concept really gained traction with a national program launched in 2007 that became known as "Met de Fiets Minder File" (With the Bicycle Less Congestion). As part of this program, five pilot routes were constructed in areas in which motorized commuter traffic experienced congestion.

The 'Met-de-fiets-minder-file' program only made funds available for project management, and additional funds were required to meet the costs of physical improvements. In light of the success of these pilot projects, the national government has encouraged the construction of cycle highways through several rounds of funding, which could be used to (partially) cover the engineering and construction costs. Similarly, provincial governments (as second-tier governments) have also established grant programs for the physical construction of bicycle highways. As a result, the number of cycle highway initiatives has expanded greatly over time, from approximately 20 projects in 2010 to over 300 currently. To date, approximately 50 projects have been fully completed in the Netherlands. The concept is now more commonly referred to as non-stop bikeways (in Dutch, "doorfietsroutes"), although other terms are also in use, such as fast cycle routes (in Dutch, "snelfietsroutes").

Among the most common cycle highway design standards in the Netherlands (see examples in Fig. 1), several can be mentioned: (i) having wide lanes (3–4 m), (ii) being separated from motorized traffic and pedestrians, (iii) having gradual curbs and overall mild gradients, (iv) road surfaces of "flat and non-slip" asphalt or concrete (v) designed for high cycling speeds (25–30 km/h), and (vi) avoiding frequent stops and having priority at crossings to enable higher cycling speeds (CROW, 2014, 2016). It should be emphasized that these criteria are indicative and allow for adaptation to local contexts. In addition, provincial governments[5] have designed policy frameworks and grant programs for cycle highways that establish specific requirements (Lagendijk and Ploegmakers, 2021).

In terms of design and implementation costs, cycle highways can quickly become more expensive than the usual bicycle paths. Calculations based on a national inventory of cycle highway initiatives in the Netherlands reveal that average expenditure amounts to 500.000 Euros per km. This figure relates to more than 30 projects that had been fully completed as of 2020.[6] Substantial variations in costs exist. Five projects have costs of over a million euros per km, while four projects required expenditure of less than 100.000 Euros per km. The lack of previous road infrastructure and the need to build fixed links, such as bridges and tunnels, strongly influences the cost of infrastructure delivery.

[4] Already in the 1970s, two demonstration routes were built in the cities of Tilburg and the Hague that shared many of the elements currently associated with a cycle highway. However, these routes were built within one city. The first route to connect two cities was inaugurated in 2004 as a 7 km-long path between the cities of Breda and Etten-Leur. See Lagendijk and Ploegmakers (2021) and Bruno and Nikolaeva (2020) for a further discussion of the origin and evolution of the concept in the Netherlands.

[5] Since cycle highways normally span several municipal boundaries, provincial governments are actively involved in the planning and construction of cycle highways. A recent survey among provincial officials reveals that 9 out of 12 provinces provide co-funding for cycle highways (Tour de Force, 2017). One of the three remaining provinces takes responsibility for the entire project from plan development to implementation, including all funding. In other cases, municipalities are responsible.

[6] For some 15 projects that have also been built no such financial information is available, but most of these projects were implemented before 2010.

Fig. 1. Cycle Highway examples. Left: Section of the Arnhem-Nijmegen cycle highway (Source: www.gelderlander.nl); middle: cycling bridge over the Maas River in Nijmegen (Source: https://mapio.net/); right: cycling tunnel in Nijmegen (Source: www.hetccv.nl/).

4. Materials and methods

4.1. Data collection

The Dutch Travel Survey (DTS) is our source of travel data in order to investigate whether people are more or less likely take the bicycle for trips that benefited from the construction of a cycle highway.[7] This origin–destination (O-D) survey takes place every year and provides travel information for an average day in the week for all residents in the Netherlands. To this end, a representative (stratified) sample is drawn in which each respondent is asked to provide detailed information for every trip made on a certain pre-determined day of the year. For each individual trip, information is provided on the trip origin and destination (specified at the four-digit postcode level), the purpose of the trip and the (main) modes of travel. This means that our analyses are based on the self-reported mode choice of respondents and the DTS does now allow us to examine changes in travel frequency. In addition to the reported travel behavior, details are collected about various socioeconomic characteristics, such as income, education, place of residence, and others. We use the annual O-D surveys for the period 2010–2021. After merging the datasets and cleaning the data, we have information on 423,689 respondents who have made almost 1.4 million different trips. It should be noted that individuals do not necessarily participate in consecutive rounds of the survey and therefore are not followed over time.

The final sample used in the analyses is based on several exclusion criteria. First, only trips made for commuting purposes are retained, as this study assesses the impact of bicycle highways on the mode of travel to work. As a commuting journey will typically involve one outward and one return trip, only respondents who made a maximum of two commute trips are included in the analysis. Furthermore, our analysis is confined to commuting journeys where the shortest network distance between origin and destination postcodes ranged from 5 to 15 km. This decision is influenced by the fact that officials involved in the planning of cycle highways typically assume that their potential is greatest within this particular distance range.[8] The upper range of 15 km is motivated by the assertion that the (electric) bicycle is a cheap and convenient mode of transport for distances up to 15 km. The sample is further limited to respondents in possession of a driving license who are aged 18 and older, as individuals aged 16 to 17 are not permitted to drive unaccompanied in the Netherlands. Respondents with missing values for demographic and socioeconomic variables are excluded from the study. Finally, for the main analysis of this paper, only trips made by car or bicycle are selected. As a result of these choices, our main results are based on a sample of 28,829 respondents, who undertook a total of 49,732 unique commuting trips.

4.2. Defining treatment and control groups

In order to ascertain whether a particular origin–destination pair was affected by the construction of a cycle highway during the study period, we exploit detailed information from a comprehensive dataset of routes in the Netherlands. The dataset is compiled by *Anonymized organization* through an annual inventory of cycle highways, which records all routes that have been completed, are currently under planning or implementation, or may be constructed in the future (see Fig. 2). Part of this inventory is a detailed geographic information system (GIS) map that delineates the precise routes of completed cycle highways and those for which the

[7] The official designation "Onderweg in Nederland" (ODiN) can be translated as "On the Road in the Netherland". Prior to 2017, it was referred to as "Onderzoek Verplaatsingen in Nederland" (OViN), which translates to "Travel Survey in the Netherlands". Some survey questions were added or reformulated during the transition from OviN to ODiN. We implemented alterations to the original codes to ensure comparability of data gathered from the distinct surveys. The ODiN sample was also restricted to persons aged 6 years or older, but this does not affect our results because the analysis pertains to work-related journeys made by individuals aged 18 or older.

[8] This view is reflected in in a number of national policy documents and visions on cycling promotion, including those produced by the Fietsersbond and Ministry of Infrastructure and the Environment and the Dutch Cyclists' Union (2015) and Tour de Force (2017, 2021). Tour de Force is a collaboration between national and regional governments, interest groups, and knowledge institutes aimed at the promotion of cycling and the facilitation of knowledge exchange.

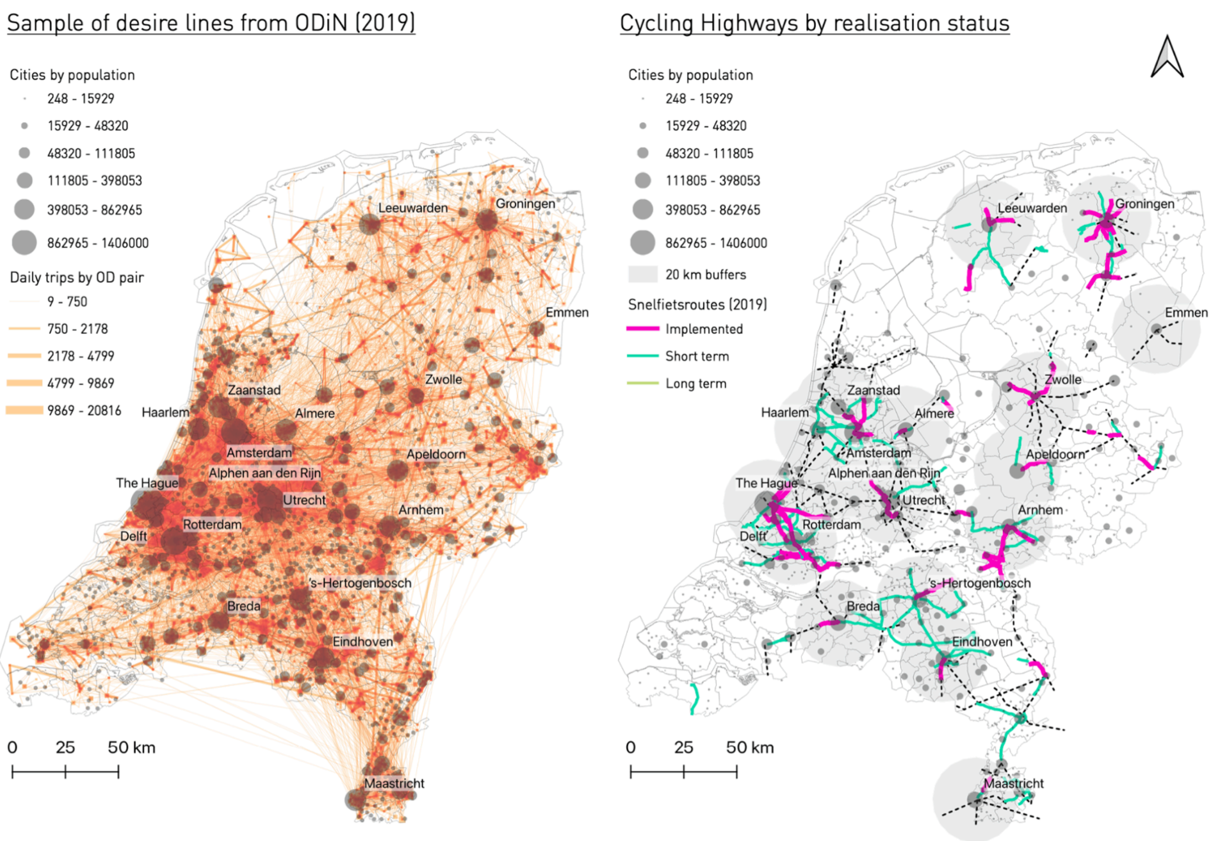

Fig. 2. ODiN sample of origin–destination OD pairs (left); Cycle highways by completion status (right).

future course is known because they are in or near the implementation stage. The information in the dataset on the routes listed as completed has been augmented by adding the specific year that construction works began and the year that all construction was concluded. This information was obtained from various sources, including available project documents and media coverage.

The database indicates that 40 regional bicycle routes were completed by 2018, corresponding to more than 400 km of new infrastructure. However, we only utilize a subset of these routes in the empirical analyses for two main reasons. The first reason for this is that we lack access to pre-intervention travel data for 10 routes that were completed in 2009 or earlier, given that we our DTS sample is for the period 2010–2021. A second reason is that not all routes in the dataset qualify as a cycle highway in terms of design. The dataset records a wide variety of bikeway initiatives that facilitate longer-distance commutes between residential areas and locations of work and study, under the label "regional routes". However, not all of these meet the minimum design standards for a cycle highway. To determine which routes meet these design criteria, we use information from a user test conducted by the Royal Dutch Touring Club (ANWB) in 2019, which assessed several routes completed at that time. For the routes not included in this assessment, we employ information from individual project evaluations in which routes are scored based on user intercept surveys. This selection was discussed with responsible government officials from the *anonymized organization 2*. As a result, a further 15 routes are excluded from the analysis.[9]

In this study, we follow the recommendation by Humphreys et al. (2016) and create a "dynamic" exposure measure that explicitly takes into account the routine commute mobility of the research participants.[10] As the DTS records home and workplace postcodes for each commute trip, we calculate the portion of the commuting route (in terms of distance in km) traversing a new cycle highway. The underlying assumption is that when a larger section of the commute trip can be traversed over a cycle highway, the potential benefits of this route will be greater, resulting in a higher level of exposure. We prefer this measure to the change in travel time or distance to work induced by the new infrastructure for each respondent. This is because cycle highways are designed not only to provide more direct

[9] The following routes are included in the analysis: Amsterdam – Purmerend; Amsterdam – Zaandam; Apeldoorn – Deventer;Arnhem – Nijmegen; Arnhem – Zevenaar; Dordrecht – Papendrecht – Sliedrecht; Eindhoven – Valkenswaard; Enschede – Hengelo; Houten – Utrecht; Leiden – Voorburg – Nijmegen – Beuningen (Noord); Nijmegen – Beuningen (Zuid); Venlo-Greenport; Zwolle – Staphorst; 's-Hertogenbosch – Oss.

[10] Interestingly, the authors illustrate this type of measure with the case of a bicycle superhighway. In this regard, they propose a measure that is similar to ours, which is based on the modelling of commute distances and times, taking into account the new bicycle infrastructure as well as the home and work locations of individuals.

connections, thereby reducing travel time and distance, but also to increase the safety, comfort, and convenience of cycling (CROW, 2014, 2016). In the Netherlands, these benefits may be of greater importance, as the bikeway network is already quite complete. Indeed, nearly all sections of the new routes under consideration involve the improvement of existing cycle infrastructure rather than the addition of new links.

The exposure measures were calculated using geographic information system (GIS) software QGIS. The basis for this calculation was the OpenStreetMap (OSM) network, to which GPS data on actual bicycle speeds was added. These data were obtained during a nationwide initiative in the Netherlands called the 'Bicycle Counting Week' (see Van de Coevering et al., 2014). For this initiative, the cycling movements of participants were tracked using a smartphone application, resulting in the most comprehensive dataset of cycling speeds in the Netherlands. However, the data only cover part of the study period, as the initiative only took place annually between 2015 and 2017.[11] We therefore assume that cycling speeds have not significantly changed on the majority of network connections in the remaining years of the study period. As the exposure measure is not defined in terms of reduced distance or travel time to work, it is unlikely that this will significantly affect the validity of the results. For road sections with a minimum of four observations, the measured speed from the 'Bicycle Counting Week' data was utilized, ensuring it ranged between 4 km/h and a maximum of 25 km/h. In instances, where there were fewer than four observations, a deliberately low speed of 12 km/h was applied. This approach allows for the inclusion of these connections, while acknowledging that unmeasured road sections are often less significant, as they involve forest paths, park roads, or parking lots.

In order to capture all commuting trips where the route over the cycle highway might present an attractive alternative, even if it is not the fastest one between the origin and destination, the speed on cycle highways was artificially raised to 30 km/h. To assess the sensitivity of our findings for this choice, we also calculated a measure where the speed on cycle highways was raised to 25 km/h and a measure based route with the shortest distance over the network. Furthermore, we also calibrated exposure measures using a complementary approach, where the road geometry of the cycle highways was perpendicularly projected onto each O-D pair. This complementary projection-based approach assumes that individuals would benefit from a cycle highway if the straight-line (Euclidean) connection between each O-D pair runs parallel to a route and (ii) if both the origin and destination postcode centroids are located within a maximum area of influence (buffer) from a given cycle highway. Since there is no strong a priori evidence regarding the potential zone of influence of a cycle highway, we have calculated projections using buffers of 2 km and 3 km. Fig. 3 illustrates how both the routing- and projection-based measures were calculated. In Fig. 4 we show results for our three main exposure measures based on the fastest route, shortest route and perpendicular projection.

4.3. Empirical strategy

We use a difference-in-differences (DiD) design to compare commuting bicycle mode choice for trips that benefited from a cycle highway, before and after its implementation, to trips that did not experience an improvement. This approach has previously been utilized to examine the impact of infrastructure improvements by comparing bicycling behavior in areas with and without new bikeway facilities, before and after their installation (e.g. Dill et al., 2014; Rodriguez-Valencia et al., 2019). Our application of the approach differs in three important ways from the "classical" DiD design, which is based on two groups (treatment and control) and two periods (before and after). Firstly, in our case, as in many others, the treatment occurs at different times, since the 15 routes considered in this study were completed in different years. Such variation in the timing of treatment can be accounted for by a generalization of the DiD in which time and group fixed effects are included in the model (see, for example, Wing et al., 2018).

Secondly, we employ DiD estimation with a binary logit model, given that the outcome of interest – bicycle mode choice for commuting – is of a binary nature. Although DiD is typically applied with continuous dependent variables, it can also be used in nonlinear models such as a logit Karaca-Mandic et al., 2012; Puhani, 2012). Thirdly, treatment is not defined by a binary variable but rather is measured on a continuous scale, specifically, the distance that can potentially be cycled on a cycle highway for each OD-pair. Here, we adopt the approach proposed by Humphreys et al. (2016), who argue that when it is unclear at what level individuals are actually exposed to an intervention, it is preferable to use a 'graded' measure of exposure to capture the intensity of influence of an environmental change.

The outcome of interest in the binary logit model is the choice of bicycle versus the car for commuting trips. Although our measure of exposure is continuous, to avoid making parametric assumptions, we group trips into discrete bands for different distance ranges that can potentially be cycled on a bicycle highway. There are many trips with a modelled distance of zero, indicating that no part of fastest the route between the specific origin and destination postcodes traverses any of the bicycle highways considered in this study. These trips will not be affected by the construction of a cycle highway and therefore serve as the control group. The following equation is used to estimate the probability to cycle:

$$ln\left(\frac{\mathrm{Pcycle}_{it}}{1-\mathrm{Pcycle}_{it}}\right) = a_{ij} + \sum_{z} a_z\, dist_{it\,z} + \sum_{z} \gamma_z\, dist_{it\,z}\, \mathrm{PC}_{it} + b_t + \beta X_{it} + \varepsilon_{it}$$

where Pcycle_{ijt} is the outcome of interest, which takes a value of 1 if a respondent decides to use the bicycle as the main mode of transport to make commuting trip *i* in year *t*. This binary variable equals zero if the car is chosen. The term b_t indicates year and month fixed effects, which allow for the possibility that bicycle mode choice may differ in each year and month. These *time* fixed effects

[11] The total number of participations was approximately 38,000, 30,000, and 15,000 in the years 2015, 2016, and 2017, respectively.

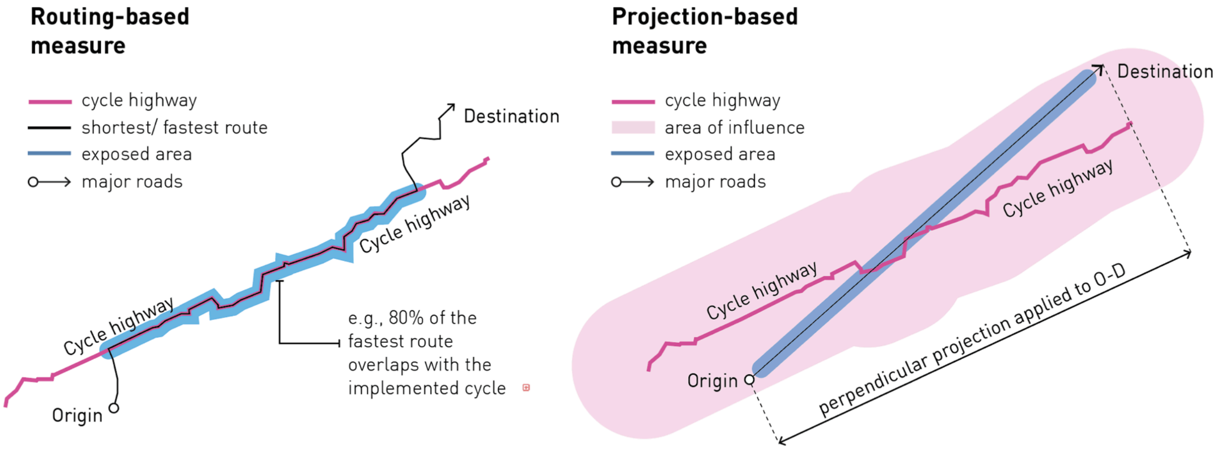

Fig. 3. Comparison of different exposure calculation methods used in this study.

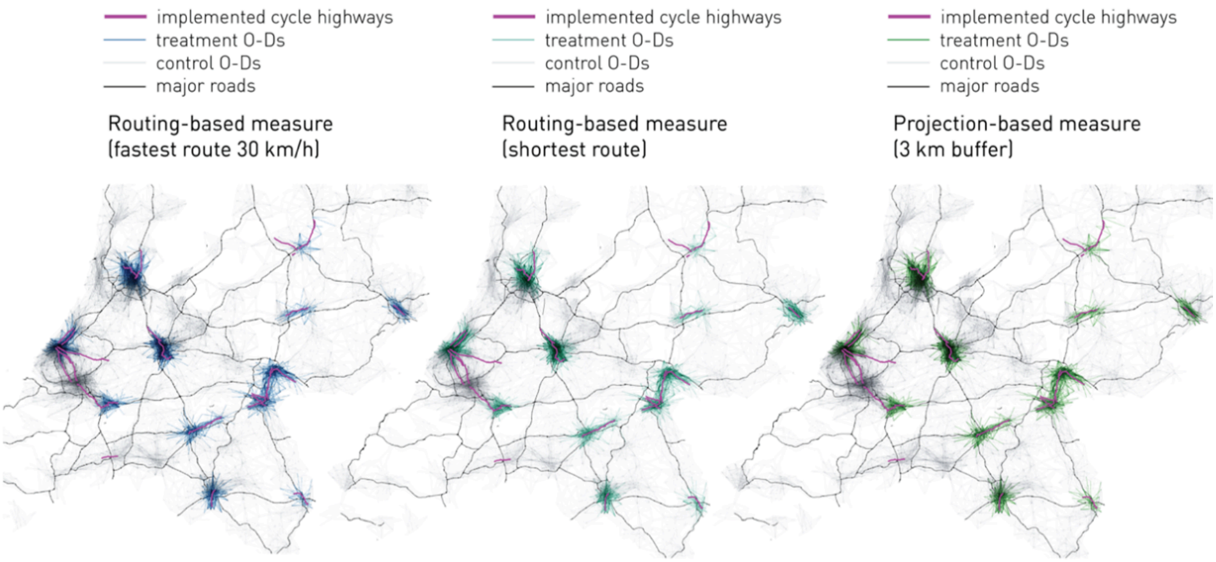

Fig. 4. Distribution of control and treatment groups across different exposure calculations.

control for autonomous trends in bicycle use and seasonal influences.

The term $dist_{ijtz}$ denotes the various distance bands that are employed to define exposure status and, thus, represents the *group* fixed effect. Four distance bands are defined: no traverse, less than 2.5 km, 2.5 to 5.0 km, and over 5.0 km. The term PC_{ijt} is an indicator variable for the post-treatment period and does not need to be included separately because it is absorbed by the year fixed effects. The interaction $dist_{ijtz}\,\mathrm{PC}_{ijt}$ indicates trips within the z-th distance band after the construction of the bicycle highway. This variable is comparable with the treatment × post interaction in the ‘classical’ two-group × two-period DiD. The coefficients for the exposure measures can be interpreted as follows: a_z captures the pre-treatment difference in the probability to cycle for each distance band relative to trips that do not have the potential to traverse a cycle highway, γ_z is our main coefficient of interest and represents the mean effect of a cycle highway on bicycle mode choice for each distance band. Specifically, it indicates how the probability of cycling changes for each distance band after the construction of a cycle highway.

We include several sets of controls, denoted by X_{it}, to account for the demographic and socioeconomic characteristics of the commuters and the characteristics of each trip. These variables correct for any differences in the composition of the control and treatment groups that might influence the choice of transport mode. Variables representing individual-level characteristics include gender, age and educational attainment, and we also add three household-level characteristics that capture household income, household composition and car ownership. We also control for trip distance measured as the shortest cycling distance between each OD pair, and an indicator variable for the degree of urbanization of each respondent’s home postcode (measured as the number of addresses per square kilometer). These variables have been used in related studies (see, for example, Heinen et al., 2015a; Zahabi et al., 2016; Rodriguez-Valencia et al., 2019; Piras et al., 2022). Finally, ε_{it} is the error term.

Table 1
Descriptive statistics for the control and the treatment group by period.

	2010–2012		2013–2015		2016–2018		2019–2021		2010–2021		
	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Total
Transport mode											
Car	0.78	0.79	0.78	0.79	0.74	0.72	0.72	0.66	0.75	0.73	0.75
Bicycle	0.22	0.21	0.22	0.21	0.26	0.28	0.28	0.34	0.25	0.27	0.25
Gender											
Male	0.54	0.53	0.54	0.53	0.54	0.58	0.54	0.53	0.54	0.54	0.54
Female	0.46	0.47	0.46	0.47	0.46	0.42	0.46	0.47	0.46	0.46	0.46
Age											
18–24 years	0.08	0.06	0.07	0.08	0.08	0.05	0.08	0.06	0.08	0.06	0.08
25–34 years	0.18	0.20	0.16	0.17	0.20	0.20	0.19	0.20	0.18	0.20	0.18
35–44 years	0.26	0.29	0.24	0.21	0.19	0.20	0.20	0.21	0.22	0.22	0.22
45–54 years	0.30	0.29	0.29	0.29	0.28	0.30	0.27	0.27	0.29	0.29	0.29
55–64 years	0.17	0.14	0.20	0.22	0.21	0.21	0.21	0.22	0.20	0.20	0.20
65 or older	0.02	0.02	0.03	0.03	0.04	0.04	0.06	0.04	0.04	0.03	0.04
Background											
Dutch native	0.89	0.85	0.88	0.84	0.88	0.84	0.85	0.80	0.87	0.83	0.87
Western immigrant	0.07	0.09	0.07	0.08	0.07	0.06	0.07	0.10	0.07	0.08	0.07
Non-western immigrant	0.04	0.06	0.05	0.08	0.06	0.10	0.08	0.11	0.06	0.09	0.06
Education level											
Primary education	0.20	0.15	0.18	0.18	0.15	0.15	0.14	0.10	0.17	0.14	0.17
Secondary education	0.44	0.36	0.45	0.38	0.43	0.35	0.41	0.35	0.43	0.36	0.42
Higher education	0.34	0.45	0.36	0.42	0.40	0.49	0.43	0.53	0.38	0.48	0.39
No or other	0.02	0.03	0.01	0.01	0.02	0.02	0.02	0.03	0.02	0.02	0.02
Income											
Lowest income group	0.27	0.29	0.27	0.25	0.20	0.19	0.17	0.17	0.23	0.22	0.22
Middle income group	0.48	0.44	0.47	0.47	0.48	0.51	0.50	0.45	0.48	0.47	0.48
Highest income group	0.24	0.27	0.26	0.28	0.31	0.30	0.33	0.38	0.29	0.32	0.29
Household composition											
Single person	0.12	0.12	0.13	0.15	0.14	0.19	0.15	0.14	0.14	0.15	0.14
Couple without child(ren)	0.28	0.23	0.28	0.32	0.29	0.26	0.29	0.32	0.29	0.29	0.29
Couple with child(ren)	0.54	0.59	0.53	0.46	0.50	0.49	0.50	0.48	0.52	0.50	0.51
Parent with child(ren)	0.05	0.05	0.05	0.07	0.06	0.04	0.05	0.05	0.05	0.05	0.05
Other composition	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Car ownership											
no car	0.02	0.04	0.02	0.03	0.04	0.06	0.05	0.05	0.04	0.05	0.04
1 car	0.46	0.48	0.47	0.52	0.45	0.50	0.43	0.49	0.45	0.50	0.45
2 or more cars	0.52	0.48	0.51	0.45	0.50	0.43	0.52	0.45	0.51	0.45	0.51
Trip distance											
5.0–7.5 km	0.35	0.27	0.36	0.27	0.37	0.29	0.38	0.31	0.37	0.29	0.36
7.5–10.0 km	0.28	0.30	0.25	0.30	0.26	0.30	0.26	0.27	0.26	0.29	0.27
10.0–12.5 km	0.20	0.22	0.21	0.24	0.20	0.22	0.20	0.23	0.20	0.23	0.21
12.5–15.0 km	0.16	0.20	0.17	0.20	0.16	0.20	0.16	0.19	0.17	0.20	0.17
Degree of urbanization											
Extremely urbanized	0.10	0.16	0.12	0.18	0.15	0.19	0.16	0.21	0.14	0.19	0.14
Strongly urbanized	0.20	0.36	0.22	0.38	0.22	0.37	0.25	0.33	0.22	0.36	0.24
Moderately urbanized	0.18	0.24	0.18	0.24	0.20	0.26	0.20	0.25	0.19	0.25	0.20
Hardly urbanized	0.22	0.13	0.22	0.12	0.21	0.12	0.20	0.13	0.21	0.12	0.21
Not urbanized	0.29	0.10	0.26	0.08	0.21	0.06	0.19	0.08	0.24	0.08	0.22
Observations	**10,937**	**929**	**9,614**	**956**	**11,078**	**1,296**	**13,443**	**1,675**	**45,072**	**4,856**	**49,928**

Note. Results are organized by period and exposure status. Sample totals are also reported. Exposure is defined as the portion of the fastest route between each O-D pair that traverses a newly constructed bicycle highway (imposing a speed of 30 km/h on this infrastructure). The treated group refers to trips that, by 2018, would potentially traverse a new bicycle highway for some portion of the commuting route. The control group refers to trips that were not affected by the construction of a cycle highway as of 2018. Trip distance is measured by the shortest route over the cycling network. The degree of urbanization is established at the postcode of the home address.

In light of the fact that each observation represents a discrete trip and that a typical commute journey comprises both an outward and a return trip, it is evident that the observations are not independent. One potential solution to address this issue would be to allow for clustering of the standard errors at the respondent level. Nevertheless, this approach may still result in biased standard errors, given that there are repeated observations for a considerable number of two-way OD pairs, with different individuals in the sample undertaking the same commute journey. We therefore cluster the standard errors at the level of the two-way OD pair. This is deemed the most appropriate level of clustering given that exposure to the intervention will also vary at this level. In DiD settings, cluster-robust standard errors are considered valid (although potentially conservative) if the clustering is done at the level at which the treatment varies (Angrist and Pischke, 2009).

It is important to note that our DiD design makes use of repeated cross-sectional data, as the DTS does not permit the same individuals to be followed over time. Repeated cross-sectional designs have been commonly employed in natural experimental evaluations of cycling interventions. (see, for example, Chang et al., 2017; Hosford et al., 2018; Rodriguez-Valencia et al., 2019; Karpinski, 2021; Piras et al., 2022). The broader (economic) literature concerned with identifying and estimating causal effects with observational data also maintains that DiD methods can accommodate repeated cross-sectional data. In such cases, this literature commonly imposes the so-called no-compositional change assumption. This assumption could be violated when there is a substantial change in the composition of the treatment group over time, which results in a growing imbalance between the treatment and control group across time. While there may be some plausible scenarios where this occurs, we do not expect it to be the case in this study, given that the observations are drawn from the same population across time periods. Nevertheless, we have examined the possibility of compositional changes and discuss the results in Section 5.

5. Results

5.1. Descriptive statistics

Table 1 presents descriptive statistics for the DTS sample, organized period and by exposure status, with sample totals included. Exposure is defined as the portion of the fastest route between each O-D pair that traverses a newly constructed bicycle highway. The control group comprises respondents who made one or more trips that were not affected by the construction of a cycle highway as of 2018. The treatment group includes all respondents who made at least one trip that would, by 2018, traverse a new bicycle highway for some part of the commute route. The share of respondents who drove to work decreased gradually during the study period, while the share who cycled to work demonstrated a corresponding increase. The respondents were between the ages of 18 and 89 (with a mean age of 43.4). 46 % were women, 42 % had either completed secondary or higher education (42 % and 38 %, respectively). Furthermore, the majority live as couples (with or without children) and have at least one car in their household (92 %). The respondents in the treatment group exhibit slightly higher levels of education, tend to have higher incomes and are more likely to have only one or no cars in their household. In addition, they tend to live in more urbanized areas and make longer commute trips.

Table 1 also indicates that the composition of the sample has slightly changed over time in terms of demographic and socioeconomic characteristics. However, the observed changes over time are largely comparable for the control and treatment groups. Consequently, any potential effect of these changes on the likelihood of taking the bike will be captured by the year fixed effects. This also suggests that the assumption of no compositional change is not likely to be violated. It is important to note that there appear to be some minor imbalances over time regarding household composition and income levels between the control and treatment groups. Specifically, the share of respondents in the higher income category increased slightly more in the treatment group between 2010 and 2021, while the share of respondents in the middle income category experienced a corresponding decline. The treatment group also experienced a more pronounced increase in terms of the share of respondents living as a couple without children over time. To test whether the trend for the different income and household categories indeed differs between the control and treatment groups, we estimated separate logistic regressions for each category. Our findings indicate that there are no statistically significant differences in the trend between the exposed and unexposed groups, a finding that is consistent across the other demographic or socioeconomic characteristics.

5.2. Main results

Table 2 presents our main findings on the effect of bicycle highways on the probability of bike mode choice versus the car on commuting trips within a 5–15 km range. We report results for three different specifications. Model 1 reports the estimates of a DiD model, which controls for year (and month) fixed effects. In Model 2, we add respondent characteristics, urban density and trip distance as additional control variables. In Model 3, we restrict the control group to only home postcodes that are part of at least one O-D pair affected by the construction of a new route. These postcodes provide a plausibly more credible counterfactual as residents living in the same postcode are more likely to face similar (unobserved) local trends affecting cycling levels and to experience common shocks (e.g., the COVID-19 pandemic) at around the same time. The exposure measure used in all three specifications establishes the portion (in kilometers) of the fastest route between the origin and destination of each trip traversing a new cycle highway (imposing a

Table 2
Effects of new bicycle highways on mode of travel to work (bicycle × car).

	Model 1		Model 2		Model 3	
	Odds Ratio (Z-value)	Marginal Effect	Odds Ratio (Z-value)	Odds Ratio (Z-value)	Marginal Effect	Odds Ratio (Z-value)
Potential use (ref. no traverse)						
less than 2.5 km	0.998	−0.000	0.852	−0.025	0.778*	−0.046
	(−0.018)		(−1.346)		(−1.949)	
2.5–5.0 km	1.248*	0.044	1.185	0.029	1.101	0.019
	(1.752)		(1.150)		(0.617)	
over 5.0 km	0.539***	−0.097	0.667**	−0.057	0.631**	−0.079
	(−3.479)		(−1.963)		(−2.131)	
*Potential use * Completed*						
less than 2.5 km	1.331**	0.057	1.371**	0.050	1.332*	0.051
	(2.040)		(2.147)		(1.814)	
2.5–5.0 km	1.036	0.007	0.971	−0.005	0.922	−0.016
	(0.217)		(−0.150)		(−0.400)	
over 5.0 km	1.726**	0.083	1.999***	0.106	1.959**	0.119
	(2.460)		(2.707)		(2.529)	
Gender (ref. Male)						
Female			0.807***	−0.034	0.835***	−0.034
			(−6.563)		(−3.201)	
Age (ref. 18–24 years)						
25–34 years			0.665***	−0.057	0.661***	−0.071
			(−5.454)		(−3.098)	
35–44 years			0.792***	−0.034	0.757**	−0.050
			(−3.193)		(−2.101)	
45–54 years			1.267***	0.040	1.262*	0.047
			(3.363)		(1.814)	
55–64 years			1.492***	0.071	1.373**	0.065
			(5.357)		(2.316)	
65 or older			0.798**	−0.033	0.653**	−0.073
			(−2.078)		(−2.230)	
Background (ref. Dutch native)						
Western immigrant			0.738***	−0.046	0.747***	−0.054
			(−4.644)		(−2.828)	
Non-western immigrant			0.396***	−0.116	0.400***	−0.141
			(−11.547)		(−7.735)	
Education level (ref. Primary)						
Secondary education			1.173***	0.022	1.264**	0.035
			(3.245)		(2.453)	
Higher education			1.980***	0.109	2.392***	0.157
			(13.586)		(9.205)	
No or other			1.242	0.030	1.484	0.062
			(1.559)		(1.623)	
Income (ref. Lowest income)						
Middle income group			1.246***	0.033	1.125	0.021
			(5.030)		(1.564)	
Highest income group			1.497***	0.064	1.351***	0.056
			(7.872)		(3.483)	
Household composition (ref. Singe Person)						
Couple without child(ren)			2.560***	0.112	2.568***	0.144
			(16.306)		(9.872)	
Couple with child(ren)			3.429***	0.163	3.052***	0.179
			(21.711)		(11.629)	
Parent with child(ren)			1.159	0.013	1.180	0.019
			(1.621)		(1.105)	
Other composition			2.449***	0.105	2.839***	0.164
			(5.216)		(3.977)	
Car ownership (ref. No car)						
1 car			0.075***	−0.542	0.067***	−0.540
			(−26.523)		(−17.975)	
2 or more cars			0.018***	−0.762	0.016***	−0.778

(*continued on next page*)

Table 2 (*continued*)

	Model 1		Model 2		Model 3	
	Odds Ratio (Z-value)	Marginal Effect	Odds Ratio (Z-value)	Odds Ratio (Z-value)	Marginal Effect	Odds Ratio (Z-value)
			(−38.165)		(−24.801)	
Constant	0.215***		2.532***		3.179***	
	(−21.282)		(6.568)		(4.815)	
Year fixed effects	Yes	No	Yes	No	Yes	No
Month fixed effects	Yes	No	Yes	No	Yes	No
Cycling distance	No	No	Yes	No	Yes	No
Degree of urbanization	No	No	Yes	Yes	Yes	Yes
Only trips originating from affected postcodes	No	No	No	No	Yes	Yes
Observations	49,928		49,928		15,710	
Pseudo R^2	0.009		0.193		0.224	
LR Chi^2	272.2		4,089.0		1,499.2	

Notes. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010–2021. All models include fixed effects for year and month. For each model, odds ratios and marginal effects are reported alongside each other. Z-values are reported in brackets and are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10 %, **5 %, ***1 %.

speed of 30 km/h on cycle highways). To facilitate the interpretation of the results, both odds ratios (OR) and marginal effects are presented.[12] When ORs are greater than 1, an increase in the independent variables is associated with an increase in the odds of commuting by bicycle.

The first set of coefficients measures the difference in bicycle mode choice between the different distance bands relative to the 0 km distance band, which encompasses all trips where the commute route would not traverse a bicycle highway. These coefficients capture the effect of the different distance bands *prior* to the construction of a bikeway, as all models incorporate an interaction term between these distance band indicator variables and a post-construction variable, which represents our DiD estimator.[13] All models indicate that commuters were less likely to choose a bicycle instead of a car for trips where the commute route could potentially traverse a future bicycle highway for 5 km or more. For example, Model 1 indicates that the odds of using a bicycle for such trips decrease by 46 % compared to trips on routes that did not benefit from the construction of a bicycle highway. The probability of cycling to work does not differ significantly for the other, shorter distance bands. This finding implies that prior to its implementation, commuters were less likely to use the bike for trips that would benefit significantly from a bicycle highway.

The second set of coefficients for the distance bands is of primary interest to this paper as they represent the DiD estimates. More specifically, they capture the estimated effect of the construction of a bicycle highway for each distance band. The coefficients for the first distance band, which indicates trips made by individuals that could potentially traverse a cycle highway for up to 2.5 km, are positive and significant at the 5 % level in Models 1 and 2. The point estimates indicate that the odds of commuters choosing a bicycle for these trips are, respectively 1.33 and 1.37 times higher. The corresponding marginal effects imply that the completion of a cycle highway increases the probability of cycling by 5 % points. In contrast, the coefficients for the 2.5–5 km distance band are not statistically significant and in Models 2 and 3, they are even below zero. It can be reasonably assumed that this distance band represents the highest level of exposure, as it indicates trips where the section of the commute route that can be potentially traversed on a cycle highway is largest. As a result, these trips are likely to benefit most from the construction of a bicycle highway. The coefficients for this distance band are positive and statistically significant at the 1 % level in Models 1 and 2 and the 5 % level in Model 3. The estimated odds of using the bicycle for these trips are between 1.73 and 2 times higher after the construction of a cycle highway. If we interpret these results in terms of marginal effects, the probability to cycle increases by 8.3 to 11.9 % points after the construction of a bicycle highway.

The observed positive effects for the shortest distance band are somewhat unexpected, as one would particularly expect trips in the 2.5–5 km and the > 5 km distance bands to benefit more from the construction of a bicycle highway. One possible explanation is that our estimates for this distance band do not reflect the effect of a new bicycle highway, but are driven by an idiosyncratic trend in cycling levels specific to this group. Indeed, trips in this distance band appear to be concentrated in urban areas, where cycling levels have steadily grown over the study period.[14] It is, however, reassuring to note that when the control group is confined to postcodes that are part of at least one O-D pair affected by the construction of a bicycle highway, the effect for the < 2.5 km distance band is no longer

[12] Marginal effects are calculated at the means of the covariates using Stata's margins command. We follow the procedure outlined by Karaca-Mandic et al. (2012) to calculate the marginal effect of the coefficients representing the DiD estimate, as they involve an interaction between the distance bands and a post-completion variable.

[13] As previously noted, the main effect of the post-completion variable is absorbed by the year fixed effects.

[14] The imposition of an artificially high speed of 30 km per hour on all sections of the cycle highways may result in routes traversing this infrastructure being identified as the fastest alternative, while in fact they represent a significant detour from the fastest route, based on real speeds. This is especially likely to occur in urban areas with a more dense bikeway network.

statistically significant at the 5 % level, while the coefficient for the > 5 km distance band remains significant and the implied marginal effect becomes even larger. As previously stated, these postcodes provide a better counterfactual for trips that benefited from the construction of a bicycle highway.

Most of the other covariates in Models 2 and 3 have statistically significant coefficients, with the estimates being largely similar across both models. There is a negative association between the likelihood of cycling and being female, with the probability decreasing by approximately 3.4 % points for females. This finding is not consistent with the suggestion by Heinen et al. (2010) that in countries with high cycling rates, such as the Netherlands, women cycle more frequently than men. This may be attributed to the fact that we restrict the sample to longer travel distances (5 km to 15 km). Age also influences cycling levels, with individuals aged between 45 and 54 and, in particular, those aged between 55 and 64 being more likely to cycle compared to individuals aged between 18 and 24 years. Similar to findings in other studies (see Ton et al., 2019), the probability to choose the bicycle decreases by 11.6 to 14.1 % points for individuals with a non-Western background compared to Dutch natives. Educational attainment is also a significant predictor of the choice to cycle to work, with especially individuals who have completed higher education demonstrating a higher probability of choosing the bicycle. The likelihood of cycling increases by 10.9–15.7 % points for this group compared to individuals with only primary education.

With regard to household-level characteristics, our findings indicate that individuals living in middle and high-income groups are more likely to commute by bicycle compared to individuals in low-income households. Individuals who are part of couples with or without children are also more likely to choose to bicycle. The point estimates in Model 3 indicate that the probability increases by 14.4 % points for couples without children and 17.9 % points for couples with children compared to single-person households. Finally, individuals that live in a household with at least one car have a reduced likelihood of cycling to work compared to those living in a household with no private vehicles. This is in consistent with previous mode choice studies, which have demonstrated a strong association between car ownership and a reduced likelihood of cycling (Zahabi et al., 2016; Rodriguez-Valencia et al., 2019; Ton et al., 2019).

5.3. Sensitivity analyses

As a robustness check of our main results, we have estimated models with different 'dynamic' measures of exposure to test the sensitivity of our findings to alternative ways of measuring exposure. Table 3 presents the results of this analysis, using the specification that includes time fixed effects and the full set of control variables. Models 1 and 2 report estimates for an exposure measure where a projection-based approach was used to establish the portion of the commute route (in km) that could be potentially traversed over a bicycle highway. In this case, a 2 km buffer was used to define the maximum area of influence of the new route. Models 3 and 4 present results for a similar exposure measure but using a 3 km buffer instead. The exposure measures in Models 5 and 6 were calculated using the shortest route between each OD-pair. Finally, the exposure measure employed in Models 7 and 8 is similar to that used in Table 2, but with an imposed speed of 25 km/h instead of 30 km/h on bicycle highways. In Models 2, 4, 6, and 8 the control and exposed groups are more similar to each other because we restrict the sample to commuting trips originating from postcodes that are part of at least one O-D pair affected by the construction of a bicycle highway. We report only the coefficients representing the DiD estimates.

The estimated effects of a new bicycle highway for the > 5 km distance band are positive across all models. The point estimates are qualitatively similar to the main results presented in Table 2, except for Models 5 and 6, and indicate that the odds of using a bicycle for trips within this distance band are 1.4 to 2.1 times higher after the construction of a cycle highway. In Models 5 and 6, where the exposure measure is calculated using the shortest route, the estimated odds are considerably higher. This difference in effect size may be attributed to the fact that this exposure measure only identifies trips where the new bicycle highway provides a realistic alternative, given that the shortest route traverses the new infrastructure for more than five kilometers. However, the estimated standard errors are also large, and as a result, we cannot precisely identify the effect of a bicycle highway for the exposure measure based on the shortest distance.[15] In the other models, the estimates for this distance band are statistically significant at the 5 % level, even in specifications where a control group is used that is more similar to the exposure groups. This finding provides further evidence to rule out the presence of unobserved trends specific to our exposure groups that might confound the estimates of the effect of a new bicycle highway. It is also noteworthy that the estimated effects for the < 2.5 km distance band are smaller in magnitude and not statistically significant for the models where the exposure measure is most similar to the one used for the main results, except that a lower (more realistic) speed of 25 km/h is imposed on bicycle highways.

Our main results focus on the decision to use either a bicycle or a car for a commuting trip. One potential concern is that the observed increase in the probability of cycling is not due to an increase in the number of individuals choosing the bicycle for these trips, but rather to a decrease in the number of car drivers who have switched to other modes such as public transport. As a further test, we therefore estimate binary logistic regression models where the outcome of interest is the choice of cycling over all other modes. Table 4 displays the results of these analyses, using the same specifications as in Table 3, except for Models 7 and 8 where the exposure measure based on the fastest route, is now calculated assuming a speed of 30 km/h on bicycle highways instead of 25 km/h. As a result, the specifications are similar to those used for our main analyses reported in Table 2. Comparing these results with the estimates in Tables 2 (for Models 7 and 8) and 3 (Models 1 to 6), we find them to be largely similar. The estimates for the > 5 distance band calculated

[15] It is possible that this is due to the relatively small number of observations for this exposure measure, with only 124 trips for the >5 km distance band.

Table 3
Effects of bicycle highways: sensitivity to different approaches to measuring exposure (bicycle × car).

	Projection (2 km buffer)		Projection (3 km buffer)		Shortest route		Fastest route (new routes: 25 km/h)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Potential use × Completed								
less than 2.5 km	1.154	1.194	1.234*	1.290*	1.106	1.068	1.234	1.153
	(1.242)	(1.425)	(1.673)	(1.895)	(0.715)	(0.423)	(1.447)	(0.904)
2.5–5.0 km	1.333*	1.330*	1.132	1.152	1.704	1.657	1.030	0.962
	(1.811)	(1.710)	(0.820)	(0.889)	(1.550)	(1.436)	(0.134)	(−0.169)
over 5.0 km	1.558**	1.573**	1.415**	1.454**	8.137*	7.466*	2.164**	2.019**
	(2.149)	(2.108)	(2.245)	(2.287)	(1.742)	(1.646)	(2.285)	(2.035)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Only trips from affected postcodes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	49,928	18,524	49,928	18,726	49,928	12,540	49,928	15,059
Pseudo R^2	0.194	0.216	0.194	0.216	0.193	0.225	0.193	0.223
LR Chi^2	4,073.3	1,707.0	4,077.2	1,729.1	4,070.6	1,132.7	4,077.5	1,416.5

Note. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010–2021. The fastest route is calculated imposing a speed of 25 km/h on bicycle highways. All models include fixed effects for year and month and a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. The control group in models 2, 4, 6 and 8 is restricted to home postcodes that are part of at least one O-D pair affected by the construction of a new bicycle highway. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10 %, **5 %, ***1 %.

Table 4
Effects of bicycle highways: sensitivity to using a different outcome variable (bicycle × all other modes).

	Projection (2 km buffer)		Projection (3 km buffer)		Shortest route		Fastest route (new routes: 30 km/h)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Potential use × Completed								
less than 2.5 km	1.100	1.118	1.182	1.212	1.071	1.004	1.283*	1.222
	(0.889)	(0.965)	(1.397)	(1.512)	(0.522)	(0.026)	(1.749)	(1.318)
2.5–5.0 km	1.332*	1.299*	1.110	1.112	1.423	1.322	0.995	0.917
	(1.917)	(1.678)	(0.751)	(0.723)	(1.103)	(0.852)	(−0.028)	(−0.462)
over 5.0 km	1.536**	1.509**	1.416**	1.413**	7.461*	6.847*	1.929***	1.840**
	(2.329)	(2.146)	(2.451)	(2.311)	(1.787)	(1.689)	(2.848)	(2.551)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Only trips from affected postcodes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	49,928	18,524	49,928	18,726	49,928	12,540	49,928	15,059
Pseudo R^2	0.194	0.216	0.194	0.216	0.193	0.225	0.193	0.223
LR Chi^2	4,073.3	1,707.0	4,077.2	1,729.1	4,070.6	1,132.7	4,077.5	1,416.5

Note. Each observation represents an unique trip. The outcome variable is bicycle mode choice versus all other modes. Data cover the period 2010–2021. The fastest route is calculated imposing a speed of 30 km/h on bicycle highways. All models include fixed effects for year and month and a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. The control group in models 2, 4, 6 and 8 is restricted to home postcodes that are part of at least one O-D pair affected by the construction of a new bicycle highway. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10 %, **5 %, ***1 %.

using the shortest route are smaller though and more precisely identified in Model 5.

As we explained in section 4, our main results focus on trips between 5 and 15 km, because bicycle highways are primarily designed to facilitate commuting over these distances. We have also checked our main results using two extended trip distance intervals of 4–16 km and 2–18 km. The results are presented in Table A1 in Appendix A. The estimated effects of the completion of a bicycle highway for the > 5 km distance band are always positive, but smaller in magnitude compared to the estimates presented in Table 2. The coefficients are statistically significant at the 5 % level for the models that include the full set of controls. In the models where the control and exposed groups are more similar, the estimates are significant at the 5 % and 10 % level for the for the 4–16 km and 2–18 km samples, respectively. In Table A1 in Appendix A, we report estimates for models similar to Table 4, where the distance bands are based on 2 km intervals. We find that the effects of the construction of a bicycle highway are less pronounced and not always statistically significant for the > 4 km distance band, which represents trips where the longest distance can be travelled on a bicycle highway. The estimates for the other distance bands are qualitatively similar. Overall, the robustness of our estimated effects to the use of alternative exposure measures and a different outcome variable provides additional internal validity to our research design.

Table 5
Heterogeneity in the effect of new bicycle highways.

	Model 1 Gender	**Model 2** Age	**Model 3** Education level	**Model 4** Income group	**Model 5** Car ownership	**Model 6** E-bike ownership
Potential use × Completed	1.573 (1.627)					
… × Female	1.732** (1.964)					
Potential use × Completed		2.108** (2.240)				
… x 35–54 years		0.919 (−0.269)				
… × over 54 years		0.863 (−0.397)				
Potential use × Completed			2.362* (1.673)			
… × Secondary education			0.824 (−0.363)			
… × Higher education			0.818 (−0.403)			
Potential use × Completed				1.794 (1.314)		
… × Middle income group				1.092 (0.202)		
… × Highest income group				1.142 (0.294)		
Potential use × Completed					4.067* (1.700)	
… × 1 car					0.448 (−1.041)	
… × 2 or more cars					0.529 (−0.821)	
Potential use × Completed						1.348 (1.021)
… × 1 or more e-bikes						1.477 (1.299)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	No
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,928	49,928	49,928	49,928	49,928	38,060
Pseudo R^2	0.193	0.187	0.193	0.193	0.193	0.206
LR Chi^2	4,078.9	3,954.7	4,084.4	4,081.8	4,086.4	3,443.2

Note. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010–2021. The exposed group is confined to trips made within the > 5 km distance band. An additional interaction is included between the > 5 km distance band × post-completion term and the individual characteristics of interest. All models include fixed effects for year and month and a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10 %, **5 %, ***1 %.

5.4. Heterogeneity in the effects of bicycle highways

The estimates that have been presented thus far have assumed that the effects of a new cycle highway are similar for all individuals. However, it is reasonable to assume that not all individuals attach the same value to the benefits of new cycling infrastructure, such as comfort, safety, and directness. To examine this possibility, we estimate logistic regressions where the exposed group is restricted to trips in the $>$ 5 km distance band only and where we include an additional interaction between the $>$ 5 km distance band $\times$ post-completion term and a given characteristic of the individual undertaking the trip. The following individual-level characteristics are considered: gender, age, and educational attainment. We also investigate whether the impact of a new route differs between individuals living in households within the high and low income groups and those in households with or without access to private vehicles. Finally, we investigate whether the impact of a new cycle highway differs between individuals in households with one or more e-bikes and individuals who do not have access to an e-bike in their household. These estimates are presented in Table 5.

The estimates in Model 1 indicate that after the construction of a bicycle highway, females are more likely to choose the bicycle than males. Female commuters, who were previously found to be less likely to cycle compared to males, may attach greater value to comfortable and safe routes. Nevertheless, the coefficient is only statistically significant at the 10 % level. Model 2 suggests that individuals aged between 35 and 54 or 55 and older are less likely to use the bicycle highway for their daily commute than individuals aged between 18 and 34. The estimated effects in Model 3 indicate that individuals with a secondary or higher level of education have a lower probability to use the bicycle when a new route is completed. However, these odds are not found to be significantly different from those observed for individuals with only primary education. Model 4 indicates that the impact of a new bicycle highway does not vary significantly across income groups. The estimates in Model 6 suggest that individuals living in households with one or more cars have a lower probability to use the bike for commute trips compared to individuals without a car in their household. Finally, Model 7 suggests that individuals with access to an e-bike in their household are more likely to cycle to work after the construction of a bicycle highway, but the estimate is statistically indistinguishable from zero. It is important to note that the (pre-intervention) sample for this model is smaller than for the other models, as the information on e-bike ownership by household is only available from 2013.

6. Discussion

6.1. Strengths, limitations, and future research

This study represents one of the first systematic evaluations of the impact of cycle highways on the mode of travel to work. However, the validity of our results depends on three key assumptions. First, our DiD design is based on the assumption that the change in outcome between the pre- and post-intervention periods in the unexposed control group represents a good approximation for the counterfactual change in the exposed group. To assess the validity of this assumption, we have estimated several specifications in which the control group is restricted to postcodes that are part of at least one O-D pair affected by the construction of a bicycle highway, which provide a more credible counterfactual because individuals living in the same postcode are generally affected by similar local trends and shocks that might affect cycling levels. The fact that the estimated effects for these models are quite similar suggests that our results are not primarily driven by unobserved trends specific to the exposed groups.

Second, the use of repeated cross-sectional data for our DiD approach, requires the assumption of no-compositional change. In this particular case, this assumption is unlikely to be violated, as the observations are sampled from the same population over time. Indeed, there is no evidence to suggest that the observed changes over time in terms of demographic and socio-economic characteristics differ between the control and treatment groups. Third, although our approach to defining exposure represents an improvement on the more static distance-based measures used in the majority of existing evaluations, it crucially depends on the assumption that, at least in the Netherlands, the primary benefits of this type of cycling facility are increased safety, comfort and convenience of cycling. While new cycling infrastructure may also result in significant reductions in travel time or cycling distance to work, this is not explicitly accounted for with our exposure measure. This is because the bicycle network in the Netherlands is already complete, and because the bicycle highways considered in the analyses have not resulted in the removal of major physical barriers, such as large rivers or highways (i.e. by building a bridge), that would lead to substantial changes in travel time or distance to work.

While the results of this study are encouraging, it is important to acknowledge the limitations of the study. There is potential for improvement in the approach used to measure exposure, as information on the location of the origin and destination of each trip was available at the 4-digit postcode level. The use of exact locations would result in more precise exposure measurements. Furthermore, future evaluations of bicycle highways and other infrastructure of similar scale and design could also define exposure in terms of the reductions in travel time or cycling distance to work induced by this type of infrastructure. This could now even be relevant in the context of bicycle highways in the Netherlands, where recent projects have involved the removal of major physical barriers.

In this study, we have examined heterogeneity in the effects across different groups of individuals. However, the impact of cycling facilities may also vary according to their specific design and the characteristics of the route environment (e.g., land-use mix, access to destinations). As Aldred (2019) already observed, facilities developed under the same broad label are often somewhat amorphous and may represent very different route environments or designs. This is certainly the case for cycle highways in the Netherlands. Although designed to be high-quality routes reserved for fast and direct commuting and to follow specific design standards, these bikeways can have quite different physical qualities in practice (ANWB, 2019). Nevertheless, few evaluations of new cycling infrastructure have examined the role of the quality of the facility (such as pavement), exact design (such as color, width, and/or type of separation), and/or specific location (such as left- or right-side positioning on one-way streets). Finally, future work should assess the evolution of the effects of cycle highways on cycling levels over time.

6.2. Practical implications of this study

The estimated marginal effects presented in our main results indicate that the probability to cycle can increase by 10 % after the construction of cycle highways for trips highly exposed by these infrastructures. This shift towards cycling is slightly larger, but qualitatively similar in scale to the effects established in an earlier Dutch stated preference experiment study, which was carried out earlier, predicted that the maximum effect on the percentage of cyclists for this group would up to 9 % for various selected routes (MuConsult, 2007). Another study by the same firm (MuConsult (2010), an ex-post evaluation of the first five pilot routes constructed within the earlier mentioned "Met de Fiets Minder File" program, found the effect of cycle highways on cycling probability to range between 1 % and 3 % for different routes. It should be noted, however, that this calculation was done for a larger target group, including people traveling more than 20 km.

Policymakers can use our results to support future cycling investments by building the case for cycle highways as facilities that will produce net benefits even in countries already well-equipped with transport infrastructure. More specifically, our findings can inform existing economic appraisal tools, such as the Health Economic Assessment Tool (HEAT)[16] and the Integrated Transport and Health Impact Model (ITHIM),[17] to monetize the health (all-cause mortality and morbidity) costs and benefits from additional exposure to physical activity, air pollution, traffic collisions, and the reduction of carbon transport emissions.

7. Conclusions

While cycle highways are considered promising developments due to their additional safety and comfort, they can be financially demanding, especially if their design includes robust features like tunnels or bridges. Therefore, gaining a better understanding of their success in promoting cycling is crucial for the development of future cycling programs and investments. In this context, our main goal was to assess whether the emerging network of regional cycle highways in the Netherlands has contributed to a shift in travel behavior from driving to cycling. To achieve this, a DiD research design was employed with a binary logistic model, comparing the choice of bicycle versus car for commute trips that benefited from a new cycle highway, before and after the introduction of the new infrastructure, with a control group of trips that were not affected by the construction of a new route. As one of our main contributions, we use information on both the home and work locations of travelers to determine the degree to which they are exposed to cycle highways and test the sensitivity of our effect estimates against a variety of treatment definitions.

Overall, our results point in the same direction of other cycling studies – new and high quality infrastructure have a positive effect on travel behavior, increasing the demand for cycling (Mölenberg et al., 2019; Xiao et al., 2022). Specifically, our effect estimates have remained stable across treatment specifications, indicating that the introduction of cycle highways has contributed to a shift in commuting behavior toward cycling, with an increase of approximately 10 % in cycling probability post-intervention for trips highly exposed to cycle highways. Covariates' effects have been found to be generally aligned with previous cycling studies.

It is also important to emphasize that the effects presented in this study are contingent upon on key assumptions: the change in the outcomes for the unexposed control group between the pre- and post-intervention periods approximates the counterfactual change for the exposed group; there are no significant demographic or socio-economic compositional change in the sampled population over time; and the estimated effects primarily depend on the additional comfort, safety and convenience provided by these infrastructures. Assumptions assured, our study provide policymakers with valuable insights to support future cycle highway planning and investment, demonstrating their potential benefits, even in countries with consolidated cycling networks such as the Netherlands. By intergrating these results into existing economic appraisal tools, policymakers can further assess additional benefits related to physical activity, health, and emissions reduction.

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CRediT authorship contribution statement

Francisco Edson Macedo Filho: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Huub Ploegmakers:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Joost de Kruijf:** Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dirk Bussche:** Validation, Software, Methodology, Formal analysis, Data curation.

[16] HEAT is a tool used to assess the economic benefits of policies promoting physical activity through activities like walking and cycling. It helps calculate health gains and economic savings resulting from such initiatives, aiding decision-making for policymakers and health professionals.

[17] The Integrated Transport Health Impact Model (ITHIM) is a mathematical model that integrates data on travel patterns, physical activity, fine particulate matter, GHG emissions, and disease and injuries based on population and travel scenarios.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Effects of bicycle highways: sensitivity to using different trip distance ranges.

	Trip distance range: 4–16 km			**Trip distance range: 2–18 km**		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
*Potential use * Completed*						
less than 2.5 km	1.215	1.260*	1.213	1.251**	1.268**	1.198
	(1.607)	(1.757)	(1.371)	(2.243)	(2.081)	(1.505)
2.5–5.0 km	0.957	0.903	0.851	1.000	0.914	0.848
	(−0.287)	(−0.573)	(−0.863)	(−0.001)	(−0.528)	(−0.934)
over 5.0 km	1.493**	1.683**	1.626**	1.480**	1.606**	1.520*
	(1.971)	(2.184)	(1.976)	(2.067)	(2.131)	(1.838)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	Yes	No	Yes	Yes
Only trips from affected postcodes	No	No	Yes	No	No	Yes
Observations	80,364	80,364	28,459	86,003	86,003	32,649
Pseudo R^2	0.008	0.243	0.272	0.008	0.257	0.282
LR Chi^2	420.1	8,334.7	3,282.3	449.2	9,035.4	3,751.7

Note. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010–2021. The fastest route is calculated imposing a speed of 30 km/h on bicycle highways. All models include fixed effects for year and month and models 2, 3, 5 and 6 add a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. The control group in models 3 and 5 is restricted to home postcodes that are part of at least one O-D pair affected by the construction of a new bicycle highway. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10 %, **5 %, ***1 %.

Table A2
Effects of bicycle highways: sensitivity to using a different outcome variable (bicycle × all other modes).

	Projection (2 km buffer)		**Projection (3 km buffer)**		**Shortest route**		**Fastest route (new routes: 30 km/h)**	
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
*Potential use * Completed*								
less than 2 km	1.258*	1.301*	1.225	1.282*	1.176	1.140	1.423**	1.376*
	(1.780)	(1.916)	(1.469)	(1.699)	(1.114)	(0.825)	(2.210)	(1.870)
2–4 km	1.193	1.199	1.314*	1.352*	1.021	0.971	0.968	0.922
	(1.078)	(1.052)	(1.796)	(1.878)	(0.062)	(−0.086)	(−0.165)	(−0.393)
over 4 km	1.382**	1.398**	1.235	1.262	2.922*	2.825*	1.596**	1.560**
	(2.026)	(1.988)	(1.582)	(1.629)	(1.908)	(1.814)	(2.302)	(2.091)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Only trips from exposed postcodes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	49,928	18,524	49,928	18,726	49,928	12,540	49,928	15,710
Pseudo R^2	0.193	0.216	0.194	0.216	0.193	0.225	0.193	0.224
LR Chi^2	4,074.1	1,708.9	4,075.4	1,726.3	4,082.2	1,145.2	4,086.2	1,495.2

Note. Each observation represents an unique trip. The outcome variable is bicycle versus car mode choice. Data cover the period 2010–2021. The fastest route is calculated imposing a speed of 30 km/h on bicycle highways. All models include fixed effects for year and month and a full set of controls: age, gender, background, education level, household income, household composition, car ownership, cycling distance and degree of urbanization. The control group in models 2, 4, 6 and 8 is restricted to home postcodes that are part of at least one O-D pair affected by the construction of a new bicycle highway. Z-values (reported in brackets) are based on robust standard errors clustered at the two-way OD pair. Significance levels: *10 %, **5 %, ***1 %.

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