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The effects of a subvention scheme for e-bikes on mode share and active mobility

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ABSTRACT

Introduction: Previous studies show substantial mode share effects from e-bikes. E-bike owners cycle more and drive less car than they would without access to an e-bike. Support schemes for e-bikes exist in a number of countries, but knowledge about the effect of subsidies on active transport is limited. The aim of this study is to assess the mode change and active mobility effects of a subvention scheme for e-bikes in Norway.
Methods: To boost the uptake of e-bikes, Oslo City Council introduced a subvention program (€500) for e-bike purchasers in 2016. Applicants answered to a web-survey at two time points, including a travel diary and questions about overall bicycle usage. In addition, a sub sample used an app to track all their transport activities for two following months (one period of time).
Results: The survey results from the trial group (N = 382) were compared with two control groups: one from an outside sample of individuals (N = 665) and one consisting of subvention receivers who had not yet purchased the e-bike (N = 214). The survey data shows that the cycling mode share for the trial group increased in the range of 17–22 per cent-points (depending on comparison group) after subsidised e-bike purchase, whereas the app data (comparing mode distribution according to the length of e-bike ownership) suggest a 5 to 14 per cent-point increase. For overall bicycle usage, the survey data shows a significant increase for the trial group in the range of 11.6–19.3 km, compared to the control groups.
Conclusion: The subvention led to a modal shift (i.e. more cycling) and more overall cycling activity. Our findings indicate that financial incentives may contribute to a boost in active transport, even when the subvention is of a simplistic kind that does not target specific population segments.

1. Introduction

During the last few decades, e-bikes have increased in popularity worldwide and represent the fastest growing segment of the transport system (MacArthur et al., 2014). In a European context, e-bikes refer to the pedelec type, where an electric motor (limited to 250 W) assist up to 25 km/h. Within these regulations the pedelces are classified as bicycles, as they require pedalling for the assistance to be provided (European Committee for Standardization, 2011). Throughout this paper, the term e-bike will refer to a pedelec type and c-bike to a conventional bicycle.

One aspect of e-bikes that is attracting more and more research interest is their effect on mobility patterns, in general, and active

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mobility, in particular (Peterman et al., 2016). The e-bike has a relative strength when it comes to the impact on transport mode distribution in daily travel, compared to regular cycling and walking, in that it extends the potential distances covered by active transport and reduces some barrier effects for cycling (de Geus and Hendriksen, 2015). The e-bike may also reach population segments that are not prone to regular cycling or walking for transport. Hence, the e-bike could be considered particularly important for countries with current low bicycle mode shares. Still, it seems that the most rapid uptake has occurred in countries with high existing bicycling shares (Fishman and Cherry, 2016).

1.1. E-bikes and mobility patterns

Previous studies using cross-sectional or retrospective designs have found mode-change effects from e-bikes ranging from 16 to 76 per cent (Cairns et al., 2017). A challenge with these studies is the design, making it difficult to draw causal conclusions regarding changes in travel mode. In a Dutch prospective study by Sun et al. (2020), the combined cycling level almost doubled as a result of the purchase of an e-bike. A similar study from Norway controlled for seasonal variations in bicycle use by comparing mode-change effects for e-bike purchasers with a control group, they found that people who purchased an e-bike increased their daily bicycle use from 2.1 to 9.2 km on average. This represented a change in cycling as a share of all transport from 17 to 49 per cent (Fyhri and Sundfør, 2020). In a recent Swedish randomised controlled study (Söderberg f.k.a. Andersson, Adell, & Winslott Hiselius, 2021) the treatment group had a 25 per cent increase in total cycling compared to the control group, all at the expense of the car. However, the study sample had a high share of car trips at baseline (close to 100 per cent), indicating that the substitution effect of mode share is likely to be smaller in the general population. A scoping review by Bourne et al. (2020) highlight that the impact of the e-bike on travel behaviour is largely influenced by the primary mode of travel prior to the introduction of the e-bike. In a population with high bicycle shares, there will be a larger shift from c-bike to e-bike, compared to populations with low levels of cycling where the primarily transport shift will be from cars. Historically, most studies of mode change effects relay on self-reported measures (e.g. Bourne et al., 2020). To date, only a limited number of studies have used objectively measured data to report travel behaviour in a large scale (e.g Nahmias-Biran et al., 2018; Söderberg f.k.a. Andersson et al., 2021).

1.2. E-bikes and physical activity

It is well established that physical activity (PA) has both an acute - and long term benefit and reduces the risk of several non-communicable diseases (Hartog et al., 2010; Warburton and Bredin, 2017). Due to the electrical motor assistance, barriers as long distances and hills becomes easier to overcome (de Geus and Hendriksen, 2015), and hence facilitate more physical activity in everyday life (Oja et al., 2011). The potential downside of the motor assistance, is that it requires less self-generated power (i.e. energy expenditure) for a given time and distance, compared to a non-assisted bicycle (Berntsen et al., 2017; de Geus and Hendriksen, 2015). However, the e-bike is found to require physical activity of at least moderate intensity (Bourne et al., 2018). Following this, it is of interest to explore the total amount of cycling as a result of subsidising e-bikes, compared to a control group, giving an indication of the potential public health effect. Self-reported physical activity is often measured for a longer interval (Adams et al., 2014; Craig et al., 2003), due to the notion that physical activity (cycling included) is somewhat more of an occasional activity than daily travels. In transport mode research, one is interested in the amount of cycling in relation to all travels and cycling for exercise and recreation are not included in the measures.

1.3. E-bikes and support schemes

To boost e-bike sales, various forms of support schemes or incentives have been introduced. The political initiative for a subvention scheme is often driven by a concern for the environment (i.e. mode substitution). However, such schemes also have implications for public health, through the potential to increase overall amount of physical activity induced by cycling. Some schemes are purely fiscal, such as in Sweden, where a national scheme refunded 25 per cent of the purchase price of an e-bike (limited to 10 000 SEK ≈ €1,000) (Regeringskansliet, 2017). Other schemes are more targeted and can, for instance, only cover electric cargo bikes, public employees, or businesses, or they can be for bikes to be used as part of work-related travel. Try-out schemes are also common (Cairns et al., 2017). A 6–8-week trial scheme from UK found that 38 per cent of the participants expected to cycle more in the future, and at least 70 per cent said that they would like to have an e-bike available for use in the future and that this would lead them to cycle more (Cairns et al., 2017). There are also some examples from the US (e.g. Boudway, 2021; Herbert, 2022). Subvention schemes often involve some sort of data collection in relation to the payment of a fiscal subvention (e.g. the applicant needs to fill out a survey about transport needs or a travel diary), but data from these schemes are rarely used to evaluate the success of the scheme on the environment and public health.

Studies have indicated that e-bikes seem to have a special appeal to early adopters (Wolf and Seebauer, 2014). Participants who have been recruited to take part in a subvention scheme might differ from early user groups or from people who buy one without any form of support. Hence, learning about the mode-share effects and changes in overall cycling of such schemes is of particular interest, as it is an open question whether the motivation to use the e-bike after purchase is the same among subvention receivers as among "normal" e-bike purchasers (e.g. Fyhri and Sundfør, 2020; Sun et al., 2020). The number of studies on the effect of subsidies on active transportation is limited. Hence, and the concerns that subvention schemes may lead to people only buying e-bikes without subsequently using them and people using the incentives to buy e-bikes mainly for recreational purposes remains unexplored.

1.4. Objectives

The main aim of the present study is to assess the effect of subsidising the purchase of e-bikes on users' daily mobility patterns, and overall bicycle usage. The first research question explores whether a subvention for e-bikes will lead to an increase in the bicycle mode share. The second research question explores whether a subvention will lead to an increase in reported weekly cycling distance.

This is, to our knowledge, the first study to examine the effects of a subvention program for e-bikes on mode share and overall bicycle usage.

1.5. Study context

The context of the study is a subvention program carried out in Oslo, the capital of Norway. The city has a cycling mode share of seven per cent, varying from two per cent in winter to above 20 per cent in summer (Hjorthol et al., 2014). Oslo City Council implemented in 2016 (from 1st of January) a subsidy program for e-bike purchasers whereby the first 1000 applicants were awarded a subsidy of 25 per cent of the cost up to a maximum of 5000 Norwegian kroner (NOK), about €500. Subventions were awarded on a first-come, first-served basis, which in practice meant that applications were not accepted after the last week of January. For receiving the subvention, they were obligated to answer to a baseline survey. The subvention had to be used within the following year (2016), and the only criteria for applying was domicile in Oslo (Norway).

2. Material and methods

2.1. Study design

The present study was carried out as a multi-method study in 2016 with two main data collection procedures: a survey and a mobile app (Sense.DAT). Data collection was carried out over two rounds. At baseline (T0, from February to start of May), respondents answered a survey. They were also asked if they wanted to use an app, to record all their travels for a period. The app data collection started in beginning of April and were completed between 26 May and 3 June. Information and login details was sent by e-mail. The follow-up survey (T1) was carried out from end of May to early June. The setup for the data collection procedure is illustrated in Fig. 1.

The study was approved by the Norwegian Centre for Research data.

2.2. Participants

2.2.1. Survey participants

Respondents were recruited from two sample populations; 1000 individuals who had applied to take part in the e-bike subvention program and; 10 000 individuals from a bike insurance register (Falck registry of bicycle owners) with domiciles in Oslo. Fig. 2 shows a flow diagram of the samples from recruitment to final analysis. The final groups used for analysing survey data are: Receivers (R), Control Receivers (CR) and Control (C).

To see the effect of the measure on bicycle use and transport distribution, we need to know how those who applied for support would have travelled without the measure (i.e. control group). Only those who stated to be interested in buying an e-bike, and who also responded to the follow-up questionnaire at T1 were considered as eligible for a control group. Further, many of the subvention receivers (i.e. 31 per cent) had not bought an e-bike before the study trial period ended (in June). To include these participants in the trial group could therefore dilute the effect of the measure compared to its expected effect in the longer term. We therefore only included the subvention receivers who actually had purchased an e-bike (69 per cent) in the trial group, termed "Receivers" (R). Those who had not yet bought an e-bike constituted an internal control group, termed "Control Receivers" (CR). Table 1 shows background characteristics of the trial and control group participants, at baseline and follow-up.

Both at baseline and at follow-up there was some differences between the groups. In control group CR, there was a higher level of males. In control group C, a higher number had access to a c-bike, were employed and had more previous cycling experience. The average age was significantly higher for the trial group, compared to both control groups. In all groups, approximately 10 per cent had access to an e-bike before the intervention (i.e. at baseline).

2.2.2. App participants

Of the total sample of 3120 participants who answered the survey at T0, a sub sample of 1376 agreed to register their travels using the app. Fig. 3 show a flow diagram of the process from recruitment to final analysis. The final groups used for analysing app data were: Condition 1: e-bike, Condition 2: main control group and Condition 3: prospective buyer.

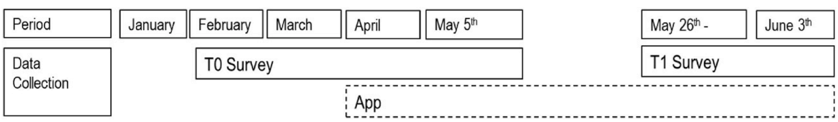

Fig. 1. Study setup.

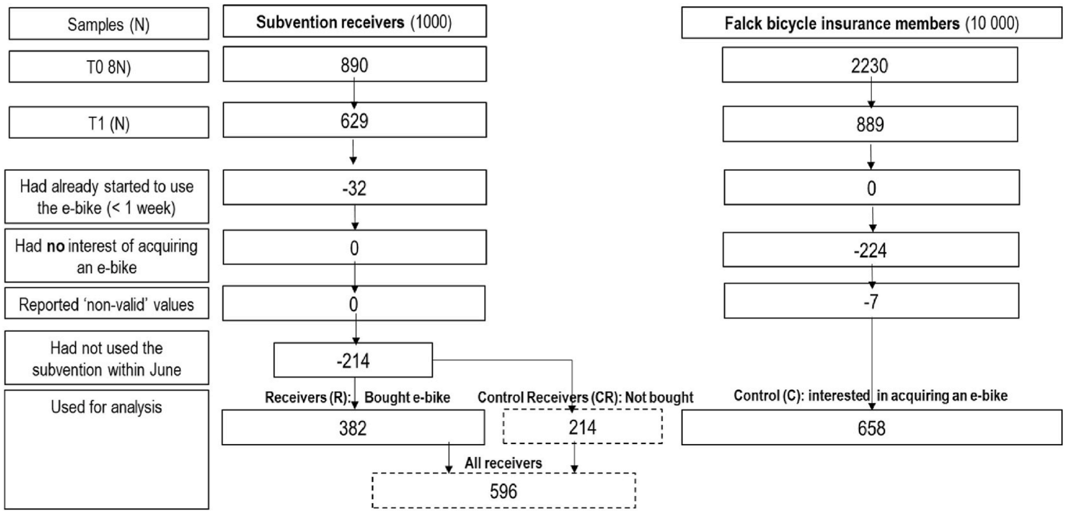

Fig. 2. Flow diagram of the samples from recruitment to final analysis, survey data.

Table 1
Background variables for the trial- and control groups at baseline (T0) and follow-up (T1). Trial group R, Control group CR, and Control group C (per cent and mean values).

Group	T0, baseline			T1, follow-up		
	R	C	CR	R	C	CR
% Male	58	51	64*	56	53	64*
% Employed	82	87***	80	81	88**	80
% Access to car at baseline	89	85	87	88	85	87
% Access to c-bike at baseline	88	98***	89	90	98***	89
% Access to e-bike at baseline	9	11	8	11	13	8
Mean, age	49.2	47.2	46.8	50.0***	45.7	46.8
Mean, cycle months (0–12), last year	4.9	6.5***	5.2	4.9	6.9***	5.2
Mean, response week baseline	13.9***	12.7***	15.2***	13.4***	12.7***	15.2***
N	*669*	*1620*	215	*382*	*658*	214

*p < 0.5 ** p > 0.01 ***p > 0.001.

In total, 717 participants (161 subvention receivers and 556 from Falck) of the 1376 logged into the app. Some dropped out early in the first registration week. After removing those in the control group who were not interested in buying an e-bike (N = 233), we were left with useful app registrations from 386 app users. Of these, 153 were *originally* from the group of subvention receivers and 233 from the Falck bicycle insurance members. Only two per cent of the trips resulted from participants changing status (e-bike/no e-bike) during the period. We divided the trips into three categories: those taken by a person who purchased an e-bike with a subvention (Condition 1: e-bike), those taken by a person from the main control group (Condition 2: main control group) and those taken by a prospective e-bike subvention purchaser (Condition 3: prospective buyer). Hence, any trips taken by a person from Condition 1: e-bike prior to the reported purchase date were coded as belonging to Condition 3: prospective buyer. The sub sample (i.e. app users) had a comparable distribution for gender, age and previous cycling experience as the survey participants.

2.3. *Measures and data preparation*

2.3.1. *Survey instruments and analyses*

Both questionnaires had a one-day travel diary section that captures travel mode share, starting with an explanation of the procedure for how to define a trip, i.e. to travel between two places and associated with a travel purpose. If the participant had travelled outside the home yesterday, subsequent questions required answers about travel mode, trip purpose, distance and time spent, in a matrix. The first matrix had a limit of 6 trips; those who had more than this could go on to another matrix (maximum 12 trips). The travel mode could be on foot or by c-bike, e-bike, moped/motorbike, public transport, or private car. For the purpose of classifying trips, 14 categories of travel were used, borrowed from the Norwegian National Travel Survey (e.g. to work, shopping) (Vågane et al., 2011).

We measured total bicycle usage by two items. "Approximately how far (in kilometres) did you ride your bike during the past week?" The respondents were to distinguish between transport objectives and cycling for exercise.

The trial group were also asked if (and when) they had bought the e-bike. "How far have you come in the process of buying the

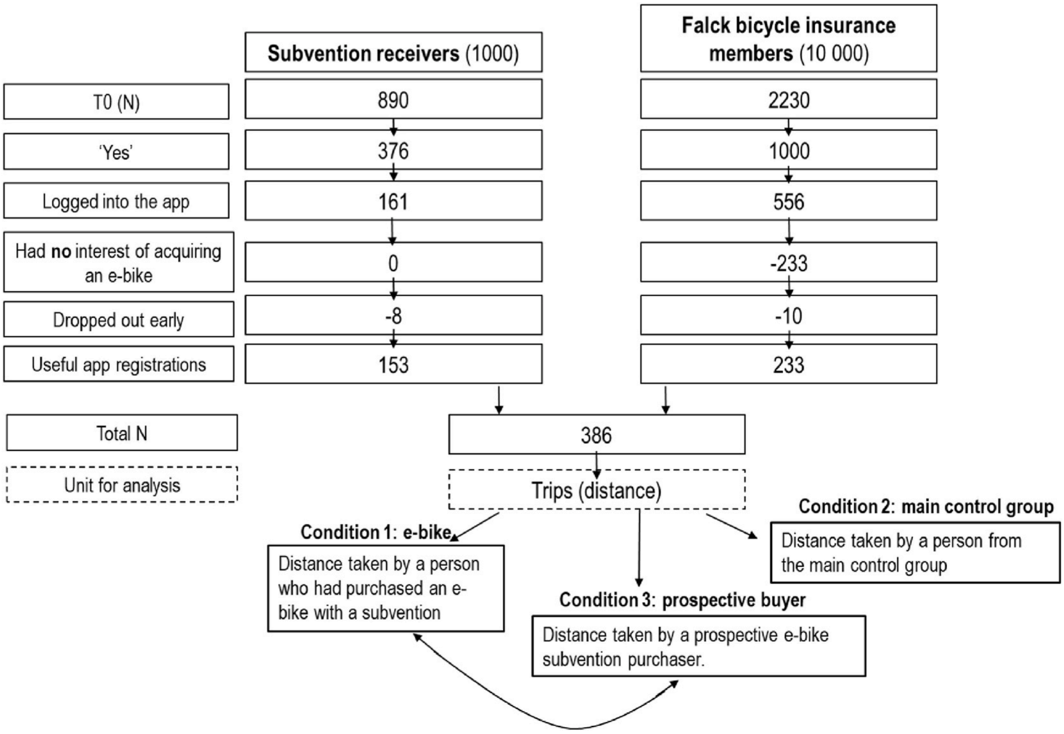

Fig. 3. Flow diagram of app users.

electric bike for which you have received support?" ("not bought one yet", "bought, but not started to use", "bought one and have started to use it"). They further stated on which date they had purchased the e-bike and first put it to use. To match the control group to the trial group they were also posed the question: "If you were to buy a bike today, would you consider an electric bike?" Possible answers were: "Yes, absolutely"; "Yes, maybe"; "I don't think so"; "Don't know" and "No, certainly not".

The data was prepared and analysed using SPSS Statistics 22 and R 4.1.1. The travel diary data were cleaned so that trips exceeding 50 km were excluded. We use km travelled per mode per day for an individual as the main unit of analysis. For weekly cycling distance, we excluded values above 350, as these are most likely reporting errors. For comparisons between groups, we used one-way between-groups analysis of variance (ANOVA) and one-way between-groups analysis of covariance (ANCOVA). In the analysis we adjusted for baseline differences between the groups (i.e. gender, employment status, mean age, baseline values for cycling and response week at baseline).

2.3.2. App data

The app (Sense.DAT, a part of the Mobidot platform[1]) automatically register route choice, transport mode and distance travelled. It is so-called "self-learning", and use a combination of Wi-Fi, GPS and mobile network to decide the position of the phone. Raw data is collected as the participant moves around, and then processed in a server. The positions are projected to an Open Street Map-network. The algorithm for identifying transport mode is based on characteristics with the particular trip (i.e. speed and route choice), alongside making use of the sensors inside the phone (e.g. accelerometer) and real time data from the public transport services. As the app is a commercial software, all algorithms and processing of the data were not available for the researchers. However, Thomas et al. (2018) report an accuracy depending on trip distance ranging between 78 per cent (short trips) and 95 per cent (long trips) for identifying mode. The app identified cycle trips but were not able to distinguish between e-bike and c-bike. The users could correct and change the trips (i.e. mode and purpose). They were not obligated to do so, resulting in some trips still identified with "other" as transport mode.

The app data was collected over a period of two months. The total number of trips recorded was 219 105. After removal of trips taken place outside of the geographical influence area (i.e. not relevant types of trips for our analysis), the total number of trips amounted to 170 294. Trips that had been coded as "other" (no identification of mode) by the app (902 trips covering 7046 km) were removed from the data. Table 2 shows the number of trips per condition and total amount of transport (distance).

For the app data, we do not have a proper before-after test with a control group, but we compare transport mode distribution according to the length of e-bike ownership. Participants provided the date on which they purchased the e-bike and the date on which they began using it. The purchase date was used to split participants into conditions according to ownership status. Hence, the

[1] The app has changed name to *Sesamo* (see https://www.sesamo.nl/).

Table 2
Overview of trips per condition and total distance (km) (N = 386).

	Number of trips	All transport (km)
Condition: e-bike	30 248	178 068
Condition: prospective buyer	61 714	334 238
Condition: main control group	11 837	71 958

conditions do not consist of the same individuals as for the groups in the survey data.

3. Results

3.1. Mode share results from survey

The trial group R had taken an average of 2.5 trips with any transport mode (0.4 bike trips) on the day of registration, whereas the control group (C) had taken 2.9 trips (0.5 bike trips). The number of trips and distance (Table A. 1 and Table A. 2) for each mode of transport at baseline and at follow-up are displayed in the appendix. The trial group had fewer c-cycling kilometres ($p < 0.001$) than control group C at baseline. Beside this, there were no significant difference between the groups at baseline. To assess if the subvention for e-bike influenced mode choice, we calculated the change in transport mode (delta value) by subtracting kilometres per mode at T1 from kilometres per mode at T0. The distance travelled at baseline and the change from baseline to follow-up are displayed in the appendix (Table A. 3 and Table A. 4). Table 3 shows results of the mean difference in change in distance travelled, as well as levels of significance and confidence intervals for all means of transport, between trial group R and control groups C and CR, respectively.

There was a statistically significant effect on e-bike distance ($F (2,1251) = 74.7$, $p > 0.001$) and public transport ($F (2,1251) = 5.52$, $p = 0.004$). The trial group R had a larger increase in e-bike kilometres ($p < 0.001$) than both control groups from T0 to T1, and a larger decrease in public transport kilometres ($p = 0.002$) than of control group CR. The effect sizes, calculated using partial eta2 for change in e-bike kilometres, were 0.11, which are medium effect sizes according to conventions. There was a tendency for the trial group to have a larger reduction (non-significant) in walking and car than both the control groups, and a larger reduction in c-bike compared to control group C.

In order to calculate cycling mode shares, we combined kilometres travelled by e-bike and c-bike and divided it by all kilometres travelled. All groups showed an increase in cycling mode share from T0 to T1. The cycling mode share for the trial group R is 11 per cent at baseline and increases to 41 per cent at T1, whereas the cycling mode share of control group C increases from 22 to 35 per cent, and that of control group CR from 9 to 18 per cent. To assess if a subsidised e-bike influenced the size of these changes, we calculated the change in cycling mode share (delta value) by subtracting the share at T1 from the share at T0. The results are presented in Fig. 4.

The trial group had the largest increase in cycling mode share (30 per cent-points), control group C increased by 13 per cent-points and control group CR had the lowest increase (8 per cent-points). The relative difference between the change among the trial group R and the different control groups can be interpreted as the mode-share effect of acquiring an e-bike. The difference between the groups was statistically significant: $F (2,1251) = 22.92$, $p < 0.001$. Pairwise comparisons showed a significant difference between group R and C of 17 per cent-points ($p < 0.001$) and between group R and CR of 22 per cent-points ($p < 0.001$). The effect size, calculated using eta squared, was 0.04. When adjusting for baseline differences (i.e. gender, employment status, mean age, baseline values for cycling and response week at baseline) between the groups (ANCOVA), the groups were still significantly different: $F (8\ 1249) = 21.88$, $p > 0.001$. Post hoc tests showed a significant difference between trial group R and control group C of 17 per cent-points ($p < 0.001$) and R and CR of 19 per cent points ($p < 0.001$).

3.2. Mode share results from app data

In the following, data are analysed with distance per trip as the unit of measurement (and not respondents as in the previous section). We use data from the 386 participants who in the survey data belonged to either trial group R, the main control group C or control group CR. Any trips taken by a person from trial group R prior to the reported purchase date were coded as belonging to Condition 3: prospective buyer. Fig. 5 shows how the total distance travelled can be distributed for these different user groups (i.e.

Table 3
Mean difference in change in distance travelled, for walking, c-bike, e-bike, car, public transport and in total between the trial group R and control groups C and between R and CR. Includes level of significance (p-value) and 95% CI.

	R–C			R - CR		
	Mean	Sig	95% CI	Mean	Sig	95 %CI
Walking	−0.6	0.147	(-1.4, 0.15)	−0.6	0.290	(-1.6, 0.4)
C-bike	−1.1	0.134	(-2.3, 0.2)	0.4	0.862	(−1.3, 2.07)
E-bike	**4.8**	**<0.001**	(3.8, 5.7)	**5.1**	**<0.001**	(3.7, 6.4)
Public transport	−1.5	0.129	(-3.2, 0.3)	**−3.3**	**0.002**	(-5.7, −0.95)
Car	−1.2	0.521	(-3.8, 1.4)	−0.5	0.948	(-3.9, 2.98)
All transport	0.5	0.938	(-2.7, 3.6)	1.1	0.825	(-3.2, 5.3)

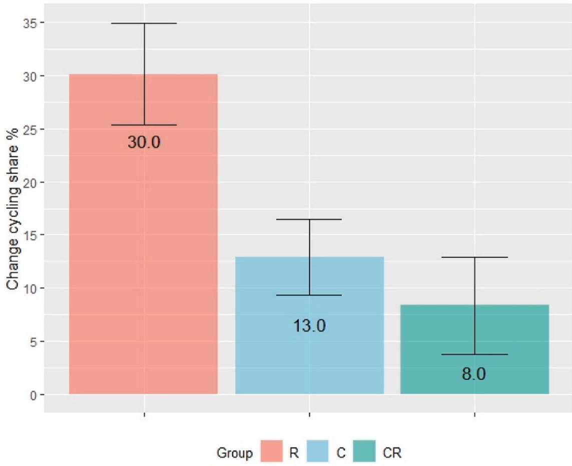

Fig. 4. Change in cycling mode share from baseline to T1 for trial group R (N = 382), control group C (N = 658) and control group CR (N = 214). Percentage points and CI.

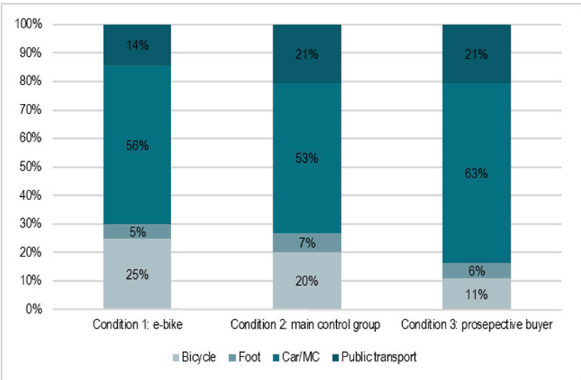

Fig. 5. Mode share (distance) for Condition 1: e-bike (30 248 trips), Condition 2: main control group (61 714 trips) and Condition 3: prospective buyer (11 837 trips). Total N = 386).

conditions).

After having purchased an e-bike, the Condition 1: e-bike cycled for 25 per cent of their travelled distance, compared to Condition 2: main control group (20 per cent), and Condition 3: prospective buyer (11 per cent). By using the differences as a proxy for change, this indicates an increase of cycling of 14 per cent-points, when comparing to trips made by prospective e-bike owners (Condition 3) and 5 per cent-point when comparing to trips made by the main control group (Condition 2). The largest difference in car share is between prospective buyers and those from the main control group, closely followed by those who had purchased an e-bike (Condition 1) used public transport for 14 per cent of their travelled kilometres, compared to 21 per cent in both condition 2 and 3, indicating that some of the higher cycling mode share was due to decreased use of public transport. Due to the large number of trips, all differences between the groups above 2 per cent-points are significant ($p < 0.001$).

3.3. Overall cycling distance from survey data

The baseline values for cycling distance are displayed in the appendix (Table A. 5). At baseline, the trial group R and the CR group reported less cycling for transport ($p < 0.003$) than the control group C. The baseline differences in cycling between the CR and R groups were non-significant. To assess how an e-bike bought with subvention, influenced amount of overall cycling usage, we look at the change in weekly cycling distance, as reported in the survey. We calculated the change in cycling (delta value) by subtracting distance cycled at T1 from distance cycled at T0. The results are displayed in Fig. 6.

All groups increased their weekly cycling from baseline. One-way between-groups ANOVAs with post hoc tests showed a significant difference in kilometres cycled for transport between the groups: $F (2,1251) = 35.94$, $p < 0.001$. The effect size, calculated using eta squared, was 0.05. Pairwise comparisons showed a significant difference between group R and C of 12.6 km ($p < 0.001$) and between group R and CR of 20.2 km ($p < 0.001$). When adjusting for baseline differences between the groups (ANCOVA), the groups were still

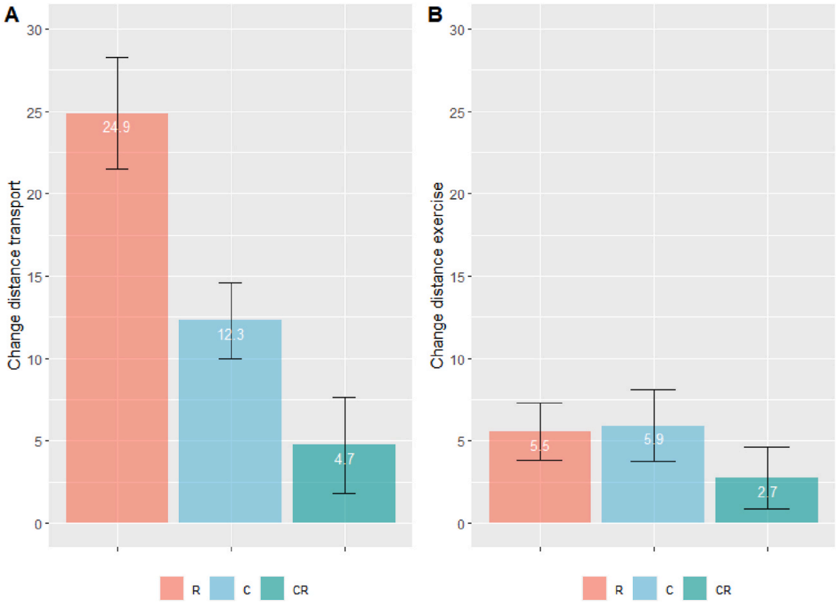

Fig. 6. Reported change (from baseline to follow-up) in distance (mean and 95% CI) cycled for transport and exercise, for the trial group R (N = 382), control group C (N = 658) and control group CR (N = 214).

significantly different: F (8, 1246) = 34.32, $p > 0.001$. Post hoc tests showed a significant difference between trial group R and control group C of 11.6 km ($p < 0.001$) and R and CR of 19.3 km ($p < 0.001$). For cycling as exercise, there was no significant difference between the groups: F (2,1251) = 1.51, p = 0.221.

4. Discussion

The e-bike subvention program was associated with a change in modal split among the trial group, in the form of an increased share of daily travel being conducted on bicycle. To control for the seasonal variation in cycling, we subtract the increase for the control group C (13 per cent) from that of the trial group (30 per cent), resulting in a 17 per cent-point increase in cycling mode share. This change amounted to 22 per cent-points when compared with control group CR (e-bike applicants who had yet not purchased an e-bike). The app data suggests an increase in cycling mode share of 5–14 per cent-points (depending on condition). The program also yielded a significant change in overall cycling distance for the subvention receivers, relative to the control groups, indicating a public health effect, by increased physical activity.

In the present study, we have combined data from a traditional prospective travel behaviour survey (i.e. the same person is measured prior to and post-e-bike acquisition), and a more innovative approach using app data (i.e. cross-sectional). To our knowledge, this is one of few studies using an automated travel behaviour app to report travel behaviour on such a large scale (e.g. Nahmias-Biran et al., 2018). Furthermore, such a comprehensive study has not been conducted previously on the mode-change effects of e-bikes, following a subvention program.

Deciding which of the effect estimates (17 or 22 per cent-point) is most representative is not straightforward. The CR control group had a lower level of bicycle use than the main control group and a smaller increase from T0 to T1. Hence the effect of the e-bike on cycling mode share is larger when we use CR as a control group than when we use C. One could argue that these groups might be more similar to each other, as they both applied for a subvention. At the same time, the CR group might be less eager, given that they had not yet (within our trial period) procured an e-bike. The other control group C was matched to the trial group, by only including people who were interested in buying an e-bike. This matching could still result in the comparison group being a more cycling motivated group than the trial group, which was indicated by their higher level of cycle use at baseline, which again would deflate the estimated effect. Based on this, our verdict is that the estimated effect of the subvention is with most likelihood somewhere between 17 and 22 per cent. This estimate is comparable with previous studies, in which individuals have gained access to an e-bike without subvention (Bourne et al., 2020; Fyhri and Fearnley, 2015; Fyhri and Sundfør, 2020). The concern that subvention schemes may lead to people only buying an e-bike without subsequently using it, seems to be unwarranted. However, this might still be a public perception and policy issue.

The present study differs somewhat from previous studies exploring mode share and cycling activity, as e-bikes where present at baseline, both in the trial and control groups. These were included in the analysis as the objective was to explore the effect of the subvention program, not merely access to, or owing an e-bike (e.g. Bourne et al., 2020; Fyhri and Fearnley, 2015; Fyhri and Sundfør, 2020; Sun et al., 2020). A small number in the main control group had also bought an e-bike at T1. This might have diluted some of the effect of the subvention when comparing the groups. Hence, one would expect to have found somewhat lower effects for the subvention compared to the mentioned previous studies. The fact that a small number in the control group did in fact buy an e-bike, independently of subvention, illustrates that some of those in the trial group would also most likely have bought the e-bike without an incentive.

Still, regardless of challenges with the matching of the control group, we believe that including a comparison group is crucial when evaluating cycling policy measures, such as the effects of subsidising e-bikes on transport behaviour and overall bicycle usage. For making valid assumptions, a properly designed study with the right control group is particularly important in situations where the general patterns of travel behaviour are in flux (such as in the early spring). Norway has a clear seasonal variation (Hjorthol et al., 2014). As a result, one would expect a linear increase in all groups as the cycling season commence.

The comparison of the app and survey data deserves some comment. These data are not completely comparable: The survey results are based on users and measure change (from baseline to follow-up), whereas the app results are based on trips and measure difference between groups at one period of time (i.e. cross-sectional). At T1, the trial group R reported a cycling mode share of 41 per cent in the travel behaviour survey, whereas the app data indicated a cycling mode share of 25 per cent after e-bike purchase (Condition 1). For control group C and Condition 2, these figures were 35 and 20 per cent. This might imply that the survey data exhibit an over-reporting of cycling compared to the app. By contrast to the argumentation that self-reported measures often lead to underreporting of walking and cycling (Handy et al., 2014). A recent study by Storesund Hesjevoll, Fyhri, and Ciccone (2021), found that the app (Sense.DAT) overall recoded substantially more kilometres for cycling than a one-day self-report travel survey (i.e. when comparing the same days). However, these participants were motivated to correct wrongly identified cycling trips in the app. In our study, we note that over-estimation occurs for both the trial and control groups, so this cannot solely be attributed to a response bias in favour of bicycles. One explanation might be that the app recorded data continuously over a longer period, whereas the participants responded to the survey on one day only. At T1, only 13 per cent of the survey responses were from Sunday or Monday, which led to weekend travel being under-represented. Inspection of our data (not displayed) indicates that cycling mode shares are much lower (approximately half) at weekends compared to weekdays; thus, this response-day bias could explain some of the difference we observe. Another explanation is that the app was not able to distinguish between utilitarian travel purposes, meaning that some of the cycling trips might be for recreational purposes.

Neither the survey data nor the app data are likely to capture the true levels of travel behaviour. Hence, just as interesting as the absolute differences in mode shares between the app data and the survey data are the differences in the changes that are recorded. The app data, for its part, does not record a change as nearly all trips were recorded after e-bikes were purchased (only two per cent of the trips resulted from participants changing status during the period). We can, however, use the differences between conditions as a proxy for change. The difference between the cycling mode share for the trial group (i.e. Condition 1) and the control groups (i.e. Condition 2 and 3) were in the range of 5–14 per cent-points based on the app data. In absolute terms, this is less than the 17 to 22 per cent-point difference we calculate when looking at the relative difference from T0 to T1 based on the survey data. However, relative to the baseline cycling mode shares (i.e. the control group C cycled more), these effects are quite comparable, lending credence to the results.

The travel diary intends to capture travelling for utilitarian purposes, so cycling for recreational purposes is not included in our measure of daily travel behaviour. We also look at overall cycling activity (including both transport and recreational purposes) in one week, as a proxy for a public health effect. The results indicate that e-bike purchase led to more cycling for utilitarian purposes, but not for exercise. Still, a more thorough approach is needed for claiming a public health effect, due to the notion that an e-bike requires less time and lower levels of intensity than a c-bike for the same time, distance and topography (Berntsen et al., 2017; Bourne et al., 2018). At the same time, given that the e-bike is found to require physical activity of at least moderate intensity (Bourne et al., 2018), we argue for there to be a public health effect as the trial group cycle significantly more kilometres. In the present study we only included measures of distance, so future studies should also include measures of time (both self-report and objectively measured data), to further explore the difference in time spent cycling, and intensity minutes (i.e. MET-values, see Ainsworth et al. (2000)). With a complete assessment of these measures, including also measures for physical activities in other domains, a more precise estimation can be made for the public health effect of a subvention program for e-bikes.

4.1. Strengths and limitations

An important strength of the present study is the combination of a quite large sample with a prospective research design that allows adjusting for confounding variables (a before-after study with a control group). A further important strength is the combination of self-report measures and objective measurements with app-data, as most studies of e-bike use are conducted with self-report measures (Bourne et al., 2020). The major strength of the app data is that they are not influenced by any response bias or bias related to the survey procedure. The major limitation is technical aspects related to how the app tracks journeys.

Trip purpose was recorded in the travel diary, but the number of participants was too low to make an analysis of travel replacement by trip purpose, and this was in any case outside of the main scope of the current study. Future studies should investigate if certain trip purposes are more likely to be replaced than others. As previously mentioned, the travel diary intended to capture travels for utilitarian purposes (and not for recreational purposes). However, there was one category meant to include the purpose of getting to a place to perform physical activity (i.e. fitness center, park etc.). This category could have been misinterpreted as being a recreational trip by some (i.e. that the trip itself was an exercise). To check for this, we tested if removing these trips influenced our main results but found no difference with what is here reported, indicating that the majority interpreted this in the way intended.

A limitation with this study is related to the timing of T1. Due to the setup of the subvention program, people were given a full year to complete their e-bike purchase. Therefore, some participants had not yet bought an e-bike when T1 took place, whereas others had owned if for as much as five months. We tried to deal with this by only including participants who had purchased an e-bike in our trial sample. It is hard to know what the effects would have been if we had waited for the last remainders to have gone through with their purchase. It can be speculated that these individuals, being less eager, would cycle less, and hence reduce the total effect of the intervention.

Related to this, the study was only designed to look at relatively short-term effects of the subvention program. As noted, some participants had owned it for five months. The data could indicate that the earliest adopters cycled more at T1 than the latecomers, but this could just as well be a result of stronger motivation as of length of ownership. Typically, many people will cycle less or stop cycling completely in the winter months. It would therefore be of interest to study what this habit break would do for the intervention group. To see if the effect remains over time, future research should therefore explore long term (more than a year) effects of such interventions.

Another important limitation of the study is that it is based on self-selection. In order to properly attribute causality, one should use a random selection procedure (i.e. randomised controlled study). There are few examples of truly random experiments regarding e-bikes in the literature (Fyhri and Fearnley, 2015; Söderberg f.k.a. Andersson et al., 2021). Fyhri and Fearnley (2015) (successfully) assigned users at random to the test and control groups, but still found that there were differences between the groups that ended up taking part. This could be attributed to differences in *motivation,* which again resulted in a certain degree of self-selection. Söderberg f.k.a. Andersson et al. (2021) also assigned participants randomly, however this sample was not representative of the general population due to high car share and an overrepresentation of males. Future research should aim for a randomised controlled design and investigate if similar results can be obtained in other contexts, as the observed behaviour changes could be specific of the population studied (cyclists in the capital of Norway).

4.2. Perspectives

Our study has indicated that financial incentives can contribute to a boost in active transport even when the subvention is of a simplistic kind that does not target specific population segments. Indeed, the first-come, first-served basis will yield lower implementation costs versus a project targeting specific population segments. In Norway there are Value-added-tax (VAT) exemptions for electric cars. Based on these findings we argue that this exemption should also include e-bikes, supported by both environmental (i.e. reduced local and global pollution) and public health objectives (i.e. more cycling related physical activity). The study highlights the need for more automated survey instruments that allows for a comprehensive assessment of both physical activity and travel behaviour, in combination.

5. Conclusion

We have reported on a before-after study of an e-bike subvention program implemented by the municipality of Oslo. Grant applicants could obtain a €500 subsidy when purchasing a new e-bike. For subvention receivers participating in our study, we estimated an increase in cycling that was significantly higher than the typical seasonal increase we observed in the control groups. The subvention led to a modal shift (more cycling), and more cycling related physical activity. Hence, promoting e-bikes with fiscal incentives seems to work as intended in a Nordic country with relatively low cycling levels.

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Sample CRediT author statement

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Data availability

Data will be made available on request.

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Appendices.

Table A1
Number of trips (mean and SD) at baseline (T0) for walking, bicycle, e-bike, car public transport and in total for the trial group (R), control group C and control group CR.

	R		C		RC	
	Mean	SD	Mean	SD	Mean	SD
Walking	0.8	1.2	0.9	1.2	0.7	1.0
Bicycle	0.2	0.7	0.6	1.1	0.3	0.8
E-bike	0.2	0.7	0.1	0.4	0.0	0.1
Car	0.9	1.2	0.6	1.1	1.1	1.5
Public transport	0.5	0.9	0.6	1.0	0.5	1.0
All transport	2.5	1.7	2.8	1.6	2.6	1.9
N	382		658		214	

Table A2
Number of trips (mean and SD) at follow-up (T1) for walking, bicycle, e-bike, car public transport and in total for the trial group (R), control group C and control group CR.

	R		C		RC	
	Mean	SD	Mean	SD	Mean	SD
Walking	0.5	0.8	0.8	1.1	0.6	1.0
Bicycle	0.3	0.9	1.0	1.3	0.5	1.0
E-bike	0.9	1.4	0.1	0.6	0.0	0.4
Car	0.6	1.1	0.6	1.1	0.9	1.4
Public transport	0.3	0.7	0.5	0.9	0.5	1.0
All transport	2.6	1.8	3.0	1.7	2.5	1.8
N	382		658		214	

Table A3
Baseline values for distance travelled (mean and SD) for each transport mode and in total on the registration day at baseline (T0) for the trial group (R), control group C and control group CR.

	R		C		CR	
	Mean	SD	Mean	SD	Mean	SD
Walking	1.94	3.51	2.31	3.87	1.84	3.83
Bicycle	1.25	5.18	3.13	6.74	1.71	5.33
E-bike	0.41	2.70	0.41	2.71	0.08	1.23
Public transport	4.45	9.10	5.33	11.33	4.01	10.39
Car	7.86	15.03	6.53	13.96	9.00	16.50
All transport	15.90	16.84	17.71	16.82	16.65	18.93
N	382		658		214	

Table A4
Change (T1-T0) for distance travelled for each transport mode and in total for the trial group (R), control group C and control group CR.

	R		C		RC	
	Mean	SD	Mean	SD	Mean	SD
Walking	−0.80	3.79	−0.20	5.66	−0.16	4.77
C-bike	1.13	7.39	2.17	9.69	0.75	5.89
E-bike	5.27	10.48	0.50	3.94	0.18	1.30
Public transport	−2.88	11.03	−1.42	10.96	0.42	14.91
Car	−2.11	18.52	−0.91	16.45	−1.66	16.64
All transport	0.60	22.76	0.14	20.02	−0.47	21.71
N	382		658		214	

Table A5
Baseline values for weekly cycling for the trial group (R), control group C and control group CR.

	R		C		CR	
	Mean	SD	Mean	SD	Mean	SD
Cycling for Transport	9.47	21.22	16.40	27.63	8.64	20.31
Cycling for Exercise	2.67	15.25	4.24	17.16	3.87	19.85
N	382		658		214	

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