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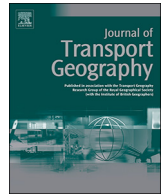
Does new bicycle infrastructure result in new or rerouted bicyclists? A longitudinal GPS study in Oslo

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ABSTRACT

Well-connected bicycle infrastructure networks are widely accepted to be an important factor for increasing the level of bicycling in urban environments where motorised and active transport modes must co-exist. However, little is known about the extent to which new bicycle infrastructure results in changes of route amongst existing bicyclists as opposed to changes in the mode of transport. This article addresses the route-mode research gap through a panel study in which participant travel behaviour ($n = 113$) is recorded with a smartphone Global Positioning System (GPS) application. The study observes short-term changes to route and mode choice of participants before and after the establishment of a contraflow bicycle lane in Oslo, Norway. Video and radar-based traffic counting are used as supplementary methods to affirm bicycle volume changes in the broader population.

The bicycle lane intervention resulted in a shift in the preferred route in the neighbourhood. The intervention street saw increased numbers of bicycle trips taken whilst the two nearest parallel routes in the same neighbourhood witnessed a decrease. For bicycle trips taken on the intervention street, the mean deviation from the shortest path increased (from 171 to 221 m, $p < .05$). Bicycle counts based on video observations also support the route shift finding. Bicycle modal share did not significantly increase when comparing the panel sub-group exposed to the intervention ($n = 39$) with a quasi-control group ($n = 47$) who were not exposed but had made at least one trip in the near vicinity of the intervention in both time periods.

This natural experiment study provides evidence to suggest that route substitution from nearby streets and paths can explain more of the change in bicycling levels than modal shifts to bicycling in the short term following the opening of the bike lane.

1. Introduction

High quality and separate bicycle infrastructure has been frequently established as a precondition for achieving high levels of utility bicycle use (Dill, 2009; Hull and O'Holleran, 2014; Wahlgren and Schantz, 2014). Many studies of environmental correlates have established a link between cycling rates and infrastructure (Mertens et al., 2017; Nielsen et al., 2013; Saelens et al., 2003; Schneider and Stefanich, 2015), however, the empirical data is somewhat limited with respect to single project infrastructural impacts within bicycle networks (Handy et al., 2014; Yang et al., 2010).

This panel study analyses the route and mode choice effects of a contraflow bicycle lane built in August 2017 in Oslo, Norway. GPS-based tracking is used to identify changes before and after the intervention for a group of participants who were recruited specifically for

this study. Video observations and radar traffic counts provide volume changes as a supplementary data source to the GPS panel.

This paper is structured as follows: the background introduces existing research connected to bicycle interventions, the methods section describes the data collection approach, including a description of the intervention area. The timeline of the data collection and intervention is also described here. This is followed by the results section, which reports the changes observed within the GPS panel and comparisons with bicycle count data. Finally, the discussion and conclusion of this paper summarise the main findings, limitations of the study together with recommendations for future research.

2. Background

This paper's study design makes use of GPS for data collection, a

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longitudinal natural experiment for bicycling and a focus on both route and mode choice behaviour. To the authors' knowledge, the combination of all these three methodological elements in a single study has not been previously published. Existing research has, however, addressed these component elements individually and this is summarised below. Firstly, a number of review studies connected to GPS and bicycle research are reported on, followed by summaries of the relevant results from three systematic reviews on bicycle infrastructure interventions. Subsequently five descriptive studies are introduced with focus on route changes resulting from bicycle infrastructure interventions, whilst the final section of the background summarises two studies that use the same type of contraflow bicycle lane as this case study.

The use of GPS in bicycle research is becoming increasingly common and is now utilised in approximately two-thirds of all studies connected to bicycle route choice (Pritchard, 2018). The use of GPS within active transportation and bicycling has been the subject of two comprehensive reviews (Patricia J. Krenn et al., 2011; Loveday et al., 2015), whilst GPS in combination with other methods have been reviewed by several other researchers, covering more recent combinations of GPS in studies using crowdsourcing, 'big app' data aggregators, instrumented bicycle setups and bike sharing operator data (Buehler and Dill, 2015; Pritchard, 2018; Romanillos et al., 2016).

In a 2017 systematic review of built environment effects on physical activity and active transport, 11 of 28 reviewed articles had levels of cycling as a specific outcome (Smith et al., 2017). The reviewed articles used natural experiments or prospective, retrospective, experimental or longitudinal study designs and all but one demonstrated either a positive or non-significant relationship between infrastructure provision and levels of cycling. Infrastructure types found to have a positive effect on cycling include: combined pedestrian and bicycle access bridges and boardwalks (Goodman et al., 2014), urban trails (Fitzhugh et al., 2010), traffic calming (Morrison, 2004) and bicycle lanes (Lott et al., 1978; Parker et al., 2013). In Portland, USA, the effect of bicycle boulevards was evaluated, however, the length and frequency of bicycle trips performed decreased following the intervention (Dill et al., 2014).

A second systematic review concerning the physical activity impact of built environment infrastructural changes reviewed eight articles that reported on changes in levels of bicycling (Stappers et al., 2018). Positive effects were found for separate bicycle paths which are sometimes also referred to as bikeways (Heesch et al., 2016; Rissel et al., 2015).

Three cross-sectional bicycle infrastructure intervention studies from the grey literature are discussed in a systematic review of 25 cycling interventions studies, with all three found to result in increased cycling frequency (Yang et al., 2010). Evidence regarding net effects on cycling modal share was also reported in two of the three studies. The first, based in Delft in The Netherlands revealed a 3% increase in bicycle modal share in the intervention area compared to a 1% increase elsewhere in the city (Wilmink & Hartman, 1987). The second study from Odense, Denmark revealed a 3.4% increase in cycling modal share from a combination of initiatives including infrastructure improvements but did not have a control group (Troelsen et al., 2004).

Early evaluations of Dutch bicycle planning policies in Tilburg and The Hague in the 1970s and 1980s contributed in part to the widespread development of bicycle infrastructure across much of the Netherlands (van Goeverden et al., 2015). Both cities experienced greatly increased cycling volumes along the routes which received bicycle infrastructure (140% in Tilburg and 76% in The Hague) whilst only a 10–20% increase was observed in the corridor bicycle volumes for both cities. Comparable although less significant changes were observed from a before-after study in Davis, California, where a bicycle volume increase of 87% was observed on the intervention bicycle lane versus 57% for the corridor (Lott et al., 1978). Furthermore, up to 45% of the interviewed bicyclists that took alternative routes prior to the intervention modified their route post-completion to use the new lane. A traffic count study performed in New Orleans demonstrated increase

bicycle volumes on a new bicycle lane and a simultaneous reduction in bicycle volumes in the streets parallel to the intervention (Parker et al., 2013). With a large increase in corridor bicycle volumes, this study's findings suggest that a significant mode and route change occurred as a result of the bicycle lane.

Concerning route change effects, a cross-sectional Global Positioning System (GPS) study from San Francisco found evidence of route substitution through significantly increased bicycle volumes on four intervention streets whilst a decline was observed in neighbouring streets (Fitch et al., 2016). A separate bicycle route choice model using GPS data from the same city quantified the preference for bicycle infrastructure using the Marginal Rate of Substitution (MRS) (Hood et al., 2011). The model estimated an MRS of 0.49, meaning that the average cyclist would rather cycle on 100 m along bicycle lanes to avoid cycling on 49 m of ordinary roads. In addition, the model estimated an MRS of 4.02 for cycling the wrong way down a one-way street, meaning that cyclists will only ride against the traffic flow if it saves them more than four times the distance of a conventional street. This is assumed to apply to streets for which contraflow cycling is not permitted.

Two studies specifically on the effects of contraflow bicycle lanes were uncovered, the first of which demonstrated significant increases in the use of contraflow bicycle lanes and simultaneous reduction in footpath cycling in Oslo, Norway (Bjørnskau et al., 2012). The second study involved an intercept survey of bicyclists in Washington, D.C. which revealed that participants' weekly usage of the bidirectional contraflow bicycle lane street increased from 15% pre-intervention to 80% post-intervention (Goodno et al., 2013).

This paper contributes both to the knowledge regarding this specific type of initiative and more importantly, to the empirical knowledge regarding intervention studies and bicycle route choice. The literature reveals that whilst there are several studies that demonstrate a generally positive association between bicycle infrastructure provision and bicycle modal share, the state of knowledge regarding changes in route choice is less mature. This applies particularly for longitudinal intervention studies, since most of the research presented up to this point uses forms for cross-sectional study design such as traffic counting. Several reviews of research on bicycle travel behaviour have noted the rarity of longitudinal studies using control groups (Handy et al., 2014; Smith et al., 2017; Yang et al., 2010). This paper has made an effort to capture the intervention effects separate from population changes through the use of a quasi-control respondent group.

3. Methods

3.1. Study area

A contraflow bicycle lane (i.e. in the opposite direction to one-way vehicular traffic) in Markveien in Oslo, Norway, was opened for cyclists at the end of August 2017. Markveien extends north-south through the district of Grünerløkka and is one of several parallel streets connecting the suburb of Torshov with Oslo city centre. The contraflow bicycle lane is a part of the City of Oslo's City Route 1 bicycle infrastructure project which commenced in 2016. City Route 1 is one of eight City Route bicycle infrastructure projects in Oslo covering 55 km of streets within Oslo's outermost ring road: Ring 3. The planned completion of the City Routes is 2020 and is seen by the City of Oslo as its most important bicycle promotion initiative. The changes are pictured in Fig. 1 whilst the map in Fig. 2 illustrates the bicycle lane together with the existing bicycle infrastructure in Grünerløkka and Torshov.

The 'intervention' (or natural experiment) is a 400 m long section of Markveien, between Grüners gate and Øvrefoss (59°55′32.2″N, 10°45′25.6″E), in which a 2.4 m wide red asphalt bicycle lane substituted parallel car parking on the eastern side of the street. Parallel car parking on the western side of the street remained unchanged. Bicyclists have been permitted to ride contraflow in this street since 2015. There are no bicycle lanes in the same direction as traffic,

Fig. 1. Before and after changes in Markveien (top and bottom images respectively), completed in August 2017 (view to the north from the intersection with Seilduksgata). Source: the City of Oslo Agency for Urban Environment.

meaning cyclists must ride on the road lane. The intervention extends the total length of contraflow bicycle lanes on Markveien from 447 m to 847 m, as shown in Fig. 2. Following the intervention, only 100 m of the City Route 1 section of Markveien lacks contraflow bicycle lanes.

Two other streets in the same neighbourhood received bicycle infrastructure modifications during the analysis period (thus making the isolation of the intervention effects harder since they also affect bicycle behaviour). The first was a 245 m segment of Sandakerveien, a one-way street 1 km to the north of Markveien, which received the same treatment as the intervention site in late September 2017 (contraflow bicycle lane in lieu of parallel car parking). Sandakerveien is also part of Oslo's City Route 1 project. The second infrastructure upgrade involved the recolouring (from black to red) and widening of 745 m of bicycle lanes along both sides of Toftes gate in June 2017, a parallel street two blocks to the east of Markveien. Both Toftes gate and Sandakerveien are illustrated together with Markveien in Fig. 2.

3.2. Participants

This study tracked the mobility behaviour of a panel of residents from the northern suburbs of Oslo who would be most exposed to a new bicycle lane constructed in Markveien, Grünerløkka. Participants were recruited to the study using multiple approaches. 3000 personalised invitational letters were mailed to addresses < 400 m from the northern section of City Route 1. The mailing area was entirely north of the intersection between Markveien and Grüners gate, where the intervention begins. This was done since it was assumed that the dominant destination for cyclists in the neighbourhood would be central Oslo, south of the intervention.

The study was also distributed through a local newspaper advertisement, flyers, posters and social media connected with the area of interest. Except for social media targeting specific interest groups, the recruitment process was randomised. In total 113 Oslo residents participated in both data collection rounds, 51 of whom were recruited via the letters and unknown numbers recruited via other means.
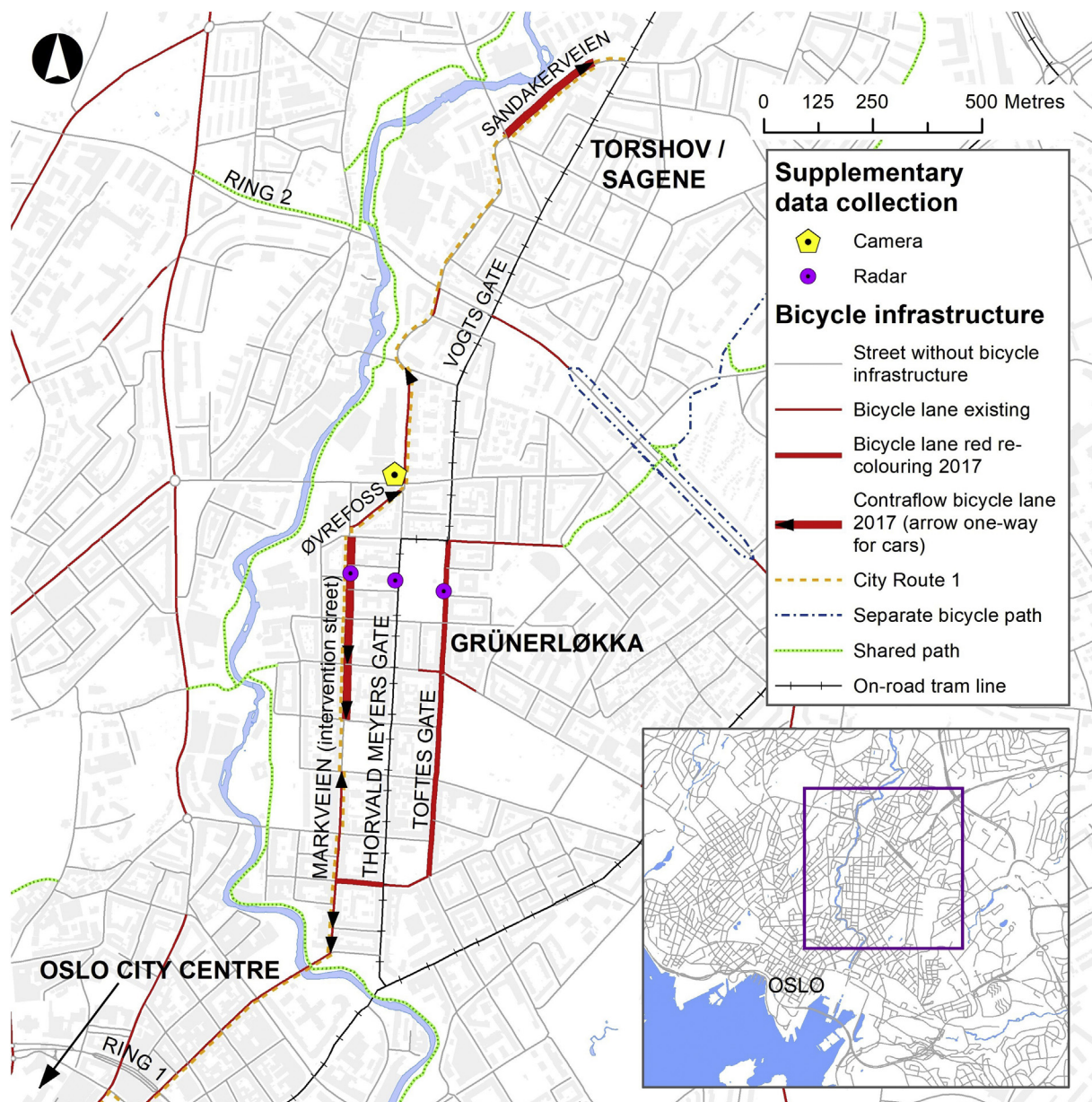
Fig. 2. The intervention street Markveien in Oslo together with existing bicycle infrastructure in Oslo's inner northern suburbs of Grünerløkka and Torshov. Arrows indicate the one-way direction for cars since bicycles are permitted in both directions on all streets.

The bicycle lane intervention was constructed between the 14th and 31st August 2017. The bicycle lane and the study's focus on bicycle travel behaviour were deliberately not referenced in the invitational material in the interest of reducing response bias (Envall, 2007, p. 164). The study purpose was instead described as being related to longitudinal travel behaviour changes in the local environment. Participant travel behaviour was recorded in two four-week periods pre-intervention between 13th May and 9th June and post-intervention from 12th September to 9th October 2017.

3.3. Instrumentation: GPS-enabled smartphone application (app)

Participants' own smartphones with integrated Global Positioning System (GPS) were used for gathering panel mobility data from the participant panel. 91% of the Norwegian population had access to a smartphone in 2017 and thus selection bias through this choice of method was considered minimal (Vaage, 2018).

Whilst a number of travel survey-specific commercial apps exist

(Berger and Platzer, 2015; Flügel et al., 2017), a more affordable solution was found that built upon a passive physical activity monitoring app called Moves® (shut down in July 2018). A second app, *GoEco!* Tracker,[1] was required to extract information from Moves® and reclassify the mode of transport used for motorised journeys, which are classified in Moves® as 'transport'. GPS data is recorded first in Moves®, and via an application programming interface (API), is automatically collated to a secure server by the *GoEco!* Tracker app (Bucher et al., 2016). This required participants to download both apps and authorise the transfer of data from Moves® to *GoEco!* Tracker. More detailed information on the data collection protocol (approved for this study by the Norwegian Centre for Research Data) can be found in the methodological paper from the *GoEco!* project team (Bucher et al., 2016).

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[1] www.goeco-project.ch
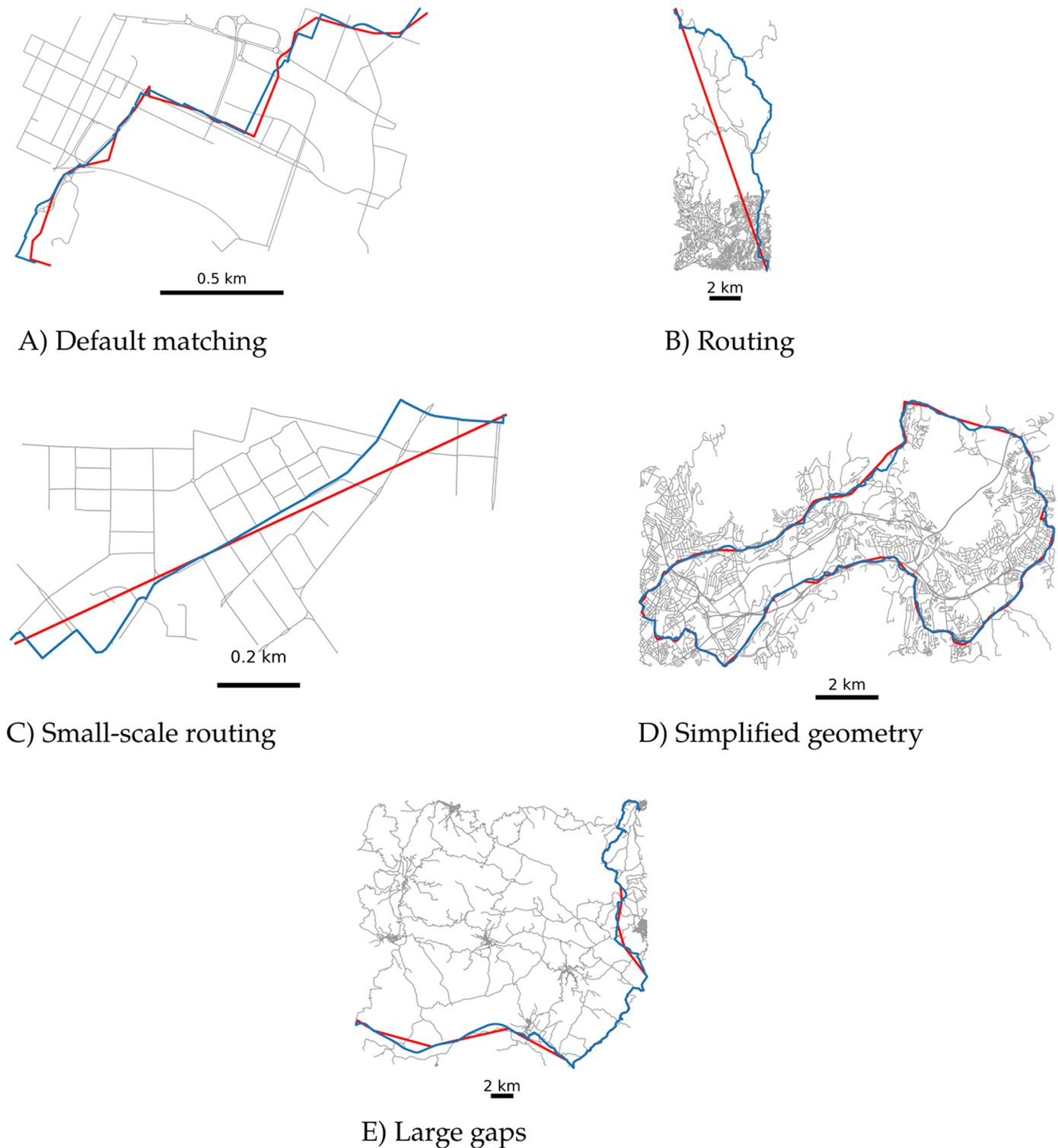
Fig. 3. Examples of the different matching approaches used to handle the varying route data quality. Red lines indicate raw data and blue are matched to the street network. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.4. Pre-processing GPS data

Map-matching is a necessary procedure in the preparation of GPS data for subsequent analysis, to determine the distance travelled and to be able to count the number of trips along a specific street or path. Hidden Markov Model-based map-matching was performed on the raw data (after mode validation in GoEco! Tracker) using the Open Source Routing Machine (OSRM) matching profiles for car and walking trips

(Project OSRM, 2018). Additional matching profiles were created for trains, trams and buses, and the profiles for bicycle journeys were adapted by the GoEco! Tracker developers to allow matching to both bicycle-specific and generic routes within OpenStreetMap.

To handle the variable raw data quality (due to different tracking resolution from dissimilar recording devices), several map-matching strategies were used to pre-process the GPS trajectories, as illustrated in Fig. 3 below. By default, OSRM applies a matching algorithm similar to

the one described by Newson and Krumm (2009) (Panel A in Fig. 3). The matching process first locates network nodes in the proximity of each raw GPS point by searching within a radius determined by the tracking device's reported accuracy (for example 20 m). The map-matched route must pass through at least one of the nearby nodes from each GPS point. OSRM maps all possible combinations of nodes between consecutive GPS points and repeats this procedure for the full GPS trajectory. From the many combinations created, an optimum route is determined based primarily on the time difference between consecutive GPS points and the typical speeds of the transport mode.

In case there are too few GPS points along a recorded route, OSRM simply "routes" journeys on the shortest path between the start and end points (see panels B and C in Fig. 3 with two different scales) (Huber and Rust, 2016). In some cases, the opposite situation occurs in which there are very large numbers of GPS points (due to high resolution and/or long journey distance). This results in problems for the computation of a map-matched route in OSRM – potentially due to limitations in the memory for storing all node combinations for routes with large numbers of GPS points. For these journeys, as illustrated in panel D, the number of GPS points is repeatedly simplified using a Douglas-Peucker algorithm (Douglas and Peucker, 1973). This procedure removes the least critical GPS points (based on proximity to consecutive points), yielding a smaller number of possible node-to-node combinations until the matching algorithm delivers a route. Despite the reduced data resolution, this procedure was found to provide satisfactory results. Finally, for recorded journeys in which there are large gaps between consecutive GPS points (more than three kilometres, E), the gaps are individually routed while the parts without large gaps are matched (i.e. a combination of A and B is applied).

The panel produced 36,153 trips (across all modes) during the two months of data collection, 2.7% of which were taken outside of Norway and were not considered for matching. The approach described above allowed the direct matching (A) of 87.3% of all trips, routing (B and C) of 6.0%, simplification and matching (D) of 1.6%, 'large gap' routing of 0.3% (E) whilst the remaining 2.1% had missing mode information or failed. The data collection approach was found to correctly identify the travel mode in approximately 80% of cases in a test of Swiss GoEco! Tracker travel data in which participants were requested to confirm travel mode (Bucher et al., 2016).

3.5. Supplementary data collection: video observations and automated traffic counting

In addition to GPS data collection, two further before and after methods were used: bicycle counts extracted from video observations and automated traffic counting of bicycles and motorised vehicles with Doppler radar traffic counters.

In the interest of capturing route choice changes, an elevated Miovision Scout camera (720 × 480 pixels, 30 fps) was temporarily installed above a forked intersection near to the intervention street (see Fig. 2). The forked intersection was chosen as it forms a natural decision point where bicycle users can select one of two alternative routes when cycling towards the city centre (one of which is the intervention street). Similarly, bicycle movements along the same two alternative routes coming from the city centre merge at this point when continuing further north. Cyclist movements in the video recordings were extracted by Miovision through their automated traffic data processing tool. With the configuration shown in Fig. 4, Miovision guarantees ≥85% intersection count accuracy (an accurate count correctly registers a cyclist's movement between any two of the three coloured zones). Video data was uploaded to the Miovision Traffic Data Online server and bicycle counts were received in 15-minute intervals going into and out of the two streets of interest.

Radar-based traffic counting was also deployed in three locations including the intervention street Markveien and two nearest parallel alternative streets Thorvald Meyers gate and Toftes gate (see Fig. 2).

The ViaCountII mobile traffic counters use integrated Doppler radar devices (24,165 GHz/100 mW EIRP) to determine the speed, length, vehicle class (including bicycle) and direction of travel (Via Traffic Controlling GMBH, 2016). The accuracy of the counters is not stated in the technical product specifications, but are regularly used by the City of Oslo for traffic counting.

3.6. Analytical approach

Data from the three sources were recorded before and after the intervention completion during the time periods illustrated in Table 1. Pre-processed GPS data (after conversion to .shp format) were processed using a combination of software including a Geographic Information System (GIS) program, statistical software and spreadsheets. The automated traffic counts from the video footage (recorded from 6 am to 9 pm excluding start and end days) and radar traffic data (24 h per day) were analysed in spreadsheets.

In order to observe changes in route choice, all bicycle trips (as classified by the GoEco! Tracker app) taken by the panel participants were accumulated for each link in the transport network in the before and after time periods. For any given link, this resulted in two counts for the number of bicycle trips that passed the link during the before and after periods respectively. Thereafter the number of link bicycle trips (num) in each period was normalised by dividing by the sum of all link volumes from the corresponding period for the map extent indicated in Fig. 2. The change in bicycle volumes is calculated in GIS using the expression below for each link in the transport network where the before period is 1 and the after period is 2. This mitigates for potential confounding factors such as weather variability or other seasonal variation between the two data collection periods.

$$\Delta\ Adjusted\ bicycle\ volume_{link\ x} = (num_{x2}/\Sigma num_{N2} - num_{x1}/\Sigma num_{N1})$$
$$\cdot \Sigma num_{N1} \tag{1}$$

The scale of the intervention and limited time to adjust behaviour is such that short term modal changes cannot be expected for all journeys taken by the panel. To account for potential modal changes, it was, therefore, necessary to remove journeys that are not in the immediate vicinity of the intervention (defined as being the area bounded by the four nearest parallel streets, two on each side of Markveien). This was done by creating a modal analysis zone (a polygon) in ArcMAP covering this immediate vicinity and selecting only those GPS journeys which intersect with this zone. This zone is shown in Fig. 7 with the red shaded polygon. In this manner, only the subset of journeys that are taken in proximity to the intervention is considered. This is an important consideration given the dataset covers trips taken by the participants across the whole of Oslo and beyond.

Checking for mode substitution was performed by firstly selecting panel participants who had taken at least one journey in the modal analysis zone in both periods ($n = 86$). From this group, a subset of respondents ($n = 39$) was exposed to the intervention, whilst the remainder are considered as a quasi-control group (n = 47). Exposure was defined as having used at least one segment of the 400 m intervention section of Markveien in the after period with any mode (excluding trips that cross Markveien since the bicycle lane does not extend through intersections). In other words, the criterion for exposure requires intervention link utilisation (to travel on or alongside the contraflow bicycle lane). This approach was adopted since it is not guaranteed that users crossing Markveien will register changes in side-street appearance if they are more occupied with traffic hazards (and given the dark red bicycle lane has low conspicuity in wet weather and at night).

Existing approaches for exposure typically rely upon area or proximity based measures, often categorised using distance from the intervention (Stappers et al., 2018). Alternative approaches attempt to demonstrate the diminishing influence of the intervention with
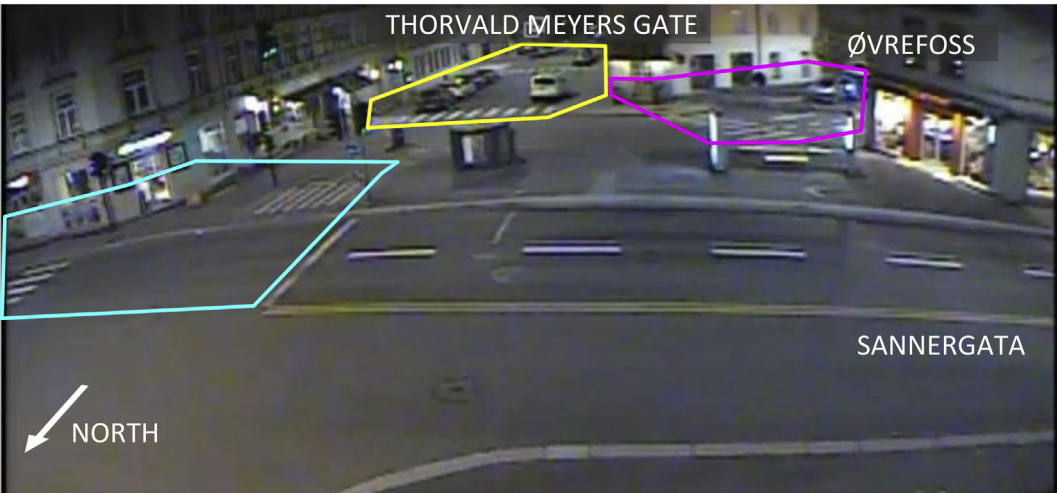
Fig. 4. Video camera perspective with bicycle counting zones for automated counting of bicycle movements between the three zones.

Table 1
Data sources recording periods.

Source	Before	After	Data processing
GPS	28 days 13th May – 9th Jun	28 days 12th Sep – 9th Oct	ESRI ArcMap 10.6, Microsoft Excel, IBM SPSS Statistics 25
Video observation	39 h 12th, 13th, 15th, 16th May	86 h 21st Sep – 26th Sep	Microsoft Excel
Radar traffic counting	7 days 8th May – 14th May	7 days 18th – 24th Sep	Microsoft Excel

proximity through the use of the negative square root of distance (Heinen et al., 2017). The strict link-utilisation definition used in this paper was chosen in favour of the broader definitions above due to a) the short time frame of post-intervention travel behaviour measurement, b) smaller scale of the intervention compared to the examples reviewed by Stappers et al. (2018) above and c) the ability to be able to select participants based on their actual use of a road (due to the GPS data).

The journeys that intersected the modal analysis zone were summarised into a modal share for each user in this sub-group for the before and after periods. Paired samples *t*-tests were then used to compare the change in bicycle modal share for the exposure group and the non-exposure group (a quasi-control group) between the before and after periods.

3.7. Difference in differences

Since both the quasi-control and exposure group experience increases in bicycle modal share, the difference in differences approach is used to quantify the changes. This involves considering the difference between the trends (such that when the two groups of interest increase, it is the differences in the increase that are measured).

Since the intention of this paper is to measure the significance of the changes, the classic regression approach is used to calculate the difference in differences for the dependent variable bicycle modal share given by y_{it} in equation 1 below (Donald and Lang, 2007).

$$y_{it} = \alpha + \beta_1 \cdot Exposure_i + \beta_2 \cdot Post_t + \beta_3 \cdot (Exposure \cdot Post)_{it} + \varepsilon \qquad (2)$$

$Exposure_i$ and $Post_t$ are dummy variables introduced to distinguish group membership in which $Exposure_i$ equals one for the participants in the exposure group ($n = 39$) and is zero for the quasi-control group, and $Post_t$ equals one for the post-intervention time period and is zero for the pre-intervention period. Running this as linear regression in SPSS provides an estimate for the difference in differences given by the parameter β_3 together with the necessary outputs to report statistical significance.

4. Results

4.1. Characteristics of study participants

The numbers of men and women participating in the panel ($n = 113$) were approximately equal, although men were generally older as can be seen in Fig. 5. The education level of the sample was considerably higher than that of the local population. Eigty five percent of the panel had some form of higher education, compared with census records for Sagene and Grünerløkka that show 60% of the intervention area population had higher education (Holseter, 2018). Before the intervention, 86 members of the GPS panel had conducted 4 or more trips by bicycle during the first month of data collection (or an average of
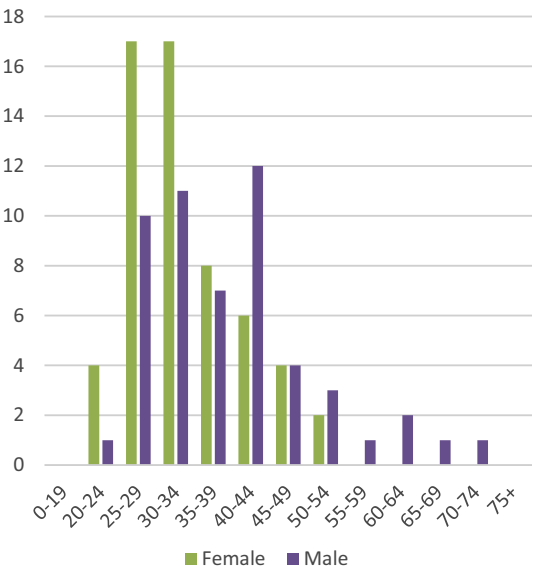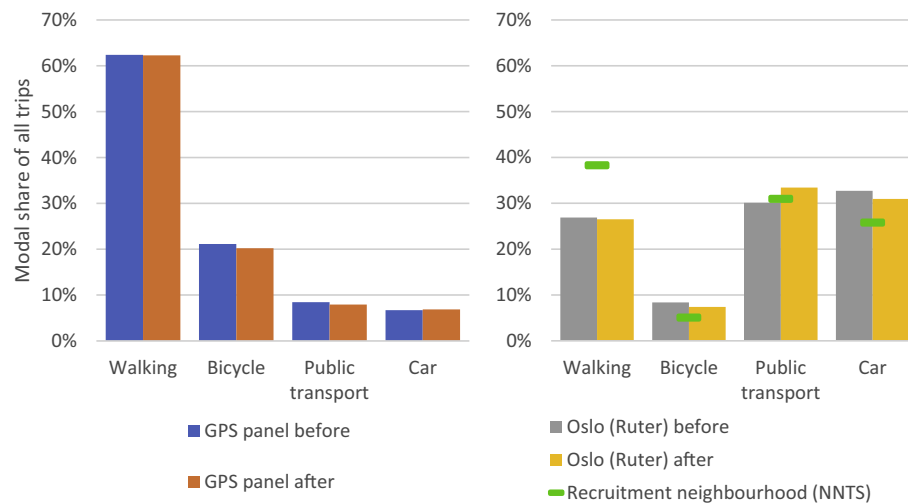

Fig. 5. Age distribution of GPS panel.

Fig. 6. Transport modal share for the GPS panel (left) relative to the general Oslo population (right) for the before and after data collection intervals. NNTS data is additionally shown to the right for the recruitment neighbourhood in Oslo.

one or more trips per week). There were 83 panel members who took 4 or more bicycle journeys following the intervention (also over a period of one month). As a proportion (76% and 73% respectively) this is significantly higher than the weekly cycling levels for the Grünerløkka (52%) and Sagene (49%) city districts where most participants live (Bayer, 2018).

Seasonal variation in Scandinavia as with many other countries with snowy winters results in variability in the levels of bicycling. The GPS panel modal share data for each month was compared with travel survey data from Ruter, the public transportation authority in Oslo. Ruter's market information system, a type of continuous travel survey has a sample size of approximately 3400 Oslo residents spread throughout the year. The comparison of the GPS data with the population sample from Ruter is shown in Fig. 6 below. Minimal seasonal variation is observed during the before and after data collection periods, however cyclists and pedestrians are greatly overrepresented whilst car drivers and public transport users are underrepresented.

In addition, Fig. 6 displays the modal split for the recruitment neighbourhood (defined as the zone in which invitation letters were distributed). This data is taken from the 2013/2014 Norwegian National Travel Survey (NNTS) (Hjorthol et al., 2014). This reveals that the (average annual) neighbourhood modal shares of public transport (31%) and cycling (5%) are approximately equal to that of Ruter's sample in Oslo. However, walking is more common in the neighbourhood (38%) than the Ruter sample (27%), whilst car journeys are less common (26% versus 32%).

4.2. Route substitution

Positive values for changes in normalised bicycle volume, depicted in light turquoise in Fig. 7, indicate the approximate increase in bicycle trips made by the panel after the intervention compared to before. Negative values, drawn in dark orange, show the corresponding reductions in panel bicycle volumes. The intervention street Markveien has clearly increased in popularity amongst the panel, whilst neighbouring streets Thorvald Meyers gate and the riverside shared path experienced a reduction. Although infrastructural changes were made in Sandakerveien and Toftes gate (as depicted in Fig. 2) during approximately the same time interval as Markveien, mixed results are observed in these streets with a smaller change in travel behaviour. Monthly volumes are used preferentially to daily volumes since the data comes from two one-month-long periods, first in May/June 2017 and afterwards in September/October 2017.

4.3. Deviation rate

A form of quantification for the change in bicycle route choice can be made by considering the deviation distance from the shortest path (calculated in ArcMAP) (Krenn et al., 2014). An independent samples *t*-test was performed using all the bicycle trips taken on Markveien before and after the intervention. The deviation from the shortest path (in metres) after the intervention was built in Markveien was greater (mean = 221, SE = 18), than before (mean = 171, SE = 15), and the difference, −50, 95% CI [−96, −4] was significant t (289) = −2.16, p = .032. In other words, the upgraded Markveien was able to induce a 221 m deviation from the shortest path (compared to 171 m before). This demonstrates that the average bicycle user of Markveien had a significantly increased detour from the shortest path in order to use the contraflow bicycle lane configuration than the same street pre-intervention. Existing users presumably continued to use Markveien, so the increase in the mean suggests that the new cyclists who began to use Markveien took greater detours than 221m to use the intervention infrastructure.

4.4. Video comparison

More than 100 h of video footage was processed by Miovision to count the number of bicycles taking Øvrefoss, which leads directly to the intervention street Markveien, and the alternative street Thorvald Meyers gate. Since only bicycles were counted in the footage, the video data cannot be used to determine any changes in modal share – but allows observation of any changes to bicycle route choice. In Table 2 below the percentages of cyclists choosing each of these two streets is shown and compared with the GPS panel counts on the same two streets. It should be noted that not all traffic through the intervention goes through this intersection, and therefore it is only indicative of changes that occur in the intervention. Immediately apparent in Table 2 however is that the scale of the change for the video observations is much less than the GPS panel.

4.5. Directional changes

The contraflow bicycle lane undoubtedly improved the bicycling conditions for northbound cyclists using the intervention, since the replacement of a parking lane with a bicycle lane provided much greater separation from the flow of one-way southbound traffic. The directional flows are displayed in Table 3 below for those routes passing through the directional analysis zone indicated in yellow in Fig. 7. The
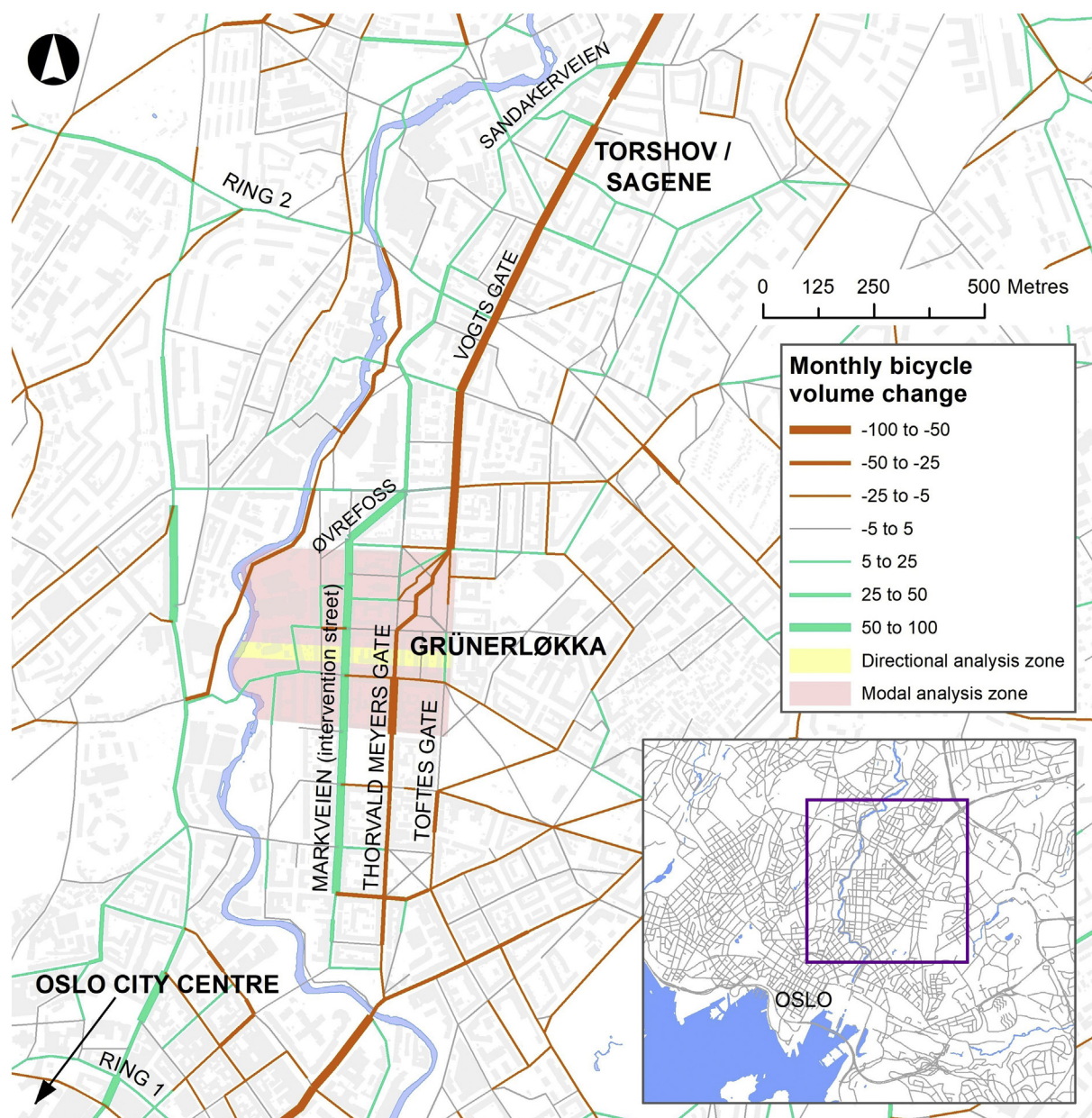
Fig. 7. Change in the number of monthly recorded bicycle trips taken before and after intervention adjusted for seasonal variation. The intervention stretch of Markveien is shown by the dashed violet line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Average daily number of observed trips taken by bicycle (in both directions) at the intersection of Øvrefoss and Thorvald Meyers gate (see video camera location in Fig. 2).

	GPS panel (*n* = 113)		Video observation (population)	
Time period	Intervention 'tributary' (Øvrefoss)	Thorvald Meyers gate	Intervention 'tributary' (Øvrefoss)	Thorvald Meyers gate
Pre-intervention	4.19 (43%)	5.60 (57%)	374 (46%)	439 (57%)
Post-intervention	5.69 (70%)	2.41 (30%)	563 (50%)	566 (50%)

Table 3
Percentage of bicycle journeys on Markveien relative to the total number of trips that cross the directional analysis zone.

Time period	Northbound	Southbound
Pre-intervention	16.0% of 318	16.4% of 372
Post-intervention	29.2% of 226	31.1% of 302

Markveien: Fossveien and Steenstrups gate and three to the east: Thorvald Meyers gate, Bjerkelundgata and Toftes gate.

Markveien is found to become a more popular choice amongst the six streets in both the northbound and southbound direction, with a near-doubling in the percentage of trips taken on this street. No evidence is found in the GPS data to suggest that northbound cycling increased any more than southbound cycling. Video data also supports this finding in which the proportion of northbound cyclists entering the

directional analysis zone is a single cross-section of streets surrounding Markveien and all trips that intersect it were counted and sorted by street and direction. This included two parallel streets to the west of

intersection Øvrefoss increases from 48% to 52% (compared only with Thorvald Meyers gate rather than the 5 other streets). Southbound cycling from the intersection into Øvrefoss also increases from 45% to 48% following the intervention. The difference in proportions between the GPS data and the video data is a limitation of the method in which the video observations can only record directional preferences against one other street. More importantly, however, is the similar increase in cycling independent of direction within each method.

The small difference in north and southbound cycling in both data sources is contrary to expectations, given that the conditions for cycling southbound were largely unchanged. However, the lack of change in directional utilisation of Markveien can potentially be explained by the change in contraflow bicycle direction on the sections of City Route 1 both north and south of the intervention (see Fig. 2). The contraflow bicycle lane alternates between the west and east sides of the road (given the shift in one-way direction for cars). This means that cyclists who are unwilling to share a street with cars are unlikely to utilise City Route 1 since there is no bicycle infrastructure in the car travel direction. The low degree of directional difference may also be the result of the improved perceived safety and comfort of Markveien also when travelling southbound with cars due to the removal of parked cars on the east side of the street (see Fig. 1).

4.6. Mode substitution to bicycle

For the exposure group (n = 39), the modal share is calculated based on the 2032 trips they made in the modal analysis zone in both periods. The exposure group had a higher bicycle modal share in the after period (mean = 0.499, SE = 0.056), than the before period (mean = 0.422, SE = 0.053), however the difference, −0.077, 95% CI [−0.166, 0.012] was only weakly significant t (38) = −1.743, $p = .089$. The modal shares above are presented as decimal values but indicate the percentage of all trips taken by bicycle: 42.2% before and 49.9% after for the exposure group.

The quasi-control group (n = 4) for the modal analysis is the subset of the panel that was not exposed to the intervention but still performed at least one trip in the modal analysis zone in the before and after period. For the quasi-control, the modal share is calculated based on the 1193 trips they made in the modal analysis zone in both periods. They had a higher bicycle modal share in the after period (mean = 0.342, SE = 0.058) than the before period (mean = 0.312, SE = 0.053). The difference, −0.030, 95% CI [−0.11, 0.05] was not significant t (46) = −0.728, $p = .471$.

Since both the exposure and quasi-control groups experience an increase in bicycle modal share, the difference in differences approach can be used to reveal the effect of the intervention. Linear regression in SPSS provided the difference in differences coefficient $\beta_3 = 0.047$, or a treatment effect of 4.7% change in bicycle modal share. The difference (95% CI [−0.065, 0.159]) was not significant t (171) = 0.419, $p = .676$. The 4.7% difference in differences was confirmed through the manual calculation of the means from each combination of the dummy variables (Lechner, 2010).

To make a comparison with volume data in which modal information is available the radar data can be used. The radar counting device registered traffic volumes in each of the three parallel streets for one week at a time in two time intervals as detailed in Table 1. The data is not directly comparable as only three north-south streets are compared instead of all trips in the modal analysis zone, but it approximates the same conditions. The corridor bicycle volumes across the three streets increase from 13.7% to 16.8%. Markveien meanwhile observed a decrease in the bicycle modal share amongst the three streets from 31.5% to 27.8%. The finding does not corroborate either the video evidence or GPS data. Inconsistencies in the radar data are further discussed in the following section.

5. Discussion

5.1. New infrastructure: rerouted or new bicyclists?

Study designs for longitudinal bicycle infrastructure evaluation studies such as this vary widely; however, few studies register changes of bicycle route choice as well as mode choice. This paper provides evidence for route substitution both through the GIS-plotted changes in Fig. 7, bicycle counts from the video observations and through a significant increase in deviation from the shortest path (by 50 m) on the intervention street. However, the increase in the rates of cycling following the intervention was not found to be significant for the group exposed to the intervention using the difference in differences approach (4.7% increase in modal share, $p = .676$). This is despite reducing the number of trips under consideration to those in the immediate vicinity of the intervention and taking into consideration only the panel subgroup directly exposed to the change.

The lack of significant modal increase may be a result of the small sample size in the exposure group (n = 39). Alternatively, it may simply be a function of the relatively minor scale of the intervention – 400 m of bicycle lanes on one side of a street, or the short period of time (one month) residents had to adapt to the intervention changes in the after period. It could be that alternative study designs (including a longer follow-up period) would be able to demonstrate a significant modal shift.

Although route substitution of bicyclists has not been thoroughly researched, existing literature suggests that it can vary greatly depending on the type of intervention and context (Fitch et al., 2016; Lott et al., 1978; Parker et al., 2013; van Goeverden et al., 2015). The aforementioned studies principally use volume or cross-sectional methods to assess changes across two time periods rather than longitudinal study designs, making a generalised assessment of route substitution difficult. The phenomenon is of key importance for regional and national transport models, which until now have rarely considered other effects than minimisation of travel time when routing cyclists (van Wee and Börjesson, 2015). For this study, the intervention did not provide a new network connection but improved the quality of an existing route. Travel time benefits are therefore marginal, however, benefits in terms of traffic safety and thereby attractiveness to existing cyclists are worth considering in future research seeking to model the route substitution effect.

From a theoretical perspective, the observation of changes in route but no (significant) changes in bicycle modal share can be partly explained by the concept of utility maximisation (or optimisation). Utility maximisation is a central concept in microeconomic theory in which actors always make optimal decisions. The assumption is that people make rational decisions which offer a level of utility (or satisfaction) that is greater than or equal to any other option open to them. The theory therefore implies that new bicycle infrastructure will only result in changes to route or mode if it provides a more attractive transport option compared to existing alternatives. Thus should bicycle infrastructure be developed near to competing routes, the marginal utility can be expected to be reduced according to this approach (Broach, 2016). Although information about the intervention was unlikely to be known by all study participants, it was able to provide a degree of utility sufficient to cause route change. Since cyclists have many similar options available to them in this gridded street suburb of Oslo, small changes on the intervention street can make this a superior alternative. The similarity between modes meanwhile is less pronounced for most travellers - thereby requiring a greater change in utility to result in significant change. That route change was clearly witnessed whilst mode change did not significantly change is in line with utility maximisation theory and the relative differences within route and mode choice sets.

A similar study to this paper in the Norwegian context required users to draw their typical routes rather have their travel

behaviour tracked by GPS. It demonstrated significant changes to both route and mode choice, however the initiative was for bi-directional cycling and was longer (1.8 km versus 400 m), objectively safer (physically separated bicycle path versus contraflow bicycle lane) and included greater restrictions to car usage (two of four road lanes replaced and no-through driving restriction versus substitution of parking lane) (Vasilev et al., 2018). Considering these substantial contextual differences, a much larger change in utility can be expected compared to this paper's intervention – thereby possibly accounting for significant (p = .0014) changes also in travel mode. The drawn routes study does have weaknesses in terms of sample representativity, a post-intervention only evaluation (with routes recalled from pre-intervention phase) and lack of complete travel mode information (such as a travel diary). Combining the approaches from this paper and Vasilev et al. (2018) over multiple post-intervention follow-ups would make for a more rigorous bicycle infrastructure intervention study design that can state travel behaviour effects with greater certainty.

The remainder of the discussion section highlights the considerations made in selecting this study design, limitations and makes recommendations for future studies.

5.2. Strengths and weaknesses of selected methods

A passive smartphone app was selected for this study as it runs in the phone background, reducing participant burden relative to active start-stop apps and more easily enabling the capture of all travel behaviour (Pritchard, 2018). Such apps have the advantage of counting all traffic movements rather than only bicycle journeys, thus providing an indication of modal effects in addition to route changes. The disadvantage with Moves® and many other passive apps is high battery use and a low GPS sampling rate, with GPS points recorded on average once every 76 s for bicycle journeys. The frequency was higher for journeys associated with physical activity (walking GPS points every 45 s) – than motorised travel (105 s between consecutive car GPS points). This is perhaps unsurprising given the measurement of physical activity is the principal aim of Moves®. Since cycling journeys have an average origin-destination speed of 13.1 kph, the mean spacing between consecutive GPS points is 277 m. Given typical distance between parallel streets in the gridded study area are around 100 m, nearly three city blocks can be traversed in the time between GPS points.

A literature review of bicycle route choice data collection methods (Pritchard, 2018) revealed three papers which use passive smartphone GPS, however only one of these stated the GPS sampling rate: one point per second (Sandsjö et al., 2015). For this study, Moves® did not state the GPS point frequency but early trials revealed that the GPS sampling rate to be considerably lower than 1 Hz. The trials suggested that bicycle route choice would remain clear despite the lower sampling rate, however the 76-second period between GPS points was greater than expected (corresponding with an average frequency of 0.013 Hz), potentially due to wide variability between smartphone models.

Although the point frequency from the GPS method used in this paper is low, the process for mode and route matching is automated, thus providing a consistent means of analysing the data across the two time periods. The point frequency did not appear to be highly problematic for mode identification, however walking trips were found to be correctly matched at a higher rate than other trips (most likely due to the combination of characteristic accelerometer movements and low speeds) (Bucher et al., 2016). For map-matching, slightly > 6% of GPS routes required the routing engine in OSRM as described in methods Section 3.4. This uses a shortest path search on the OpenStreetMap network, thereby providing a consistent approach for routing (Huber and Rust, 2016). Comparison of GPS data collected before and after the bicycle lane intervention in Fig. 7 should therefore effectively cancel the impact of potential routing errors that result from low GPS point frequency.

Despite the challenges this created for map-matching and route

quality at higher speeds, the adopted method had many benefits (Moves was shut down in July 2018): compatibility with both Android and iPhone smartphones, automatic trip segmentation, partial mode classification, a freely available API and no need for technical support. The smartphone GPS methodology is, however, challenging in terms of recruitment as data privacy concerns made response rates very low (152 responses from 3000 mailed invitation letters – 51 of whom provided sufficient data for inclusion in the panel).

Portable GPS units have also been used in bicycle route choice research. A review of 21 bicycle route choice studies employing such units found the median rate of geo-location to be one point per second, however concurrent data collection would require the acquisition of many GPS devices, thereby being very costly for a study with similar numbers of participants (Pritchard, 2018).

The average number of daily trips recorded for each panel participant was 6.00 pre-intervention and 5.46 post-intervention. By comparison, 3.40 daily trips were made per person amongst inner Oslo residents in the Norwegian National Travel Survey (NNTS) from 2013 to 2014 (Ellis et al., 2015). The discrepancy is likely the result of two factors: over-segmentation of trips from the app and under-reporting of (especially short) trips in telephone-based travel surveys like the NNTS.

The video recordings provided a means with which the route choice changes of the GPS panel could be compared with population route choice in an intersection. The volumes of bicycles counted on Øvrefoss increased but not to the same degree as the GPS panel, as shown in Table 2. This is likely a result of a combination of factors, including the small sample size, different time periods for recording and a lower trip rate in the GPS panel after the intervention was completed. The video data is reliable, however, only one location is available for any recording, limiting the comparison opportunities with GPS data.

The radar traffic counts on the other hand were problematic from a data consistency perspective. The post-intervention data collection in Markveien revealed an 83% decrease in volumes of northbound cyclists despite the contraflow bicycle lane specifically providing for this group. Directional data, whilst not obviously inconsistent in the two parallel streets could not be used as a result. When considering overall volumes, the intervention street Markveien experienced a reduction as discussed in the results section whilst neighbouring streets experienced an increase in cycling levels. Such a finding conflicts with the GPS and video data and is likely a result of improper radar installation. The manufacturers of the ViaCountII device do not recommend the use of their product where parked cars or other objects may cause reflection of the radar beam from the opposite side of the road. In this highly urban area, video, manual or pneumatic tube counts may have been more appropriate options to understand volume changes in parallel streets.

5.3. Potential other causes of variability

Before and after travel behaviour studies must be considerate of several other confounding factors. The intervention was selected as a natural experiment due to the absence of nearby planned bicycle infrastructure projects in early 2017. However as previously mentioned, two other streets received bicycle infrastructure modifications as illustrated in Fig. 2. Sandakerveien was completed in late September and was thus still under construction during the second phase of GPS data collection, which may have led to the modest increases in bicycle volumes here (see Fig. 7). The existing bicycle lane in Toftes gate was widened and marked red, however, this did not lead to travel behaviour changes as substantial as the primary intervention.

Variable weather can strongly impact the modal share of bicycles with cycling rates typically three to four times lower in the winter months compared to the summer in Norway (Hjorthol et al., 2014). For this study, it was a specific aim to avoid data collection during the winter months. The public transport operator Ruter's Market Information Survey shows that the bicycle modal share was not greatly different between the before (8.4%) and after (7.4%) periods in Oslo as

illustrated in Fig. 6. The slight difference can, however, partly explain the reduction in corridor volumes of bicyclists observed in Table 2.

Long term effects are typically larger than short term ones, as collective improvements begin to improve connectivity in the neighbourhood and the level of exposure to infrastructure changes increases. Cross-sectional travel behaviour surveys commissioned by the City of Oslo in 2013 and 2017 show that the two city districts of Sagene and Grünerløkka had statistically significant increases in the numbers of residents who cycled at least once per week. For Sagene, north of the intervention area, this corresponded to an increase from 39 to 49%, whilst for Grünerløkka, the city district containing the intervention, the proportion of residents who used a bicycle once or more per week increased from 40 to 52% (Bayer, 2018). Approximately 0.5% of the adult population of these city districts were sampled (in 2017 this corresponded to 240 of 48,158 residents in Grünerløkka and 168 of 35,377 residents in Sagene). Although a significant change in the number of residents who regularly cycle is observed over the four-year time interval – it is not possible to determine which factors had the most influence on the change using this approach.

Within the infrastructure intervention literature, follow-up periods of up to two years are not uncommon (Smith et al., 2017). A paper which reviewed 17 natural experiments and their impact on physical activity revealed that studies with positive results generally had follow-up times of > 6 months (Mayne et al., 2015). Only one of the 17 studies reviewed had a comparable timeframe to this paper. It evaluated a 23-mile-long multi-use trail (converted from an unused railway) in North Carolina two months after opening and found no statistically significant changes in the levels of physical activity or walking for transportation amongst residents located within 2 miles of the intervention. In addition, 11% of the survey sample was not aware of the trail's presence whilst 23% had made use of it (Evenson et al., 2005). Although the study did not assess travel behaviour in the same manner as this paper (using mode or route choice), it highlights that even relatively large infrastructural changes are not noticed by the entire population. This is supported by feedback provided at the conclusion of the study (in October 2017) from a small selection of the participants ($n = 14$) in which 8 participants reported that they had noticed the contraflow bicycle lane installation in Markveien when prompted: 'Did you observe any changes in your neighbourhood between the two data collection periods? If so, please describe.'

The importance of differences in context, intervention types and follow-up timings makes it difficult to precisely determine the importance of post-intervention follow-up time (Smith et al., 2017). One study which performed two follow-ups of travel behaviour is the UK iConnect study. The iConnect project found that residents located within one kilometre of three selected bicycle infrastructure intervention sites had increased their average weekly physical activity by 45 min after two years, a finding which was not reflected in the one-year post-completion survey (Goodman et al., 2014). Future research should consider adopting this approach with multiple follow-ups in order to provide insights into short-term versus long-term effects of bicycle infrastructure.

6. Conclusion

The aim of the study was to observe bicycle route and mode choices in a panel of residents. A natural experiment study design was used in which residents were recruited specifically in connection with the construction of a contraflow bicycle lane in Oslo. The study's principal finding is the demonstration of the route substitution effect. The study additionally shows that the observed increase in the modal share of bicycles was not statistically significant. Route substitution of existing bicyclists is critically important when estimating the network impacts of new bicycle infrastructure (change of route has a very different meaning for the transport network than change of mode). Failing to account for route substitution can lead to an overestimation of the

benefits of bicycle infrastructure development (since more cyclists are estimated than are present).

The paper outlines a smartphone GPS approach to collecting in-depth travel behaviour data from a respondent panel, however achieving satisfactory numbers of responses was troublesome, detrimentally impacting the ability to assess the significance of the intervention. With a panel participation rate of only 2% from the mailed invitations, alternative means of recruitment may be necessary when using similar approaches going forward. Natural experiments are receiving increased attention in the literature, furthering our knowledge about the effects of specific types of bicycle infrastructure provision. Future research efforts should attempt to compare such initiatives and control for contextual differences where possible.

To date, existing research on the impact of bicycle infrastructure has been mostly focussed on either mode or route change. This study contributes to a small but growing body of research that maintains a holistic perspective considering both mode and route factors in the evaluation of bicycle infrastructure over time. Future studies of this nature will assist in bettering our understanding of how bicycle infrastructure is utilised, assisting planners, policymakers and engineers in their efforts to create safe and attractive people-focussed (rather than car-centric) urban areas.

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