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## Road Pricing: Travel Behavior and Public Support

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# Road Pricing: Travel Behavior and Public Support

Alice Ciccone\*, Cloé Garnache,<sup>†</sup> and Gøril L. Andreassen<sup>‡</sup>

## Abstract

We conduct a large-scale randomized controlled trial to examine the effects of time- and location-specific, distance-based road pricing on travel behavior and driving externalities. Using financial incentives and a smartphone app that automatically tracks participants' travel behavior across different modes, we find that road pricing reduces driving externalities by 5.3%, implying a price elasticity of -0.07 to -0.15 for the external costs of driving. Our findings suggest that drivers of battery-electric vehicles (BEVs) are much less responsive to road pricing than drivers of non-BEVs. Furthermore, we find that providing information on the expected benefits of road pricing enhances public support for such policies, whereas experience with road pricing has little impact.

**JEL codes:** H23, R41, D83, C93, Q54

**Keywords:** Road pricing, public support, electric vehicles, driving externalities, field experiment, information provision

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# 1 Introduction

Driving externalities, such as congestion and pollution, adversely affect public health, the environment, and the economy. For instance, in 2024, the economic costs associated with congestion exceeded \$88 billion across the United States, the United Kingdom, and Germany (Pishue and Kidd, 2025). Such staggering figures underscore the need for effective policies to address these challenges. Cities like Singapore, London, Milan, Stockholm, Bergen, and most recently, New York City have implemented measures such as congestion charges to address driving externalities. Even though such measures have shown to reduce traffic volumes and air pollution to some extent (e.g., Leape, 2006; Eliasson et al., 2009; Börjesson et al., 2012; Gibson and Carnovale, 2015; Agarwal and Koo, 2016), they lack spatial and temporal precision, leading to inefficiencies – such as driving around the cordon (Isaksen and Johansen, 2025) – and potential fairness concerns (Kristoffersson et al., 2017; Eliasson, 2016).

Unlike congestion charges, which one pays when crossing a gantry or cordon, first-best road pricing involves distance-based pricing, where unit prices, e.g., per kilometer, dynamically adjust based on the time- and location-specific levels of driving externalities.<sup>1</sup> As a result, time- and location-specific, distance-based road pricing—hereafter referred to as road pricing—offers an efficient mechanism to reduce driving externalities by aligning road prices with the marginal social costs of travel across different times and locations (Cramton et al., 2018a,b). Despite its theoretical appeal, road pricing is likely to face significant public resistance. Widespread opposition to environmental taxes has been observed globally, with notable examples including France’s “yellow vest” protests against an increase in the carbon tax (Douenne and Fabre, 2022). These instances highlight the importance of ensuring public buy-in for sustainable transport policies (Börjesson et al., 2012).

This paper has two overarching goals: (1) evaluating the effects of time- and location-specific, distance-based road pricing on travel behavior and driving externalities, and (2) investigating factors affecting changes in public support for road pricing policies.

To address the first goal, we conduct a large-scale road pricing RCT in the field, with participants recruited from a representative sample of residents living in the Oslo metropolitan area in Norway. Oslo offers an exceptional setting to investigate the effect of road pricing given its large share of battery-electric vehicles (BEVs) – accounting for

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<sup>1</sup>Advances in GPS and communication technologies have made road pricing feasible (Arnesen et al., 2023), and satellite-based road pricing system can be designed to offer better privacy protection than current road toll solutions (Norwegian Data Protection Authority, 2023).

40% of the vehicle fleet. The study leverages a unique dataset of over 700,000 trips collected through a mobile app that automatically tracks all travel behavior, allowing us to observe detailed travel patterns, including changes in car usage and mode switches. Participants are randomly assigned into a control group, a road pricing treatment group, and a road pricing combined with subsidy for walking and cycling treatment group.<sup>2</sup> The experimental design consists of a four-week observation period and a seven-week treatment period, during which about 3,000 participants receive weekly feedback on their mobility. Participants in the treatment groups also receive feedback on their externalities. Behavior change is incentivized by the possibility to save or earn money by reducing externalities relative to their baseline.

To address the second goal, we investigate the effect of information provision about road pricing’s potential to reduce congestion and pollution, experience with road pricing (with or without subsidy for walking and cycling) in reshaping public support for road pricing policies. Prior to the road pricing field RCT, a pre-experimental survey (23,600) collects socio-economic characteristics and public support towards road pricing. In the post-experimental survey (12,800), participants are randomized into the information treatment – and stratified based on their participation and treatment exposure in the road pricing field experiment. This design allows us to compare the effects of information provision and experience with road pricing on changes in public support before and after these interventions. Additionally, it enables us to examine how these interventions interact, providing insights into whether information and experience may act as complements or substitutes.

Results from the field experiment indicate that the road pricing treatment leads to a 5.3% decrease in driving externalities, with an estimated elasticity of -0.07 to -0.15 for the external costs of driving.<sup>3</sup> These effects come from reductions in kilometers driven (4.1%) and in number of car trips (2.8%), primarily observed during off-peak hours and in urban and suburban areas. The results are mostly driven by non-BEV drivers, who reduce driving externalities by 8.2% and kilometers driven both in peak (8.7%) and

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<sup>2</sup>Given that road pricing functions as a tax on driving, public support may increase when revenues are visibly reinvested in transportation, such as through subsidies for walking and cycling (e.g., [Givoni, 2014](#)). We therefore examine a subsidy for active transport, as walking and cycling are widely promoted for their health and environmental benefits ([World Health Organization, 2022](#)). For instance, the World Health Organization recommends at least 150 minutes of physical activity per week for adults, which is associated with a 10% reduction in mortality risk compared to inactivity ([World Health Organization, 2022](#)).

<sup>3</sup>All reported elasticities likely represent lower bounds, as our random incentive design reduced expected marginal prices by a factor of seven—implying true elasticities could be up to seven times higher.

off-peak hours (6.8%), with an elasticity of -0.15 to -0.26, and in particular from -0.21 to -0.35 during off-peak hours for the external costs of driving. These elasticities are comparable to those found in other studies (e.g., [Hintermann et al., 2024](#)). We further document a mode shift from car towards biking and public transport. In contrast, road pricing has a limited effect on BEV drivers (54% of our sample), who only reduce their driving externalities by 2.4% and kilometers driven by 1.4%, with neither estimate being statistically significant at the 10% level. The estimated elasticities of external costs of driving range from -0.02 to -0.06 (p-value>0.1).

Overall, we find that effects on driving externalities and kilometer driven are not statistically different under the road pricing policy combined with a subsidy for walking and cycling, compared to road pricing alone. However, we document a greater reduction (8 percentage points) in driving externalities and kilometers driven during off-peak hours among non-BEV drivers. Notably, the addition of the subsidy results in a strong and significant shift toward cycling (a 14.8% increase among all participants, and a 24.0% increase among non-BEV drivers in particular), while walking remains largely unchanged.

Results on public support for road pricing show that information provision increases support by approximately 4.4% across all model specifications. Combining road pricing with subsidies for walking and cycling yields a 2.6% increase in support (statistically significant only at the 10% level), while experience with road pricing alone does not significantly affect support.

Our contributions to the literature are threefold. First, we contribute to the small literature on distance-based road pricing.<sup>4</sup> Overall, our study supports findings from experiments conducted in other settings, showing that distance-based road pricing effectively reduces externalities from driving ([Nielsen, 2004](#); [Martin and Thornton, 2021](#); [Hintermann et al., 2024](#)). However, it differs in several important dimensions. Studies often focus only on car trips –and thus cannot observe mode switch– and/or use road prices that are not time- and location-specific Pigouvian road prices (e.g., [Nielsen, 2004](#); [Martin and Thornton, 2021](#)). In contrast, we track all trips, across all transport modes to investigate the effect of time- and location-specific Pigouvian road prices for passen-

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<sup>4</sup>A large, non-experimental literature shows that congestion charges implemented in cities such as Gothenburg, London, Milan, Stockholm, and Singapore reduce traffic volumes and/or pollution levels ([Olszewski and Xie, 2005](#); [Leape, 2006](#); [Eliasson et al., 2009](#); [Börjesson et al., 2012](#); [Gibson and Carnovale, 2015](#); [Agarwal and Koo, 2016](#); [Börjesson and Kristoffersson, 2018](#)). In contrast, studying the peak-hour traffic congestion equilibrium from an experiment in Bangalore, India, [Kreindler \(2024\)](#) finds a small reduction in travel times and small commuter welfare gains. While some of these studies describe congestion charges under the broader term ‘road pricing,’ they do not analyze distance-based road pricing.

ger vehicles on travel behavior. The closest to our study is [Hintermann et al. \(2024\)](#) who study the effect of Pigouvian pricing on all transport modes combined on household travel behavior in Switzerland. They find a 4.5% reduction in the external costs of transport due to a mode shift away from driving and, to a lesser extent, due to a shift in departure times. In contrast, our study investigates road pricing for passenger vehicles as driving accounts for the largest share of transport-related externalities.

Second, this is the first paper to implement a large-scale road pricing RCT with a large share of BEV drivers (54%). We are not aware of any study investigating how BEV drivers respond to road pricing. Our study fills this gap by documenting evidence that BEV drivers reduce driving externalities to a lesser degree than non-BEV drivers. This limited response may be partly attributed to BEV drivers facing lower Pigouvian road prices, having higher income levels, and exhibiting differences in their baseline travel behavior. For instance, BEVs drivers are more likely to commute to work by car and to drive during peak hours, compared to non-BEV drivers. Yet, across all vehicle types, we observe minimal changes in work-related trips, with all adjustments occurring in non-work-related trips. These findings are consistent with [Gillingham and Munk-Nielsen \(2019\)](#) who show that work-related car trips tend to be relatively inelastic in the short term. This is because work-related trips are typically homogeneous and routine, making the decision to commute to work by car largely binary.

Our third contribution is to the literature investigating the factors influencing public support for policies. For example, [Dechezleprêtre et al. \(2025\)](#) emphasize the potential of information treatment to shape policy support and belief revision across countries and cultural contexts. Furthermore, empirical studies find that providing information on the expected benefits of congestion pricing can enhance public support (e.g., [Baranzini et al., 2021](#); [Arlinghaus et al., 2024](#)). Another strand of this literature explores the impact of experience with a policy on belief revision and subsequent changes in public support ([Schuitema et al., 2010](#); [Börjesson et al., 2012](#); [Andersson and Nässén, 2016](#)). This study contributes to both strands of literature by implementing a unified framework to investigate how information provision and direct experience with road pricing—albeit in the absence of general equilibrium effects due to the limited size of our pilot—influence public support, both individually and in combination.

The next section describes the experimental design. Section 3 presents the data. Section 4 discusses the empirical frameworks. Section 5 shows the results. Section 6 discusses and interprets our key findings. Last, Section 7 concludes.

## 2 Experimental design

### 2.1 Study area

The study area encompasses Oslo, the capital of Norway, along with its surrounding municipalities, covering a total population of 1.6 million.<sup>5</sup> Congestion remains a significant challenge in the Greater Oslo area, particularly during peak hours. According to the 2024 TomTom Traffic Index, the Oslo metropolitan area ranks as the 328th most congested metropolitan area out of 500 worldwide. While it experiences less congestion than the Los Angeles, Miami, Chicago, Rio de Janeiro, and London metropolitan areas, it is more congested than Stockholm, San Antonio, and Phoenix (TomTom, 2024).

Two key characteristics of the Oslo metropolitan area relevant to our study are its extensive road toll system and the high prevalence of electric vehicles (EVs). Oslo introduced a comprehensive road toll system in 1990, originally designed to finance infrastructure projects.<sup>6</sup> Over time, toll rates have increased slightly to incorporate congestion and pollution externalities, though to a limited extent. The toll system applies differentiated pricing by vehicle type, with higher-emission vehicles facing higher tolls. While EVs have historically benefited from toll exemptions, in 2024 they pay fees that are still more than 50% lower than those paid by gasoline vehicles. Meanwhile, hybrid and plug-in hybrid vehicles are subject to the same toll rates as gasoline vehicles. Accordingly, throughout this study, we differentiate between battery-electric vehicles (BEVs) and all other vehicle types, referred to as non-BEVs. Toll pricing in Oslo is also time-differentiated, with rates increasing during peak hours by 18% for gasoline and plug-in hybrid vehicles and 19% for BEVs.<sup>7</sup> However, these increases remain significantly lower than the estimated external costs of congestion during peak times (see Section 2.4). This is because Oslo’s road tolls are not primarily designed to mitigate peak-hour congestion or to efficiently internalize the external costs of driving.

Norway is a global leader in the adoption of battery-electric vehicles (BEVs). In

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<sup>5</sup>The municipalities comprising the Greater Oslo area include: Oslo, Bærum, Asker, Lillestrøm, Nordre Follo, Ullensaker, Nesodden, Frogn, Vestby, Ås, Enebakk, Lørenskog, Rælingen, Aurskog-Høland, Nes, Gjerdrum, Nittedal, Lunner, Jevnaker, Nannestad, Eidsvoll, Hurdal, Drammen, Lier, Øvre Eiker, Asker, and Holmestrand.

<sup>6</sup>Road tolls are often implemented to recover infrastructure investments and maintenance costs rather than to fully internalize the external costs of transport (Parry et al., 2007). This applies also in Norway (Halse et al., 2025)

<sup>7</sup>These figures refer to 2024 and are based on prices from AutoPass, an automated toll collection system that offers a 20% discount when a vehicle is equipped with a toll tag—a system used by nearly all drivers.

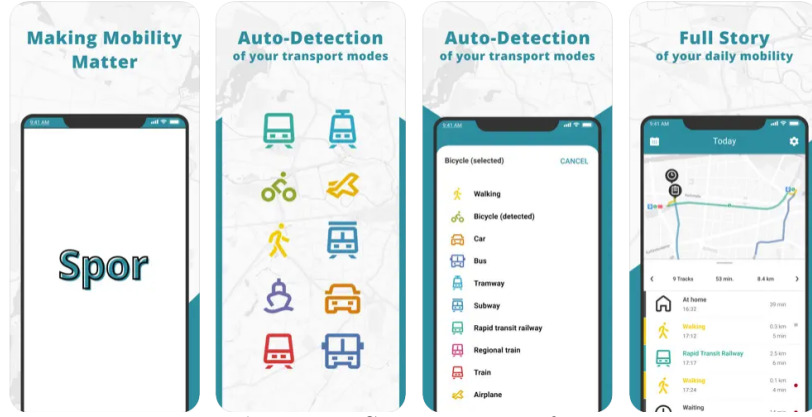


Figure 1 Spor app interface.

2024, more than 88% of new car sales were electric, and BEVs made up 29% of the total vehicle fleet nationwide. In Oslo and the surrounding areas, the share of BEVs in the overall fleet is even higher, reaching 40% ([Norwegian Public Roads Administration, 2025](#)).

## 2.2 Spor app

We partnered with the company Motiontag to customize a mobility tracking app for our experiment. The resulting application, Spor, automatically records trips using GPS and sensors on participants' mobile devices.<sup>8</sup> Using machine learning and advanced algorithms, the app detects participants' transport modes, achieving a 97% mode recognition accuracy according to Motiontag. Trips and transport modes are automatically recorded without requiring participant input, as the app operates in the background.<sup>9</sup> Users can review and correct their recorded trips if needed. Additionally, participants were explicitly informed that fraudulent behavior would result in disqualification and forfeiture of rewards (see Appendix C-3 for an assessment of cheating).

<sup>8</sup>This app is similar to the one used by [Hintermann et al. \(2024\)](#). It is compatible with both iPhone and Android devices. For more details, see [www.toi.no/spor](http://www.toi.no/spor). Notably, 75% of survey respondents reported no significant battery consumption, and only 91% found the app easy to use, underscoring its user-friendly design.

<sup>9</sup>A notable exception is e-scooters, which are automatically classified as bicycles. To improve data accuracy, participants were asked to manually record any e-scooter trips.

## 2.3 Recruitment and Timeline

### 2.3.1 Pre-experimental survey

We invited a representative sample of approximately 200,000 individuals residing in the Greater Oslo area to participate in a study on transport habits and policies. This sample was randomly selected from the population registry by the Norwegian Tax Agency. Recruitment was conducted via email, with two follow-up reminders, between April 9 and May 8, 2024. Importantly, to avoid attracting a sample biased by strong opinions on road pricing, the invitation email did not mention road pricing. (The full recruitment email is provided in Appendix D.) Upon receiving the invitation, individuals were asked to complete a pre-experimental survey designed to gather information on vehicle access, travel habits, socio-demographic characteristics, and policy attitudes. Specifically, the survey collected data on whether participants had access to a car and a bicycle, the number of cars in the household (and in case of multiple cars, which one they used most frequently), and the type of fuel used. It also inquired about travel habits, education, income, employment status, and household composition, including the number of children. Furthermore, the survey assessed attitudes towards transportation and environmental policies, including road tolls and road pricing. A total of 23,571 individuals completed the pre-experimental survey between April 9 and May 8, 2024.

### 2.3.2 Road pricing field experiment

Of the 23,571 people who responded to the pre-experimental survey, 58% (13,635) satisfied our criteria for participating in the RCT and were invited to download the Spor mobility tracking app upon finishing the pre-experimental survey.<sup>10</sup> Of these, 46% agreed to download the app (6,249). Participants who agreed to download the app were incentivized to use it for the entire duration of the experiment to remain eligible for a lottery with a NOK 9,000 prize (approximately USD 800). A total of 3,399 individuals downloaded the app and recorded at least one trip, resulting in a dataset of about one million tracks and more than 700,000 trips, collected between April 9 and July 1, 2024. Note that trips consist of a single track or a series of tracks, provided that each subsequent track

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<sup>10</sup>The criteria are the following: being between 18 and 65 years old, reporting traveling by car on average at least two weekdays per week, owning an iPhone or Android smartphone to install the tracking app. The study focuses on business days as weekends and public holidays are more likely to include long trips outside the study area as Norwegians tend to drive to their cabins on weekends. Furthermore, we exclude respondents who work as professional drivers, on oil platforms, or who hold a disability card to ensure that participants have relatively free mode choice.



begins within 20 minutes of the previous track’s end. This period spans approximately 11 weeks, including 54 workdays, after excluding weekends and public holidays.

The road pricing RCT includes an observation period of approximately four weeks, beginning the day after a participant downloads the tracking app and continuing until May 8. Participants who were still actively recording trips by this date were randomly assigned to one of three groups (discussed in Section 2.5). During the seven-week treatment period from May 13 to June 28, participants in all three groups received weekly feedback, every Monday morning, summarizing their travel behavior from the previous week. A total of 2,943 participants received at least the first feedback, with an average of 36.4 days of recorded trips per person. After excluding individuals who downloaded the app after May 8 and therefore lacked an observation period, the main sample consists of 2,846 participants. Those who joined late and used the app for fewer than five days during the pre-experimental period, but still downloaded the app before May 8, were assigned a synthetic budget, calculated as the average budget of participants with similar driving habits (see Section 2.5.2 for details).

### **2.3.3 Midway survey**

The midway survey, distributed via email on May 9, 2024, assessed participants’ understanding of our road pricing experiment by asking them to calculate the total road price for a specific trip that involved driving through different areas during both peak and off-peak hours. A total of 1,232 individuals responded to the survey. Across the four test questions, the proportion of correct responses ranged from 96% to 99%, with an average of 97%, suggesting a good comprehension of the road pricing design among respondents.

### **2.3.4 Post-experimental survey and information treatment**

In the post-experimental survey, participants who completed the pre-experimental survey were randomly assigned to an information treatment experiment and were asked once again to state their attitudes toward road pricing (see Section 5.5 for details). A total of 12,813 individuals completed the survey between June 29 and July 11, 2024.

## **2.4 Externalities related to driving and active transport**

We follow a report from the Institute of Transport Economics commissioned by the Norwegian transport agencies to identify the externalities associated with driving in Norway



(Rødseth et al., 2019). These externalities include congestion, local air pollution, greenhouse gas emissions, traffic accident risk, noise, and road wear.<sup>11</sup> These externalities vary depending on vehicle type, location, and time of travel, with detailed values presented in Table A-1 and Figure A-1. We note that our road pricing experiment does not implement dynamically adjusting prices across space and time as proposed in Cramton et al. (2018b).<sup>12</sup> Instead, we apply fixed, distance-based prices that reflect average Pigouvian costs, differentiated by vehicle type, location, and time of travel—consistent with the approach used in Hintermann et al. (2024). Congestion represents the largest externality in urban areas during peak hours, with an estimated cost of 2.92 NOK/km across all vehicle types (or \$0.27/km using the exchange rate of 1 NOK = 0.09118 USD on April 1, 2024). Urban, suburban, and rural classifications are based on population density, as depicted in Figure 2.<sup>13</sup> Outside peak hours in urban and suburban areas, the primary external costs from non-BEVs stem from air pollution, noise, and CO<sub>2</sub> emissions. In rural areas, CO<sub>2</sub> emissions alone account for nearly half of the total external costs. The total external costs of driving, categorized by vehicle type, time, and location, are presented in Table 1, panel A.

According to guidelines for impact assessments from the Norwegian Public Roads Administration, active transport, defined as walking and cycling, generates positive externalities because of avoided hospital stays and sick days (Norwegian Public Roads Administration, 2021).<sup>14</sup> The detailed external benefits associated with walking and cycling are presented in Table A-2. We set the subsidies for walking and cycling equal to their total external benefits, which are summarized in Table 1, panel B.

## 2.5 Road pricing treatments implementation

Participants were randomly assigned to one of three treatment arms, with 928 participants in the Control group (C), 965 in the Road Pricing group (RP), and 953 in the

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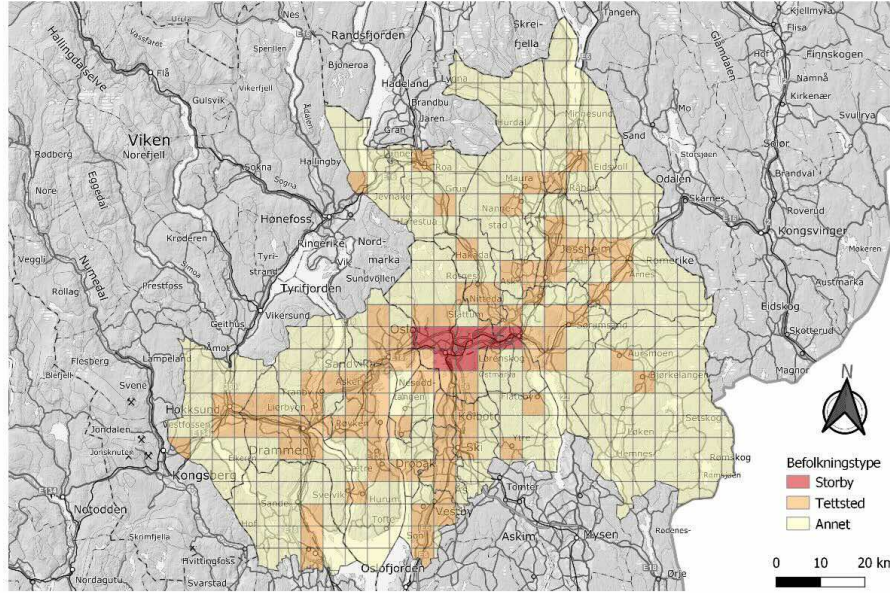
<sup>11</sup>Estimates for congestion pricing are based on Steinsland et al. (2022) and further supplemented by Steinsland (2024). For CO<sub>2</sub> pricing, we rely on Wangsness and Rosendahl (2022), whose methodology is extended in Rosendahl and Wangsness (2024) to provide recommended CO<sub>2</sub> price levels for investment appraisals aligned with the EU’s 2050 net-zero emissions target, as adopted by the European Investment Bank.

<sup>12</sup>This was due to limitations in technological infrastructure for real-time pricing, as well as the practical advantage that static pricing is generally easier for participants to understand and is preferred by many, as shown in Baranzini et al. (2021).

<sup>13</sup>Areas are classified as urban ( $\geq 50,000$  inhabitants/km<sup>2</sup>), suburban (2,500–49,999 inhabitants/km<sup>2</sup>), and rural ( $< 2,500$  inhabitants/km<sup>2</sup>).

<sup>14</sup>One difference with Hintermann et al. (2024) is that the Norwegian government does not include external costs related to increase in cycling accident risk if more people start to bike, see for instance Municipality of Oslo (2014).

**Figure 2** Map of the urban, suburban, and rural areas in our study.



**Table 1** Road prices and subsidies for active transport

Panel A: Road prices (NOK/km)				
Where	When	Electric car	Gasoline car incl. plug-in hybrids	Diesel car
Urban	Peak	3.80	4.10	5.30
	Off-peak	0.80	1.20	1.50
Suburban	Peak	1.20	1.50	1.60
	Off-peak	0.50	0.90	0.90
Rural	All-day	0.20	0.50	0.50
Panel B: Subsidies (NOK/minute)				
Cycling			1	
Walking			1.30	

Road Pricing and Subsidy for active transport group (RPS).<sup>15</sup> Instructions sent to each group are shown in Appendix D.

### 2.5.1 Treatment groups

Participants in the RP and RPS groups received detailed instructions via email on May 13, corresponding to their assigned group. Participants in the RP group were introduced to the concept of road pricing and informed about the monetary incentives in the study. Specifically, they could “save” money by reducing the external costs of their car travel relative to their weekly individual budget. This budget was determined based on each participant’s own weekly average driving externalities generated during the observation period, applying the road prices reported in Table 1, panel A and adjusted upward by 5% to account for minor deviations from the baseline. Weekly savings were calculated as the difference between the budget and the actual external costs incurred. Importantly, negative savings were capped at zero, ensuring that participants never had to ‘pay’ for road pricing out of pocket. The potential impact of receiving zero payment due to exceeding the budget is discussed in Section 5.3, while the effect of not implementing road pricing as a tax on travel behavior is discussed in Section 6.

Participants in the RPS group received the same information about road pricing as those in the RP group but were additionally informed about the opportunity to earn monetary rewards for increased physical activity, specifically walking and cycling. Rewards for active transport were based on the minutes of activity exceeding each participant’s own weekly average baseline, as established during the observation period, with subsidies specified in Table 1, panel B. Only active trips exceeding 10 minutes qualified for rewards, and weekly earnings from active transport were capped at NOK 300. Notably, we did not observe an increase in the number of participants reaching the 300 NOK cap after the RPS treatment was introduced, suggesting that cheating in this dimension was not prevalent. This issue is explored further in Section 5.3.

*Restrictions:* Participants were informed that the study focused on weekday transport behavior within the Greater Oslo area (as illustrated in Figure 2) and excluded weekends and public holidays. Travel occurring outside the study area, including domestic and international, was not considered.

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<sup>15</sup>Our power analysis reported sample size of 1,100 per treatment group in order to estimate a reduction of 5% in driving external cost at the 95% level of accuracy. We failed to reach this sample size due to time constraints in the recruitment.

### 2.5.2 Synthetic budget

Several participants (915) downloaded the Spor mobility tracking app late relative to the start of the treatment on May 13, resulting in fewer than five weekdays of observation. To ensure these participants had a baseline budget, they were assigned a “synthetic budget” based on the average budget of participants with similar driving habits, as reported in the pre-experimental survey. Specifically, participants were matched based on their self-reported number of weekdays driven per week. For instance, a participant who joined late and who stated driving three weekdays per week in the pre-experimental survey was assigned the average budget of all participants who had at least five weekdays of observation during the pre-treatment period and had also reported driving three weekdays per week in the pre-experimental survey.

### 2.5.3 Weekly feedback

All participants, including those in the control group, received weekly feedback by email summarizing their travel patterns from the previous week.<sup>16</sup> Participants in the RP and RPS treatment groups received additional information on the external costs generated by their car travel and the savings achieved through behavioral changes. Additionally, participants in the RPS group were provided with information on externalities from active transport and the savings earned from increased walking and cycling, relative to their baseline. Participants in the RP and RPS groups also received behavioral prompts to increase their savings, such as reducing car travel, using public transport, walking and cycling more frequently, working more from home, consolidating errands to minimize trips, and adjusting travel times by driving outside peak hours (06:30-09:00, 15:00-17:00) or avoiding urban areas when possible. Appendix D.5 provides examples of the weekly feedback distributed to the control and treatment groups.

### 2.5.4 Incentives

Participants were incentivized at multiple stages of the experiment. First, completion of the pre-experimental survey was encouraged through entry into a lottery with a prize of NOK 3,000 (approximately \$290). Participants who agreed to download the mobility tracking app were then incentivized to use it throughout the entire study period to remain eligible for a separate lottery with a NOK 9,000 prize (approximately \$860). Respondents to the mid- and post-experimental surveys were further incentivized with the chance to

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<sup>16</sup>The code used for the weekly feedback was developed by [Weber \(2025\)](#).

win lottery prizes of NOK 1,000 and NOK 5,000, respectively (approximately \$100 and \$480).

In addition to these incentives, participants in the treatment groups could earn monetary rewards based on their travel behavior. They were informed that one of the seven weekly feedback periods would be randomly selected, and they would receive a payout corresponding to their earnings in that specific week. Participants could choose to receive their reward as a gift card, convert it into entries for a NOK 9,000 lottery, or donate the amount to a charity of their choice.

## 2.6 Public support and Information treatment implementation

As part of the analysis on public support for road pricing, participants were randomly assigned to the information treatment, with stratification based on their road pricing treatment group: Control (C), Road Pricing (RP), or Road Pricing with Subsidy for active transport (RPS). The purpose of the information treatment was to highlight the broader benefits of a real-world road pricing policy—benefits that would not fully emerge in a small-scale pilot such as ours. For example, participants were reminded that the introduction of congestion charges in cities like London, Milan, and Stockholm resulted in traffic reductions of 20% to 30%. In addition, participants in the RP and RPS groups were informed that, because only a limited number of individuals were subject to road pricing in the experiment, they could not fully experience the broader general equilibrium effects typically associated with large-scale implementation. These include, for instance, shifts in travel demand across modes and time periods. The complete information treatment text is provided in Appendix [D.6](#).

## 3 Data

### 3.1 Road pricing experiment

The app data include detailed information on trip itineraries, start and end times, durations, and transport mode for each segment of a trip. Using these trip records, we calculate the kilometers driven by transport mode across urban, suburban, and rural areas, as well as during peak and off-peak hours. Peak hours are defined as 06:30–09:00 and 15:00–17:00, consistent with Oslo’s road toll system.<sup>17</sup> Throughout the study, we

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<sup>17</sup>For simplicity, a trip is classified as occurring during peak hours if its start time falls within the peak period.

aggregate trip data at the person-day level. Details on the data cleaning procedure for individual trips are provided in Appendix A.3. The trip data are then merged with information from the pre-, midway-, and post-experimental surveys.

Descriptive statistics for the control (C), RP, and RPS treatment groups in both the pre- and post-treatment periods are presented in Table 2. During the pre-treatment period, the daily external costs of driving (Car EC) range from 38.6 to 40.9 NOK, while the external benefits of active transport (Active EB) range from 39.8 to 41.4 NOK. As a result, the total daily external costs ( $\text{Tot EC} = \text{Car EC} - \text{Active EB}$ ) vary between -2.7 and 0.9 NOK.

In the pre-treatment period, participants drive an average of 32.9 to 35.3 km per day, with approximately 13 km driven during peak hours and 22 km during off-peak hours. BEV drivers and non-BEV drivers drive similar distances, averaging around 34 km per day<sup>18</sup>. However, BEV drivers differ from non-BEV drivers in key dimensions (see Table A-10). Specifically, BEV drivers drive more frequently during peak hours and in urban areas compared to non-BEV drivers. Additionally, BEV drivers are more likely to be in the high-income group, with a 13 percentage point higher share of high-income individuals compared to non-BEV drivers. Regarding active transport, participants walk an average of 33 minutes per day, bike for 6 minutes, and use public transport (PT) for 15 minutes. Walking is widespread, with 69% of participants walking every day during the pre-treatment period and only 1% walking on fewer than 50% of the days. By contrast, biking is far less common, with 87% of participants biking on fewer than 50% of the days, and only 3% cycling daily.

The travel behavior of our participants is comparable to data from the National Transport Survey, which indicates that a typical resident of the Greater Oslo area who drives at least once per week travels an average of 37.6 km per day by car, 3 minutes by bike, 15 minutes walking, and 14 minutes by public transport (see Table A-5).

Additional descriptive statistics are provided in Appendix A.4. In particular, balance Table A-5 shows that travel behavior and socioeconomic characteristics that may influence the response to road pricing are well balanced between the treatment and control groups. This supports the validity of the randomization process across the sample. Furthermore, the distribution of external costs and travel behavior by income group, illustrated in Figures A-2 and A-2, reveals that, conditional on stating driving at least two weekday per week in the pre-experimental survey, low-income participants gener-

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<sup>18</sup>BEV drivers are identified based on self-reported data from the pre-experimental survey. Participants who report access to more than one vehicle are classified as BEV drivers only if they indicate that a BEV is the vehicle they use most frequently.

**Table 2** Summary statistics of daily travel behavior using the mobility tracking app Spor for participants randomized into the control group and two treatment groups (RP and RPS).

	Pre-treatment			Post-treatment		
	Control (1)	RP (2)	RPS (3)	Control (4)	RP (5)	RPS (6)
Total EC	-2.7 (52.0)	0.9 (53.0)	0.8 (49.8)	-3.8 (48.3)	-3.3 (48.5)	-2.9 (48.6)
Car EC	38.6 (37.2)	40.9 (39.1)	40.6 (36.9)	38.8 (34.2)	38.7 (35.1)	39.6 (34.9)
Active EB	41.4 (28.1)	40.0 (27.0)	39.8 (26.7)	42.6 (26.7)	42.1 (26.2)	42.5 (27.5)
Km car	32.9 (29.7)	34.8 (29.2)	35.3 (29.9)	33.6 (27.3)	34.3 (26.5)	35.1 (27.9)
Km car peak	12.4 (14.6)	13.0 (14.9)	13.0 (14.6)	12.1 (12.5)	12.2 (12.6)	12.8 (13.4)
Km car non-peak	20.5 (20.6)	21.8 (21.0)	22.3 (21.6)	21.4 (18.6)	22.0 (18.7)	22.2 (18.9)
Km car urban	8.6 (11.3)	9.2 (11.5)	9.1 (11.8)	8.9 (11.0)	8.9 (10.7)	9.0 (11.4)
Km car rural	5.0 (8.9)	5.5 (9.4)	5.8 (9.8)	5.2 (8.3)	5.7 (9.0)	5.9 (8.9)
Min PT	13.2 (18.8)	14.8 (21.8)	15.7 (24.1)	14.2 (18.6)	15.0 (19.3)	15.8 (20.7)
Min bike	6.1 (14.3)	5.6 (13.2)	5.4 (13.4)	6.6 (13.6)	6.8 (13.2)	6.9 (14.8)
Min walk	33.7 (22.2)	33.1 (22.0)	33.1 (21.9)	34.3 (20.2)	33.6 (19.9)	33.9 (20.3)
Share car	0.6 (0.3)	0.6 (0.3)	0.6 (0.3)	0.6 (0.3)	0.6 (0.3)	0.6 (0.3)
Share bike	0.1 (0.2)	0.1 (0.2)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.2)
Share walk	0.1 (0.2)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)	0.1 (0.1)
Share PT	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)
# trips	4.3 (1.3)	4.3 (1.3)	4.3 (1.4)	4.5 (1.2)	4.5 (1.2)	4.5 (1.2)
# car trips	3.0 (1.8)	3.0 (1.7)	3.1 (1.9)	2.9 (1.7)	2.9 (1.6)	3.0 (1.7)
Km BEV	34.6 (31.0)	34.3 (26.8)	36.1 (29.5)	34.3 (27.3)	33.8 (24.2)	36.9 (27.7)
Km non-BEV	31.0 (28.1)	35.4 (32.0)	34.4 (30.4)	32.8 (27.3)	34.9 (29.1)	33.0 (27.9)
Observations	928	965	953	928	965	953
BEV observations	491	533	511	491	533	511
Non-BEV observations	437	432	442	437	432	442

**Notes:** All travel variables are per day. Km BEV (km non-BEV) are calculated conditional on participants owning an BEV (non-BEV). RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, PT: public transport. Standard deviation in parentheses. Note that car trips denote here single car tracks, where several car tracks may be contained in a single trip, provided that each subsequent track begins within 20 minutes of the previous track's end.



ate the highest externalities from driving, followed by high-income participants, with middle-income participants generating the least. This pattern is driven by low-income participants traveling the most kilometers, both during peak and off-peak hours, followed by high-income participants, and then middle-income participants. When considering kilometers driven by non-BEVs, the same ranking holds: low-income participants drive the most, followed by high-income and then middle-income participants. However, this ranking is reversed when examining the external benefits of active transport. Middle-income participants generate the highest benefits, followed by high-income participants, while low-income participants generate the least. Figure A-3 reveals a similar spatial pattern when analyzing participants' residential zip codes: areas with both the lowest and highest income levels tend to be associated with the highest average kilometers driven.

*Sample representativeness:* Our sample was drawn from a representative population of the Greater Oslo area by the Norwegian Tax Administration. Among those who completed the pre-survey, the distribution of age, gender, number of children, and income closely reflects that of the broader population in the study area (see Table A-9).<sup>19</sup> However, our pre-survey sample tends to be more educated, more likely to be employed, and less likely to be retired than the Greater Oslo population. Compared to the National travel survey, participants in our RCT sample walk more, drive less, and take more trips than the surveyed population (Table A-8). These differences may be due to different data collection methods –i.e., survey data compared to app data– and because the National travel survey focuses on respondents driving at least once per week, while eligibility in the RCT requires participants to drive at least two weekdays per week.

To assess the generalizability of our findings, we compare individuals who expressed interest in participating in the field experiment and agreed to download the app with those who chose not to participate.<sup>20</sup> As shown in Table A-6, while differences exist across several variables, they are modest. Interested individuals tend to be slightly younger, more educated, more likely to be employed, have lower income, more children, fewer cars, drive less, be less negative about road tolls, trust government less, care more about the environment, view air pollution as a problem, support policy action, and value privacy less.

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<sup>19</sup>Note that population income data is only available for Oslo and not for the other municipalities included in our study.

<sup>20</sup>In the survey, participants were informed that the study offered an opportunity to learn more about their transport habits, contribute to research, and enter prize draws. A brief explanation of the app and the study's functionality was provided. Importantly, neither road pricing nor road tolls were mentioned explicitly.



We also compare those who intended to join the study but did not with those who actually participated (Table A-7). Although differences are again small, participants tend to be younger, more educated, more likely to be employed, have higher income, drive less (especially to work), have more flexible schedules, be less negative about road tolls, trust government less, and show greater environmental concerns.

Overall, our RCT sample appears to broadly reflect the region’s driving population, with the exception of some differences in socioeconomic characteristics and travel behavior. Furthermore, due to self-selection into the RCT, we cannot exclude that our sample differs along unobservable dimensions relative to the general population of drivers in the Oslo metropolitan area. For these reasons, the external validity of our findings should be interpreted with caution.

### 3.2 Information treatment experiment

Turning to our second research question on public support for road pricing, we examine the distribution of respondents’ views. Figure 3, panel (a), illustrates that in the pre-experimental survey, 39% of respondents are either quite positive or very positive toward road pricing, while 31% are quite negative or very negative. The remaining 30% are either indifferent or unsure. Panel (b) illustrates changes in attitudes between the pre- and post-experimental surveys, where 0 denotes no change, 1 represents a one-step increase in public support, and  $-1$  represents a one-step decrease on a five-point Likert scale. (Only respondents who complete both surveys are included.) While the majority (46%) does not change their views, a slightly higher proportion of respondents become more positive (30.3%) compared to those who become more negative (26.3%). The full information treatment text is provided in Appendix D.6.

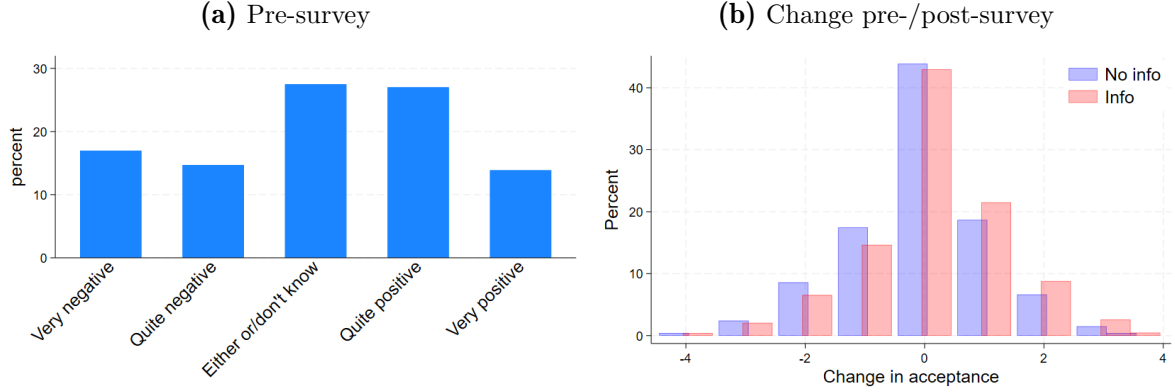
## 4 Empirical frameworks

### 4.1 Changes in travel behavior and externalities

We estimate the Average Treatment Effect (ATE) using the following difference-in-differences specification with ordinary least squares (OLS):

$$Y_{it} = \beta_0 + \beta_1 RP_{it} + \beta_2 RPS_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

**Figure 3** Public support for road pricing. Left panel: Public support for road pricing in the pre-experimental survey Right panel: Change in public support for road pricing between the pre- and post-experimental survey. Sample size= 12,699.



where  $Y_{it}$  denotes an outcome variable for individual  $i$  aggregated at the day  $t$  level.  $RP_{it}$  is an indicator variable that takes value one if person  $i$  is subject to RP treatment on day  $t$  (i.e., the interaction  $RP_i \times Post_t$ ),  $RPS_{it}$  is an indicator variable that takes value one if person  $i$  is subject to RPS treatment on day  $t$  (i.e., the interaction  $RPS_i \times Post_t$ ).  $\mu_i$  and  $\lambda_t$  are individual and day fixed effects, respectively.  $\varepsilon_{it}$  is the error term. In all specifications, standard errors are robust and clustered at the individual level.

We use a Difference-in-Differences (DiD) model with individual and time fixed effects because it can improve precision of the estimates in several ways. First, unlike simple t-tests or pre-post comparisons, the DiD framework is better suited to handling panels, especially if unbalanced, as it leverages all available within-individual variation. Second, the inclusion of individual fixed effects also directly controls for time-invariant unobserved heterogeneity across individuals, such as preferences or other stable traits that may influence outcomes. Third, by including time fixed effects, we capture shocks or trends that affect all individuals simultaneously, such as changes in weather—a well known predictor of transport choices. Last, this specification also allows us to cluster standard errors at the individual level, accounting for within-individual correlation over time and ensuring correct inference. In addition, by using each individual as their own control, the model improves statistical power, making it more likely to detect treatment effects when they exist.

The estimates  $\beta_1$  and  $\beta_2$  indicate the effect of road pricing (RP) and road pricing and subsidy (RPS), respectively, on the outcome variable  $Y$ . The difference,  $\beta_2 - \beta_1$ , denotes the effect of the subsidy (S) on the outcome variable  $Y$ .

In cases where the outcome variable is non-negative, such as for the external costs of

driving (Car EC), external benefits of active transport (Active EB), kilometers or trip duration, we estimate the alternative specification below with Poisson Pseudo Maximum Likelihood (PPML):

$$Y_{it} = \exp(\beta_0 + \beta_1 RP_{it} + \beta_2 RPS_{it} + \mu_i + \lambda_t) \quad (2)$$

where the outcome variable  $Y_{it}$  denotes non-negative outcomes for individual  $i$  on day  $t$ . Fixed effects,  $\mu_i$  and  $\lambda_t$ , are identical to those in model (1). Standard errors are robust and clustered at the individual level. PPML is particularly suited for data that have many zero-valued observations and remains consistent even under mis-specified error distributions. Zero values occur in our data because there are multiple days  $t$  when a given individual  $i$  may not use a particular transport mode.

## 4.2 Changes in public support for road pricing

We estimate the effects of the information treatment and experience with road pricing on respondents' changes in public support for road pricing using the following difference-in-differences (DiD) model as our main specification:

$$S_{it} = \beta_0 + \beta_1 Info_{it} + \beta_2 Info_{it} \times BEV_i + \beta_3 RP_{it} + \beta_4 RPS_{it} + \xi Post_t + \mu_i + \varepsilon_{it} \quad (3)$$

where  $S_{it}$  denotes public support for road pricing in the pre- ( $t = 0$ ) and post-experimental surveys ( $t = 1$ ) for individual  $i$ . It is measured on a 5-point Likert scale, i.e.,  $S_{it} \in [1, 5]$ . The indicator variable  $Info_{it}$  takes the value of one if individual  $i$  was randomized into the information treatment group at the time of the post-experimental survey ( $t = 1$ ). The interaction term  $Info_{it} \times BEV_i$  captures potential heterogeneity in treatment effects between BEV and non-BEV drivers. Accordingly, the coefficient on  $Info_{it}$  identifies the information treatment effect for the reference group—non-BEV drivers—controlling for covariates and individual fixed effects, while the information treatment effect for BEV drivers is given by the sum of the coefficients on  $Info_{it}$  and  $Info_{it} \times BEV_i$ . Last, the average information treatment effect across all respondents is given by the sum of the coefficients on  $Info_{it}$  and  $\alpha \cdot Info_{it} \times BEV_i$ , where  $\alpha$  denotes the share of BEV drivers in the sample.

Similarly,  $RP_{it}$  and  $RPS_{it}$  are indicator variables taking value one if individual  $i$  was randomized into the road pricing (RP) or road pricing and subsidy for walking and cycling (RPS) treatment prior to the post-experimental survey ( $t = 1$ ).  $Post_t$  takes value

one in the post-experimental survey ( $t = 1$ ).  $\mu_i$  denotes individual fixed effects.  $\varepsilon_{it}$  is the error term. This DiD specification takes advantage of the panel structure of our data, with a pre- and post-period, incorporates individual fixed effects, and allows for clustered standard errors at the individual level to account for within-individual correlation.

To test whether information and experience with road pricing are complements or substitutes, we add the following interaction effects to model (3):  $Info_{it} \times RP_{it}$  and  $Info_{it} \times RPS_{it}$ . Furthermore, when estimating model (3) on the full sample, i.e., including individuals who did not participate in the road pricing RCT, we additionally control for participants who were randomized into the control group of the road pricing RCT,  $Control_{it}$ . (Note that this road pricing control group partially overlaps with the control group of the information treatment. Because of the stratified randomization of the information treatment, half of the participants in each of the three road pricing RCT groups are assigned to the information treatment, while the other half are assigned to the control group.)

We further estimate ordered logit model specifications to explore the ordinal structure of the outcome variable in Appendix B.2 as robustness checks.

## 5 Results

### 5.1 Effect of road pricing on travel behavior

We report the effects of Road Pricing (RP) and Road Pricing with Subsidy for active transport (RPS) on daily transport externalities in Table 3. Outcome variables consist of total externalities (Total EC=Car EC-Active EB), external costs of driving (Car EC), and external benefits of active transport (Active EB). We estimate model (1) using Ordinary Least Squares (OLS) in columns (1)–(3), while model (2) is estimated using Poisson Pseudo-Maximum Likelihood (PPML) in columns (4)–(5) for the two non-negative outcome variables (Car EC and Active EB).

The OLS estimates suggest that RP reduces daily total external costs of transport by an average of 2.8 NOK (p-value<0.05; column (1)) per participant compared to the control group, while RPS leads to a reduction of 3.2 NOK (p-value<0.01). The difference between RPS and RP, which captures the effect of the subsidy alone, is 1.4 NOK, though this effect is not statistically significant (p-value>0.1). The daily external costs of driving decrease by 2.1 NOK under RP and 1.9 NOK under RPS (both with p-value<0.05; column (2)). In contrast, the daily external benefits of active transport increase by 0.7 NOK for RP and 1.3 NOK for RPS, where only the latter effect is

**Table 3** Effect of RP and RPS on daily total external costs (Total EC), external cost of driving (Car EC), and external benefits of active transport (Active EB).

	OLS			Poisson PML	
	Total EC (1)	Car EC (2)	Active EB (3)	Car EC (4)	Active EB (5)
RP	-2.794** (1.23)	-2.058** (0.93)	0.736 (0.75)	-0.053** (0.024)	0.015 (0.018)
RPS	-3.235*** (1.23)	-1.929** (0.92)	1.306* (0.76)	-0.048** (0.023)	0.031* (0.018)
Ymean	-4.34	39.09	43.43	39.09	43.43
RP rel.effect	-0.645	-0.053	0.017		
RPS rel.effect	-0.746	-0.049	0.030		
S rel.effect	-0.102	0.003	0.013	0.005	0.016
se	0.287	0.022	0.018	0.022	0.019
N	104899	104899	104899	104870	104899

**Notes:** All specifications include date and individual fixed effects. OLS specifications in levels are in NOK. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. *Ymean* denotes the outcome variable's sample mean in the pre-treatment period in NOK. Robust standard errors clustered at the individual level in parentheses.

\* p<0.1, \*\* p<0.05, \*\*\* p<0.01.

significant (p-value<0.1; column (3)).

The PPML estimates indicate that RP and RPS reduce daily external costs of driving by 5.3% and 4.8%, respectively, compared to the control group (p-value<0.05; column (4)), while they increase the daily external benefits of active transport by 1.5% and 3.1%, respectively, where only the latter effect is significant (p-value<0.1; column (5)). These PPML estimates are quantitatively similar to those obtained with OLS. To illustrate this similarity, the OLS estimates in levels can be converted into relative effects by dividing them by the mean of the outcome variable in the control group during the treatment period (reported in Table 2, column (4)). The corresponding relative effects, denoted 'RP rel. effect' and 'RPS rel. effect,' are reported in the bottom part of Table 3. These estimates suggest that RP and RPS reduce daily external costs of driving by 5.3% and 4.9%, respectively (column (2)), while they increase the daily external benefits of active transport by 1.7% and 3.0%, respectively (column (3)). (Note that the relative effects of RP and RPS on total external costs (column (1)) appear mechanically large, as the OLS estimates in levels are divided by a relatively small mean value of total external costs.) Consequently, we focus the remainder of our analysis on the results from model

(2) estimated using PPML, due to its greater suitability for handling zero outcomes and its straightforward interpretation of relative effects.

Both OLS and PPML estimates indicate that the subsidy for active transport (S=RPS-RP) has a small and statistically insignificant effect ( $p\text{-value}>0.1$ ) on all three types of external costs and benefits considered.<sup>21</sup>

### 5.1.1 Elasticity of external costs of driving with respect to road pricing

Using the estimates from Tables 3 and B-1, we evaluate the short-run effect of road pricing on the external costs of driving, aiming to quantify how internalizing driving externalities affects behavior. A key challenge in this analysis lies in identifying the marginal private cost of driving—that is, which marginal costs drivers actually consider when deciding whether or not to drive. This is not straightforward, as individuals may differ in their perceptions of what constitutes their marginal private cost. In much of the existing literature, this cost is often approximated using fuel costs alone (e.g., Gillingham, 2011). Our study area features road tolls, suggesting that the marginal cost should include both fuel and road tolls. Additional components such as vehicle wear and tear and depreciation are also relevant for the marginal private cost (Norwegian Public Roads Administration, 2021), although it is uncertain which share of drivers include these in their marginal private cost of driving.

Given the potential variation in perceived marginal private cost, we report a range of implied elasticities reflecting two ends of the marginal private cost spectrum. On one end, we assume a narrow definition of marginal cost – including only fuel and tolls – while on the other end, we adopt a broader view that incorporates wear and tear as well as depreciation. Table A-3 provides the complete breakdown of these private cost components and illustrates how they vary by vehicle type. This approach allows us to capture the range of implied elasticities under varying assumptions about which components of the marginal private cost are most salient to drivers.

Table 4 reports the marginal private costs per kilometer, for different vehicle types and time of day, depending on whether the calculation is based solely on fuel and road tolls or whether it also includes wear and tear and depreciation. Marginal private costs per kilometer range from 0.8 to 2.6 NOK for BEVs and 2.4 to 4.2 NOK for non-BEVs (Panels B and C, respectively). The weighted average marginal private costs across all vehicle types range between 1.5 and 3.4 NOK per kilometer (weights: 54% BEV; Panel

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<sup>21</sup>In the context of non-financial incentives in Finland, Ahlvik and Sahari (2023) find that information about the health benefits of active transport does not affect participants' travel behavior.

A).

The marginal external cost of driving is calculated using our experimental data for the control group during the treatment period – it varies by vehicle type and across time of day. The tax-related price increase induced by the road pricing scheme, i.e., the ratio of marginal external cost to marginal private cost, ranges from 22% to 204% for BEVs, 23% to 81% for non-BEVs, and 22% to 117% for the average car in our sample. The variation in these estimates reflects the range of marginal private costs across different vehicles and time of day.

We obtain elasticities of external costs of driving with respect to road pricing (RP) by dividing the relative reduction in external driving cost estimates from Tables 3 and Table B-1, corresponding to  $\beta_1$  in model (2), for BEV and non-BEV drivers by the tax-related price increase per kilometer. Similarly, we obtain elasticities of external costs of driving with respect to a road pricing and subsidy for active transport scheme (RPS) by using the relative reduction in external driving cost estimates corresponding to  $\beta_2$  in model (2) as numerator instead.

For all vehicles across the full day (Panel A; columns ‘All’), the estimated elasticities range from -0.07 to -0.15 under RP and -0.07 to -0.14 under RPS. In off-peak hours (columns ‘Off-peak’), the estimated elasticities are about one third larger under RP – they range from -0.12 to -0.25 – and are about three times larger under RPS – they range from -0.21 to -0.45. In peak hours (columns ‘Peak’), although the tax-related price increase is the highest, the corresponding reduction in driving externalities is not statistically significant (p-value>0.1), neither under RP nor RPS (although the point estimate for RP is similar to that in columns ‘All’ and ‘Peak’). In addition to not being significant, the elasticities are over three times smaller than during peak hours.

For non-BEVs (Panel B), elasticities range from -0.15 to -0.26 with RP and -0.20 to -0.34 with RPS (columns ‘All’), while they increase from -0.21 to -0.35 with RP and -0.41 to -0.70 with RPS during off-peak hours (columns ‘Off-peak’), and are not significant during peak hours (p-value>0.1; columns ‘Peak’). For BEVs (Panel C), RP and RPS do not lead to statistically significant reductions in driving externalities for any of the times of day considered (p-value>0.1). In addition to not being significant, the elasticities for BEVs are over four times smaller than those for non-BEVs.

Our elasticities likely represent lower bounds. This is primarily due to two factors: (1) participants are not directly taxed for their external driving costs, but instead had these costs deducted from a pre-assigned budget, and (2) the use of a random incentive mechanism, where only one out of seven weeks is randomly paid out, may reduce the perceived marginal cost of driving by lowering the expected road price. We discuss these



**Table 4** Short-term elasticities of external costs of driving with respect to road pricing, for all vehicles and separately for drivers of non-BEVs and BEVs, and including during peak and off-peak hours.

	All		Peak		Off-peak	
	RP	RPS	RP	RPS	RP	RPS
Panel A: All participants						
Marginal private costs (NOK/km) <sup>§</sup>	[1.57, 3.28]		[1.64, 3.35]		[1.53, 3.24]	
Marginal EC (NOK/km) <sup>†</sup>	1.16		1.92		0.72	
Tax-related price increase per km (%)	[35, 74]		[57, 117]		[22, 47]	
Reduction in EC of driving (%)	5.3	4.8	5.1 <sup>¶</sup>	1.5 <sup>¶</sup>	5.7	10.0
Elasticity of EC of driving <sup>‡</sup>	[-0.07, -0.15]	[-0.07, -0.14]	[-0.04, -0.09] <sup>¶</sup>	[-0.01, -0.03] <sup>¶</sup>	[-0.12, -0.25]	[-0.21, -0.45]
Panel B: Participants with non-BEVs						
Marginal private costs (NOK/km) <sup>§</sup>	[2.43, 4.14]		[2.53, 4.24]		[2.38, 4.09]	
Marginal EC (NOK/km)	1.32		2.04		0.93	
Tax-related price increase per km (%)	[32, 54]		[48, 81]		[23, 39]	
Reduction in EC of driving (%)	8.2	10.7	8.4 <sup>¶</sup>	6.5 <sup>¶</sup>	8.0	15.8
Elasticity of EC of driving <sup>‡</sup>	[-0.15, -0.26]	[-0.20, -0.34]	[-0.10, -0.17] <sup>¶</sup>	[-0.08, -0.13] <sup>¶</sup>	[-0.21, -0.35]	[-0.41, -0.70]
Panel C: Participants with BEVs						
Marginal private costs (NOK/km) <sup>§</sup>	[0.83, 2.54]		[0.89, 2.60]		[0.80, 2.51]	
Marginal EC (NOK/km)	1.01		1.81		0.54	
Tax-related price increase per km (%)	[40, 122]		[70, 204]		[22, 68]	
Reduction in EC of driving (%)	2.4 <sup>¶</sup>	1.1 <sup>¶</sup>	2.5 <sup>¶</sup>	2.5 <sup>¶</sup>	2.5 <sup>¶</sup>	1.7 <sup>¶</sup>
Elasticity of EC of driving <sup>‡</sup>	[-0.02, -0.06] <sup>¶</sup>	[-0.02, -0.03] <sup>¶</sup>	[-0.01, -0.04] <sup>¶</sup>	[-0.01, -0.04] <sup>¶</sup>	[-0.04, -0.12] <sup>¶</sup>	[-0.03, -0.08] <sup>¶</sup>

**Notes:** EC denotes external costs. <sup>§</sup>: details provided in Table A-3. <sup>†</sup>: calculated for the control group in the post-period. <sup>‡</sup>: calculated by dividing the reduction in EC of driving by the tax-related price increase per km. <sup>¶</sup>: Estimates (and the corresponding elasticities) are not statistically significant (p-value > 0.1), see Table B-1 for details.



two points further in Section 6.

Nevertheless, these elasticities are consistent with those from other road pricing studies, albeit using different designs.<sup>22</sup> For instance, [Hintermann et al. \(2024\)](#) calculate an elasticity of external costs with respect to a Pigouvian tax on all transport activities, namely driving, walking, cycling, and public transport combined. Given the 4.5% estimated reduction in all transport external costs and the 19.3% tax-related price increase, they calculate an elasticity of -0.24. [Hintermann et al. \(2024\)](#) asked participants to report their perceived private costs of driving, finding an average of 0.59 CHF per kilometer, which corresponds to 7.16 NOK based on the exchange rate of 1 CHF = 12.126 NOK on April 1, 2024. These self-reported private costs in Switzerland are about two thirds higher than the upper bound of marginal private costs that we calculated for the Oslo metropolitan area for non-BEVs, despite not too dissimilar fuel prices and the presence of an extensive road toll system. This gap suggests that participants in [Hintermann et al. \(2024\)](#) may have been more likely to account for wear and tear, or even depreciation, in their perceived marginal private costs, and/or may have conflated average costs with marginal costs. Furthermore, at the time of their experiment in 2019, battery electric vehicles (BEVs) made up just 0.6% of the total vehicle fleet in Switzerland ([Swiss Federal Office of Transport, 2025](#)). Consequently, when comparing elasticities, it may be more appropriate to compare the -0.24 elasticity computed in [Hintermann et al. \(2024\)](#) for all transport activities to the upper bound of our estimated RP elasticity range for non-BEVs, i.e., -0.26 for the entire day ('All'; Panel B), -0.35 in off-peak hours ('Off-peak'), and -0.17 in peak hours ('Peak'), although the latter is not statistically significant (p-value>0.1).

Using a pilot featuring several rounds of congestion charges and road pricing in Melbourne, [Martin and Thornton \(2021\)](#) estimate a price elasticity of kilometers traveled with respect to a uniform AUD 0.1 per kilometer driving charge of -0.10 overall, -0.09 in off-peak hours, and 0.02 in peak hours, although the latter is not significant (p-value>0.1). Considering road charges that vary by time-of-day, they estimate a price elasticity of -0.67 overall, 0.05 in off-peak hours, and -0.10 in peak hours, although only the latter is significant (p-value<0.1).

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<sup>22</sup>These elasticities are also in line with those from studies on congestion charges. For instance, [Olszewski and Xie \(2005\)](#) estimate congestion charge elasticities in Singapore between -0.11 and -0.20 for cars during the morning peak hours (07:30–09:30), depending on location (city center vs. expressway), and -0.32 during the afternoon peak (17:30–19:00) in the city center. Outside peak hours, elasticities range from -0.08 to -0.12. Similarly, [Gibson and Carnovale \(2015\)](#) find an elasticity of -0.17 for passenger cars in Milan, where tolls are levied between 07:30 and 19:30.

## 5.2 Mechanisms

In this section, we examine the mechanisms underlying the observed changes in transport externalities. Figure 4 presents the estimated effects of road pricing (RP) and road pricing combined with subsidies for active transport (RPS) on key dimensions of travel behavior. All specifications are estimated using model (2) with PPML. The full set of corresponding regression results is reported in Tables B-2 and B-3.

We begin by discussing the results for all participants (left panels). Road pricing significantly decreases both total kilometers driven (RP: -4.1%, p-value<0.05; RPS: -5.3%, p-value<0.01) and the number of car trips (RP: -2.8%, p-value<0.1; RPS: -3.2%, p-value<0.05). Kilometers driven decrease in off-peak hours (-4.7% and -7.3% for RP and RPS, respectively) and across urban and suburban areas (p-value<0.05), while the effects are not significant in peak hours or in rural areas (-3.2% and -2.0% for RP and RPS, respectively; p-value>0.1).<sup>23</sup>

To assess potential substitution away from driving, we analyze the impact of road pricing on the use of alternative transport modes. In particular, we document a 6.7% and 14.9% increase in minutes cycled under RP and RPS, respectively, although only the latter is statistically significant (p-value<0.01). These effects translate into a 5.1% and 14.8% increase in the share of travels by bike under RP and RPS, respectively, with only the latter being statistically significant (p-value<0.01). Together, these findings provide evidence of substitution from car travel to cycling under RPS. Notably, despite walking being incentivized under RPS, we find limited effects of RPS on minutes walked or in the share of travel done by foot (p-value>0.1). Last, we find little evidence of substitution towards public transport.

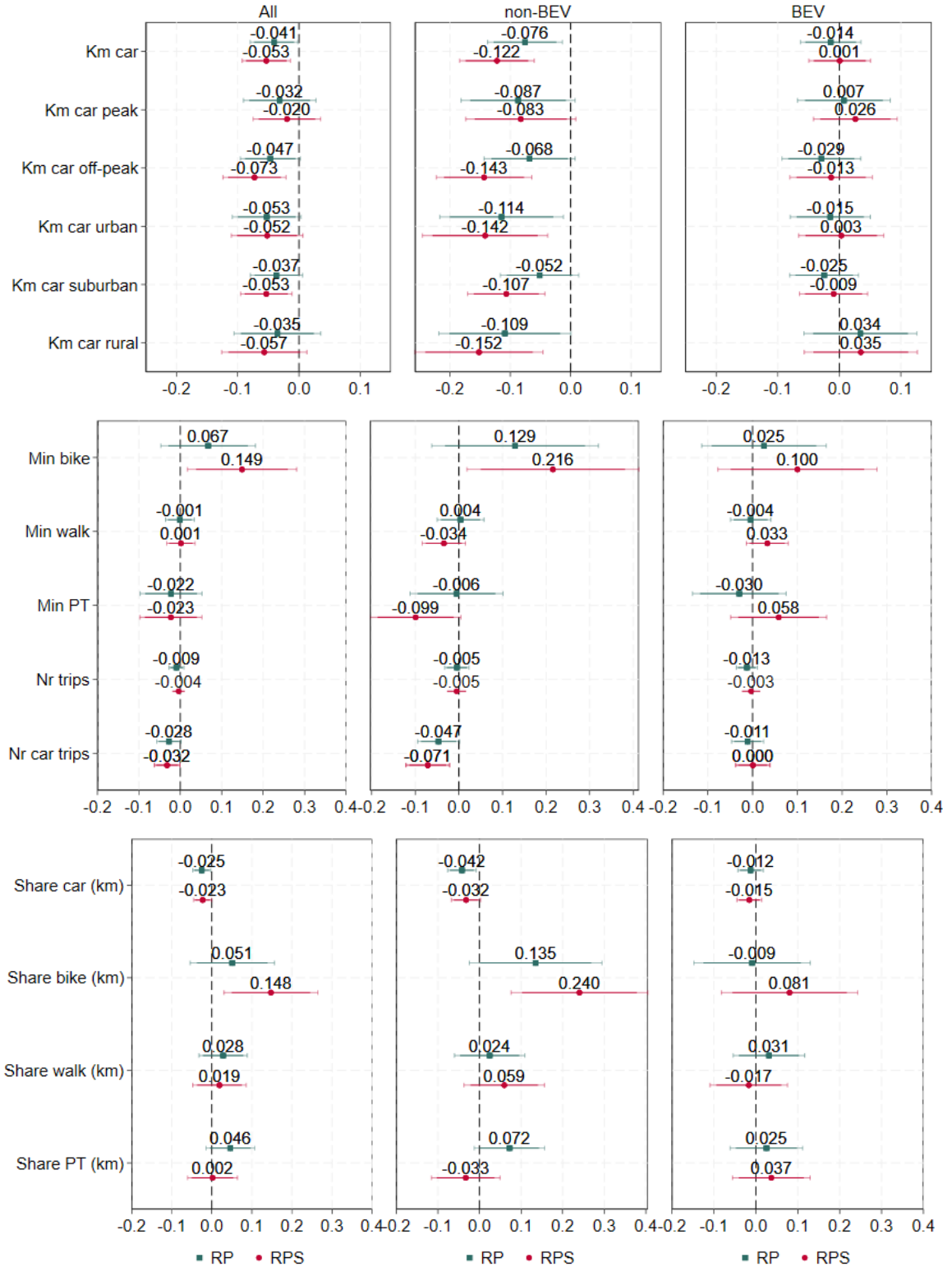
### 5.2.1 Mechanisms by vehicle type

To explore how participants with BEVs and non-BEVs may respond differently to RP and RPS, we analyze the effects separately for non-BEV drivers (Figure 4, middle panels) and BEV drivers (right panels). In terms of reductions in kilometers driven, non-BEV drivers account for the majority of the observed treatment effects, while we find no significant effects for BEV drivers (p-value>0.1). Specifically, non-BEV drivers reduce kilometers driven by 7.6% and 12.2% under RP and RPS (p-value<0.05), respectively, including 6.8% and 14.3% in off-peak hours, and 8.7% and 8.3% in peak hours under RP and RPS (p-value<0.1). We document reductions in the number of car trips in

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<sup>23</sup>Martin and Thornton (2021) similarly find that participants cut back on trips that contribute minimally to overall congestion.

**Figure 4** Effects of road pricing (RP) and road pricing with subsidy for active transport (RPS) on additional measures of travel behavior, for all participants (left panels), for non-BEVs (middle panels) and BEVs drivers (right panels).



**Notes:** RP: road pricing, RPS: road pricing and subsidy for active transport. Top panels: daily kilometers driven, including during peak and off-peak hours, and across urban, suburban, and rural areas; Middle panels: daily minutes biked, walked, or in public transport (PT), and the daily number of trips and car trips; Bottom panels: Mode shares based on distances. Car trips denote here single car tracks, where several car tracks may be contained in a single trip, provided that each subsequent track begins within 20 minutes of the previous track's end. All specifications are estimated using model (2) with PPML. Both 90%- and 95%-confidence intervals are depicted with horizontal bars.

the order of 4.7% and 7.1% under RP and RPS ( $p\text{-value}<0.1$ ), respectively. We also observe significant reductions in kilometers driven in urban (-11.4% and -14.2% for RP and RPS) and suburban areas (-5.2% and -10.7% for RP and RPS, although the former is not significant ( $p\text{-value}>0.1$ ), and rural areas (-10.9% and -15.2% for RP and RPS). In addition, we find a 21.6% increase in minutes cycles under RPS ( $p\text{-value}<0.05$ ), and a 13.5% and 24.0% increase in the share of travels by bike under RP and RPS, respectively ( $p\text{-value}<0.1$ ). Notably, the share of travels by public transport increases by 7.2% under RP ( $p\text{-value}<0.1$ ). These results suggest a substitution from car travel to bike and public transport for RP and to bike for RPS. These results suggest that subsidies for active transport complement road pricing by reinforcing shifts toward cycling while having limited effects on other transport modes. While under road pricing treatment (RP), drivers substitute driving with both public transport and cycling.

### 5.2.2 Travel purposes

To investigate whether the limited observed responses during peak hours may be associated with less flexible travel purposes, we analyze trip destinations as recorded by the Spor tracking app. We classify destinations into two broad categories: “work” and “non-work”.<sup>24</sup> Table A-11 shows that work-related trips are more likely to happen during peak hours, which may explain the limited responsiveness of peak-hour trips to road pricing. Furthermore, we find that BEV drivers take more work-related trips during peak hours (64% of the work-related trips) than non-BEV drivers (58%), suggesting that their lower responsiveness to road pricing during peak hours may be due to the relative inflexibility of these trips, at least in the short-term.

In Table B-4, we show that neither non-BEV nor BEV drivers significantly adjust their work-related trips under RP or RPS. However, non-BEV drivers reduce kilometers driven for non-work trips under RP in both peak and non-peak hours, by 10.0% and 7.5% ( $p\text{-value}<0.1$ ), respectively.

## 5.3 Robustness and sensitivity analysis

In this section, we assess the robustness of the main results by considering several factors, including alternative fixed effect specifications, sensitivity to imputing missing trip days, attrition, zero-payments (arising when external costs exceed the weekly allocated budget), and the exclusion of late-signup participants who are assigned a synthetic budget.

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<sup>24</sup>“Work” trips consist of trips whose destination is work (98%) or study (2%), while “non-work” trips include all other destinations such as home (44%), shopping (19%), errands (9%), or leisure (7%).

The corresponding tables and figures are provided in Appendix C.

### 5.3.1 Sensitivity to alternative fixed effects specifications

We replicate Table 3 under different fixed effect specifications, including omitting both date and individual fixed effects, including only date fixed effects, and including only individual fixed effects. Table C-1 demonstrates that, overall, the point estimates for the effects of RP and RPS on external driving costs and external benefits of walking and cycling remain qualitatively similar to those in Table 3. However, the statistical significance of the results depends on the inclusion of individual fixed effects, underscoring their role in enhancing estimation precision.

### 5.3.2 Sensitivity to sample choice

#### *Non-zero weekly budget*

Since participants were assigned a weekly budget set 5% above their baseline total external costs, some exhausted their allocated budget within a given treatment week. This feature of the experimental design may attenuate the observed effect of road pricing, potentially leading to an underestimation of the true behavioral response and, by extension, the estimated elasticities.

Table C-2 indicates that 5.6% of RP participants and 0.1% of RPS participants experienced a discontinuity in price at the end of each of the seven treatment weeks, while 84.8% of RP participants and 51.5% of RPS participants had at least one week where their budget was fully exhausted.

Table C-3 presents summary statistics and compares participants who exhausted their budget in three or more weeks with those who did so fewer than three weeks out of the seven weeks of treatment. While the overall differences between these two groups are modest, they differ along several dimensions. Specifically, the group that frequently exhausts their budget tend to have a higher proportion of females, fewer children, lower education levels, and lower incomes. They also drive more frequently to work and on weekdays, use public transportation less often, exhibit more negative attitudes toward tolls, and perceive the general tax burden as excessively high.

To assess the impact of budget exhaustion on our estimates, we re-estimate Table 3 using only participants and treatment weeks with non-zero remaining budgets. The PPML results in Table C-4 indicate a much stronger response among these participants, with RP reducing driving externalities by to 42.9% and RPS by 13.8%, while the subsidy for active transport, S, now reduces driving externalities by 29.1% (p-value<0.01;

columns (4)). Furthermore, RP and RPS lead to a 4.4% and 9.1% increase in active external benefits (p-value<0.01; columns (5)), respectively. These findings provide an upper bound of the effects of road pricing, and road pricing with subsidy for active transport, on transport externalities.

#### *Days with no trips*

Whenever the phone remains stationary for at least five minutes, the app registers a “stay.” To identify stay-at-home days, we select stays that last at least an entire day and are both preceded and followed by a track.<sup>25</sup> Using this approach, we set transport externalities to zero during ‘stay-at-home’ days, instead of missing, and re-estimate Table 3. The findings in Table C-5 remain qualitatively similar. Consequently, we choose to use the non-filled data as our main specification, as filling missing values with zeros for stay-at-home days may introduce potential errors, particularly due to uncertainties surrounding app deactivation or phone shutdown.

#### *Restriction to non-synthetic budget*

App users who recorded fewer than five weekdays during the observation period (915) were assigned a synthetic budget. This budget was calculated as the average budget of participants with a similar stated number of driving weekdays, as reported in the pre-survey. Synthetic- and non-synthetic-budget participants are broadly comparable across observable characteristics, with only minor differences in gender and income (Table C-6). As a robustness check, we re-estimate the main results presented in Table 3, excluding synthetic-budget participants. The findings, shown in Table C-7, remain qualitatively consistent with our main results.

### **5.3.3 Attrition**

Figure C-1 illustrates the daily cumulative number of participants who stop using the Spor mobility tracking app (defined as non-compliers if they drop out before treatment, and as partial-compliers if they drop out during treatment) across the control, RP, and RPS groups. The figure reveals no systematic differences in dropout rates between the RP and RPS groups compared to the control group, alleviating concerns that treated participants may behave differently from control participants after receiving treatment.

Another way to assess whether attrition may bias our results is by comparing participants who received all seven feedback messages (full compliers; 2,254) with those who received fewer than seven feedback messages (partial compliers; 593). Balance Ta-

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<sup>25</sup>Stays that are preceded or followed by another stay, or by a missing record, are excluded, as these likely reflect instances in which the app or the phone was turned off.

ble C-8 shows only minor differences between these groups: partial compliers tend to drive slightly more during peak hours, take fewer trips in general and fewer car trips in particular, and be less likely to have children in the household.

Finally, if partial compliers differ in their behavioral responses from full compliers, one would expect treatment effect estimates to vary over time as partial compliers drop out. To test this, we modify model (2) to an event study specification. The results, shown in Figure C-2, indicate that treatment effects remain relatively stable throughout the treatment period, suggesting that attrition is unlikely to bias our estimates. It is worth noting that the confidence intervals are wide, as the sample size was powered to detect a single post-treatment effect rather than weekly effects.

### 5.3.4 Potential cheating

Participants are encouraged to correct any erroneous tracks detected by the app during the pre-treatment period—given that the app may occasionally misclassify the transport mode. Because participants retain the ability to make corrections during the treatment period, there is some potential for strategic behavior.<sup>26</sup> Table C-9 reports the number of corrected tracks, i.e., tracks detected by the app that were subsequently corrected by users during the experiment. Overall, only 1.6% of tracks were corrected during the experiment (16,177 out of 985,685). Car mode accounts for the largest share of corrections (0.8%), followed by public transport (0.3%), and walking (0.3%). Estimating model (2) using the number of corrected tracks aggregated at the person-day level as the dependent variable shows no significant effect of either RP or RPS on the overall correction rate (Table C-10, column (1); p-value>0.1). Further analysis of the number of corrected tracks by transport mode similarly reveals little evidence of systematic treatment effects.

To further assess the potential for cheating, we examine earnings from active transport. Specifically, we examine whether participants in the RPS group strategically “corrected” their trips to walking or cycling in order to increase their rewards to the maximum allowed. Figure C-3 shows no evidence of bunching at the NOK 300 daily cap on incentivized external benefits, suggesting minimal strategic behavior aimed at maximizing payouts.

Taken together, these results suggest that cheating is unlikely to significantly affect our estimates.

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<sup>26</sup>Note that corrections take place at the track level. A trip consists of a single track or a series of tracks, provided that each subsequent track begins within ten minutes of the previous track’s end.



## 5.4 Heterogeneity

Figure B-1 illustrates the effects of RP and RPS on daily driving externalities across different participant subgroups. Individuals who are least responsive to road pricing (RP; left panel) include those with children under 18 years old in the household, those who are not employed, those stating in the pre-survey that they commute to work daily, that they are dissatisfied with public transport, that they are frustrated with the existing road toll system, and that they have low trust in government. In contrast, those who are most responsive to road pricing combined with a subsidy for active transport (RPS; right panel) tend to be non-BEV drivers, have a public transport subscription, and individuals who express satisfaction with public transport services. In particular, those who state having a public transport subscription (or driving a non-BEV) reduce driving externalities significantly more than those who do not (or who drive a BEV).

## 5.5 Results on public support for road pricing

Table 5 presents the effects of the information treatment and experience with road pricing on respondents' change in public support for road pricing, using difference-in-differences (DiD) model (3). The information treatment is designed to inform respondents about the anticipated long-term benefits of road pricing, particularly reductions in congestion and pollution. In contrast, experience with road pricing—offered to participants in the RP and RPS treatment arms of the field road pricing RCT—primarily allows individuals to observe its effect on their own travel behavior. However, this experience does not include the broader general equilibrium effects that would accompany a large-scale, real-world implementation, such as system-wide changes in travel demand or congestion levels.

The effects of the information treatment for BEV respondents and for all respondents are given in the bottom part of Table 5, denoted 'Info BEV' and 'Info All', respectively. The coefficient *Info* in the main part of the table identifies the information treatment effect for the reference group—non-BEV drivers, while the coefficient  $Info \times BEV$  denotes the additional effect for BEV drivers.

Column (1) reports estimates without fixed effects or covariates (except for a dummy indicating BEV respondents), while all subsequent columns include individual fixed effects. We focus hereafter on our preferred specifications — those with individual fixed effects — as they control for unobserved heterogeneity. The point estimates remain largely unchanged when adding fixed effects, except for the relative information treatment effects across BEV and non-BEV respondents, highlighting the importance of accounting



for unobserved individual differences.

The first three columns present the effects for participants who took part in the road pricing field RCT. Due to the random assignment into the three road pricing groups and the stratified randomization of the information treatment across these groups, the estimates capture the causal effects of both the information treatment and experience with road pricing (RP and RPS). The information treatment increases public support for road pricing for the average respondent ('Info All') by 0.17 on a five-point Likert scale, corresponding to an increase of 4.4% on the full Likert scale (i.e., 0.17 divided by 4 steps;  $p\text{-value} < 0.01$ ; column (2)). This effect is driven by BEV respondents, who increase support by 0.27 on a five-point Likert scale ('Info BEV';  $p\text{-value} < 0.01$ ), while non-BEV respondents increase support by only 0.06, which is not statistically significant (*Info*;  $p\text{-value} > 0.1$ ).

Experience with road pricing (RP) is associated with a small increase in public support, 0.05 on the Likert scale, although not statistically significant ( $p\text{-value} > 0.1$ ). Policy packaging, where road pricing is combined with a subsidy for walking and cycling (RPS), leads to a 0.1 increase in public support on a five-point Likert scale, corresponding to a 2.6% increase on the full scale ( $p\text{-value} < 0.1$ ). Next, we examine whether experience with road pricing and the information treatment act as complements or substitutes by including interaction terms in column (3). The positive coefficient on the  $\text{Info} \times \text{RPS}$  interaction term suggests that experience with road pricing combined with a subsidy and information provision may act as complements, while the negative coefficient on the  $\text{Info} \times \text{RP}$  interaction points to potential substitutability. However, neither estimate is statistically significant ( $p\text{-value} > 0.1$ ; column (3)).

The last two columns present estimates for the full sample of respondents to the pre-experimental survey, including those who did not participate in the road pricing field RCT, conditional on their completion of the post-experimental survey—to allow us to observe changes in their support for road pricing. Since participation in the field experiment was subject to self-selection—both through eligibility criteria (driving at least two weekdays per week) and the voluntary decision to download the app—the experience effects in columns (4) and (5) may reflect selection bias and may not be interpreted as causal. For this reason, we consider the estimates based on the RCT sample in columns (2) and (3) as our preferred specification.

In the full sample, the information treatment increases public support for road pricing for the average respondent by 0.17 on a five-point Likert scale, corresponding to a 4.3% increase on the full scale ('Info All';  $p\text{-value} < 0.01$ ; column (4)). The information treatment effect is over two times stronger for BEV respondents ('Info BEV'; 0.26 on

**Table 5** Effect of the information treatment and experience with road pricing on changes in public support for road pricing, estimated using DiD model (3)

	RCT sample			Full sample	
	(1)	(2)	(3)	(4)	(5)
Info	0.193** (0.093)	0.063 (0.063)	0.053 (0.097)	0.108*** (0.028)	0.110*** (0.029)
RP	0.052 (0.097)	0.054 (0.062)	0.094 (0.086)	0.045 (0.046)	0.098 (0.063)
RPS	0.099 (0.096)	0.102* (0.061)	0.046 (0.084)	0.092** (0.045)	0.050 (0.061)
InfoxBEV	-0.036 (0.093)	0.203*** (0.073)	0.204*** (0.073)	0.148*** (0.034)	0.149*** (0.034)
InfoxRP			-0.083 (0.12)		-0.109 (0.092)
InfoxRPS			0.107 (0.12)		0.080 (0.089)
Control				-0.009 (0.046)	-0.009 (0.046)
Info BEV	0.157* (0.090)	0.266*** (0.061)	0.258*** (0.094)	0.256*** (0.030)	0.259*** (0.032)
Info All	0.174** (0.079)	0.172*** (0.050)	0.164* (0.088)	0.173*** (0.024)	0.175*** (0.025)
N	4762	4762	4762	21746	21746
Individual FE		✓	✓	✓	✓

**Notes:** Info: respondents who received the information treatment in the post-experimental survey; RP: road pricing treatment group; RPS: road pricing and subsidy for active transport treatment group. BEV: respondents with battery-electric-vehicles. Columns (1)-(3): the ‘RCT sample’ consists of only those who participated in the road pricing field RCT. Columns (4)-(5): the ‘Full sample’ consists of all who responded to the pre- and post-experimental surveys having access to a car, i.e., including those who did not participate in the road pricing field RCT. Control: control group in the road pricing field RCT. ‘Info BEV’: effect of information for BEV respondents, computed with the `lincom` command in Stata 18 as the sum:  $Info + Info \times BEV$ . ‘Info All’: effect of information for all respondents combined, computed with the `lincom` command in Stata 18 as the sum:  $Info + \alpha Info \times BEV$ , where  $\alpha$  denotes the share of BEV (0.54 and 0.44 in the RCT and Full samples, respectively).  $Info$ : effect of information for non-BEV respondents. Column (1) controls for  $BEV$ . Robust standard errors in parentheses, \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

a five-point Likert scale;  $p$ -value $<0.01$ ) than for non-BEV respondents ( $Info$ ; 0.11 on a five-point Likert scale;  $p$ -value $<0.01$ ). Experience with policy packaging, where road pricing is combined with subsidies for walking and cycling (RPS), leads to a 0.09 increase in public support on a five-point Likert scale, corresponding to a 2.3% increase on the full scale ( $p$ -value $<0.05$ ). In contrast, experience with road pricing alone (RP) has an effect that is two times smaller, i.e., 0.05 on a five-point Likert scale, that is not significant ( $p$ -value $>0.1$ ). The specification with interaction terms in column (5) produces estimates similar to those in column (3) based on the RCT sample. Although standard errors are slightly smaller, the interaction terms remain statistically insignificant ( $p$ -value $>0.1$ ),

offering only limited evidence for the complementarity between RPS and information or the substitutability between RP and information.

Results from ordered logistic regressions, which account for the ordinal nature of the public support variable, are presented in Table B-5. They are qualitatively consistent with the main findings.

## 6 Discussion

This study provides new experimental evidence on driver responses to road pricing in an urban context marked by a high prevalence of battery electric vehicles (BEVs). In this section, we discuss the limitations of our study, highlight features of the experimental design that may contribute to our elasticity estimates representing lower bounds, and explore possible explanations for the differing behavioral responses observed between BEV and non-BEV drivers.

### 6.1 Road pricing as a potential reward, not a direct tax

In our experimental design, participants were granted a virtual weekly budget from which road use charges were deducted at the end of each week. This differs from real-world road pricing, where drivers pay directly out of their disposable income rather than from a pre-allocated budget. This framing may influence behavior. According to the “house money effect” (Thaler and Johnson, 1990), individuals are generally less sensitive to losses when the money is perceived as a windfall or bonus. In this context, participants may have viewed the budget as a bonus, reducing their responsiveness to deductions. Consequently, behavioral responses in our experiment may be attenuated compared to real-world settings, where financial costs are more immediate and salient—implying that our elasticity estimates likely represent a conservative lower bound.

In addition, we observe weeks in which participants had fully exhausted their allocated budget, meaning they were no longer incentivized at the margin—any additional driving during those weeks had no financial consequence (see Section 5.3.2). This further supports the interpretation that our elasticity estimates likely represent a lower bound, since the full pricing signal was not consistently active throughout the treatment period.

## 6.2 Interpreting elasticities under random incentives

A key feature of our experimental design is that participants were informed that only one week out of the seven treatment weeks would be randomly selected for payment. This *random incentive mechanism* helps reduce experimental costs while maintaining incentive compatibility. However, it introduces uncertainty about how participants perceive the marginal cost of travel, which has implications for how we interpret the estimated elasticities from Table 4.

Suppose the posted road price in week  $t$  is  $p$ , and participants are aware that only one of the seven weeks will determine their payout, chosen with equal probability. Under a standard expected utility framework with time-separable utility, participants maximize the expected payoff:

$$\max_{x_1, \dots, x_7} \mathbb{E} \left[ \sum_{t=1}^7 u(x_t, p) \cdot \mathbb{1}\{t = t^*\} \right] = \frac{1}{7} \sum_{t=1}^7 u(x_t, p)$$

where  $x_t$  are the external costs of driving in week  $t$ , and  $\mathbb{1}\{t = t^*\}$  is an indicator function equal to 1 if week  $t^*$  is selected for payout. Because the utility from each week has an equal chance of being realized, participants effectively optimize with respect to the expected marginal price  $\frac{1}{7} \cdot p$ . Under these assumptions, the behavioral response observed in our data reflects sensitivity to a discounted price, and the elasticity,  $\hat{\varepsilon}$ , that we estimated in Table 4 with respect to  $p$  should be corrected to:

$$\varepsilon = \left( \frac{\partial x}{\partial (\frac{1}{7}p)} \right) \cdot \frac{p}{x} = 7 \cdot \hat{\varepsilon}.$$

Thus, under the assumption of full rationality and expected utility maximization, the elasticity with respect to price is seven times higher than the elasticity we estimated.

However, not all participants may fully internalize the randomization structure. Such participants may act as if each week *might* be the one that counts, and perceive the marginal price as  $p$ . In that case, our estimated elasticity,  $\hat{\varepsilon}$ , is correct.

Given the uncertainty about the share of participants that may respond to the marginal price  $p$  or  $\frac{1}{7} \cdot p$ , the true elasticity  $\varepsilon_{\text{true}}$  likely lies between two bounds:

$$\hat{\varepsilon} \leq \varepsilon_{\text{true}} \leq 7 \cdot \hat{\varepsilon}.$$

Depending on participants' beliefs about the payout structure and how they process uncertainty, the true price elasticity may be closer to either end of this range. Impor-

tantly, this suggests that our estimated elasticities are likely conservative, especially in real-world settings where pricing would be continuous and deterministic.

### 6.3 Limited behavioral response among BEV drivers

One of our most striking findings is the markedly weaker response to road pricing among BEV drivers compared to non-BEV drivers. While non-BEV drivers reduce the external costs of driving by 8.2% ( $p\text{-value} < 0.05$ ), BEV drivers show only a 2.4% decrease in external costs of driving, which is not significant ( $p\text{-value} > 0.1$ ).

Several factors may explain this difference. First, BEV and non-BEV drivers differ systematically in travel behavior, socio-economic characteristics, and attitudes toward policy. BEV drivers may choose electric vehicle ownership due to a higher demand for car use – given the lower per-kilometer cost of driving a BEV – and in particular for work commute during peak hours. For example, the combined fuel and road toll cost per kilometer of driving a BEV during peak hours is only 35% of that for a non-BEV, as shown in Table A-3. Furthermore, until recently BEV drivers were permitted to use public transport lanes, thus incentivizing individuals particularly eager to commute by car into congested, urban areas to purchase BEVs (Halse et al., 2025).

Our pre-survey data support this interpretation: more BEV drivers state commuting to work by car (59% compared to 52% for non-BEV drivers), driving daily (53% compared to 44% for non-BEV drivers), fewer have public transport subscriptions (21% compared to 26% for non-BEV drivers), and fewer live in rural areas (7% compared to 10% for non-BEV drivers). On average, BEV drivers also report higher incomes (46% earn over NOK 900k compared to 33% for non-BEV drivers), higher employment rates and more children – characteristics which may be associated with less transport choice flexibility and lower price sensitivity. BEV drivers are also less likely to report concerns about the overall tax burden and exhibit less opposition or frustration toward road tolls compared to non-BEV drivers (Table A-10). In addition, the data collected in the observation period confirm that BEVs drive on average 1.5 kilometers more in peak hours per day, 2.5 kilometers more in urban areas, and the share of kilometer driven for work-related trips during peak hours is 6 percentage points higher compared to non-BEVs (Tables A-10 and A-11). If work-related trips are less responsive to road pricing—and BEVs are more frequently used for such trips—this may help explain the lower responsiveness observed among BEV drivers.

Second, BEV drivers face lower road pricing rates in our experiment (Table 1) due to their lower environmental externalities (especially CO<sub>2</sub> emissions). As a result, they

are subject to smaller financial incentives to modify their driving behavior. Third, BEV drivers may perceive their vehicle choice as a pro-environmental action, which may lead to *moral licensing*—a psychological effect where individuals feel justified in engaging in less environmentally friendly behaviors afterward. This mindset can reduce their willingness to further adjust their travel behavior, such as reducing driving (Kosmidis et al., 2023; Nauze, 2023). Taken together, these differences may explain why road pricing may be less effective in influencing BEV driver behavior.

The absence of statistically significant effects among BEV drivers may, in part, be due to limited statistical power. Our initial power calculations indicated that detecting a 5% reduction in driving externalities with 95% confidence would require a sample of at least 3,300 participants, evenly distributed across the two treatment arms and and control group. However, our final sample consists of 2,846 individuals, of whom 1,535 are BEV owners, which limits our ability to detect more modest effects within this subgroup. For example, we estimate a 2.4% reduction in driving external costs among BEV drivers—a result that is not statistically distinguishable from zero. This may reflect either a true null effect or a small effect that the sample is underpowered to detect. Given the direction of the point estimate and our original power assumptions, we caution against interpreting the lack of statistical significance as definitive evidence of no behavioral response among BEV drivers. To more accurately assess how BEV users respond to road pricing, future research with larger and more targeted samples is warranted.

## 6.4 Short-term responses

Our experiment is suited to capture short-term behavioral responses to road pricing—specifically those that can unfold within a seven-week treatment period. It is important to acknowledge that long-term responses—particularly on the extensive margin—may evolve differently over time. Such adjustments could include changes in vehicle ownership, residential or workplace location, or the adoption of alternative transport modes. For instance, previous studies document shifts in vehicle ownership as a longer-term response to road toll exposure and pricing changes (Isaksen and Johansen, 2025; Halse et al., 2025).

In particular, the dynamics of behavioral change are likely to vary by trip purpose. For work commute trips, which tend to be regular and less flexible, changes in behavior may be more closely tied to structural decisions like vehicle ownership. If commuting by car generates higher marginal utility than marginal cost, then all work commute trips

are done by car (Gillingham and Munk-Nielsen, 2019). However, if commuting by car becomes more expensive, individuals may abandon the practice altogether, triggering a binary shift from daily driving to not driving for work at all. Such binary shifts are unlikely to manifest over a short period and are not thus captured by our experiment.

By contrast, non-work trips—such as for shopping, leisure, or errands—are often more discretionary and varied. These trips are more amenable to incremental adjustments in response to higher driving costs, such as selectively forgoing lower-value trips. As long as the household retains a vehicle, such marginal adjustments are feasible without needing to make structural changes.

This distinction helps explain why we observe more pronounced reductions in driving in off-peak hours and for non-work travel, while we observe a more limited response among BEV drivers, who tend to take more work-related trips. In summary, our findings capture short-run behavioral responses to road pricing. While these immediate effects are informative for understanding how drivers react to pricing signals in the near term, we recognize that longer-term effects may differ as individuals adapt more fundamentally to persistent pricing policies, for instance through vehicle ownership adjustments.

## 7 Conclusions

This study evaluates the effects of time- and location-specific road pricing on travel behavior and driving externalities, as well as the impact of information and experience with road pricing on public support for such policies. Using a randomized controlled trial (RCT) in the field combined with a survey-based RCT, we find that road pricing reduces driving externalities by 5.3%. From a policy perspective, these results highlight the potential of road pricing as a tool for reducing driving externalities.

Importantly, we document substantial heterogeneity in behavioral response across battery-electric vehicle (BEV) drivers and non-BEV drivers. Reductions in external costs are primarily driven by non-BEV drivers who reduce their external driving costs by 8.2% and reduce driving in both peak and off-peak hours. We also document mode shift from car use to cycling and public transport among non-BEV drivers. Participants in the road pricing with subsidy group respond similarly to those in the road pricing treatment, although they exhibit a stronger shift toward cycling and no shift toward public transport. In contrast, BEV drivers reduce both driving externalities and kilometers only modestly – with estimates not significant at the 10% level.

These effects may partially be explained by BEV drivers being exposed to lower



Pigouvian road prices, having higher incomes, and exhibiting baseline travel behavior that differs compared to non-BEV drivers in ways that may make BEV drivers less responsive to road pricing. This study is the first to provide empirical evidence that BEV drivers and non-BEV drivers respond differently to road pricing.

When it comes to public support, our findings emphasize the central role of information provision. Offering targeted information about the long-term benefits of road pricing — such as reductions in congestion and pollution — significantly improves public support for such policies. In contrast, we find that simply gaining experience with road pricing does not significantly improve public support, while the effect remains limited when packaging road pricing with subsidies for active transport. We note that our pilot road pricing experiment allowed individuals to experience the effect of road pricing on their individual behavior, without experiencing the general equilibrium effects, such as the expected reduced congestion and pollution, that would arise from a large-scale, real-world implementation of road pricing. Nevertheless, these results suggest that policymakers should place a strong emphasis on clear and transparent communication about the effectiveness and societal benefits of road pricing to foster broader public acceptance.

While our findings are robust across model specifications and sample restrictions, several limitations warrant consideration. First, the study focuses on the Oslo metropolitan area, which may limit the generalizability of the results to regions with different transport infrastructures, cultural attitudes, or policy environments. Second, elements of the experimental design—such as the use of a pre-allocated budget and random incentive payments—may have dampened participants’ behavioral responses, implying that our estimated elasticities are likely to understate actual responsiveness to road pricing. Finally, the study is designed to capture short-term behavioral changes, and thus does not speak to potential long-term effects on travel behavior, vehicle ownership, or public attitudes that may emerge over time.

Despite these limitations, this study provides causal evidence on the effect of road pricing on travel behavior. The experimental design—combining financial incentives with high-frequency GPS-based mobility tracking—enables detailed observation of behavioral responses across transport modes. This allows us to measure mode shifts, spatial and temporal variations in travel behavior, and trip-level patterns that are not observable in traditional surveys or administrative data. Moreover, our analysis of heterogeneous effects across income groups and vehicle types contributes insights into the equity implications of road pricing policies.

Future research should examine the long-term and large-scale effects of road pricing on travel patterns, congestion, emissions, and public opinion. Extending similar

studies to other urban and cultural contexts would strengthen the external validity of the findings. Additionally, further exploration of how fairness and equity considerations influence public support for road pricing could inform better policy design.

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## A Additional background and data description

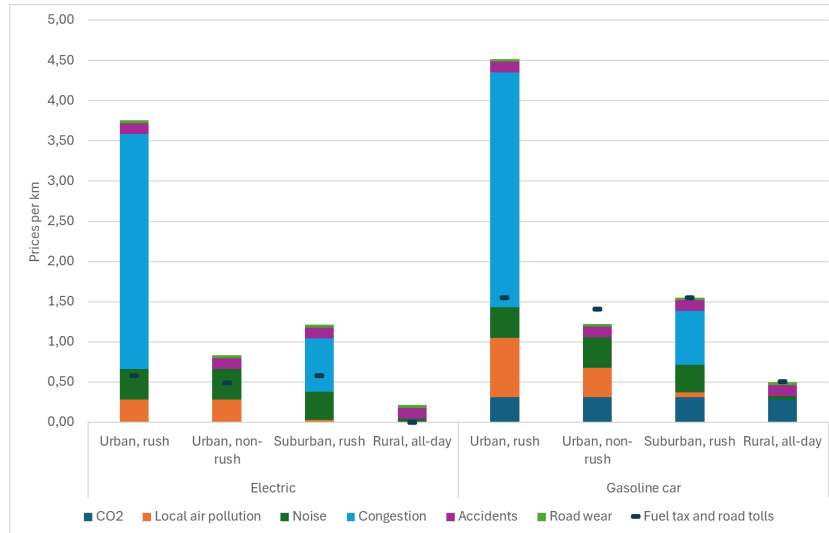
### A.1 Externalities associated with driving and active transport

**Table A-1** External costs of driving (NOK/km) by vehicle type, location, and time.

Vehicle type	Location	Time	Type of externality						
			CO2	Air pollution	Noise	Congestion	Accidents	Road wear	Total
Electric	Urban	Rush	0.00	0.29	0.38	2.92	0.13	0.03	3.8
Electric	Urban	Non-rush	0.00	0.29	0.38	0.00	0.13	0.03	0.8
Electric	Suburban	Rush	0.00	0.03	0.34	0.67	0.13	0.03	1.2
Electric	Suburban	Non-rush	0.00	0.03	0.34	0.00	0.13	0.03	0.5
Electric	Rural	All-day	0.00	0.00	0.05	0.00	0.13	0.03	0.2
Gasoline	Urban	Rush	0.31	0.37	0.38	2.92	0.13	0.03	4.1
Gasoline	Urban	Non-rush	0.31	0.37	0.38	0.00	0.13	0.03	1.2
Gasoline	Suburban	Rush	0.31	0.05	0.34	0.67	0.13	0.03	1.5
Gasoline	Suburban	Non-rush	0.31	0.05	0.34	0.00	0.13	0.03	0.9
Gasoline	Rural	All-day	0.28	0.00	0.05	0.00	0.13	0.03	0.5
Diesel	Urban	Rush	0.56	1.30	0.38	2.92	0.13	0.03	5.3
Diesel	Urban	Non-rush	0.28	0.65	0.38	0.00	0.13	0.03	1.5
Diesel	Suburban	Rush	0.32	0.12	0.34	0.67	0.13	0.03	1.6
Diesel	Suburban	Non-rush	0.28	0.11	0.34	0.00	0.13	0.03	0.9
Diesel	Rural	All-day	0.24	0.02	0.05	0.00	0.13	0.03	0.5

**Notes:** The external costs of air pollution, noise, traffic accidents, and road wear are calculated by researchers at the Institute of Transport Economics in a report commissioned by the Norwegian transport agencies (Rødseth et al., 2019). For gasoline vehicles, the external cost during peak hours in urban and suburban areas should be 0.69 and 0.05 NOK higher, respectively, due to increased fuel consumption during congestion, which results in higher CO<sub>2</sub> emissions and air pollution. These additional costs are already incorporated for diesel and electric vehicles (only air pollution for the latter). CO<sub>2</sub> prices are based on the central estimate in Option 1 of Table 9.2 in Wangsness and Rosendahl (2022), and are projected for 2024 using an annual growth rate of 7.5%. The conversion uses an exchange rate of 1 EUR = 11.65 NOK, as of September 2023. Rosendahl and Wangsness (2024) builds on the methodology developed in Wangsness and Rosendahl (2022), offering guidance to the European Investment Bank on the appropriate shadow price of CO<sub>2</sub> to align investment assessments with the EU’s net-zero emissions target for 2050. Congestion cost estimates are drawn from Steinsland et al. (2022) and supplemented by Steinsland (2024). All costs are adjusted for inflation and expressed in 2022 price levels.





**Figure A-1** Visualization of the external costs of driving (NOK/km) by vehicle type, location, and time.

**Table A-2** External benefits of active transport (NOK/min)

	Walking	Biking
Reduced short-term sickness absence (NOK/km)	4.10	2.11
Reduced risk of chronic disease - healthcare costs and production loss (NOK/km)	8.36	3.14
Reduced risk of chronic disease - own welfare effect ( <i>We assume this part is internalized</i> )	0	0
Total (NOK/km)	12.46	5.25
Km per minute	0.08	0.25
NOK/minute	1.00	1.30

**Notes:** These figures are based on estimates from [Norwegian Public Roads Administration \(2021\)](#) and [The Railway Directorate \(2019\)](#). We convert NOK/km into NOK/min assuming a walking speed of 5 km/hour and a biking speed of 15 km/hour. All figures are inflation adjusted to 2022 price levels.

## A.2 Marginal private costs of driving

**Table A-3** Marginal private costs of driving

Panel A: Marginal private costs of driving per km					
	Electric	Diesel	Gasoline	ICE	All cars
Total, all factors. All-day	2.54	4.13	4.14	4.14	3.28
Only fuel and road toll. All-day	0.83	2.42	2.43	2.43	1.57
Total, all factors. Peak	2.60	4.22	4.25	4.24	3.35
Only fuel and road toll. Peak	0.89	2.51	2.54	2.53	1.64
Total, all factors. Off-peak	2.51	4.09	4.09	4.09	3.24
Only fuel and road toll. Off-peak	0.80	2.38	2.38	2.38	1.53
Panel B: Each factor per km					
Costs per km	Electric	Diesel	Gasoline	ICE	All cars
Fuel	0.32	1.42	1.53	1.48	0.85
Road toll converted into NOK/km. All-day	0.52	1.00	0.91	0.95	0.72
Road toll converted into NOK/km. Peak	0.57	1.09	1.01	1.04	0.79
Road toll converted into NOK/km. Off-peak	0.48	0.96	0.86	0.90	0.67
Maintenance	0.51	0.51	0.51	0.51	0.51
Tire wear	0.30	0.30	0.30	0.30	0.30
Depreciation	0.90	0.90	0.90	0.90	0.90
Fuel cost without fuel tax	0.29	1.01	1.01	1.01	0.62
Fuel tax	0.03	0.41	0.51	0.47	0.23
Congestion road toll converted into NOK/km	0.07	0.10	0.16	0.14	0.10

**Notes:** Inputs to this table are shown in Table A-4. Road toll all-day is weighted by the share of peak and off-peak driving, see Table A-4. Data sources for maintenance, tire wear, depreciation: [Norwegian Public Roads Administration \(2021\)](#). ‘All cars’ are weighted by the share of car types in the experiment, see Table A-4. ‘ICE’ (Internal-Combustion-Engine) vehicles are weighted by the share of diesel and gasoline cars in the experiment. ‘Fuel tax’ for electric vehicles means tax on electricity. ‘Congestion road toll per kilometer’ is calculated as road toll per kilometer in peak hours minus road toll per kilometer in off-peak hours.

**Table A-4** Inputs into the calculation of the private marginal costs of driving (Table A-3).

Panel A: Inputs from the control group during the experimental period					
	Electric	Diesel	Gasoline	ICE	All cars
Km peak per day	12.7	13.9	9.9	11.5	12.2
Km off-peak per day	21.6	25.9	19.5	21.3	21.4
Km per day per day	34.3	39.9	29.4	32.8	33.6
Share driving peak per day	37%	35%	34%	35%	36%
EC per day	34.7	52.1	37.6	43.4	38.8
EC per day peak	23.0	27.9	19.7	23.6	23.3
EC per day off-peak	11.7	24.2	17.9	19.8	15.5
EC per km	1.0	1.3	1.3	1.3	1.2
EC per km peak	1.8	2.0	2.0	2.0	1.9
EC per km off-peak	0.5	0.9	0.9	0.9	0.7
Share in the experiment	54 %	18 %	28 %	46 %	100 %
Panel B: Inputs from other sources					
	Electric	Diesel	Gasoline		
Road toll passing (using AUTOpass)					
Road toll non-peak (NOK/passing)	12.8	29.6	26.4		
Road toll peak (NOK/passing)	15.2	33.6	31.2		
Fuel price, including taxes					
Charging at home (NOK/kWh)	1				
Fast charging (NOK/kWh)	5.5				
Share of charging at home	0.9				
Fuel price (NOK/litre)		21.8	20.3		
Fuel use (kWh/km or litre/km)	0.2	0.07	0.07		
	Taxes				
Road use tax (NOK/litre)	–	2.71	4.62		
CO2-tax (NOK/litre)	–	3.17	2.72		
Total fuel tax (NOK/litre)	–	5.88	7.34		
Electricity tax (NOK/kWh)	0.15				
Tax per km (NOK/km)	0.03	0.41	0.51		

**Notes:** ‘All cars’ are weighted based on the distribution of vehicle types in the experiment sample. ‘ICE’ (Internal-Combustion-Engine) vehicles are weighted by the relative shares of diesel and gasoline cars observed in the sample. *Sources:* Road toll prices: [Fjellinjen \(2024\)](#); charging prices: [Norwegian EV Association \(2021, 2024\)](#); fuel prices: [Statistics Norway \(2024\)](#); vehicle taxes: [Regjeringen \(2024\)](#); electricity tax: [The Norwegian Tax Administration \(2024\)](#). *Experimental data:* Average number of days per week participants drive: 3.9. Share of the sample residing in Oslo: 35%. *Assumptions:* Drivers make an average of two toll passings per day driving. The toll road is only inside of Oslo municipality and at the border to cross into Oslo municipality. The pricing structure is one paid passing for passing into Oslo municipality and one paid passing inside of Oslo during one hour of driving. Among participants living outside Oslo (65% of the sample), we assume that 50% cross into Oslo when driving, resulting in one additional toll crossing (because of the structure of the toll road pricing scheme). *Result:* The estimated average number of toll passings per driving day is 1.3.

### A.3 App data cleaning

Outliers are removed by excluding trips with implausible average speeds: over 40 km/h for biking, 20 km/h for walking, 200 km/h for public transport (PT), and 150 km/h for driving. We also exclude trips that exceed reasonable distance thresholds: more than 50 km for biking, 200 km for PT, 20 km for walking, and 250 km for driving. In addition, we drop trips lasting more than 400 minutes for car travel and more than 500 minutes for PT.

Peak hours in our road pricing experiment are defined in alignment with the Oslo road toll system, specifically from 06:30–09:00 and 15:00–17:00. A trip is classified as a peak-hour trip if it *starts* within one of these peak periods. For example, a trip starting at 6:15 and ending at 7:00 is considered off-peak, as it begins outside the defined interval. Conversely, a trip starting at 8:30 and ending at 9:15 is counted as a peak-hour trip because its departure falls within the peak window.

### A.4 Pre-treatment period travel behavior

**Figure A-2** Density observed in pre-treatment period for the entire road pricing RCT sample (All) and by income group (low, medium, high).

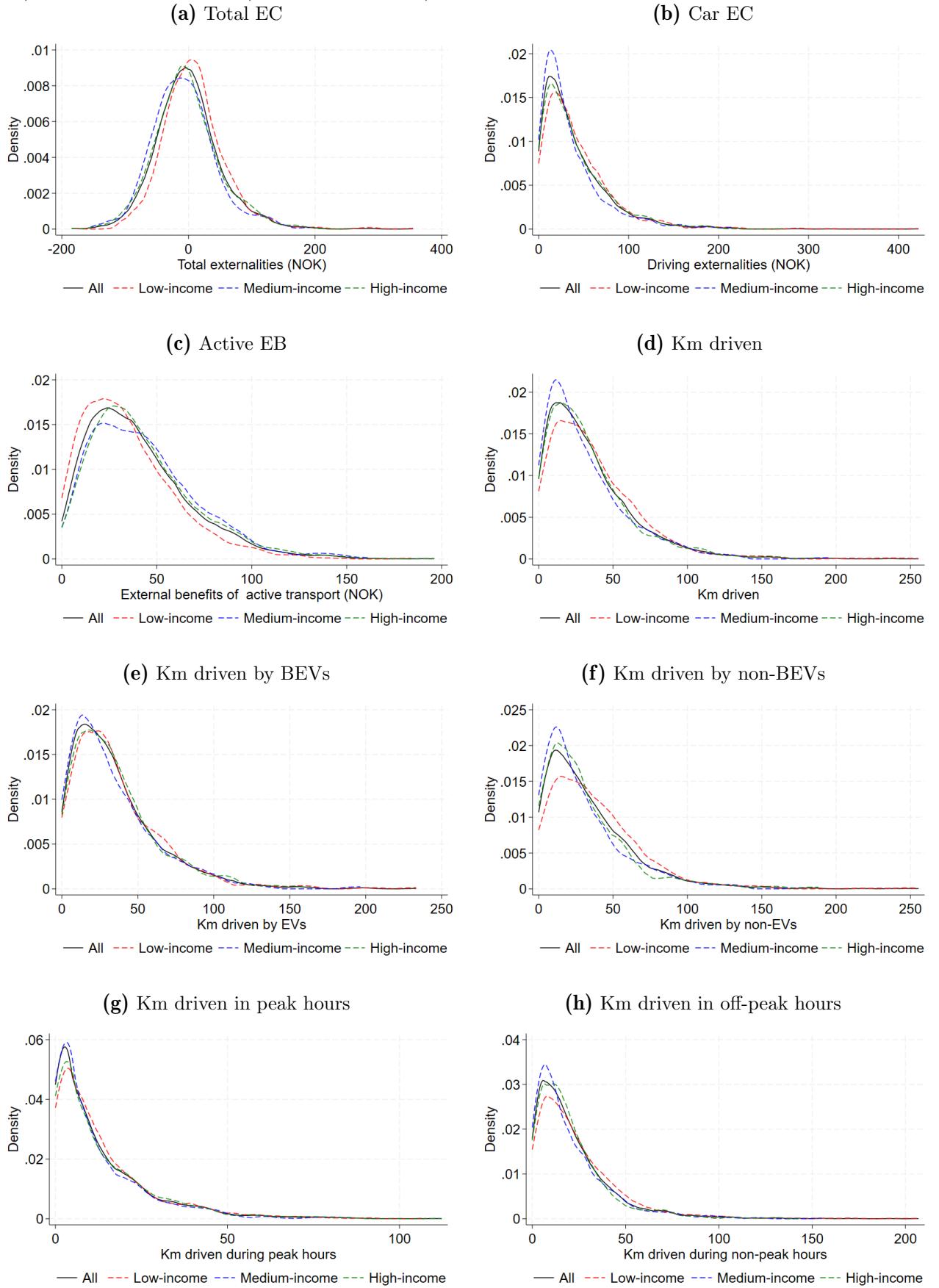
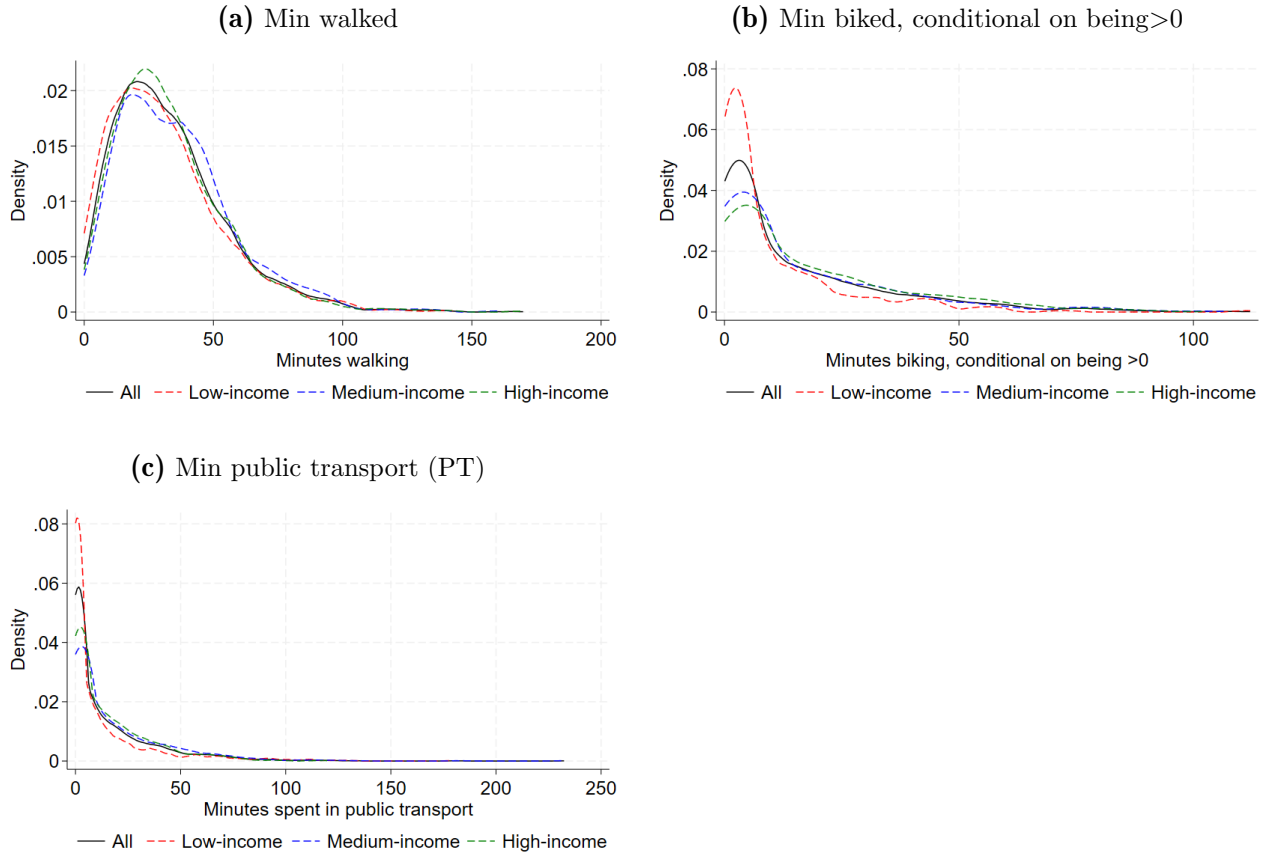
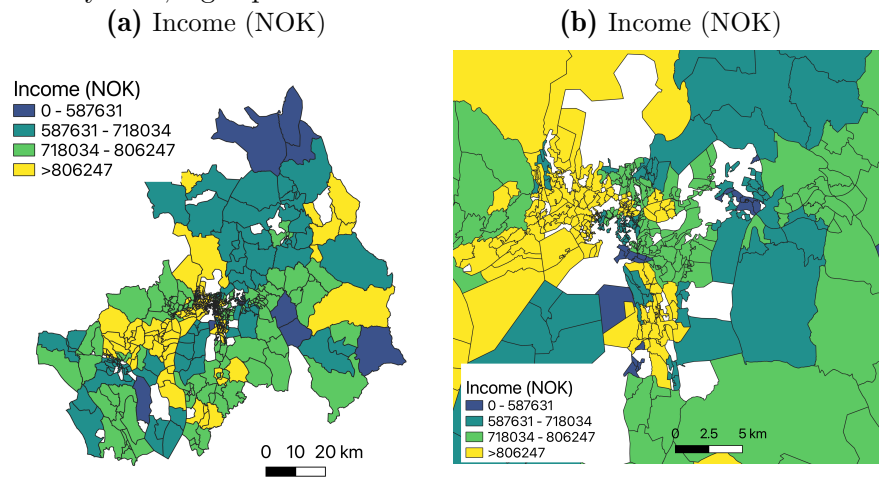


Figure A-2 Continued.



**Notes:** Income groups are determined based on the income of the participants in our experiment, i.e., who meet the eligibility criteria, such as driving at least two weekdays per week on average. Income groups are defined as: Low: <700k NOK (33% of the sample), medium:  $700\text{k NOK} \leq \text{medium} \leq 900\text{k NOK}$  (27% of the sample), high: >900k NOK (40% of the sample).

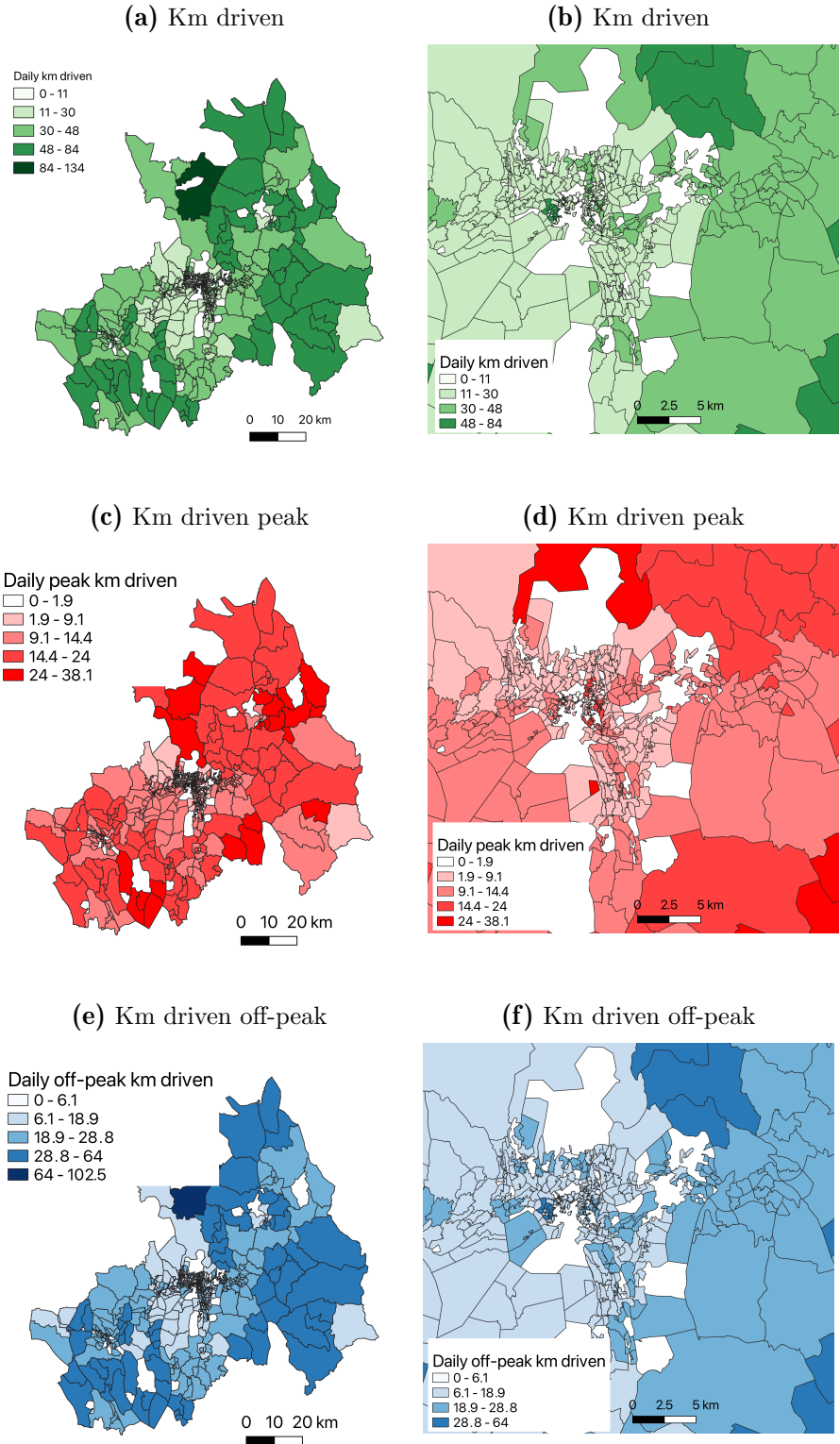
**Figure A-3** Spatial heterogeneity in income and baseline travel behavior using participants residential zipcode at the 4-digit level. Panels (a) - (b): individual annual income (NOK). Left panels: entire study area; right panels: Zoom on downtown Oslo.



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Figure A-3 Continued. Panels (a) - (b): daily km driven in pre-treatment period; Panels (c) - (d): daily peak km driven in pre-treatment period; Panels (e) - (f): daily off-peak km driven in pre-treatment period. Left panels: entire study area; right panels: Zoom on downtown Oslo.



**Notes:** Note that zipcode size is inversely proportional to population density.

## A.5 Balance tables and representativeness

All tables in this section report values for the pre-experimental period.

Table [A-5](#) summarizes daily travel variables during the pre-experimental period, with mode shares based on kilometers traveled (Columns 1-3). Columns 4-6 report differences between each column with standard errors from the t-tests and stars denoting p-value levels. The randomization appears to be well balanced as we do not observe differences across most variables.

In our sample, we ask participants whether they drive to their main activity, which could be work or study place for a student. Km BEV (km non-BEV) are calculated conditional on participants owning a BEV (non-BEV).

**Table A-5** Balance table comparing participants randomized into Control group, RP treatment group, and RPS treatment group.

	Control	RP	RPS	t-test differences		
	(1)	(2)	(3)	(1)-(2)	(1)-(3)	(2)-(3)
Total EC	-2.75 (52.03)	0.89 (52.99)	0.78 (49.78)	3.64 (2.41)	3.53 (2.35)	0.11 (2.35)
Car EC	38.62 (37.17)	40.88 (39.13)	40.59 (36.85)	2.25 (1.76)	1.97 (1.71)	0.28 (1.74)
Active EB	41.37 (28.15)	39.98 (27.04)	39.81 (26.72)	-1.38 (1.27)	-1.56 (1.27)	0.17 (1.23)
Km car	32.89 (29.71)	34.77 (29.23)	35.30 (29.91)	1.88 (1.35)	2.41 (1.37)	-0.53 (1.35)
Km car peak	12.40 (14.57)	12.98 (14.92)	12.97 (14.58)	0.58 (0.68)	0.57 (0.67)	0.01 (0.67)
Km car off-peak	20.49 (20.61)	21.79 (21.03)	22.33 (21.59)	1.30 (0.96)	1.84 (0.97)	-0.54 (0.97)
Km car urban	8.64 (11.30)	9.21 (11.53)	9.13 (11.77)	0.57 (0.52)	0.49 (0.53)	0.08 (0.53)
Km car rural	4.96 (8.92)	5.50 (9.36)	5.84 (9.81)	0.54 (0.42)	0.88* (0.43)	-0.34 (0.44)
Min PT	13.17 (18.79)	14.76 (21.76)	15.69 (24.07)	1.59 (0.94)	2.52* (1.00)	-0.93 (1.05)
Min bike	6.12 (14.28)	5.56 (13.17)	5.38 (13.41)	-0.56 (0.63)	-0.74 (0.64)	0.18 (0.61)
Min walk	33.74 (22.18)	33.09 (21.96)	33.14 (21.91)	-0.65 (1.01)	-0.60 (1.02)	-0.05 (1.00)
Share car	0.62 (0.30)	0.63 (0.29)	0.63 (0.30)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)
Share bike	0.07 (0.17)	0.07 (0.16)	0.06 (0.15)	-0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)
Share walk	0.14 (0.15)	0.13 (0.15)	0.12 (0.14)	-0.01 (0.01)	-0.02* (0.01)	0.01 (0.01)
Share PT	0.16 (0.21)	0.17 (0.23)	0.18 (0.24)	0.01 (0.01)	0.02 (0.01)	-0.01 (0.01)
# trips	4.29 (1.30)	4.29 (1.27)	4.30 (1.35)	0.00 (0.06)	0.01 (0.06)	-0.01 (0.06)
# car trips	3.00 (1.82)	3.03 (1.72)	3.09 (1.87)	0.04 (0.08)	0.09 (0.09)	-0.05 (0.08)
Km BEV	34.57 (30.98)	34.29 (26.77)	36.08 (29.51)	-0.28 (1.81)	1.50 (1.91)	-1.79 (1.74)
Km non-BEV	31.00 (28.15)	35.37 (32.03)	34.40 (30.36)	4.37* (2.04)	3.40 (1.98)	0.97 (2.11)
Observations	928	965	953	1,893	1,881	1,918

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**Table A-5 Continued**

	Control	RP	RPS	t-test differences		
	(1)	(2)	(3)	(1)-(2)	(1)-(3)	(2)-(3)
Age	46.25 (11.14)	46.22 (10.88)	46.52 (10.83)	-0.04 (0.51)	0.27 (0.51)	-0.31 (0.50)
Female	0.45 (0.50)	0.46 (0.50)	0.44 (0.50)	0.01 (0.02)	-0.01 (0.02)	0.02 (0.02)
0 kids	0.54 (0.50)	0.53 (0.50)	0.54 (0.50)	-0.01 (0.02)	-0.01 (0.02)	-0.00 (0.02)
1 kids	0.18 (0.39)	0.17 (0.37)	0.19 (0.39)	-0.01 (0.02)	0.00 (0.02)	-0.02 (0.02)
2 or more kids	0.27 (0.45)	0.30 (0.46)	0.28 (0.45)	0.02 (0.02)	0.00 (0.02)	0.02 (0.02)
University (4 years or more)	0.47 (0.50)	0.48 (0.50)	0.48 (0.50)	0.01 (0.02)	0.01 (0.02)	-0.00 (0.02)
Employed	0.90 (0.31)	0.91 (0.29)	0.92 (0.28)	0.01 (0.01)	0.02 (0.01)	-0.01 (0.01)
Student	0.04 (0.19)	0.02 (0.15)	0.03 (0.17)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Retired/Benefits	0.04 (0.20)	0.04 (0.20)	0.03 (0.17)	-0.00 (0.01)	-0.01 (0.01)	0.01 (0.01)
Low-income (<700k NOK)	0.34 (0.47)	0.33 (0.47)	0.33 (0.47)	-0.02 (0.02)	-0.01 (0.02)	-0.00 (0.02)
Medium-income ( $\geq 700k \& \leq 900k$ NOK)	0.25 (0.44)	0.28 (0.45)	0.27 (0.44)	0.03 (0.02)	0.02 (0.02)	0.01 (0.02)
High-income (>900k NOK)	0.41 (0.49)	0.39 (0.49)	0.40 (0.49)	-0.01 (0.02)	-0.00 (0.02)	-0.01 (0.02)
Observations	928	965	953	1,893	1,881	1,918

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**Table A-5 Continued**

	Control	RP	RPS	t-test differences		
	(1)	(2)	(3)	(1)-(2)	(1)-(3)	(2)-(3)
Own (e)bike	0.89 (0.31)	0.89 (0.31)	0.88 (0.32)	0.00 (0.01)	-0.01 (0.01)	0.01 (0.01)
N. cars household	1.52 (0.64)	1.53 (0.67)	1.54 (0.65)	0.00 (0.03)	0.02 (0.03)	-0.01 (0.03)
Car every weekday	0.46 (0.50)	0.49 (0.50)	0.49 (0.50)	0.04 (0.02)	0.03 (0.02)	0.00 (0.02)
PT subscription/plan to buy	0.23 (0.42)	0.23 (0.42)	0.25 (0.43)	0.01 (0.02)	0.02 (0.02)	-0.01 (0.02)
Fix work/study place	0.57 (0.50)	0.57 (0.50)	0.57 (0.50)	-0.00 (0.02)	0.00 (0.02)	-0.01 (0.02)
Satisfied with PT	0.69 (0.46)	0.70 (0.46)	0.70 (0.46)	0.01 (0.02)	0.01 (0.02)	0.00 (0.02)
Drive to work daily	0.55 (0.50)	0.56 (0.50)	0.55 (0.50)	0.01 (0.02)	0.00 (0.02)	0.01 (0.02)
Flexible	0.46 (0.50)	0.47 (0.50)	0.46 (0.50)	0.01 (0.02)	-0.00 (0.02)	0.01 (0.02)
No congestion, worktrip	0.44 (0.50)	0.44 (0.50)	0.45 (0.50)	-0.01 (0.03)	0.01 (0.03)	-0.02 (0.03)
Pay toll, worktrip	0.52 (0.50)	0.51 (0.50)	0.51 (0.50)	-0.01 (0.03)	-0.01 (0.03)	0.01 (0.03)
Pay toll above median (>=41 NOK)	0.35 (0.48)	0.30 (0.46)	0.35 (0.48)	-0.05 (0.04)	0.00 (0.05)	-0.05 (0.04)
Duration worktrip below median (<30)	0.59 (0.49)	0.57 (0.50)	0.57 (0.49)	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.02)
Urban	0.35 (0.48)	0.35 (0.48)	0.33 (0.47)	0.00 (0.02)	-0.02 (0.02)	0.02 (0.02)
Medium urban	0.58 (0.49)	0.57 (0.50)	0.58 (0.49)	-0.02 (0.02)	-0.00 (0.02)	-0.01 (0.02)
Rural	0.07 (0.25)	0.08 (0.28)	0.09 (0.29)	0.01 (0.01)	0.02 (0.01)	-0.01 (0.01)
Alt. mode takes more time	0.45 (0.50)	0.44 (0.50)	0.42 (0.49)	-0.01 (0.03)	-0.02 (0.03)	0.01 (0.03)
Negative tolls	0.42 (0.49)	0.40 (0.49)	0.40 (0.49)	-0.03 (0.02)	-0.02 (0.02)	-0.00 (0.02)
Low trust in government	0.23 (0.42)	0.24 (0.43)	0.22 (0.41)	0.01 (0.02)	-0.01 (0.02)	0.02 (0.02)
Care about environment	0.93 (0.25)	0.92 (0.27)	0.93 (0.25)	-0.01 (0.01)	0.00 (0.01)	-0.01 (0.01)
Air pollution problem	0.69 (0.46)	0.68 (0.47)	0.67 (0.47)	-0.02 (0.02)	-0.03 (0.02)	0.01 (0.02)
Congestion problem	0.78 (0.41)	0.78 (0.42)	0.78 (0.41)	-0.01 (0.02)	0.00 (0.02)	-0.01 (0.02)
Policy needed	0.75 (0.44)	0.77 (0.42)	0.74 (0.44)	0.03 (0.02)	-0.00 (0.02)	0.03 (0.02)
General tax too high	0.57 (0.50)	0.57 (0.50)	0.53 (0.50)	0.00 (0.02)	-0.04 (0.02)	0.04 (0.02)
Government wasting money	0.61 (0.49)	0.62 (0.49)	0.56 (0.50)	0.01 (0.02)	-0.05* (0.02)	0.06** (0.02)
Privacy important	0.87 (0.34)	0.89 (0.32)	0.91 (0.29)	0.02 (0.02)	0.04** (0.01)	-0.02 (0.01)
Research important	0.97 (0.16)	0.99 (0.12)	0.98 (0.13)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)
Angry about tolls	0.19 (0.39)	0.17 (0.37)	0.18 (0.39)	-0.02 (0.02)	-0.01 (0.02)	-0.01 (0.02)
Observations	928	965	953	1,893	1,881	1,918

**Notes:** RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, PT: public transport. Columns (1)-(3): Standard deviations in parentheses. Standard errors for the t-tests are reported in parentheses, \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.

**Table A-6** Comparing participants who expressed wanting to join the study and downloading the app versus those who expressed they did not want to.

Wanted to join the study	Yes (1)	No (2)	t-test difference (1)-(2)
Age	47.11 (11.27)	47.71 (12.11)	-0.61** (0.20)
Female	0.48 (0.50)	0.44 (0.50)	0.04*** (0.01)
0 kids	0.55 (0.50)	0.63 (0.48)	-0.08*** (0.01)
1 kids	0.18 (0.38)	0.15 (0.35)	0.03*** (0.01)
2 or more kids	0.27 (0.44)	0.22 (0.42)	0.05*** (0.01)
University (4 years or more)	0.46 (0.50)	0.43 (0.49)	0.04*** (0.01)
Employed	0.89 (0.31)	0.87 (0.34)	0.02*** (0.01)
Student	0.03 (0.18)	0.04 (0.19)	-0.00 (0.00)
Retired/Benefits	0.04 (0.20)	0.06 (0.23)	-0.01*** (0.00)
Low-income (<700k NOK)	0.37 (0.48)	0.39 (0.49)	-0.02** (0.01)
Medium-income ( $\geq 700k \& \leq 900k$ NOK)	0.25 (0.43)	0.22 (0.42)	0.03*** (0.01)
High-income (>900k NOK)	0.38 (0.49)	0.39 (0.49)	-0.01 (0.01)
Observations	6,250	7,325	13,575

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**Table A-6 Continued**

Wanted to join the study	Yes (1)	No (2)	t-test difference (1)-(2)
Own (e)bike	0.88 (0.32)	0.85 (0.36)	0.04*** (0.01)
N. cars household	1.54 (0.66)	1.62 (0.69)	-0.09*** (0.01)
Car every weekday	0.51 (0.50)	0.58 (0.49)	-0.07*** (0.01)
PT subscription/plan to buy	0.23 (0.42)	0.19 (0.39)	0.04*** (0.01)
Fix work/study place	0.59 (0.49)	0.61 (0.49)	-0.02* (0.01)
Satisfied with PT	0.68 (0.47)	0.59 (0.49)	0.08*** (0.01)
Drive to work daily	0.58 (0.49)	0.67 (0.47)	-0.09*** (0.01)
Flexible	0.42 (0.49)	0.40 (0.49)	0.02** (0.01)
No congestion, worktrip	0.43 (0.50)	0.43 (0.49)	0.00 (0.01)
Pay toll, worktrip	0.51 (0.50)	0.51 (0.50)	0.00 (0.01)
Pay toll above median ( $\geq 41$ NOK)	0.36 (0.48)	0.40 (0.49)	-0.03* (0.02)
Duration worktrip below median ( $< 30$	0.59 (0.49)	0.63 (0.48)	-0.04*** (0.01)
Urban	0.34 (0.47)	0.32 (0.47)	0.02 (0.01)
Medium urban	0.58 (0.49)	0.59 (0.49)	-0.01 (0.01)
Rural	0.08 (0.28)	0.09 (0.29)	-0.01 (0.00)
Alt. mode takes more time	0.46 (0.50)	0.49 (0.50)	-0.04*** (0.01)
Negative tolls	0.46 (0.50)	0.58 (0.49)	-0.12*** (0.01)
Low trust in government	0.28 (0.45)	0.37 (0.48)	-0.10*** (0.01)
Care about environment	0.91 (0.28)	0.89 (0.32)	0.03*** (0.01)
Air pollution problem	0.66 (0.47)	0.56 (0.50)	0.10*** (0.01)
Congestion problem	0.79 (0.41)	0.78 (0.41)	0.01 (0.01)
Policy needed	0.74 (0.44)	0.63 (0.48)	0.11*** (0.01)
General tax too high	0.61 (0.49)	0.68 (0.47)	-0.07*** (0.01)
Government wasting money	0.63 (0.48)	0.71 (0.45)	-0.08*** (0.01)
Privacy important	0.89 (0.31)	0.90 (0.30)	-0.01* (0.01)
Research important	0.97 (0.18)	0.95 (0.21)	0.02*** (0.00)
Angry about tolls	0.24 (0.43)	0.30 (0.46)	-0.06*** (0.01)
Observations	6,250	7,325	13,575



**Table A-7** Comparing participants who joined the study and those who did not, conditional on expressing that they wanted to join the study and download the app.

Joined the study	Yes (1)	No (2)	t-test difference (1)-(2)
Age	46.34 (10.95)	47.75 (11.49)	-1.41*** (0.29)
Female	0.45 (0.50)	0.51 (0.50)	-0.06*** (0.01)
0 kids	0.54 (0.50)	0.56 (0.50)	-0.03* (0.01)
1 kids	0.18 (0.38)	0.18 (0.38)	0.00 (0.01)
2 or more kids	0.28 (0.45)	0.26 (0.44)	0.02* (0.01)
University (4 years or more)	0.48 (0.50)	0.45 (0.50)	0.03** (0.01)
Employed	0.91 (0.29)	0.88 (0.32)	0.03*** (0.01)
Student	0.03 (0.17)	0.04 (0.19)	-0.01 (0.00)
Retired/Benefits	0.04 (0.19)	0.05 (0.21)	-0.01 (0.01)
Low-income (<700k NOK)	0.33 (0.47)	0.40 (0.49)	-0.07*** (0.01)
Medium-income ( $\geq 700k \& \leq 900k$ NOK)	0.27 (0.44)	0.24 (0.43)	0.03** (0.01)
High-income (>900k NOK)	0.40 (0.49)	0.36 (0.48)	0.04** (0.01)
Observations	2,844	3,406	6,250

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**Table A-7 Continued**

Joined the study	Yes (1)	No (2)	t-test difference (1)-(2)
Own (e)bike	0.89 (0.32)	0.87 (0.33)	0.01 (0.01)
N. cars household	1.53 (0.65)	1.54 (0.67)	-0.01 (0.02)
Car every weekday	0.48 (0.50)	0.54 (0.50)	-0.06*** (0.01)
PT subscription/plan to buy	0.24 (0.42)	0.22 (0.42)	0.01 (0.01)
Fix work/study place	0.57 (0.50)	0.61 (0.49)	-0.04** (0.01)
Satisfied with PT	0.70 (0.46)	0.66 (0.48)	0.04*** (0.01)
Drive to work daily	0.55 (0.50)	0.61 (0.49)	-0.05*** (0.01)
Flexible	0.46 (0.50)	0.39 (0.49)	0.07*** (0.01)
No congestion, worktrip	0.44 (0.50)	0.42 (0.49)	0.02 (0.01)
Pay toll, worktrip	0.51 (0.50)	0.51 (0.50)	0.00 (0.02)
Pay toll above median ( $\geq 41$ NOK)	0.33 (0.47)	0.39 (0.49)	-0.06* (0.02)
Duration worktrip below median ( $< 30$ )	0.58 (0.49)	0.60 (0.49)	-0.02* (0.01)
Urban	0.34 (0.47)	0.33 (0.47)	0.01 (0.01)
Medium urban	0.58 (0.49)	0.58 (0.49)	-0.01 (0.01)
Rural	0.08 (0.27)	0.08 (0.28)	-0.00 (0.01)
Alt. mode takes more time	0.44 (0.50)	0.47 (0.50)	-0.04* (0.02)
Negative tolls	0.41 (0.49)	0.50 (0.50)	-0.09*** (0.01)
Low trust in government	0.23 (0.42)	0.32 (0.47)	-0.09*** (0.01)
Care about environment	0.93 (0.26)	0.90 (0.30)	0.03*** (0.01)
Air pollution problem	0.68 (0.47)	0.65 (0.48)	0.03* (0.01)
Congestion problem	0.78 (0.41)	0.80 (0.40)	-0.02 (0.01)
Policy needed	0.75 (0.43)	0.73 (0.45)	0.03* (0.01)
General tax too high	0.56 (0.50)	0.65 (0.48)	-0.09*** (0.01)
Government wasting money	0.59 (0.49)	0.66 (0.48)	-0.06*** (0.01)
Privacy important	0.89 (0.32)	0.89 (0.31)	-0.00 (0.01)
Research important	0.98 (0.14)	0.96 (0.20)	0.02*** (0.00)
Angry about tolls	0.18 (0.38)	0.28 (0.45)	-0.10*** (0.01)
Observations	2,844	3,406	6,250

Table A-8 and A-9 compare the different samples with the population. In Table A-8, travel data for the population are derived from the National Travel Habits Survey (2020–2024). This data represent respondents from Oslo and surrounding municipalities included in the study area, aged 18 to 65, who drive at least once per week. Note that our sample is selected based on people who drive at least two work days (Monday-Friday).

The whole National Travel Habits Survey for the study area has 10,072 respondents, but as we only wanted to look at respondents that drive at least once per week: 4,277 respondents. Driving to work has 3,167 observations, since not everyone in the National Travel Habits Survey sample has a job.

The National Travel Habit Survey is funded by the Ministry of Transport, the Norwegian Public Roads Administration, the Norwegian Railways Directorate, Nye Veier AS, the Norwegian Coastal Administration, and Avinor. The survey data was collected by Opinion AS and anonymized by the Norwegian Public Roads Administration on behalf of these transport agencies. However, none of these organizations are responsible for the data analysis or interpretations presented in this study.

Table A-9 shows some population variables taken from Statistics Norway data bank for the municipalities included in the study, expect income, which is only for the Oslo municipality. The "Travel data" panel is also taken from the same sample as the National Travel Survey.

**Table A-8** Comparing the RCT sample's app data with the national travel survey sample.

	RCT sample	National travel survey Greater Oslo-area
Km car	34.34	37.60
Min PT	14.55	13.90
Min bike	5.68	3.00
Min walk	33.32	15.20
Share car	0.63	0.80
Share bike	0.07	0.02
Share walk	0.13	0.02
Share PT	0.17	0.17
# trips	4.29	2.90
# car trips	3.04	1.80
N	2,846	4,277

**Notes:** Travel data for the population come from the National Travel Habits Survey (2020–2024). The data cover respondents from Oslo and surrounding municipalities included in the study area, aged 18 to 65, who drive at least once per week. The municipalities comprising the Greater Oslo area include: Oslo, Bærum, Asker, Lillestrøm, Nordre Follo, Ullensaker, Nesodden, Frogn, Vestby, Ås, Enebakk, Lørenskog, Rælingen, Aurskog-Høland, Nes, Gjerdrum, Nittedal, Lunner, Jevnaker, Nannestad, Eidsvoll, Hurdal, Drammen, Lier, Øvre Eiker, Asker, and Holmestrand.

**Table A-9** Comparing our different samples with the Greater Oslo population.

	Pre-survey	Post-survey	RCT	Greater Oslo Population
Population data				
Age	45.05	46.57	46.33	40.53
Female	0.50	0.47	0.45	0.50
0 kids	0.64	0.66	0.54	0.56
1 kids	0.14	0.13	0.18	0.16
2 or more kids	0.22	0.21	0.28	0.28
University (4 years or more)	0.47	0.49	0.48	0.17
Employed	0.84	0.85	0.91	0.65
Student	0.07	0.05	0.03	0.06
Retired/Benefits	0.05	0.06	0.04	0.14
Annual gross income (NOK 100,000)	6.95	7.20	7.72	6.90
Travel data				
Own (e)bike	0.83	0.84	0.89	0.77
Car every weekday	0.40	0.38	0.48	0.52
PT subscription/plan to buy	0.34	0.32	0.24	0.23
Driving work/daily	0.40	0.40	0.55	0.57
N	23,572	12,813	2,846	4,277

**Notes:** *Population data:* are taken from Statistics Norway data bank for the municipalities/counties included in the study. Sources for population statistics: Age, Table 07459: Population, by age, contents, year and region. For age, we only consider individuals between 18 and 65 years old, as these are the ones invited into the research project. We have calculated a weighted average age. Gender, Table 07459: Population, by region, sex, contents, year and age. This includes individuals aged 18 or older. Children per household, Table 06081: Persons in private households, by type of household, contents, year and region. Education level, Table 08921: Persons aged 16 and older, by education level, contents, year and region. Here we look at 2019, because until and including 2023, Akershus county was part of Viken county in 2023. Employment status, Table 13563: Labour force status (incl. NEET) for residents aged 15 and older, by prioritized labour force status, contents, year and region. "Student" here includes those "in education". Annual gross income is divided by 100,000. Annual gross income is based on categories where "over 9" is set to 10, "7–8.99" is set to 8 "5–6.99" is set to 6, and so on. The income data is only for Oslo, as the data is only available on county level, and Akershus county was part of Viken county. Average gross income, table 08603: Taxable income and property, by region, contents, year and income and property and the number is the average for residents 17 years and older with amount (kr). *Travel data:* for the population are derived from the National Travel Habits Survey (2020–2024). This data represent respondents from Oslo and surrounding municipalities included in the study area, aged 18 to 65, who drive at least once per week. The municipalities comprising the Greater Oslo area include: Oslo, Bærum, Asker, Lillestrøm, Nordre Follo, Ullensaker, Nesodden, Frogn, Vestby, Ås, Enebakk, Lørenskog, Rælingen, Aurskog-Høland, Nes, Gjerdrum, Nittedal, Lunner, Jevnaker, Nannestad, Eidsvoll, Hurdal, Drammen, Lier, Øvre Eiker, Asker, and Holmestrand.

Table [A-10](#) reports summary statistics for BEV and non-BEV drivers in the pre-period. T-tests show the two groups are quite different from each other: BEV drivers drive more in peak hours, in urban areas and less in rural areas. They are slightly more likely to be employed, have higher education, and earn higher income. BEV drivers state that they drive more often, are more likely to drive to work and are less likely to have a public transport subscription compared to non-BEV drivers. They are less negative about the existing road tolls, and are more likely to believe that air pollution is a problem.

**Table A-10** Comparing participants with BEVs and non-BEVs in the pre-period.

Vehicle type	BEV (1)	non-BEV (2)	t-test difference (1)-(2)
Total EC	-4.34 (47.51)	4.37 (55.73)	-8.71*** (1.94)
Car EC	36.45 (33.67)	44.25 (41.63)	-7.80*** (1.41)
Active EB	40.79 (26.63)	39.89 (28.06)	0.90 (1.03)
Km car	34.98 (29.07)	33.58 (30.25)	1.39 (1.11)
Km car peak	13.48 (15.07)	11.98 (14.20)	1.50** (0.55)
Km car off-peak	21.50 (20.57)	21.60 (21.69)	-0.11 (0.79)
Km car urban	10.14 (12.34)	7.66 (10.37)	2.47*** (0.43)
Km car rural	4.96 (8.67)	5.99 (10.11)	-1.04** (0.35)
Min PT	13.82 (19.81)	15.40 (23.69)	-1.58 (0.82)
Min bike	6.07 (14.00)	5.23 (13.15)	0.84 (0.51)
Min walk	33.30 (21.48)	33.35 (22.63)	-0.05 (0.83)
Share car	0.63 (0.29)	0.62 (0.31)	0.01 (0.01)
Share bike	0.07 (0.16)	0.06 (0.15)	0.01 (0.01)
Share walk	0.13 (0.14)	0.14 (0.16)	-0.01 (0.01)
Share PT	0.17 (0.22)	0.18 (0.24)	-0.01 (0.01)
# trips	4.32 (1.25)	4.26 (1.37)	0.05 (0.05)
# car trips	3.06 (1.74)	3.02 (1.88)	0.04 (0.07)
Observations	1,535	1,311	2,846

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**Table A-10 Continued**

Vehicle type	BEV (1)	non-BEV (2)	t-test difference (1)-(2)
Age	46.79 (10.39)	45.93 (11.55)	0.86* (0.41)
Female	0.42 (0.49)	0.49 (0.50)	-0.07*** (0.02)
0 kids	0.50 (0.50)	0.58 (0.49)	-0.08*** (0.02)
1 kids	0.19 (0.39)	0.16 (0.37)	0.03 (0.01)
2 or more kids	0.31 (0.46)	0.25 (0.44)	0.05** (0.02)
University (4 years or more)	0.52 (0.50)	0.43 (0.50)	0.09*** (0.02)
Employed	0.93 (0.25)	0.88 (0.32)	0.05*** (0.01)
Student	0.02 (0.15)	0.04 (0.19)	-0.02** (0.01)
Retired/Benefits	0.03 (0.17)	0.05 (0.21)	-0.02* (0.01)
Low-income (<700k NOK)	0.26 (0.44)	0.42 (0.49)	-0.16*** (0.02)
Medium-income ( $\geq 700k$ &<900k NOK)	0.28 (0.45)	0.25 (0.44)	0.03 (0.02)
High-income (>900k NOK)	0.46 (0.50)	0.33 (0.47)	0.13*** (0.02)
Observations	1,548	1,345	2,893

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**Table A-10 Continued**

Vehicle type	BEV (1)	non-BEV (2)	t-test difference (1)-(2)
Own (e)bike	0.91 (0.29)	0.86 (0.35)	0.05*** (0.01)
N. cars household	1.56 (0.64)	1.50 (0.66)	0.06* (0.02)
Car every weekday	0.53 (0.50)	0.44 (0.50)	0.09*** (0.02)
PT subscription/plan to buy	0.21 (0.41)	0.26 (0.44)	-0.04** (0.02)
Fix work/study place	0.57 (0.49)	0.56 (0.50)	0.01 (0.02)
Satisfied with PT	0.70 (0.46)	0.70 (0.46)	-0.00 (0.02)
Drive to work daily	0.59 (0.49)	0.52 (0.50)	0.07*** (0.02)
Flexible	0.50 (0.50)	0.42 (0.49)	0.08*** (0.02)
No congestion, worktrip	0.39 (0.49)	0.50 (0.50)	-0.11*** (0.02)
Pay toll, worktrip	0.60 (0.49)	0.41 (0.49)	0.20*** (0.02)
Pay toll above median ( $\geq 41$ NOK)	0.20 (0.40)	0.56 (0.50)	-0.36*** (0.03)
Duration worktrip below median ( $< 30$ )	0.58 (0.49)	0.59 (0.49)	-0.01 (0.02)
Urban	0.36 (0.48)	0.32 (0.47)	0.04* (0.02)
Medium urban	0.57 (0.50)	0.58 (0.49)	-0.01 (0.02)
Rural	0.07 (0.25)	0.10 (0.30)	-0.03** (0.01)
Alt. mode takes more time	0.44 (0.50)	0.44 (0.50)	-0.00 (0.02)
Negative tolls	0.35 (0.48)	0.47 (0.50)	-0.12*** (0.02)
Low trust in government	0.21 (0.40)	0.25 (0.44)	-0.05** (0.02)
Care about environment	0.93 (0.26)	0.93 (0.26)	0.00 (0.01)
Air pollution problem	0.70 (0.46)	0.65 (0.48)	0.06** (0.02)
Congestion problem	0.77 (0.42)	0.80 (0.40)	-0.03 (0.02)
Policy needed	0.77 (0.42)	0.74 (0.44)	0.03 (0.02)
General tax too high	0.52 (0.50)	0.60 (0.49)	-0.08*** (0.02)
Government wasting money	0.58 (0.49)	0.61 (0.49)	-0.03 (0.02)
Privacy important	0.89 (0.32)	0.89 (0.32)	0.00 (0.01)
Research important	0.98 (0.13)	0.98 (0.15)	0.01 (0.01)
Angry about tolls	0.14 (0.35)	0.23 (0.42)	-0.08*** (0.01)
Reading emails	0.78 (0.41)	0.77 (0.42)	0.01 (0.02)
Got all 7 feedback	0.81 (0.40)	0.77 (0.42)	0.04* (0.02)
Observations	1,548	1,345	2,893



**Table A-11** Summary statistics of the external driving costs and kilometers driven using the trip destination, including by peak and non-peak hours, and by vehicle type, in the pre-treatment period.

	Daily (1)	Peak hours (2)	Off-peak hours (3)
Panel A: All participants			
Car EC work	7.3 (13.5)	6.0 (12.3)	1.3 (3.9)
Car EC non-work	32.7 (31.5)	18.6 (22.7)	14.1 (14.9)
Km car work	4.9 (9.0)	3.0 (6.0)	1.9 (5.7)
Km car non-work	29.4 (25.8)	9.8 (11.6)	19.6 (19.1)
Observations	2828	2828	2828
Panel B: Participants with non-BEVs			
Car EC work	7.0 (13.5)	5.3 (11.9)	1.6 (4.5)
Car EC non-work	37.1 (35.8)	18.9 (23.8)	18.2 (18.5)
Km car work	4.3 (8.2)	2.5 (5.5)	1.8 (4.9)
Km car non-work	29.1 (27.1)	9.4 (11.5)	19.7 (20.3)
Observations	1301	1301	1301
Panel C: Participants with BEVs			
Car EC work	7.6 (13.5)	6.5 (12.7)	1.1 (3.3)
Car EC non-work	28.9 (26.7)	18.3 (21.7)	10.6 (9.7)
Km car work	5.3 (9.6)	3.4 (6.4)	2.0 (6.3)
Km car non-work	29.6 (24.7)	10.1 (11.6)	19.5 (17.9)
Observations	1527	1527	1527

**Notes:** EC denotes external costs. “Work” trips include trips whose destination is work (98%) or study (2%), while “non-work” trips include all other destinations such as home (44%), shopping (19%), errands (9%), or leisure (7%).

## B Additional results

### B.1 Road pricing results

**Table B-1** Effect of RP and RPS on daily external cost of driving (Car EC), including during peak and off-peak hours, and external benefits of active transport (Active EB), including separately for non-BEV and BEV participants. Estimated with Poisson PML.

	Car EC			Active EB
	Daily (1)	Peak hours (2)	Off-peak hours (3)	(4)
Panel A: All participants				
RP	-0.053** (0.024)	-0.051 (0.033)	-0.057** (0.026)	0.015 (0.018)
RPS	-0.048** (0.023)	-0.015 (0.031)	-0.100*** (0.028)	0.031* (0.018)
Ymean	39.09	23.67	15.42	43.43
S	0.005	0.035	-0.042*	0.016
se	0.022	0.030	0.026	0.019
N	104870	104472	104839	104899
Panel B: Participants with non-BEVs				
RP	-0.082** (0.037)	-0.084 (0.055)	-0.080** (0.039)	0.027 (0.027)
RPS	-0.107*** (0.036)	-0.065 (0.053)	-0.158*** (0.041)	0.016 (0.027)
Ymean	43.84	24.16	19.68	43.03
S	-0.024	0.020	-0.078**	-0.011
se	0.032	0.049	0.038	0.029
N	47531	47284	47500	47560
Panel C: Participants with BEVs				
RP	-0.024 (0.030)	-0.025 (0.041)	-0.025 (0.031)	0.005 (0.023)
RPS	0.011 (0.029)	0.025 (0.037)	-0.017 (0.034)	0.044* (0.024)
Ymean	35.01	23.26	11.76	43.77
S	0.034	0.049	0.008	0.038
se	0.029	0.038	0.032	0.025
N	57339	57188	57339	57339

**Notes:** All specifications include date and individual fixed effects. Robust standard errors clustered at the individual level in parentheses. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. *Ymean* denotes the outcome variable's sample mean in the post-treatment period for the control group. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.

**Table B-2** Mechanisms for all participants, and those with non-BEVs or BEVs.

	Transport mode				Km driven					# car trips	# trips
	Km car (1)	Min bike (2)	Min walk (3)	Min PT (4)	Peak (5)	Off-peak (6)	Urban (7)	Suburb (8)	Rural (9)	(10)	(11)
Panel A: All participants											
RP	-0.041** (0.020)	0.067 (0.058)	-0.001 (0.018)	-0.022 (0.038)	-0.032 (0.030)	-0.047* (0.025)	-0.053* (0.029)	-0.037* (0.022)	-0.035 (0.036)	-0.028* (0.015)	-0.009 (0.0092)
RPS	-0.053*** (0.020)	0.149** (0.067)	0.001 (0.017)	-0.023 (0.038)	-0.020 (0.028)	-0.073*** (0.026)	-0.052* (0.030)	-0.053** (0.021)	-0.057 (0.036)	-0.032** (0.016)	-0.004 (0.0091)
Ymean	33.67	6.92	34.75	14.20	12.28	21.39	9.08	19.41	5.18	2.97	4.59
S	-0.013	0.082	0.002	-0.001	0.012	-0.026	0.001	-0.017	-0.021	-0.004	0.005
se	0.019	0.071	0.018	0.035	0.029	0.025	0.028	0.021	0.034	0.014	0.009
N	104870	71013	104899	99797	104472	104839	98010	104367	98477	104870	112547
Panel B: Participants with non-BEVs											
RP	-0.076** (0.032)	0.129 (0.098)	0.004 (0.027)	-0.006 (0.054)	-0.087* (0.048)	-0.068* (0.038)	-0.114** (0.052)	-0.052 (0.033)	-0.109* (0.056)	-0.047* (0.024)	-0.005 (0.014)
RPS	-0.122*** (0.032)	0.216** (0.10)	-0.034 (0.025)	-0.099* (0.053)	-0.083* (0.046)	-0.143*** (0.040)	-0.142*** (0.053)	-0.107*** (0.033)	-0.152*** (0.054)	-0.071*** (0.026)	-0.005 (0.013)
Ymean	32.87	6.18	35.33	15.42	11.73	21.15	7.94	19.47	5.47	3.00	4.54
S	-0.047	0.087	-0.038	-0.094*	0.004	-0.075**	-0.027	-0.055	-0.043	-0.025	-0.001
se	0.030	0.106	0.027	0.048	0.046	0.038	0.047	0.031	0.049	0.022	0.013
N	47531	30956	47560	44972	47284	47500	43329	47311	44743	47531	51084
Panel C: Participants with BEVs											
RP	-0.014 (0.025)	0.025 (0.071)	-0.004 (0.023)	-0.030 (0.053)	0.007 (0.038)	-0.029 (0.033)	-0.015 (0.033)	-0.025 (0.028)	0.034 (0.047)	-0.011 (0.018)	-0.013 (0.012)
RPS	0.001 (0.026)	0.100 (0.091)	0.033 (0.024)	0.058 (0.055)	0.026 (0.035)	-0.013 (0.034)	0.003 (0.035)	-0.009 (0.028)	0.035 (0.047)	0.000 (0.020)	-0.003 (0.012)
Ymean	34.36	7.55	34.25	13.16	12.76	21.60	10.06	19.36	4.94	2.95	4.64
S	0.015	0.075	0.037	0.088*	0.019	0.016	0.018	0.015	0.001	0.012	0.009
se	0.025	0.095	0.024	0.050	0.036	0.032	0.034	0.027	0.047	0.019	0.012
N	57339	40057	57339	54825	57188	57339	54681	57056	53732	57339	61463

**Notes:** All specifications include date and individual fixed effects and are estimated with Poisson PML. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. *Ymean* denotes the outcome variable's sample mean in the post-treatment period for the control group. Car trips denote here single car tracks, where several car tracks may be contained in a single trip, provided that each subsequent track begins within 20 minutes of the previous track's end. Robust standard errors clustered at the individual level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table B-3** Mechanisms mode shares (km)

	Car (1)	Bike (2)	Walk (3)	PT (4)	Other (5)
Panel A: All Participants					
RP	-0.025** (0.012)	0.051 (0.054)	0.028 (0.031)	0.046 (0.031)	-0.109 (0.21)
RPS	-0.023** (0.012)	0.148** (0.060)	0.019 (0.034)	0.002 (0.032)	0.190 (0.21)
Ymean	0.61	0.08	0.14	0.16	0.01
S	0.002	0.097	-0.009	-0.045	0.300
se	0.011	0.061	0.032	0.030	0.213
N	104870	71013	104899	99797	12792
Panel B: Participants with non-BEVs					
RP	-0.042** (0.017)	0.135* (0.081)	0.024 (0.043)	0.072* (0.043)	-0.222 (0.35)
RPS	-0.032* (0.018)	0.240*** (0.084)	0.059 (0.049)	-0.033 (0.042)	-0.011 (0.33)
Ymean	0.60	0.07	0.15	0.17	0.01
S	0.010	0.105	0.035	-0.105**	0.211
se	0.017	0.084	0.048	0.042	0.324
N	47531	30956	47560	44972	5502
Panel C: Participants with BEVs					
RP	-0.012 (0.015)	-0.009 (0.071)	0.031 (0.044)	0.025 (0.044)	-0.147 (0.25)
RPS	-0.015 (0.015)	0.081 (0.083)	-0.017 (0.047)	0.037 (0.047)	0.208 (0.24)
Ymean	0.62	0.08	0.13	0.16	0.01
S	-0.003	0.089	-0.048	0.012	0.356
se	0.014	0.084	0.044	0.042	0.273
N	57339	40057	57339	54825	7290

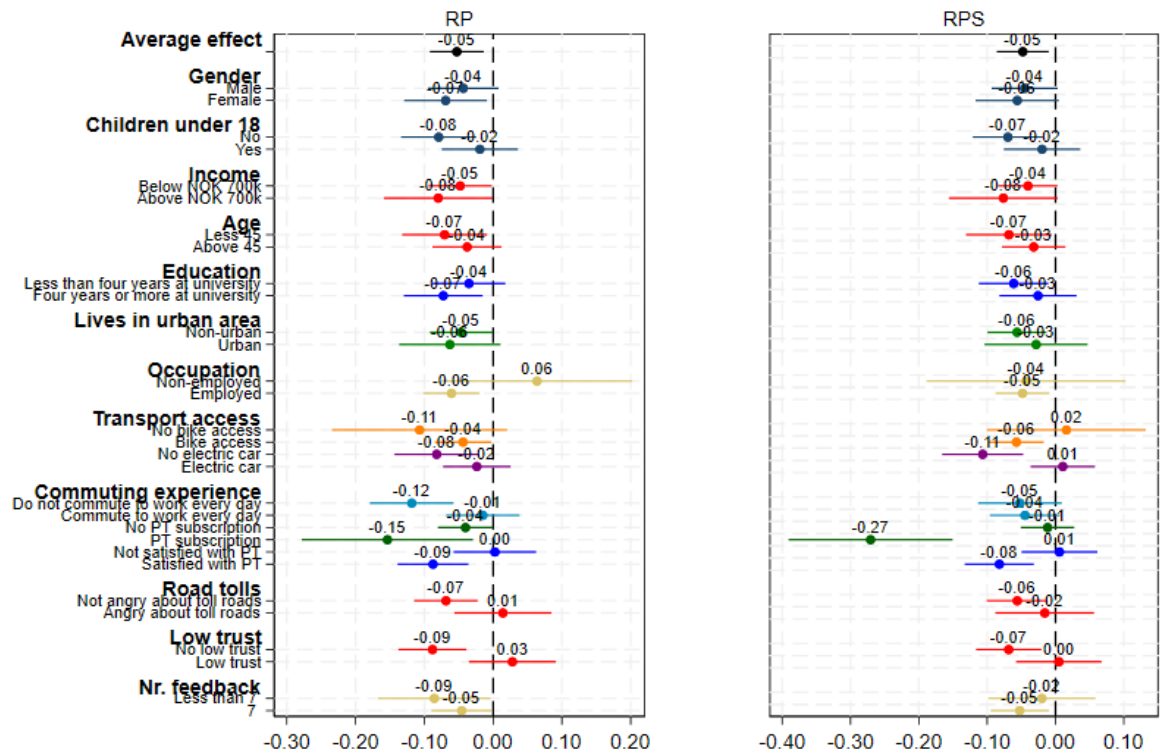
**Notes:** All specifications include date and individual fixed effects. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. PT: public transport. *Ymean* denotes the outcome variable's sample mean in the post-treatment period for the control group. Robust standard errors clustered at the individual level in parentheses. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.

**Table B-4** Effect of road pricing on external driving costs and kilometers driven based on trip destination, for all participants, and for those with non-BEVs or BEVs.

	Work trips				Non-work trips			
	EC Car (1)	km car			EC Car (5)	km car		
		All day (2)	Peak (3)	Off-peak (4)		All day (6)	Peak (7)	Off-peak (8)
Panel A: All participants								
RP	0.001 (0.053)	-0.017 (0.046)	0.054 (0.058)	-0.126 (0.079)	-0.065** (0.026)	-0.046** (0.022)	-0.055 (0.034)	-0.042 (0.027)
RPS	-0.009 (0.052)	-0.005 (0.048)	-0.003 (0.060)	-0.007 (0.081)	-0.056** (0.026)	-0.062*** (0.023)	-0.023 (0.033)	-0.080*** (0.028)
Ymean	7.09	4.69	2.81	1.88	31.96	29.00	9.48	19.52
S	-0.010	0.012	-0.057	0.119	0.009	-0.016	0.032	-0.038
se	0.048	0.046	0.055	0.079	0.024	0.021	0.034	0.027
N	83436	83436	71798	66116	104256	104256	103777	104225
Panel B: Participants with non-BEVs								
RP	0.021 (0.086)	-0.019 (0.079)	-0.005 (0.099)	-0.041 (0.12)	-0.100** (0.039)	-0.084** (0.035)	-0.100** (0.051)	-0.075* (0.042)
RPS	0.019 (0.090)	0.012 (0.079)	-0.027 (0.10)	0.059 (0.11)	-0.129*** (0.038)	-0.143*** (0.035)	-0.093* (0.048)	-0.166*** (0.044)
Ymean	6.71	4.11	2.43	1.68	37.06	28.76	9.29	19.47
S	-0.003	0.031	-0.022	0.100	-0.030	-0.059*	0.008	-0.091
se	0.073	0.070	0.085	0.120	0.036	0.033	0.052	0.041
N	37028	37028	31180	29813	47211	47211	46928	47180
Panel C: Participants with BEVs								
RP	-0.014 (0.066)	-0.015 (0.057)	0.091 (0.072)	-0.179* (0.11)	-0.029 (0.033)	-0.016 (0.028)	-0.022 (0.046)	-0.015 (0.035)
RPS	-0.032 (0.063)	-0.016 (0.061)	0.012 (0.073)	-0.047 (0.12)	0.021 (0.033)	0.003 (0.029)	0.030 (0.044)	-0.009 (0.036)
Ymean	7.42	5.20	3.14	2.06	27.61	29.21	9.64	19.56
S	-0.017	-0.002	-0.079	0.133	0.050	0.020	0.052	0.006
se	0.064	0.060	0.072	0.106	0.033	0.028	0.045	0.035
N	46407	46407	40618	36297	57045	57045	56849	57045

**Notes:** Work trips include trips whose destination is work or study, while non-work trips include all other destinations (assistance, eat out, errand, visiting family and friends, home, leisure, medical visit, other, shopping, sport, unknown, wait and work errands). Estimated with Poisson PML. All specifications include date and individual fixed effects. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. PT: public transport. *Ymean* denotes the outcome variable's sample mean in the pre-treatment period in NOK. Robust standard errors clustered at the individual level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Figure B-1** Effect of RP and RPS on the external costs of driving (EC Car) across groups using model (2). Left panel: RP; right panel: RPS. Horizontal bars denote 90%-confidence intervals.



## B.2 Public support for road pricing

We estimate the effects of the information treatment and experience with road pricing on respondents' changes in public support for road pricing using two ordered logit models to address the discrete nature of the public support variable and potential non-linearity in the treatment effect. The first alternative uses an ordered logit model of the change in public support:

$$\Pr(\Delta S_i) = \text{logit}(\beta_0 + \beta_1 \text{Info}_i + \beta_2 \text{RP}_i + \beta_3 \text{RPS}_i + \gamma \mathbf{X}_i) \quad (4)$$

where  $\Delta S_i$  denotes the change in public support for road pricing between the post-experimental and pre-experimental surveys, respectively, for individual  $i$ . It is a discrete variable with a finite range,  $\Delta S_i \in [-4, 4]$ . This specification directly models the likelihood of different levels of changes in public support.  $\text{Info}_i$  is an indicator variable for individual  $i$  being assigned to the information treatment group in the post-experimental survey, while  $\text{RP}_i$  and  $\text{RPS}_i$  are indicator variables for individual  $i$  being assigned to either the road pricing or road pricing and subsidy for walking and cycling in the road pricing field experiment. The vector  $\mathbf{X}_i$  denotes characteristics of person  $i$  that may affect acceptability towards road pricing, including income, age, access to bike, employment status, having children, driving a BEV (0/1). Survey participants without a car are included in this analysis as 'not driving a BEV' – this case may only happen in the Full sample (columns (4)-(6) in Table B-5) because only participants driving at least two weekdays per week are eligible for the road pricing field experiment, i.e., in the RCT sample (columns (1)-(3)).

The ordered logit model with  $\Delta S$  as the dependent variable estimates the odds of moving up in support conditional on treatment. This model retains the ordinal structure of the data, while modeling the direction and magnitude of the change. This approach is less flexible than model (5) below since it focuses directly on the change as the outcome.

The second alternative uses an ordered logit model on post-treatment public support, while controlling for pre-treatment support:

$$\Pr(\text{Post}S_i) = \text{logit}(\beta_0 + \beta_1 \text{Pre}S_i + \beta_2 \text{Info}_i + \beta_3 \text{RP}_i + \beta_4 \text{RPS}_i + \gamma \mathbf{X}_i) \quad (5)$$

where  $\text{Post}S_i$  and  $\text{Pre}S_i$  denote the public support for road pricing in the post- and pre-treatment periods, respectively. They are discrete variables with a finite range, taking value  $[1, 5]$ . This specification directly models the likelihood of different levels of post-treatment public support levels, retaining the ordinal structure of the data, while controlling for initial public support in a flexible way. This approach gives the treatment

effect on post-support, controlling for baseline support.

**Table B-5** Ordered logit regressions of the effect of the information treatment and experience with road pricing on the change in public support for road pricing.

	RCT sample			Full sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Outcome variable: Change in public support $\Delta S$						
Info	0.262*** (0.075)	0.270*** (0.076)	0.259* (0.13)	0.286*** (0.032)	0.297*** (0.033)	0.300*** (0.035)
RP	0.073 (0.092)	0.058 (0.093)	0.105 (0.13)	0.025 (0.071)	0.081 (0.073)	0.153 (0.098)
RPS	0.134 (0.091)	0.126 (0.092)	0.060 (0.13)	0.085 (0.070)	0.153** (0.071)	0.110 (0.095)
InfoxRP			-0.098 (0.19)			-0.150 (0.14)
InfoxRPS			0.128 (0.18)			0.084 (0.13)
Control				-0.048 (0.072)	0.020 (0.073)	0.021 (0.073)
N	2381	2381	2381	12699	12699	12699
Panel B: Outcome variable: Post-public support $PostS$						
Info	0.205*** (0.075)	0.205*** (0.076)	0.255* (0.14)	0.295*** (0.033)	0.322*** (0.033)	0.343*** (0.036)
RP	0.072 (0.093)	0.061 (0.095)	0.150 (0.13)	0.100 (0.069)	0.248*** (0.072)	0.382*** (0.099)
RPS	0.117 (0.093)	0.122 (0.094)	0.105 (0.13)	0.136** (0.068)	0.305*** (0.071)	0.338*** (0.097)
InfoxRP			-0.184 (0.19)			-0.271** (0.13)
InfoxRPS			0.029 (0.19)			-0.060 (0.13)
Control				0.030 (0.072)	0.179** (0.074)	0.181** (0.074)
N	2381	2381	2381	12699	12699	12699
Covariates		✓	✓		✓	✓

**Notes:** Info: respondents who received the information treatment in the post-experimental survey; RP: road pricing treatment group; RPS: road pricing and subsidy for active transport treatment group. Panel A: The model is estimated with the change in public support as the dependent variable; see model (4). Panel B: The model is estimated using post-public support as the dependent variable, while controlling for pre-support; see model (5). Columns (1)-(3): the ‘RCT sample’ consists of only those who participated in the road pricing field RCT. Columns (4)-(6): the ‘Full sample’ consists of all who responded to the pre- and post-experimental surveys, i.e., including those who did not participate in the road pricing field RCT. Control: control group in the road pricing field RCT. Covariates come from the pre-experimental survey and denote: Bike access, # cars in the household, Drives an BEV, Has public transport subscription, Satisfied with public transport, Pays road tolls, Has low trust in government, Is angry about road tolls, Employed, Student, Retired, Income group tertile, Higher education dummy, Has children under 18 yo in the household, Gender, Age > 45 dummy, Lives in urban or suburban areas, Lives in rural areas. Robust standard errors in parentheses, \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.



## C Robustness

### C.1 Sensitivity to model specification

**Table C-1** Effect of RP and RPS on daily total external costs (Total EC), external cost of driving (Car EC), and external benefits of active transport (Active EB) for alternative fixed effects specifications.

	OLS			Poisson PML					
	Total EC			Car EC			Active EB		
	No FE (1)	Date FE (2)	hh FE (3)	No FE (4)	Date FE (5)	hh FE (6)	No FE (7)	Date FE (8)	hh FE (9)
RP	-0.443 (1.68)	-0.402 (1.68)	-2.843** (1.23)	-0.046 (0.032)	-0.045 (0.032)	-0.053** (0.024)	-0.032 (0.023)	-0.033 (0.023)	0.018 (0.018)
RPS	-1.874 (1.70)	-1.868 (1.70)	-3.272*** (1.23)	-0.026 (0.032)	-0.027 (0.032)	-0.047** (0.023)	0.020 (0.023)	0.020 (0.023)	0.033* (0.018)
Ymean	-4.34	-4.34	-4.34	39.09	39.09	39.09	43.43	43.43	43.43
RP rel.effect	-0.102	-0.093	-0.656						
RPS rel.effect	-0.432	-0.431	-0.755						
S	-0.330	-0.338	-0.099	0.019	0.019	0.005	0.052**	0.052**	0.015
se	0.391	0.391	0.287	0.031	0.031	0.022	0.024	0.024	0.019
N	104899	104899	104899	104899	104899	104870	104899	104899	104899

**Notes:** No FE: denotes specifications without date or individual fixed effect. Date FE: denotes specifications with date fixed effects but without individual fixed effects. hh FE: denotes specifications with individual fixed effects but without date fixed effects. OLS specifications are in NOK. Robust standard errors clustered at the individual level in parentheses. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. *Ymean* denotes the outcome variable's sample mean in the post-treatment period for the control group in NOK. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## C.2 No remaining weekly budget

**Table C-2** Share of participants having exhausted their weekly budget.

Nr. of weeks	Percentage	
	RP	RPS
0	15.2	48.5
1	16.0	24.3
2	17.6	12.5
3	13.1	8.1
4	12.3	3.8
5	10.5	1.5
6	9.7	1.3
7	5.6	0.1

**Notes:** RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment.

**Table C-3** Comparing participants in the RP and RPS treatment groups with zero-budget for three or more weeks with those with zero-budget for less than three weeks.

	0-budget $\geq$ 3 weeks (1)	0-budget<3 weeks (2)	t-test difference (1)-(2)
Age	46.62 (10.82)	46.25 (10.88)	0.86 (0.50)
Female	0.46 (0.50)	0.45 (0.50)	-0.07** (0.02)
0 kids	0.56 (0.50)	0.52 (0.50)	-0.08*** (0.02)
1 kids	0.16 (0.37)	0.19 (0.39)	0.03 (0.02)
2 or more kids	0.28 (0.45)	0.29 (0.45)	0.05* (0.02)
University (4 years or more)	0.48 (0.50)	0.49 (0.50)	0.08*** (0.02)
Employed	0.94 (0.24)	0.90 (0.30)	0.04** (0.01)
Student	0.01 (0.10)	0.04 (0.18)	-0.02* (0.01)
Retired/Benefits	0.03 (0.16)	0.04 (0.20)	-0.01 (0.01)
Low-income (<700 NOK)	0.33 (0.47)	0.32 (0.47)	-0.14*** (0.02)
Medium-income ( $\geq$ 700 NOK & <900 NOK)	0.30 (0.46)	0.26 (0.44)	0.02 (0.02)
High-income ( $\geq$ 900 NOK)	0.37 (0.48)	0.41 (0.49)	0.13*** (0.02)
synthetic	0.32 (0.47)	0.27 (0.45)	-0.01 (0.02)
Observations	634	1,284	1,918

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Table C-3 continued

	0-budget $\geq 3$ weeks	0-budget $< 3$ weeks	t-test difference
	(1)	(2)	(1)-(2)
Own (e)bike	0.88 (0.32)	0.89 (0.31)	0.05*** (0.01)
N. cars household	1.59 (0.70)	1.51 (0.64)	0.06 (0.03)
Car every weekday	0.51 (0.50)	0.48 (0.50)	0.08*** (0.02)
PT subscription/plan to buy	0.22 (0.42)	0.25 (0.43)	-0.06** (0.02)
Fix work/study place	0.59 (0.49)	0.56 (0.50)	-0.01 (0.02)
Satisfied with PT	0.69 (0.46)	0.70 (0.46)	-0.01 (0.02)
Drive to work daily	0.60 (0.49)	0.53 (0.50)	0.08*** (0.02)
Flexible	0.47 (0.50)	0.46 (0.50)	0.08*** (0.02)
No congestion, worktrip	0.42 (0.49)	0.46 (0.50)	-0.10*** (0.03)
Pay toll, worktrip	0.54 (0.50)	0.50 (0.50)	0.19*** (0.03)
Pay toll above median ( $\geq 41$ NOK)	0.33 (0.47)	0.32 (0.47)	-0.38*** (0.04)
Duration worktrip below median ( $< 30$ )	0.56 (0.50)	0.58 (0.49)	0.00 (0.02)
Urban	0.32 (0.47)	0.35 (0.48)	0.04* (0.02)
Medium urban	0.60 (0.49)	0.56 (0.50)	-0.00 (0.02)
Rural	0.08 (0.27)	0.09 (0.28)	-0.04** (0.01)
Alt. mode takes more time	0.45 (0.50)	0.42 (0.49)	-0.01 (0.03)
Negative tolls	0.42 (0.49)	0.38 (0.49)	-0.12*** (0.02)
Low trust in government	0.25 (0.43)	0.22 (0.41)	-0.03 (0.02)
Care about environment	0.93 (0.26)	0.93 (0.26)	0.01 (0.01)
Air pollution problem	0.67 (0.47)	0.67 (0.47)	0.06** (0.02)
Congestion problem	0.80 (0.40)	0.77 (0.42)	-0.02 (0.02)
Policy needed	0.75 (0.43)	0.76 (0.43)	0.03 (0.02)
General tax too high	0.59 (0.49)	0.53 (0.50)	-0.07** (0.02)
Government wasting money	0.61 (0.49)	0.58 (0.49)	-0.04 (0.02)
Privacy important	0.90 (0.30)	0.90 (0.30)	0.00 (0.01)
Research important	0.99 (0.12)	0.98 (0.13)	0.01 (0.01)
Angry about tolls	0.20 (0.40)	0.16 (0.37)	-0.08*** (0.02)
Reading emails (%)	0.76 (0.43)	0.77 (0.42)	0.01 (0.02)
Got all 7 feedback (%)	0.85 (0.36)	0.77 (0.42)	0.02 (0.02)
Observations	634	1,284	1,918

**Notes:** Columns (1)-(2): Standard deviation in parentheses. Last column: Standard errors in parentheses, \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . 80

**Table C-4** Effect of RP and RPS on daily total external costs (Total EC), external cost of driving (Car EC), and external benefits of active transport (Active EB) for participant-week with non-zero remaining budgets.

	OLS			Poisson PML	
	Total EC (1)	Car EC (2)	Active EB (3)	Car EC (4)	Active EB (5)
RP	-15.983*** (1.22)	-13.985*** (0.90)	1.998** (0.79)	-0.429*** (0.024)	0.044** (0.018)
RPS	-9.420*** (1.20)	-5.372*** (0.92)	4.048*** (0.78)	-0.138*** (0.024)	0.091*** (0.018)
Ymean	-4.34	39.09	43.43	39.09	43.43
RP rel.effect	-3.686	-0.358	0.046		
RPS rel.effect	-2.173	-0.137	0.093		
S	1.514***	0.220***	0.047**	0.291***	0.047***
se	0.280	0.021	0.020	0.023	0.019
N	88079	88079	88079	88043	88072
Panel B: Participants with non-BEVs					
RP	-18.375*** (1.94)	-16.857*** (1.53)	1.518 (1.20)	-0.461*** (0.039)	0.037 (0.029)
RPS	-11.842*** (1.88)	-8.333*** (1.56)	3.509*** (1.17)	-0.198*** (0.037)	0.076*** (0.027)
Ymean	0.81	43.84	43.03	43.84	43.03
RP rel.effect	-22.662	-0.385	0.035		
RPS rel.effect	-14.605	-0.190	0.082		
S	8.057***	0.194***	0.046	0.263***	0.040
se	2.282	0.031	0.030	0.035	0.030
N	39760	39760	39760	39728	39757
Panel B: Participants with BEVs					
RP	-13.989*** (1.56)	-11.672*** (1.05)	2.317** (1.05)	-0.396*** (0.030)	0.049** (0.024)
RPS	-7.334*** (1.53)	-2.851*** (1.08)	4.483*** (1.04)	-0.077*** (0.029)	0.104*** (0.024)
Ymean	-8.75	35.01	43.77	35.01	43.77
RP rel.effect	-1.598	-0.333	0.053		
RPS rel.effect	-0.838	-0.081	0.102		
S	0.760***	0.252***	0.050*	0.319***	0.055**
se	0.183	0.030	0.026	0.029	0.026
N	48319	48319	48319	48315	48315

**Notes:** All specifications include date and individual fixed effects. Robust standard errors clustered at the individual level in parentheses. OLS specifications are in NOK. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. *Ymean* denotes the outcome variable's sample mean in the post-treatment period for the control group in NOK. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

### C.3 Filling stay-at-home days with zeros

**Table C-5** Effect of RP and RPS on daily total external costs (Total EC), external cost of driving (Car EC), and external benefits of active transport (Active EB) when replacing missing stay-at-home days with zeros.

	OLS			Poisson PML	
	Total EC	Car EC	Active EB	Car EC	Active EB
	(1)	(2)	(3)	(4)	(5)
RP	-2.676** (1.22)	-2.067** (0.92)	0.609 (0.75)	-0.053** (0.024)	0.012 (0.018)
RPS	-3.087** (1.21)	-1.882** (0.90)	1.205 (0.76)	-0.047** (0.023)	0.029 (0.018)
Ymean	-4.33	39.01	43.34	39.01	43.34
RP rel.effect	-0.618	-0.053	0.014		
RPS rel.effect	-0.713	-0.048	0.028		
S rel.effect	-0.095	0.005	0.014	0.006	0.016
se	0.285	0.022	0.018	0.021	0.019
N	105729	105729	105729	105700	105729

**Notes:** All specifications include date and individual fixed effects. Robust standard errors clustered at the individual level in parentheses. OLS specifications are in NOK. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. *Ymean* denotes the outcome variable's sample mean in the post-treatment period for the control group in NOK. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

### C.4 Synthetic budget

**Table C-6** Balance table comparing participants with and without synthetic budgets.

Synthetic budget	Control		RP		RPS		t-test differences		
	No (1)	Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)	(1)-(2)	(3)-(4)	(5)-(6)
Total EC	-3.01 (50.55)	-2.09 (55.66)	-0.35 (49.96)	3.99 (59.88)	1.13 (47.89)	-0.08 (54.30)	0.92 (3.78)	4.33 (3.77)	-1.21 (3.57)
Car EC	38.11 (36.31)	39.91 (39.26)	39.98 (37.48)	43.10 (42.95)	40.66 (35.02)	40.43 (41.14)	1.80 (2.70)	3.11 (2.79)	-0.23 (2.64)
Active EB	41.11 (26.50)	42.00 (31.94)	40.33 (25.70)	39.11 (30.16)	39.53 (24.84)	40.50 (30.96)	0.88 (2.05)	-1.22 (1.93)	0.97 (1.92)
Km car	32.68 (29.74)	33.41 (29.70)	34.33 (28.01)	35.87 (32.11)	35.51 (28.89)	34.77 (32.36)	0.72 (2.16)	1.54 (2.08)	-0.74 (2.14)
Km car peak	12.25 (13.71)	12.79 (16.56)	12.63 (13.46)	13.86 (18.05)	13.20 (14.10)	12.40 (15.70)	0.54 (1.06)	1.23 (1.06)	-0.80 (1.04)
Km car off-peak	20.44 (20.60)	20.62 (20.65)	21.70 (20.17)	22.01 (23.08)	22.31 (20.49)	22.37 (24.16)	0.18 (1.50)	0.31 (1.50)	0.06 (1.55)
Km car urban	8.62 (11.31)	8.70 (11.28)	9.08 (11.42)	9.54 (11.82)	9.00 (11.11)	9.45 (13.31)	0.08 (0.82)	0.45 (0.82)	0.45 (0.84)
Km car rural	5.07 (8.85)	4.68 (9.09)	5.45 (9.02)	5.61 (10.18)	5.70 (9.36)	6.18 (10.86)	-0.38 (0.65)	0.16 (0.67)	0.49 (0.70)
Min PT	13.37 (18.03)	12.67 (20.60)	15.45 (21.75)	13.02 (21.74)	15.66 (22.24)	15.76 (28.15)	-0.69 (1.37)	-2.43 (1.55)	0.10 (1.73)
Min bike	5.95 (13.56)	6.53 (15.96)	5.77 (13.18)	5.03 (13.14)	5.39 (12.81)	5.35 (14.83)	0.58 (1.04)	-0.74 (0.94)	-0.04 (0.96)
Min walk	33.81 (20.66)	33.58 (25.65)	33.09 (20.05)	33.09 (26.18)	32.89 (20.17)	33.77 (25.76)	-0.23 (1.61)	-0.01 (1.57)	0.89 (1.57)
Share car	0.61 (0.28)	0.64 (0.32)	0.63 (0.28)	0.64 (0.32)	0.63 (0.29)	0.63 (0.33)	0.03 (0.02)	0.02 (0.02)	0.00 (0.02)
Share bike	0.07 (0.16)	0.08 (0.20)	0.07 (0.15)	0.06 (0.16)	0.06 (0.14)	0.05 (0.16)	0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Share walk	0.15 (0.15)	0.13 (0.17)	0.13 (0.13)	0.14 (0.18)	0.13 (0.13)	0.12 (0.16)	-0.02 (0.01)	0.01 (0.01)	-0.00 (0.01)
Share PT	0.17 (0.21)	0.16 (0.22)	0.17 (0.22)	0.16 (0.24)	0.18 (0.23)	0.19 (0.27)	-0.01 (0.02)	-0.02 (0.02)	0.00 (0.02)
# trips	4.29 (1.23)	4.29 (1.46)	4.33 (1.19)	4.17 (1.44)	4.27 (1.21)	4.37 (1.66)	0.00 (0.10)	-0.16 (0.09)	0.10 (0.10)
# car trips	2.95 (1.71)	3.11 (2.08)	3.06 (1.69)	2.96 (1.79)	3.06 (1.73)	3.16 (2.19)	0.16 (0.13)	-0.11 (0.12)	0.10 (0.13)
Km BEV	33.98 (30.92)	36.16 (31.19)	34.10 (25.29)	34.80 (30.38)	36.29 (28.81)	35.55 (31.30)	2.18 (3.14)	0.70 (2.59)	-0.74 (2.89)
Km non-BEV	31.17 (28.29)	30.59 (27.92)	34.63 (31.15)	37.12 (34.07)	34.61 (28.99)	33.88 (33.63)	-0.59 (2.94)	2.49 (3.38)	-0.74 (3.19)
Observations	663	265	689	276	680	273	928	965	953

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**Table C-6 Continued**

	Control		RP		RPS		t-test differences		
Synthetic budget	No	Yes	No	Yes	No	Yes			
	(1)	(2)	(3)	(4)	(5)	(6)	(1)-(2)	(3)-(4)	(5)-(6)
Age	46.49	45.65	46.42	45.71	46.37	46.91	-0.84	-0.71	0.54
	(11.22)	(10.92)	(10.84)	(11.00)	(10.74)	(11.05)	(0.81)	(0.78)	(0.78)
Female	0.44	0.48	0.43	0.52	0.43	0.49	0.03	0.09*	0.06
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.04)	(0.04)	(0.04)
0 kids	0.54	0.55	0.54	0.53	0.53	0.56	0.01	-0.00	0.03
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.04)	(0.04)	(0.04)
1 kids	0.19	0.16	0.18	0.14	0.19	0.18	-0.03	-0.04	-0.01
	(0.39)	(0.37)	(0.38)	(0.35)	(0.39)	(0.38)	(0.03)	(0.03)	(0.03)
2 or more kids	0.27	0.29	0.29	0.33	0.28	0.27	0.02	0.04	-0.01
	(0.44)	(0.45)	(0.45)	(0.47)	(0.45)	(0.44)	(0.03)	(0.03)	(0.03)
University (4 years or more)	0.47	0.49	0.49	0.47	0.48	0.49	0.02	-0.03	0.01
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.04)	(0.04)	(0.04)
Employed	0.89	0.91	0.91	0.92	0.92	0.92	0.01	0.01	-0.00
	(0.31)	(0.29)	(0.29)	(0.28)	(0.28)	(0.28)	(0.02)	(0.02)	(0.02)
Student	0.04	0.03	0.02	0.03	0.03	0.02	-0.00	0.01	-0.01
	(0.19)	(0.18)	(0.15)	(0.17)	(0.18)	(0.15)	(0.01)	(0.01)	(0.01)
Retired/Benefits	0.05	0.03	0.04	0.03	0.03	0.04	-0.02	-0.01	0.02
	(0.21)	(0.16)	(0.20)	(0.18)	(0.16)	(0.21)	(0.01)	(0.01)	(0.01)
Low-income (<700 NOK)	0.34	0.34	0.30	0.39	0.32	0.36	-0.00	0.09**	0.04
	(0.47)	(0.47)	(0.46)	(0.49)	(0.47)	(0.48)	(0.03)	(0.03)	(0.03)
Medium-income (≥700 NOK& ≥900 NOK)	0.25	0.25	0.31	0.22	0.28	0.26	-0.00	-0.09**	-0.02
	(0.44)	(0.44)	(0.46)	(0.41)	(0.45)	(0.44)	(0.03)	(0.03)	(0.03)
High-income (>900 NOK)	0.40	0.41	0.39	0.39	0.41	0.39	0.00	-0.00	-0.02
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.04)	(0.03)	(0.04)
Observations	663	265	689	276	680	273	928	965	953

**Notes:** km BEV (km non-BEV) are calculated conditional on participants owning a BEV (non-BEV). RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, PT: public transport. Columns (1)-(6): Standard deviation in parentheses. Last three columns: Standard errors in parentheses, \* p<0.05, \*\* p<0.01, \*\*\* p<0.001.



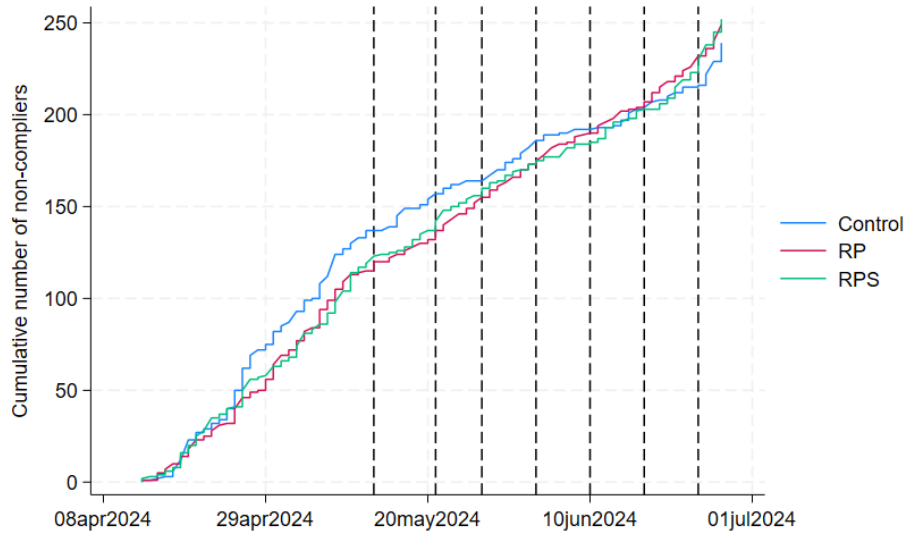
## C.5 Excluding participants with synthetic budgets

**Table C-7** Effect of RP and RPS on daily total external costs (Total EC), external cost of driving (Car EC), and external benefits of active transport (Active EB) when excluding participants who downloaded the app late (i.e., fewer than five workdays before treatment) and received a synthetic budget (see Section 2.6 for details).

	OLS			Poisson PML	
	Total EC	Car EC	Active EB	Car EC	Active EB
	(1)	(2)	(3)	(4)	(5)
RP	-2.595*	-2.069**	0.525	-0.053**	0.010
	(1.35)	(1.03)	(0.82)	(0.026)	(0.019)
RPS	-3.649***	-2.402**	1.247	-0.060**	0.029
	(1.34)	(1.01)	(0.84)	(0.025)	(0.020)
Ymean	-5.14	38.88	44.02	38.88	44.02
RP rel.effect	-0.505	-0.053	0.012		
RPS rel.effect	-0.710	-0.062	0.028		
S	-0.205	-0.009	0.016	-0.007	0.020
se	0.265	0.024	0.020	0.024	0.021
N	79737	79737	79737	79708	79737

**Notes:** All specifications include date and individual fixed effects. Robust standard errors clustered at the individual level in parentheses. OLS specifications are in NOK. RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, S: subsidy for active transport treatment, computed with the `lincom` command in Stata 18 as the difference between *RPS* and *RP*. *Ymean* denotes the outcome variable's sample mean in the post-treatment period for the control group in NOK. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.

## C.6 Attrition



**Figure C-1** Cumulative number of non-compliers per treatment group. The vertical lines indicate the start of the experimental period (with the instructions; May 13th) and the first six feedback (the seventh feedback was sent on the last day of the experimental period and is thus not depicted).

**Table C-8** Balance table comparing full compliers (who received seven feedback) and partial compliers (who received from one to six feedback).

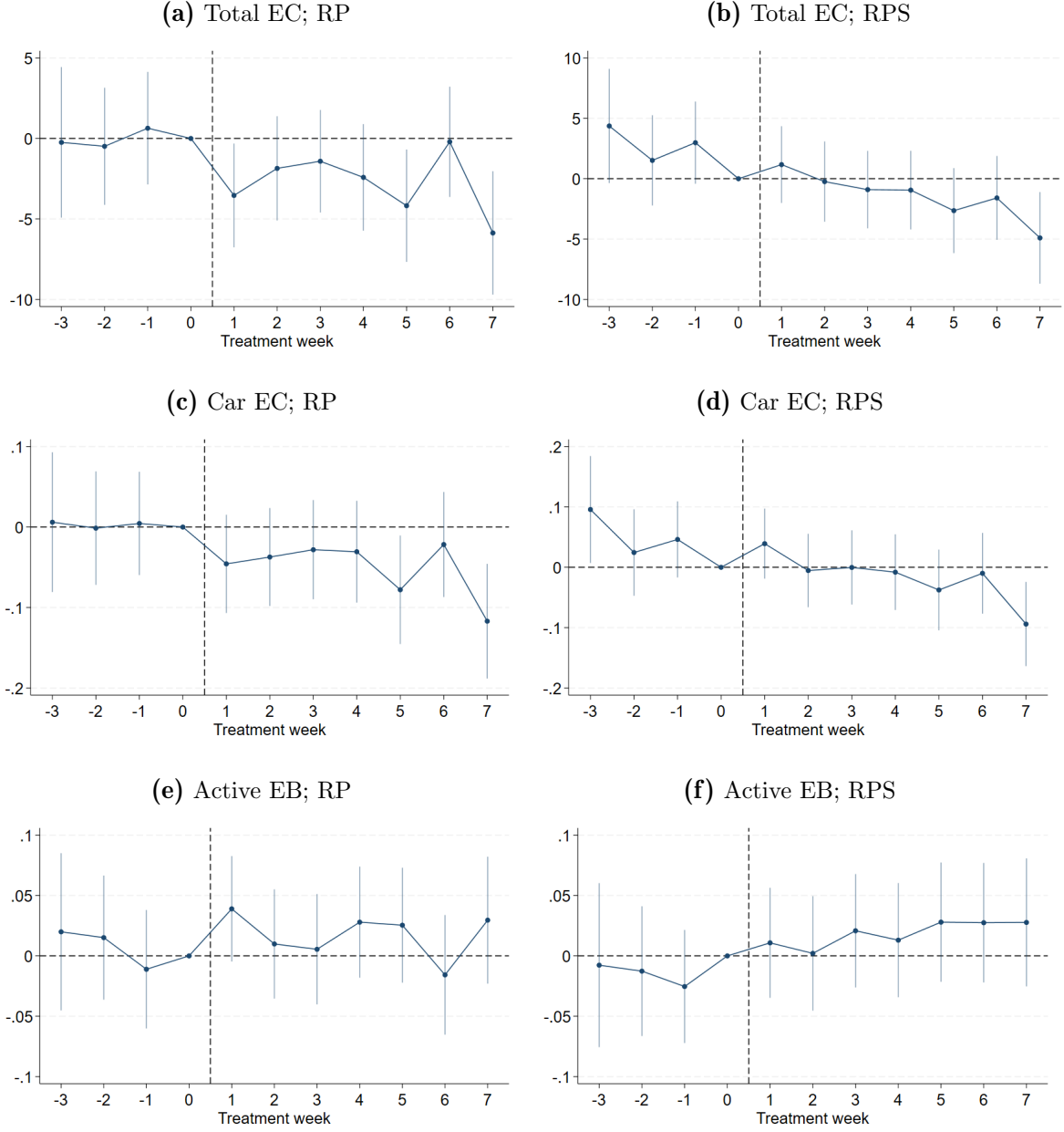
	Control		RP		RPS		t-test differences		
Full compliers	No (1)	Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)	(1)-(2)	(3)-(4)	(5)-(6)
Total EC	1.93 (51.85)	-4.01 (52.05)	7.80 (57.55)	-0.98 (51.57)	-0.43 (44.81)	1.08 (50.96)	-5.95 (4.17)	-8.78* (4.16)	1.51 (4.05)
Car EC	39.00 (39.56)	38.52 (36.52)	45.77 (43.49)	39.55 (37.78)	36.89 (32.60)	41.50 (37.79)	-0.48 (2.98)	-6.22* (3.07)	4.61 (3.00)
Active EB	37.06 (25.48)	42.53 (28.73)	37.97 (25.32)	40.53 (27.48)	37.32 (25.20)	40.42 (27.06)	5.47* (2.25)	2.56 (2.12)	3.10 (2.17)
Km car	34.00 (33.00)	32.59 (28.77)	38.09 (33.02)	33.87 (28.07)	32.70 (26.49)	35.94 (30.67)	-1.41 (2.38)	-4.22 (2.29)	3.24 (2.43)
Km car peak	12.16 (14.47)	12.47 (14.61)	15.45 (18.42)	12.31 (13.76)	12.10 (15.25)	13.18 (14.41)	0.30 (1.17)	-3.14** (1.17)	1.09 (1.19)
Km car off-peak	21.84 (23.39)	20.12 (19.78)	22.64 (22.49)	21.56 (20.63)	20.60 (18.60)	22.75 (22.26)	-1.72 (1.65)	-1.08 (1.65)	2.15 (1.76)
Km car urban	8.31 (11.48)	8.73 (11.25)	9.50 (12.28)	9.13 (11.33)	8.21 (9.48)	9.36 (12.27)	0.42 (0.91)	-0.36 (0.91)	1.15 (0.96)
Km car rural	4.84 (8.78)	4.99 (8.96)	6.43 (10.80)	5.24 (8.91)	5.94 (9.64)	5.81 (9.86)	0.15 (0.71)	-1.19 (0.73)	-0.13 (0.80)
Min PT	11.81 (17.18)	13.53 (19.20)	13.80 (20.66)	15.02 (22.06)	14.68 (24.20)	15.93 (24.05)	1.72 (1.51)	1.22 (1.71)	1.25 (1.96)
Min bike	3.94 (10.65)	6.71 (15.07)	4.63 (12.01)	5.81 (13.46)	4.89 (11.46)	5.50 (13.85)	2.77* (1.14)	1.18 (1.03)	0.61 (1.09)
Min walk	32.07 (22.32)	34.20 (22.14)	32.52 (22.07)	33.25 (21.94)	31.17 (20.66)	33.62 (22.19)	2.13 (1.78)	0.73 (1.73)	2.45 (1.78)
Share car	0.64 (0.29)	0.61 (0.30)	0.65 (0.29)	0.63 (0.29)	0.63 (0.31)	0.63 (0.30)	-0.03 (0.02)	-0.02 (0.02)	0.00 (0.02)
Share bike	0.05 (0.14)	0.08 (0.18)	0.05 (0.14)	0.07 (0.16)	0.05 (0.13)	0.06 (0.15)	0.03* (0.01)	0.02 (0.01)	0.01 (0.01)
Share walk	0.14 (0.15)	0.14 (0.16)	0.13 (0.14)	0.13 (0.15)	0.14 (0.17)	0.12 (0.13)	-0.00 (0.01)	-0.00 (0.01)	-0.02 (0.01)
Share PT	0.16 (0.21)	0.17 (0.21)	0.17 (0.22)	0.17 (0.23)	0.18 (0.24)	0.18 (0.24)	0.01 (0.02)	0.00 (0.02)	0.01 (0.02)
# trips	4.14 (1.42)	4.33 (1.27)	4.05 (1.31)	4.35 (1.25)	4.01 (1.34)	4.37 (1.35)	0.19 (0.10)	0.31** (0.10)	0.36** (0.11)
# car trips	2.87 (1.89)	3.03 (1.81)	2.88 (1.67)	3.07 (1.73)	2.67 (1.41)	3.19 (1.95)	0.16 (0.15)	0.19 (0.13)	0.52*** (0.15)
Km BEV	36.37 (36.95)	34.17 (29.49)	35.21 (31.40)	34.05 (25.45)	35.20 (27.50)	36.27 (29.98)	-2.20 (3.60)	-1.16 (2.86)	1.08 (3.37)
Km non-BEV	31.99 (29.26)	30.68 (27.81)	41.45 (34.68)	33.65 (31.08)	30.20 (25.34)	35.53 (31.52)	-1.31 (3.13)	-7.80* (3.71)	5.33 (3.52)
Observations	198	730	206	759	188	765	928	965	953
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**Table C-8 Continued**

	Control		RP		RPS		t-test differences		
	No	Yes	No	Yes	No	Yes	(1)-(2)	(3)-(4)	(5)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)			
Full compliers									
Age	47.53 (11.90)	45.91 (10.91)	46.11 (12.68)	46.25 (10.35)	47.94 (11.69)	46.18 (10.58)	-1.62 (0.89)	0.14 (0.86)	-1.77* (0.88)
Female	0.47 (0.50)	0.45 (0.50)	0.47 (0.50)	0.46 (0.50)	0.47 (0.50)	0.44 (0.50)	-0.03 (0.04)	-0.02 (0.04)	-0.03 (0.04)
0 kids	0.60 (0.49)	0.53 (0.50)	0.64 (0.48)	0.51 (0.50)	0.62 (0.49)	0.52 (0.50)	-0.07 (0.04)	-0.13** (0.04)	-0.10* (0.04)
1 kids	0.16 (0.37)	0.19 (0.39)	0.17 (0.38)	0.17 (0.37)	0.20 (0.40)	0.18 (0.39)	0.03 (0.03)	-0.01 (0.03)	-0.01 (0.03)
2 or more kids	0.24 (0.43)	0.28 (0.45)	0.19 (0.39)	0.33 (0.47)	0.19 (0.39)	0.30 (0.46)	0.04 (0.04)	0.14*** (0.04)	0.11** (0.04)
University (4 years or more)	0.47 (0.50)	0.47 (0.50)	0.49 (0.50)	0.48 (0.50)	0.48 (0.50)	0.48 (0.50)	0.00 (0.04)	-0.01 (0.04)	0.00 (0.04)
Employed	0.85 (0.35)	0.91 (0.29)	0.90 (0.30)	0.91 (0.28)	0.89 (0.32)	0.92 (0.26)	0.05* (0.02)	0.01 (0.02)	0.04 (0.02)
Student	0.05 (0.21)	0.03 (0.18)	0.03 (0.18)	0.02 (0.14)	0.05 (0.23)	0.02 (0.16)	-0.01 (0.02)	-0.01 (0.01)	-0.03* (0.01)
Retired/Benefits	0.08 (0.27)	0.03 (0.17)	0.04 (0.20)	0.04 (0.19)	0.04 (0.19)	0.03 (0.17)	-0.05** (0.02)	-0.00 (0.02)	-0.01 (0.01)
Low-income ( <700 NOK)	0.32 (0.47)	0.35 (0.48)	0.36 (0.48)	0.32 (0.47)	0.31 (0.47)	0.33 (0.47)	0.02 (0.04)	-0.05 (0.04)	0.02 (0.04)
Medium-income ( ≥700 NOK & <900 NOK)	0.24 (0.43)	0.26 (0.44)	0.21 (0.41)	0.30 (0.46)	0.28 (0.45)	0.27 (0.44)	0.02 (0.03)	0.09* (0.04)	-0.01 (0.04)
High-income ( ≥900 NOK)	0.44 (0.50)	0.40 (0.49)	0.42 (0.50)	0.38 (0.49)	0.41 (0.49)	0.40 (0.49)	-0.04 (0.04)	-0.04 (0.04)	-0.01 (0.04)
Observations	198	730	206	759	188	765	928	965	953

**Notes:** km BEV (km non-BEV) are calculated conditional on participants owning a BEV (non-BEV). RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment, PT: public transport. Columns (1)-(6): Standard deviation in parentheses. Last three columns: Standard errors in parentheses, \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.

**Figure C-2** Event studies showing the effect of RP and RPS on the following outcome variables: total external costs (Total EC), external costs of driving (Car EC), and external benefits of active transport (Active EB).



**Notes:** Panels (a) - (b): Total EC, estimated using OLS; Panels (b) - (c): Car EC, estimated using PPML; Panels (d) - (e): active EB, estimated using PPML. Left panels: Estimates of  $\sum_{w=-3}^7 RP_w$ ; right panels: Estimates of  $\sum_{w=-3}^7 RPS_w$ . Estimates are obtained from modifying models (1) and (2), where each experimental week is indexed by  $w \in [-3, 7]$ , with  $w = 0$  representing the week immediately prior to treatment. Vertical bars denote 90%-confidence intervals.

## C.7 Potential cheating

**Table C-9** Number of corrected tracks, i.e., tracks detected by the app that were subsequently corrected by app users, during both the observation and experimental periods.

Detected mode by the app	Corrected mode by users					Total
	Car	Cycle	Walk	PT	Other	
Car	0	350	46	5,916	1,990	8,302
Cycle	430	0	517	114	796	1,857
Walk	1,418	631	0	209	407	2,665
PT	3,149	72	45	0	87	3,353
Total	4,997	1,053	608	6,239	3,280	16,177

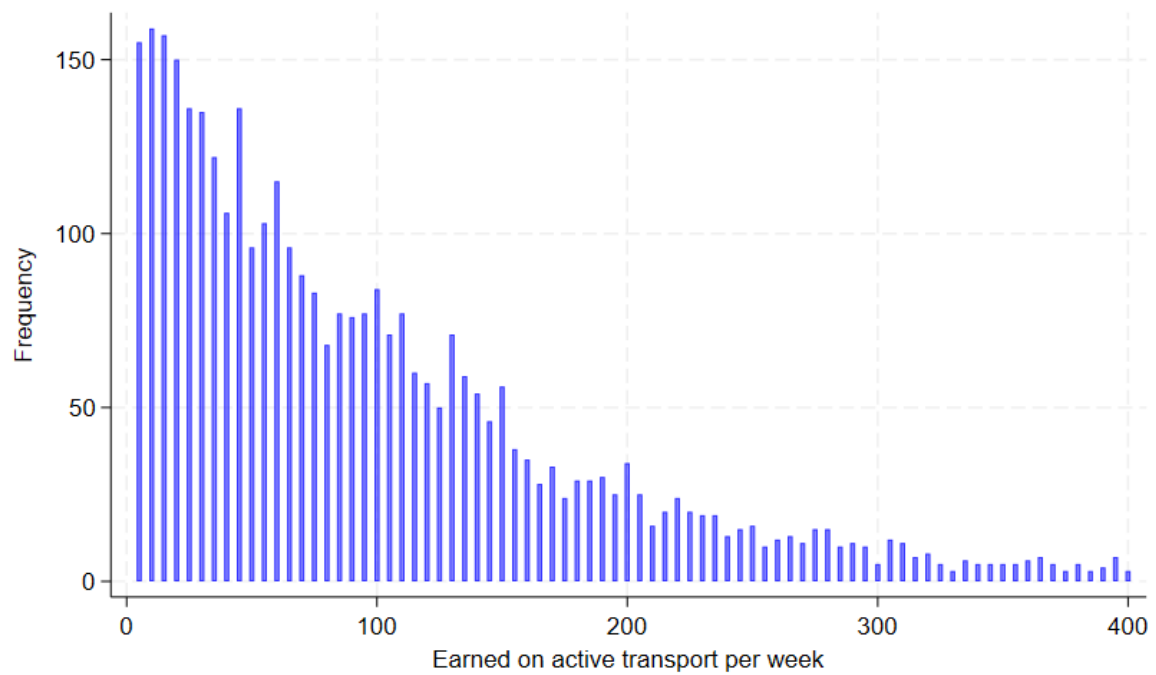
**Notes:** Tracks are categorized into the following modes: car, cycle, walk, PT (public transport), or other. Corrections are done at the track level. Note that a trip consists of a single track or a series of tracks, provided that each subsequent track begins within ten minutes of the previous track's end. Our experimental data consist of a total of 985,685 tracks.

**Table C-10** Effect of RP and RPS on the number of corrected tracks, estimated using model (2).

	Number of corrected tracks per person-day				
	All modes	By individual detected mode			
		Car	Cycle	Walk	PT
	(1)	(2)	(3)	(4)	(5)
RP	0.018 (0.081)	0.187 (0.12)	-0.178 (0.22)	-0.191 (0.16)	-0.047 (0.14)
RPS	0.051 (0.082)	0.218* (0.11)	0.019 (0.19)	0.034 (0.18)	-0.205 (0.13)
N	52008	38256	20709	23911	32231

**Notes:** Corrected tracks are tracks that are detected by the app and that were subsequently corrected by app users. The dependent variables consist of the number of corrected tracks, aggregated at the person-day level, across all modes (column (1)) and for each detected mode (columns (2)-(5)). RP: road pricing treatment, RPS: road pricing and subsidy for active transport treatment. PT: public transport. All specifications include date and individual fixed effects. Robust standard errors clustered at the individual level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Figure C-3** Distribution of weekly earnings (in NOK) from active transport in the RPS treatment group.



**Notes:** Weekly earnings are calculated as the difference between the observed external benefits during a given treatment week and the weekly average external benefits from the observation period. Only strictly positive earnings and earnings below NOK 400 are depicted.





## D Communication material

### D.1 Recruitment email

**From:** Institute of Transport Economics <spor@toi.no> **Topic:** Would you like to participate in a study on travel habits and car traffic?

The Transport Economics Institute (TØI) invites you to participate in a survey about travel habits and issues related to car traffic. The survey is part of A-planet, a large research project on the future of the transport system, funded by the Research Council of Norway.

It takes 5–10 minutes to complete. If you respond by April 26, you'll be entered into a draw to win a 3,000 NOK gift card.

The sample was randomly selected from the National Population Register, and we obtained email addresses from the Contact and Reservation Register. To ensure representative results, it's important that as many people as possible respond.

Your information is safe with us. Institute of Transport Economics handles your data confidentially and in accordance with privacy regulations. The information will only be used for research purposes. Participation is voluntary.

We hope you'll take part!

Click here to start the survey:

{surveyLink}

If the link doesn't work, please copy and paste it into your browser.

Thank you for contributing to research!

Kind regards,

The A-planet team

<https://www.toi.no/prosjektaplanet/>

[www.toi.no/spor](http://www.toi.no/spor)

You can read more about the project here: <https://www.toi.no/prosjektaplanet/> If you have any questions, contact us at spor@toi.no. Please include "A-planet" in the subject line.

If you do not wish to participate, you can click here and we won't contact you again about this: {surveyLinkOptOut}

## D.2 Instructions for the control group

Thank you for participating in the A-Planet research project on travel habits and car traffic and for using the Spor app! Your contribution is very important to us!

All you need to do is continue using the app and keep your phone with you on your daily trips. The app automatically registers your mode of transport and how far you travel.

If you keep the Spor app active on your phone until June 28, you will be entered into a lottery for a universal gift card worth NOK 9,000.

Each week, you will receive an email with an overview of your travels recorded in the Spor app.

Best regards

## D.3 Instructions for RPS

The instructions for RP are identical, but without any mention about benefits from cycling and walking.

Thank you for participating in the A-Planet research project on travel habits and car traffic and for using the Spor app! Your contribution is very important to us!

**You have been selected to participate in an extended part of the research project: Norway's largest pilot project related to road pricing.**

As a participant, you can receive rewards. Read on!

### **Keep Using the App!**

If you keep the Spor app active on your phone until June 28, you will be entered into a lottery for a universal gift card worth NOK 9,000.

### **What is Road Pricing?**

Transport is useful, but it also comes with costs:

- Some costs we pay ourselves, such as car maintenance and fuel.
- Additionally, congestion, noise, air pollution, CO<sub>2</sub> emissions, accident risks, and more are **costs borne by society** (external costs).
- Cycling and walking provide exercise that can reduce sick leave and hospital stays, **contributing positively** to society.

Introducing payment for the costs imposed on society by car driving is called **road pricing**.

### **How the Pilot Study Works**

- You are rewarded for walking or cycling more than usual.
- You are charged for the societal costs caused by your car driving. Don't worry! You won't pay out of pocket—these costs are deducted from a budget we provide to you.

We create a budget for car driving and a baseline for walking and cycling based on your travel data recorded in the Spor app so far. See the rates in the table below.

Each week, you will receive an email overview of the costs you have imposed on society, whether you have saved society costs by reducing your car driving, and the rewards you receive if you increase your cycling and walking.

### Ways to Earn a Reward

- Walk or cycle more
- Drive less
- Switch from driving to public transport
- Work more from home if you typically drive to work, if possible
- Combine multiple errands when you are out driving
- Drive outside rush periods (06:30–09:00, 15:00–17:00) or outside urban areas, if possible.

**The unused part of your budget and the rewards you earn can be paid out to you.**

When the study ends, we will randomly select one week, and your earnings from that week will be paid out.

The money can be paid out as a gift card, donated to a charity of your choice, or converted into lottery tickets for a draw where the prize is a universal gift card worth NOK 9,000. This is in addition to chances to win prizes by using the app.

### More Details on How the Study Works

1. You are rewarded for **Walking or Cycling** more than usual

- Cycling: NOK 1 per minute for the part of the trip that lasts longer than 10 minutes.
- Walking: NOK 1.30 per minute for the part of the trip that lasts longer than 5 minutes.

Each participant can earn a maximum of NOK 300 per week.

2. The societal costs of car driving vary depending on **location, time, and vehicle type**. *For example, the costs are high for a diesel car driving in a densely populated urban area, while they are lower for driving on rural roads.*

The costs associated with your car driving will be deducted from your budget.

See prices below.

Where	When	Electric car	Gasoline car incl. plug-in hybrids	Diesel car
Urban	Peak	3.80	4.10	5.30
	Off-peak	0.80	1.20	1.50
Suburban	Rush	1.20	1.50	1.60
	Off-peak	0.50	0.90	0.90
Rural	All-day	0.20	0.50	0.50

**Table D-1** Road pricing cost. NOK/km

Biking	Walking
1	1.30

**Table D-2** Subsidies. NOK/minute

### Travel Data Used in the Study

- Car driving in Oslo, Drammen, and surrounding municipalities.
- All types of trips on weekdays (weekends and public holidays are excluded from the budget).
- Trips to other parts of the country or abroad are not included.
- E-scooter trips must be logged manually.
- The app must be active to record all trips.

**Important Note:** Cheating will not be tolerated. If we detect any fraudulent activity, you will be disqualified and will not receive any payout.

Learn more about road pricing and view maps showing population density [here](#).

### D.4 Example of feedback to the control group

Feedbacks were sent weekly on monday morning to all participants starting from the 20th of May 2024.

**Feedback 1, period: May 13 - May 16**

Hi, thank you for participating in the A-planet study and using the Spor app. Your contribution is vital for gaining new insights into travel habits and car traffic!

Remember to keep the Spor app active on your phone until June 28 to participate in a lottery for a universal gift card worth NOK 9,000.

Here is an overview of your trips, showing the daily average per mode of transport. Only weekdays are included.

Best regards

Learn more: <https://www.toi.no/prosjektspor>  
Have questions? Contact us at: [spor@toi.no](mailto:spor@toi.no).



## D.5 Example of RPS feedback at the end of the first week of treatment

The distinction for the RP feedback is that that feedback does not show or mention externalities associated with walking or cycling.

### Feedback 1, period: May 13 - May 16

Hello, thank you for participating in the A-planet study and using the Spor app. This is Norway's largest pilot project on road pricing, and your contribution is vital for gaining new knowledge about travel habits and car traffic!

During this period:

- Your budget\* for **car driving** was NOK 290.  
The societal costs of your car driving were NOK 224.  
This means that you have saved NOK 66.
- Your baseline\*\* for **cycling and walking** was NOK 72.  
Your positive contribution to society from cycling and walking was NOK 98.  
This means that you have earned NOK 27.

**In total, during this period, you have earned NOK 93.**

At the end of the study, we will draw a random week where the money you've saved will be paid out.

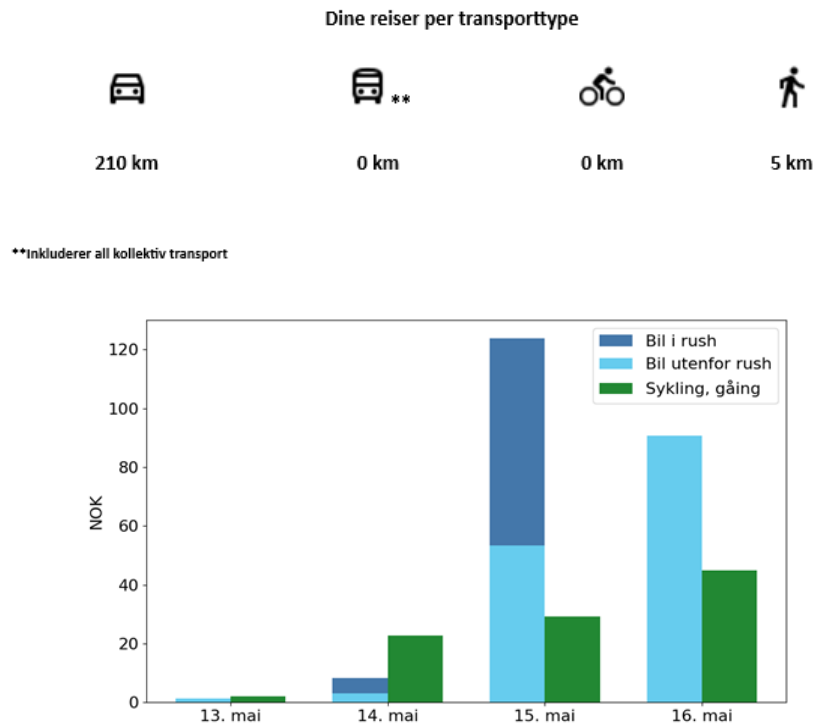
*\*The budget is based on your car trips registered in Spor app up to May 8 (weekdays only).*

*\*\*The baseline is calculated based on cycling and walking recorded in Spor app up to May 8 (weekdays only).*

The money can be redeemed as a gift card, donated to a charity of your choice, or used to purchase lottery tickets for a chance to win NOK 9,000. Additionally, by using the app until June 28, you gain entry into another lottery with a prize of NOK 9,000.

Your Travel Summary by Mode of Transportation is shown below (weekdays only).

The graph below shows an estimate of the societal costs from your car trips and your contributions from walking and cycling in NOK per day.



### Ways to Earn Rewards:

- Walk or cycle more
- Reduce car travel
- Switch from car to public transport
- Work from home more often if you usually commute by car
- Combine errands when driving
- Drive outside rush hours (06:30-09:00, 15:00-17:00) or urban areas, if possible

### More Details on How the Study Works

This pilot study is structured as follows:

- You are rewarded for walking or cycling more than usual. Each participant can earn a maximum of NOK 300 per week.
- You are charged for the societal costs caused by your car driving. But don't worry! You won't pay out of pocket—these costs are deducted from a budget we provide to you.

We create a budget for car driving and a baseline for walking and cycling based on your travel data recorded in the Spor app up until May 8. You can see the rates in the table below.

If you have limited or no data before May 8, your budget and baseline are based on the median values of other participants.



Where	When	Electric car	Gasoline car incl. plug-in hybrids	Diesel car
Urban	Peak	3.80	4.10	5.30
	Off-peak	0.80	1.20	1.50
Suburban	Rush	1.20	1.50	1.60
	Off-peak	0.50	0.90	0.90
Rural	All-day	0.20	0.50	0.50

**Table D-3** Road pricing cost. NOK/km

Biking	Walking
1	1.30

**Table D-4** Subsidies. NOK/minute

### What Travels Data Are Used in the Study?

- Car trips in Oslo, Drammen, and surrounding municipalities
- All trips during weekend only (weekends and public holidays are excluded from the budget)
- Trips to other regions or abroad are not included
- E-scooter trips must be logged manually
- The app must be active to record all trips
- Note that rush hour is determined by the trip's start time. For example, a trip starting at 16:50 and ending at 17:10 will incur 20 minutes of rush hour costs.

Be aware that cheating will not be tolerated. If we detect any fraudulent activity, you will be disqualified and will not receive any payout.

It is not necessary to approve all trips and purposes in the app.

Learn more about road pricing and view maps showing population density [here].

Best regards

Learn more: <https://www.toi.no/prosjektspor>

Have questions? Contact us at: [spor@toi.no](mailto:spor@toi.no).

## D.6 Information treatment

The participants that were treated with information received this extra information about the potential effects of road pricing:

*You participated in a pilot study in which about 2000 people were subject to road pricing. This is too few road users to experience the full benefits that a national road pricing measure would bring.*

When road pricing applies to everyone, congestion and pollution from cars will be reduced. This is because, with road pricing, it becomes more expensive to drive during rush hour and in densely populated areas. When driving becomes more expensive, those who have cheaper alternatives tend to choose those instead.

For example, results from London, Milan and Stockholm show that congestion charges reduced traffic by 20 to 30 percent, resulting in less congestion and shorter travel times.

The portion in *italics* was only shown to the respondents who participated in the RP and RPS treatment groups of the road pricing RCT.