Travel Behaviour and Greenhouse Gas Impacts of the Saanich E-Bike Incentive Program

Final Report

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research on active transportation

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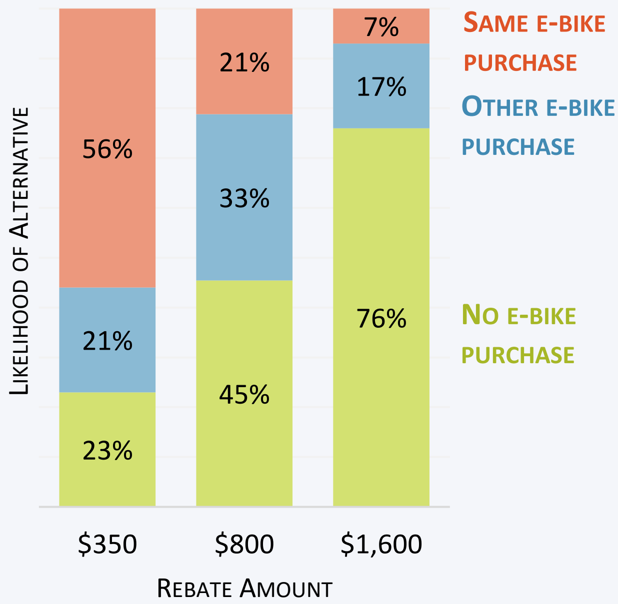
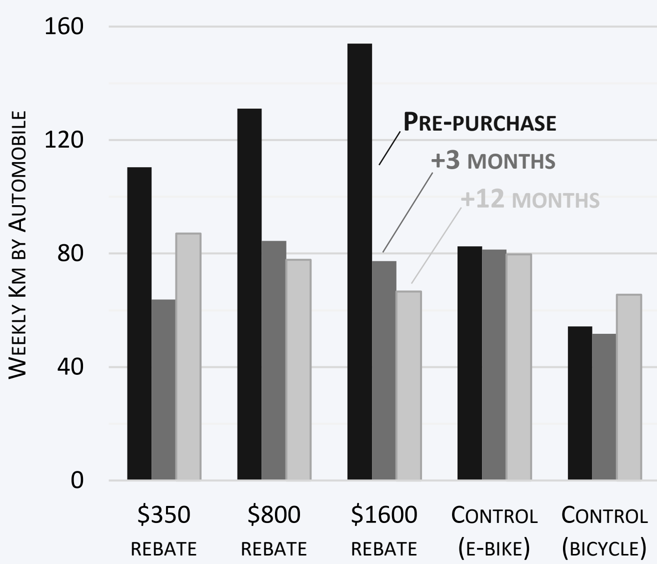
EXECUTIVE SUMMARY

This study investigates the travel behaviour and greenhouse gas (GHG) impacts of the Saanich e-bike incentive program, which distributed 389 purchase rebates of $350, $800, or $1600 (income-conditioned) to eligible residents in late 2021 and 2022. A panel of 402 study participants (164 from the incentive program and 238 non-incentivized purchasers of conventional or electric bicycles from the region) was recruited and surveyed in three waves (near purchase, and then 3 and 12 months later) to study short- and long-term impacts of incentivized bicycle purchases.



We find that the program attracted a large portion of new or marginal e-bike purchasers (23% to 76%, increasing with rebate level). These purchasers were highly satisfied with their new e-bikes, and used them regularly (3 to 4 days and 30 to 70 km per week). The incentive recipients reduced their auto use by 49 km per week a year after purchase, due to direct substitution of e-bike trips and broader shifts in their weekly travel habits. Larger incentives were associated with greater auto travel reduction due to higher pre-purchase auto use. Income-conditioned incentives likely enabled low-income households to actualize latent preferences for less auto dependence.

The long-run reduction in GHG from travel for the Saanich e-bike incentive recipients averaged 16 kg CO_2e per week, increasing with rebate amount. The calculated marginal and non-marginal GHG abatement costs are $722 and $190 per tonne CO_2e, respectively, which is cost-competitive with other types of transportation subsidies, but unlikely to be cost effective on the international carbon market. GHG reduction is one but not the only benefit of increased e-bike adoption, which can also increase physical activity, reduce local air pollutant emissions, and reduce travel costs, among other benefits. Growing interest in e-bike incentive programs creates new opportunities to investigate these co-benefits, along with program effects in various scales and settings.



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1 INTRODUCTION

1.1 Background

Energy used for transportation currently generates 30% of Canada's greenhouse gas (GHG) emissions; most concerning is that transportation is the only sector with GHG emissions still increasing – and increasing substantially (Environment and Climate Change Canada, 2021). Electric bicycles (e-bikes) are an increasingly popular mode of transportation with the potential to displace driving and so reduce GHG emissions from transportation (Mason et al., 2015; McQueen et al., 2020). The potential emissions reduction benefits have led to the implementation of e-bike promotion programs and policies as climate action strategies by Canadian governments – with expected co-benefits related to physical activity, traffic congestion, and more (McQueen et al., 2019). However, the effects of e-bike adoption on travel mode substitution are highly uncertain and heterogeneous (Bigazzi and Wong, 2020), as are the consequent net GHG impacts (Bigazzi and Berjisian, 2019; Mason et al., 2015; McQueen et al., 2020). This uncertainty limits the strategic use of e-bike promotion to achieve local, national, and international GHG mitigation goals.

1.2 Literature Review

Research on early adopters has shown that e-bikes are a viable and attractive travel option for some people uninterested or unable to use conventional bicycles, due to factors such as distance, hills, cargo, and perspiration (Fishman and Cherry, 2016; MacArthur et al., 2018; Wolf and Seebauer, 2014). Compared to travel by private motor vehicles, e-bikes enable physically active, low-cost, and low-carbon mobility (Bigazzi and Berjisian, 2019; Fishman and Cherry, 2016; Pierce et al., 2013; Sundfør and Fyhri, 2017).

The key to understanding the impacts of e-bike adoption is understanding mode substitution. A 2020 meta-analysis of survey research from around the world found that e-bike substitution of automobile trips ranged from 2% to almost 60%, depending on context, while substitution of conventional bicycle trips ranged from 5% to 70% (Bigazzi and Wong, 2020). Rates of automobile substitution were higher in North America and Europe than Asia, and in more recent studies. Modelling studies of e-bike adoption scenarios suggest that widespread uptake of e-bikes could yield GHG savings from passenger travel of 10% in Switzerland (Bucher et al., 2019), 11% worldwide (Mason et al., 2015), 12% in Portland, USA (McQueen et al., 2020), or up to 20% in Sweden (Hiselius and Svensson, 2017).

Based on the expectation that e-bikes can displace a substantial amount of motor vehicle travel, there is broad interest among government and industry stakeholders in expanding access to e-bikes, tied to goals for climate, health, costs, accessibility, equity, congestion, etc. (Aono and Bigazzi, 2019). The main barriers to e-bike adoption are safety concerns, purchase price, fear of theft, and unfamiliarity (Fishman and Cherry, 2016; MacArthur et al., 2018; Wolf and Seebauer, 2014). To address these, e-bike promotion efforts target improved cycling infrastructure (with co-benefits for conventional cycling), purchase rebates, provision of secure bicycle parking (with electric power access), and free e-bike rentals or loans (Aono et al., 2019; McQueen et al., 2019).

A study of an e-bike loan program in the United Kingdom reported driving reductions (measured in vehicle kilometers traveled, or VKT) by program participants of 20% (Cairns et al., 2017). A series of studies in Norway reported increased cycling by participants in an e-bike loan program, (Fyhri and Fearnley, 2015) and those who made non-incentivized e-bike purchases (Fyhri and Beate Sundfør, 2020), as did two other Norwegian studies involving e-bike loan interventions for parents and commuters focused on health and physical activity outcomes (Bjørnarå et al., 2019; Mildestvedt et al., 2020). Studies from the USA reported increased e-bike use from workplace loan programs (Fitch et al., 2022; MacArthur et al., 2017).

De Kruijf et al. (2018) evaluated an incentive program in the Netherlands that provided monetary incentives of €0.08 to €0.15 per km to e-bike owners to use their e-bikes for commuting (i.e., not a purchase program). The sample of 547 participants increased e-bike commute mode share from 0% to 68% after 1 month, and 73% after 6 months in the program, with half of the e-bike trips replacing car trips. Based on regression modelling, mode shift was systematically related to gender, physical condition, car ownership, and household composition.

Although e-bike purchase incentive programs have increased in recent years, to date there has been very limited quantification of the effects of e-bike purchase incentives on mode shift and GHG emissions. The first known study of e-bike purchase incentives was a non-peer-reviewed working paper from the National Bureau of Economic Research (a US non-profit) on the Swedish national e-bike purchase subsidy (Anderson and Hong, 2022). The Swedish incentive was only given out in 2018, and provided a 25% e-bike purchase price subsidy, up to CA$1,500 and averaging around CA$670. The study reports no evidence of an incomplete pass-through of the subsidy to consumers (i.e., retailers were not capturing the subsidy benefit). They estimate that 66% of the subsidized e-bike purchases were additional or marginal (i.e., purchases that would not have happened without the subsidy), based on responses to the question "How important was the subsidy for your decision to buy the electric bike?" Finally, they estimate average annual VKT reductions of 1146 km/year (22 km/week) for each e-bike purchaser, with no major difference between additional and non-additional purchasers, which translates into an average GHG reduction of 177 kg CO_2e per year (3.4 kg CO_2e per week). The estimates of travel impacts are based on self-reported primary commute mode (car, public transit, regular bicycle, or e-bike) and distance by season (summer/winter); transit use and non-commute travel were excluded from the GHG estimates.

A research report from the University of California, Davis released in January 2023 evaluated three local e-bike purchase incentive programs in California (Johnson et al., 2023). Two of the three programs were income-conditioned, and rebate amounts ranged from about US$150 to US$800 for bicycle purchases averaging US$1,553. Survey data from 617 incentive recipients in these programs (a 62% overall response rate) were used to estimate a GHG reduction of 12 to 44 kg CO_2 per month (2.8 to 10.2 kg CO_2 per week). Marginal purchases were not evaluated.

The third known empirical study of e-bike purchase incentives investigated a municipal incentive of up to €500 ($730), not income conditioned, in Oslo, Norway in 2016 (Sundfør and Fyhri, 2022). The panel survey design included two time points (up to 5 months after purchase) and a comparison sample of 658 regional cyclists (596 of the 1000 incentive recipients completed the study, for a response rate of 60%, although only 382 ultimately purchased an e-bike). Results showed that incentivized purchasers increased their daily e-bike use by 5.3 km, and decreased automobile and transit use by 2.1 and 2.9 km respectively, although the change in automobile PKT was not significantly different from the comparison groups. Marginal purchases were not evaluated, but a subset of the participants used a smartphone app to record their travel, augmenting the self-reported trip data.

Finally, a recent stated preference study used data from an online survey of 2,241 people in the USA to estimate the effect of price subsidies on e-bike purchase intentions (Jones et al., 2024). The survey included a hypothetical choice experiment, in which participants identified which of 4 alternatives they would select (conventional bicycle, standard e-bike, cargo e-bike, or no purchase), given a set of seven choice attributes for each alternative: maximum speed, throttle actuation, battery range, removable battery, retail price (from US$500 to US$5900), discount amount (from US$0 to US$1200), and discount type (point-of-sale, mail-in, or tax credit). A purchase choice model was estimated from the survey data, and the resulting parameters used to infer the price sensitivity of bicycle purchases and the effect of incentives on inducing new e-bike purchases. Over a range of assumed program parameters, they report marginal (induced) e-bike purchases averaging 14% to 18% of the incentives provided, leading to a cost per marginal e-bike of around US$3700 to US$4800. Unexpectedly, they found lower-income purchasers to be less price-sensitive, which they attribute to the high net price of e-bikes still being unaffordable for those households. They also report that each incentive dollar had around twice the effect of an equivalent reduction in retail price (excepting incentives returned as tax credit).

1.3 Pre-program analysis

To use e-bike incentive programs as a climate action strategy, it is essential that we accurately quantify the GHG impacts of these programs, and know their cost-effectiveness relative to other mitigation strategies. Misestimating program impacts can lead to either underutilization of a potentially effective strategy, or misusing climate action funds and failing to reach our climate goals. In addition, there is little information available to design a purchase incentive program beyond observing existing practice. Incentive program developers must determine factors such as eligibility, rebate amount, rebate structure, and administration – all of which can potentially impact program effectiveness. How to use limited program resources most effectively to target additional/marginal purchasers (i.e., those who would not have purchased without the availability of the rebate) and maximize mode shift and GHG reductions? (Aono et al., 2019)

In a recent study, we used econometric modelling to evaluate the expected impact of rebate incentive program designs on e-bike adoption (Bigazzi and Berjisian, 2021). Testing a range of baseline demand levels, demand elasticities, and e-bike prices, we modeled how different rebate structures impacted additional (marginal) e-bike purchases as illustrated in Figure 1. Study results showed that e-bike purchase demand is expected to exceed the available rebates (i.e., the program would not be demand-limited, and so all available rebates would be used), and that for a fixed program budget, higher rebate amounts (i.e., fewer rebates available) led to fewer additional purchases but a larger share of rebates going to marginal and low-income purchasers (increasing program equity). We concluded by recommending that future programs begin with income-tiered rebates of around $400 to $800, and also include a robust evaluation plan to inform future program designs, given the lack of empirical data on program impacts.

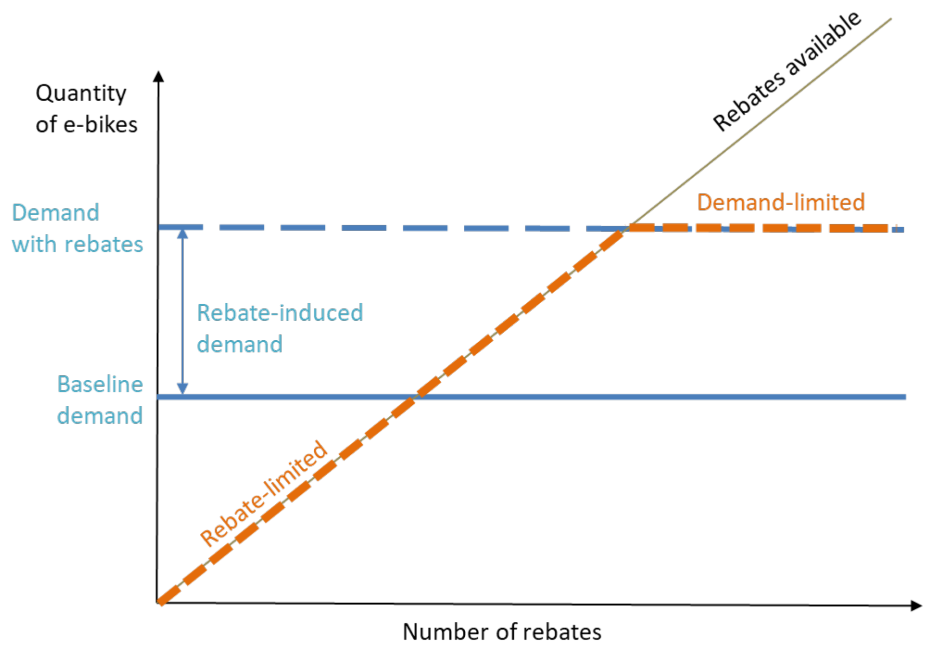


Figure 1. Illustration of marginal (additional) e-bike purchases with rebates

1.4 Saanich E-bike Incentive Program

This study is conducted in collaboration with the District of Saanich, British Columbia (BC), which launched a pilot e-bike purchase rebate program in September 2021. Saanich designed the e-bike program around the twin goals of GHG mitigation and equity, implementing three income-tiered incentive levels of $350, $800, and $1,600 per e-bike purchase, supported by our previous analysis (Aono et al., 2019; Berjisian and Bigazzi, 2019; Bigazzi and Berjisian, 2021) in addition to further elements in the business case development. Incentive program participants had to obtain pre-approval before purchasing the e-bike, but the rebate could be obtained either after purchase or at the point of sale from participating vendors. Proof of income was required for the two higher-value rebates, according to the schedule shown in Table 1. Incentive recipients must be residents of Saanich, and only one incentive was available per household address. Eligibility requirements for e-bikes were: pre-rebate sale price of at least $1,800, new (not used) e-bikes for personal (not commercial) use, meeting the definition of Motor Assisted Cycle in the BC Motor Vehicle Act (MVA).

Table 1. Income* thresholds for Saanich rebate tiers

Persons in household	Maximum household income for $1600 rebate	Maximum household income for $800 rebate
1	$42,600	$55,900
2	$53,000	$69,600
3	$65,200	$85,600
4	$79,100	$103,900
5	$89,800	$117,800
6	$101,200	$132,900
7	$112,800	$148,000

** Income of top up to two earners in the economic family in the household (e.g., excluding roommates)*

1.5 Objectives & timeline

The objectives of this study were to determine 1) the GHG mitigation impacts of e-bike adoption, across different segments of the population, and 2) the cost-effectiveness of e-bike purchase incentives as a GHG mitigation strategy. We aimed to create essential information for using e-bike promotion as a climate action strategy – including how effectiveness in GHG mitigation varies across population groups and intersects with equity considerations for transportation.

The study timeline is illustrated in Table 2. This final report is based on three waves of data collection, which were completed on October 19, 2023. An Interim Report summarizing the first two waves of data (through September 1, 2022) was produced in November 2022. The original study plan was on a shorter timeline, based on a program duration of 6 months; the timeline was extended as additional incentives became available, to increase sample size by extending Wave 1 intake to a full year.

Table 2. Timeline of data collection and major reports

Task	Fall 2021	Winter 2022	Spring 2022	Summer 2022	Fall 2022	Winter 2023	Spring 2023	Summer 2023	Fall 2023
Wave 1 data collection									
Wave 2 data collection									
Wave 3 data collection									
Reports					Interim				Final

2 METHODS

2.1 Overview

The conceptual framework for the study is shown in Figure 2. We aim to quantify the net GHG impacts of the e-bike incentive program, as well as the cost-effectiveness in reducing GHG ($ per kg CO_2e reduced). The GHG impact estimates are based on self-reported travel behaviour of study participants, including e-bike rebate recipients and non-incentivized purchasers of electric and conventional bicycles. The study methods were developed by careful consideration of the existing literature (Anderson and Hong, 2022; Andersson et al., 2021; Bigazzi and Wong, 2020; Cairns et al., 2017; de Kruijf et al., 2018; Fyhri and Beate Sundfør, 2020), and trade-offs among precision, reliability, response rate, participant burden, sample bias, and other factors.

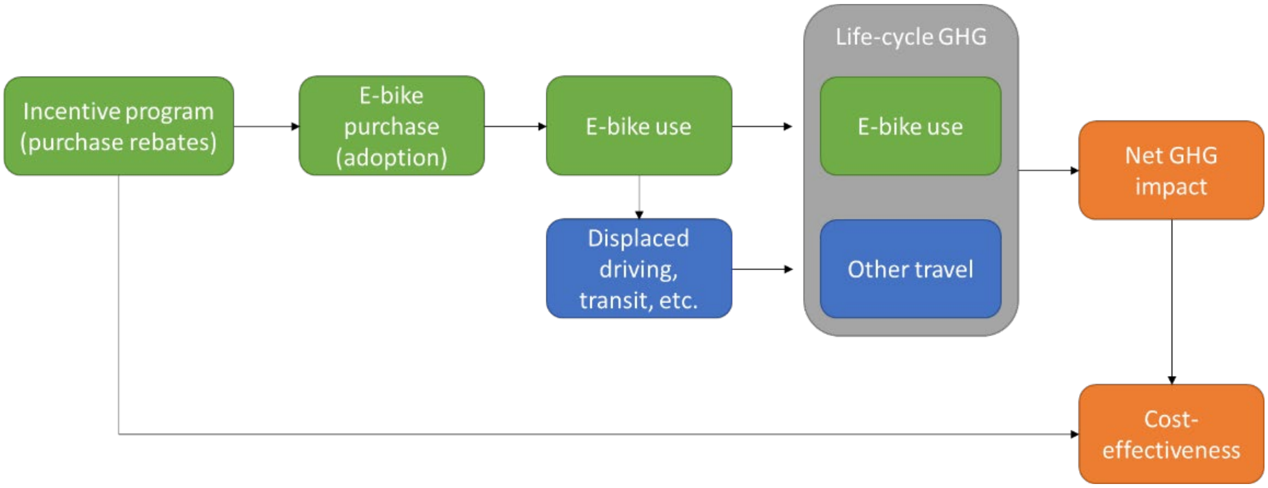


Figure 2. Conceptual framework for the study

Measuring the impacts of a transportation intervention is challenging due to the impossibility of observing the counterfactual situation in which the intervention did not occur. Typical methods of studying the impacts of an intervention are illustrated in Figure 3. The true impact of the intervention is the difference between the (observable) post-intervention behaviour, and the (unobservable) counterfactual behaviour that would have occurred if the intervention had not been implemented. One approach to measure the impact is to ask travellers to self-report their hypothetical behaviour in this counterfactual world in which the intervention had not occurred. The validity of the measurement depends on the unknown accuracy of this speculative response. Another approach is to contrast a traveller's observed post-intervention behaviour with their pre-intervention behaviour, controlling for any expected difference between the pre-intervention and counterfactual scenarios (i.e., some form of before/after analysis). The validity of the measure depends on the analyst's ability to effectively control for differences between the pre-intervention and counterfactual scenarios. This is typically done by observing a control group of travellers who did not experience the intervention over the same time period, and including time-varying exogenous factors known to influence the study variables of interest (weather, fuel prices, etc.).

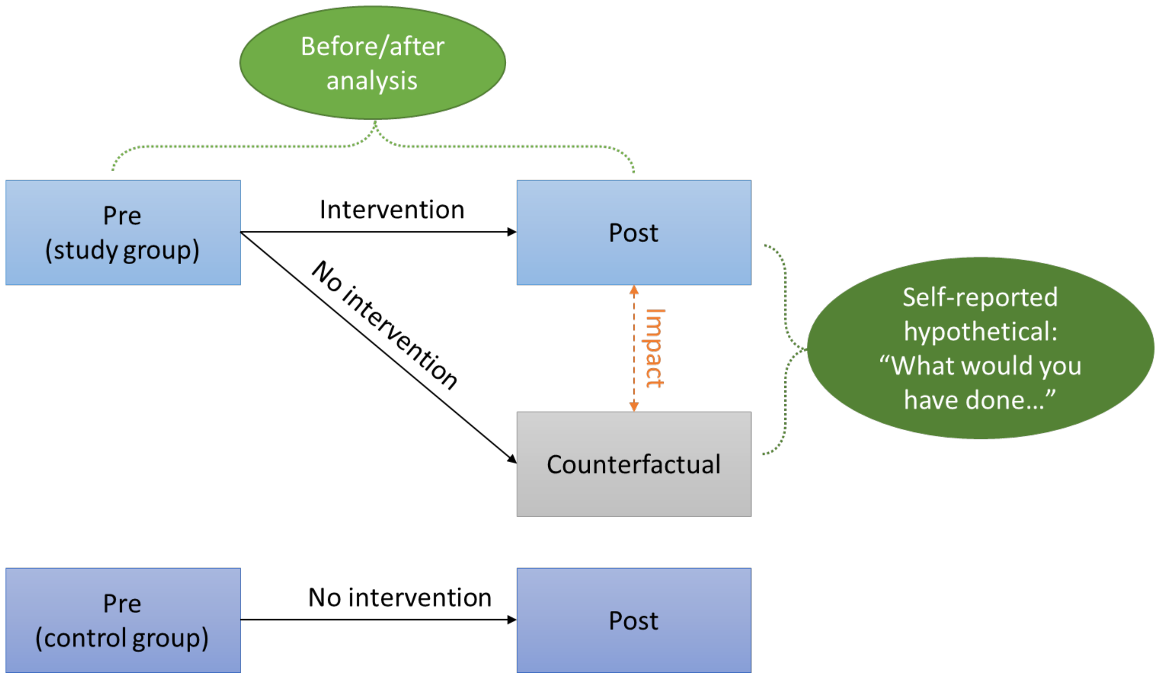


Figure 3. Illustration of measuring intervention impacts

Figure 4 expands on Figure 3 to illustrate the two dimensions of counterfactuals that must be considered to evaluate the impacts of a vehicle purchase incentive program. When the intervention is a purchase incentive, the counterfactual scenario is a world without the incentive program, in which vehicle purchases are uncertain. We identify "marginal purchasers" as those that would not have purchased a vehicle in the counterfactual scenario without an incentive program; the other group is sometimes referred to as "free-riders" – people who would have purchased the vehicle even without the incentive. The same two approaches can be used to estimate intervention impacts as above, although with increased complexity. Two different hypotheticals must be considered to characterize the counterfactual scenario: the likelihood of not purchasing a vehicle without the incentive (i.e., being a marginal purchaser), and the difference in travel behaviour if the vehicle had not been purchased. The control group for a before/after analysis is composed of people who did not receive an incentive, which can include both people who did and did not purchase a vehicle over the same time period. In this study, we implement both self-reported hypothetical and before/after measures to estimate the program impacts.

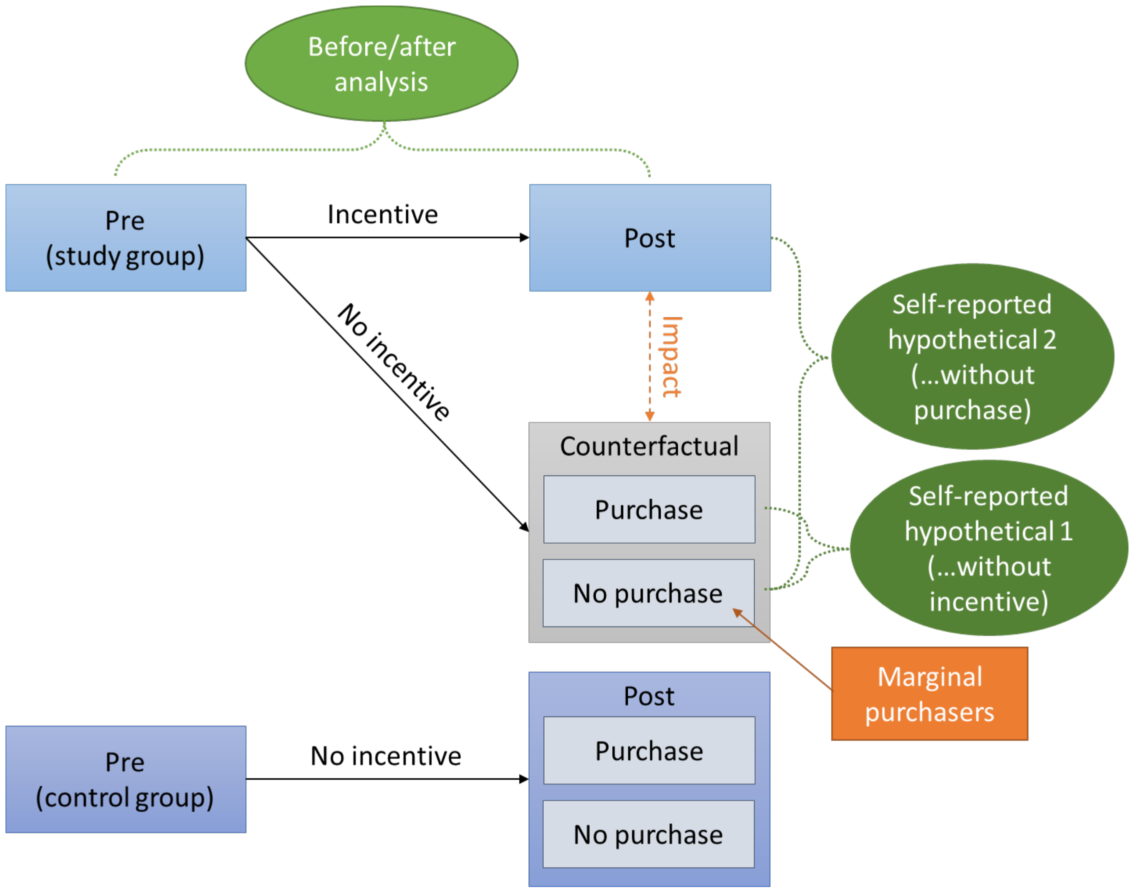


Figure 4. Illustration of counterfactuals for a purchase incentive program

2.2 Recruitment

The study population is defined as people living in the greater Victoria region who would considering purchasing a bicycle (i.e., those in the bicycle purchase market). The study design includes several participant sub-samples to enable 2 important contrasts to be analysed: incentivized versus non-incentivized purchases, and electric versus conventional bicycle purchases (see illustration in Figure 5). We define the "Study group" sub-sample as those who received a purchase incentive through the Saanich program, and the "Control group" sub-sample as all other participants. In subsequent analysis, the Control group was further subdivided based on reported purchase behaviour: those who purchased an e-bike, those who purchased a conventional bicycle, and those who did not purchase a bicycle within the study period.

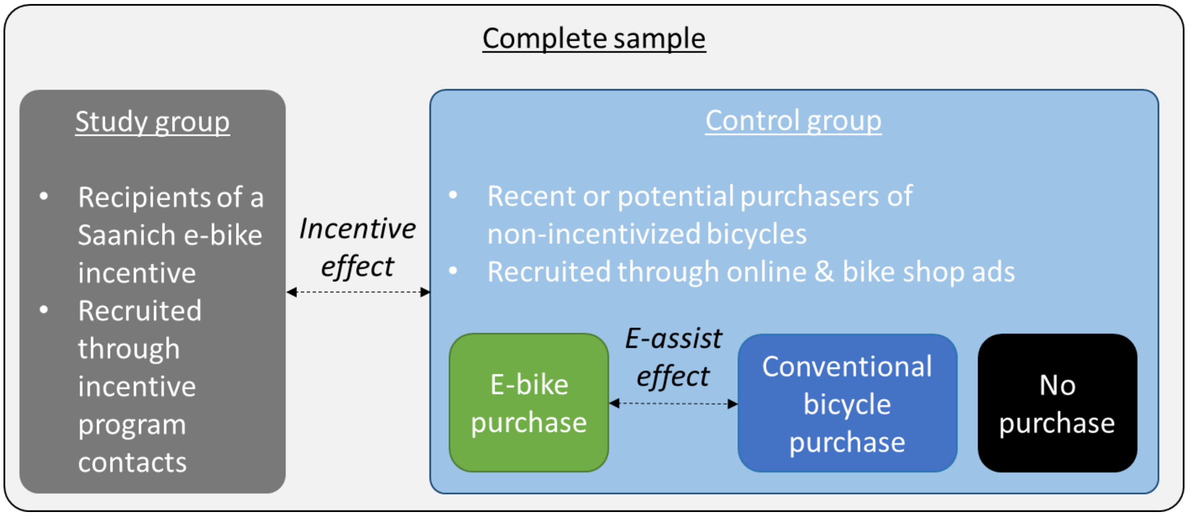


Figure 5. Illustration of recruited sub-samples and study contrasts

The Study group was recruited through Saanich program contacts. To protect participant privacy, no personal information was shared between the UBC study team and Saanich staff; opt-in survey recruitment information was sent to program participants directly from Saanich, which also shared anonymized aggregate program data with the study team for sample comparison.

The Control group was recruited through online and bike shop advertisements. Recruitment fliers and cards were distributed to 32 bicycle shops in greater Victoria, BC, on October 23, 2021, after reaching out to 47 shops for agreement to post/display. Online ads were posted on Facebook and Instagram, partially due to low responses from the bike shop recruitment materials. Online ads were run for 5 weeks (January 17 to February 20, 2022) at a rate of US$20 per day, which created around 20,000 impressions per week, yielding about 200-250 click-throughs and 60-80 raw (unfiltered) responses per week. The ad parameters were set at the approximate geography of greater Victoria, BC.

Recruitment materials are given in Appendix B. Recruitment materials were only presented in English, which was also the only language of the e-bike incentive program materials. To increase survey accessibility, recruitment materials included options for telephone-based study participation, including telephone interpretation in other languages; this option was exercised by one participant (in English). Inclusion criteria for both sub-samples were:

- Residents of greater Victoria, BC,
- Considering or having recently purchased or acquired a new bicycle (or electric converter), and
- At least 16 years of age (in accordance with the MVA).

In addition, the Study group must have received an e-bike incentive through the Saanich program.

Data were collected from study participants using a three-wave panel survey design (i.e., all participants were asked to complete a survey at 3 different points in time or "waves"). As incentives to complete all three parts of the study, survey participants (including those who withdrew or did not complete the surveys) were given the option to opt-in to draws for 5 gift cards of $25 each in Wave 1, 5 gift cards of $40 each in Wave 2, and 5 gift cards of $50 each in Wave 3. The target Wave 1 sample size was set at 150 each for the Study and Control groups, based on the literature, statistical power, expected attrition between waves, and a 50% response rate from the 300 anticipated recipients of Saanich incentives.

2.3 Survey instrument

The study used a three-wave panel survey design, with Wave 1 at the time of recruitment, Wave 2 at 3 months after Wave 1, and Wave 3 at 12 months after Wave 1 (Figure 6). Each wave recorded data on: 1) the purchased bicycle, 2) typical weekly travel activity in the preceding month, 3) the last three trips taken using the purchased bicycle, and 3) household composition and socio-demographics including vehicle ownership. Wave 2 indicates the short-term travel behaviour impacts, and Wave 3 indicates the long-term impacts. The three-wave panel survey design provides more reliable data than a cross-sectional or before/after survey, but at the cost of sample attrition due to higher participant burden.

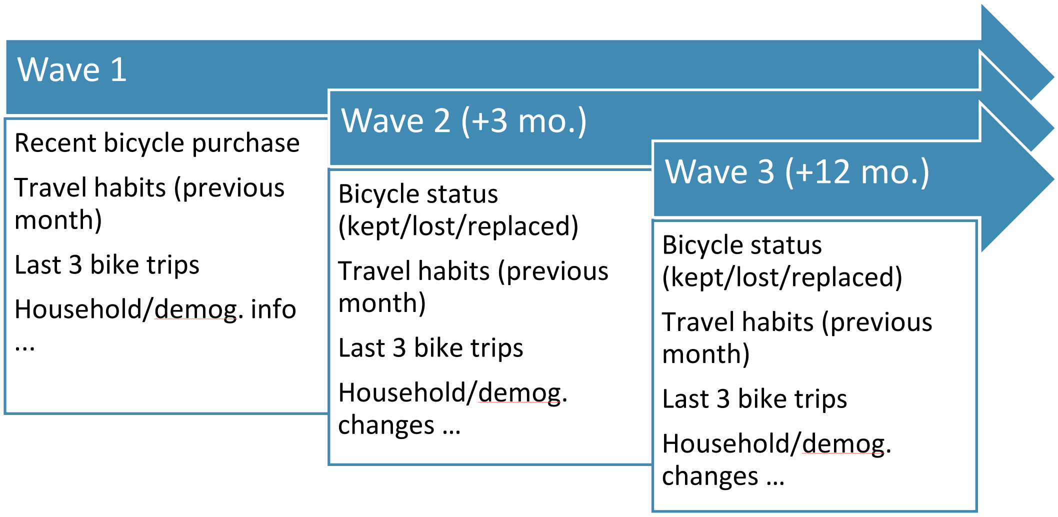


Figure 6. Illustration of three-wave survey design

The full survey instruments are given in Appendix A. The survey instruments were implemented online using Qualtrics software. The online surveys were only implemented in English. Research methods were reviewed and approved by the UBC Behavioural Research Ethics Board (#H21-02361).

2.4 Data processing

Data were downloaded from Qualtrics on October 19, 2023. Analyses were conducted on Windows 11 x64 (build 22621) using the R Statistical language, with packages 'glmmTMB', 'DirichletReg', and 'MASS' (Brooks et al., 2017; Maier, 2014; R Core Team, 2019; Venables and Ripley, 2002), and using Python version 3.7 with the packages Pandas, Numpy, and Matplotlib (Harris et al., 2020; Hunter, 2007; The pandas development team, 2022).

Data were filtered using the following steps:

- Remove pilot and testing responses from the study team and partners,
- Remove responses that declined consent,
- Review open-text comments to manually apply corrections as needed, and
- Manual review for protest or inconsistent responses.

For data cleaning, there were several prompts offering a matrix of sliders from 0% to 100%, with instructions that “numbers should add up to 100%”. Any responses that did not sum to 100% were re-scaled accordingly to total 100% over all options.

2.5 Sample weighting

Sample weights were created to compensate for non-representation of the greater Victoria population over key demographic and travel variables, following inspection of the sample characteristics (see results in Section 3.1). Sample weights were calculated by raking the respondent data (from Wave 1) to match the marginal distributions in the population for all weighting variables. Raw weights were trimmed (strictly) at lower and upper bounds of 0.3 and 3.0 times the median weight, respectively (Battaglia et al., 2009).

2.6 Mode shift calculation

Informed by the literature, we employed two widely-used self-report survey measures to quantify travel behaviour shifts. The first is respondent-identified alternative modes for the last three trips taken by the purchased bicycle. The second is changes in typical weekly travel habits between waves. The travel mode shifts are then translated into GHG impacts by applying lifecycle GHG emission rates per person-kilometer travelled (PKT) by each mode (Figure 7).

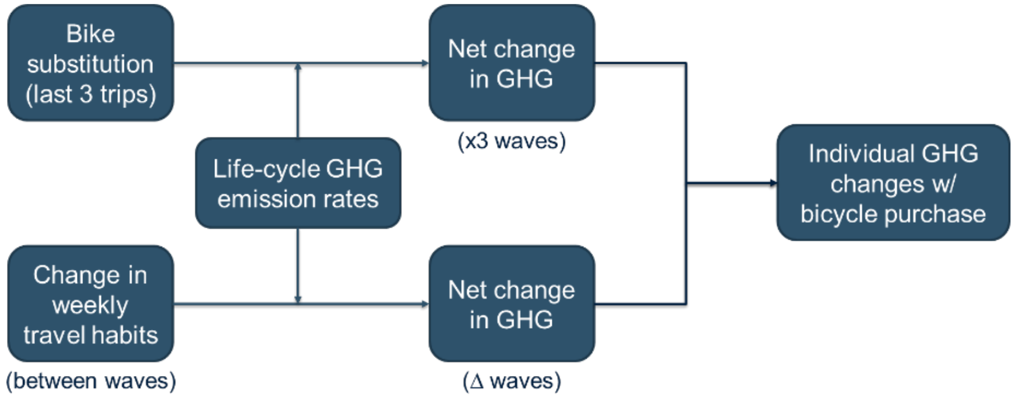


Figure 7. Illustration of method for estimating travel mode and GHG impacts

There are a range of methods of collecting travel behaviour data in surveys, with trade-offs among precision, reliability, cost, and other factors. In particular, there is a dichotomy between study methods using smartphones-tracked travel activity and self-reported travel activity, with the former providing higher data precision at the cost of participant burden, leading to greater sample bias and attrition (in other words, a trade-off between internal versus external validity). Our study design prioritized a three-wave survey, which raises attrition risk, and relatively high response rates were needed to obtain a large sample given the intended incentive program size. We also needed consistent response rates across income tiers for equity analysis, amplifying the importance of low participant burden. For these reasons, on balance, we opted not to employ smartphone-tracking in the travel survey.

We can represent mode shift in three common ways:

1. ΔPKT_m^t: Change in PKT by mode m for each (e-)bike trip
2. ΔPKT_m^d: Change in PKT by mode m for each (e-)bike PKT
3. ΔPKT_m^w: Change in weekly PKT by mode m, due to (e-)bike use overall

The survey instrument collected the following variables for each (i) of the last I (up to 3 per wave) reported (e-)bike trips ("bike trip substitution" data):

- t_i^D: Date-time of trip i, in days,
- t_i^d: Distance (PKT) of trip i, in km,
- $t_i^{a_m}$: Likelihood of alternative trip (i.e., if (e-)bike had not been purchased) being by mode m, expressed as a proportion (from 0 to 1), and
- $t_i^{a_d}$: Proportional distance of alternative trip, relative to reported trip (i.e., equal length being 1.0).

From these, we calculated mode shift based on the "bike trip substitution" data as follows. The implied frequency of (e-)bike trips per week is

$$f_{(e)bike}^t = \frac{7(I-1)}{t_I^D - t_1^D}$$

and the mode substitution metrics for non-(e-)bike travel are:

$$\Delta PKT_m^t = \frac{1}{I}\sum_{i \in I}\left[-t_i^{a_m} t_i^d t_i^{a_d}\right]$$

$$\Delta PKT_m^d = \frac{1}{I}\sum_{i \in I}\left[-t_i^{a_m} t_i^{a_d}\right]$$

$$\Delta PKT_m^w = f_{(e)bike}^t \cdot \Delta PKT_m^t$$

For (e-)bike travel, the first two mode substitution metrics are:

$$\Delta PKT_{(e)bike}^t = \frac{1}{I}\sum_{i \in I}\left[-t_i^{a_m} t_i^d t_i^{a_d} + t_i^d\right]$$

$$\Delta PKT_{(e)bike}^d = \frac{1}{I}\sum_{i \in I}\left[-t_i^{a_m} t_i^{a_d} + 1\right]$$

while the third metric is the same.

In addition, the following travel habit variables ("travel matrix" data) were collected in each wave w:

- $\delta_{m,w}^{w}$: Days per week using mode m, and
- $d_{m,w}^{\delta}$: Distance per day by mode m, on days used.

We calculated mode shift based on the "travel matrix" data as:

$$\Delta PKT_m^w = \delta_{m,2}^w d_{m,2}^\delta - \delta_{m,1}^w d_{m,1}^\delta$$

$$\Delta PKT_m^t = \frac{2 \cdot \Delta PKT_m^w}{\delta_{(e)bike,1}^w + \delta_{(e)bike,2}^w}$$

$$\Delta PKT_m^d = \frac{2 \cdot \Delta PKT_m^w}{\delta_{(e)bike,1}^w d_{(e)bike,1}^\delta + \delta_{(e)bike,2}^w d_{(e)bike,2}^\delta}$$

2.7 Greenhouse gas estimates

The climate impacts of e-bike-induced mode shift were estimated from the mode shift measures calculated as above, combined with per-PKT lifecycle GHG emission rates from a recent study of the GHG emissions of household travel in greater Vancouver, BC (Bigazzi et al., 2023). The emission rates are given in Table 3. Table 3 includes two rates: attributional and consequential. Attributional emissions are the standard method of GHG accounting in transportation, which divide vehicle emissions equally among vehicle occupants. Consequential emissions factors instead represent the change in total vehicle emissions with a marginal change in travel activity, which better suit this type of analysis because they measure impacts from travel behaviour changes. This distinction is particularly important for travel by public transit, because transit vehicle operations are only moderately responsive to travel demand fluctuations (Bigazzi, 2020). For more information about this distinction, see the generating report (Bigazzi et al., 2023), or other literature on the attributional/consequential distinction in lifecycle assessments (Bigazzi, 2019; Brander et al., 2019; Brander and Ascui, 2015; Nordenstam, 2021).

Table 3. Lifecycle greenhouse gas emission factors

Primary travel mode	g CO_2e per person-km (attributional)	g CO_2e per person-km (consequential)
Automobile	332.61	325.23
Public transit	68.78	39.69
E-bike	11.22	11.18
Conventional bicycle	10.76	10.72
Walking	0.00	0.00

The rates in Table 3 include operating (on-road) emissions, as well as lifecycle emissions for the fuel (e.g., petroleum refining and electricity generation) and vehicle (production, maintenance, and disposal); they do not include guideway lifecycle emissions due to infrastructure construction and maintenance. The rates are averaged by "primary" mode, and so include emissions from access and egress trip segments by other modes in multimodal trips (e.g., taking an automobile to a bus stop). Automobile travel includes trips by private, shared, or hailed (taxi) vehicles, using a passenger vehicle fleet based on BC vehicle registration data (primarily gasoline passenger cars, but including passenger trucks and hybrid and fully electric vehicles). Public transit includes only bus and paratransit trips (excluding Vancouver's rail transit and Sea Bus).

For e-bike trips in this study, we added upstream emissions from electricity consumed during e-bike operation to bicycle vehicle-cycle emissions. The e-bike energy consumption rate was assumed to be 14.58 Wh per km, based on the limited literature with measured consumption (Huang et al., 2022; Mendes et al., 2015). This rate is higher and more realistic than manufacturer and industry reported values around 5 Wh/km. GHG intensity of electricity consumption in BC was taken as 31.7 g CO_2e/kWh (consistent with the assumption for the other travel modes), which is higher than BC's production intensity of around 18 g CO_2e/kWh, but still far lower than the Canadian (around 100 CO_2e/kWh) or worldwide (around 200 CO_2e/kWh) intensities. Combining these, use-phase GHG emissions for e-bike travel were estimated as 0.462 g CO_2e/km. Note that this estimate does not treat food as a fuel, and so excludes upstream GHG emissions attributable to production of food consumed by people who cycle. This is a topic of some debate, but we believe there is currently insufficient evidence of the marginal effects of active travel on food consumption (Elder and Roberts, 2007; Frank et al., 2022).

The emission rates in Table 3 are representative values for passenger travel in BC, reflecting systematic modal differences, but individual GHG rates will vary with a range of factors that were not feasible to collect in this study, such as vehicle make/model, vehicle occupancy, etc. Hence, the GHG impact estimates neglect possibly unique characteristics of e-bike adopters in these aspects of their non-bicycle travel activity. For example, if e-bike adopters systematically owned higher-emitting automobiles than others, or were less likely to share rides, we would underestimate the GHG impacts of e-bike mode substitution (and vice versa). The rates also do not reflect some of the unique transportation system characteristics of greater Victoria, in contrast to greater Vancouver and other cities in BC, such as potentially different passenger vehicle fleets and bus operating characteristics.

Using the modal lifecycle GHG emission factors EF_m (in g CO_2e per PKT) shown in Table 3, we calculated the weekly g CO_2e per person from reported travel in each wave as:

$$\sum_{m}\left[\delta_{m,w}^{w} d_{m,w}^{\delta} EF_m\right]$$

with the other variables defined above. From the calculations in the previous section we have mode shift represented in three ways (reduced PKT by mode m per week, per km of e-bike travel, and per e-bike trip): ΔPKT_m^w, ΔPKT_m^d and ΔPKT_m^t. We converted mode shift into climate impacts by multiplying the emission factors and then summing across modes.

- Net g CO_2e reduced per week from (e-)bike use:

$$\sum_{m}[\Delta PKT_m^w EF_m]$$

- Net g CO_2e reduced per (e-)bike trip:

$$\sum_{m}[\Delta PKT_{m}^{t}EF_{m}]$$

- Net g CO_2e reduced per (e-)bike km travelled:

$$\sum_{m}[\Delta PKT_{m}^{d}EF_{m}]$$

2.8 Physical activity estimates

The travel matrix data were also used to estimate the changes in physically active transportation between survey waves. A common approach to quantifying physical activity level is the measure of Metabolic Equivalent Task (MET), which is the physical intensity of an activity in terms of energy expenditure relative to the participant at rest. For example, someone doing an activity at a MET of 3 is expending energy at 3 times the rate of if they were simply lying down. Representative MET values applied to the travel modes in this study are given in Table 4, based on relevant literature (Ainsworth et al., 2011; Bourne et al., 2018; Castro et al., 2019; Gojanovic et al., 2011; Mageau-Béland and Morency, 2021). Note that energy expenditure can vary widely for a given trip or context, with factors like terrain, speed, walking access to transit, etc. The third column in Table 4 gives the non-sedentary MET increment, which indicates the additional physical activity achieved during travel by that mode, relative to sedentary time which has a MET of 1 (i.e., non-sedentary MET is simply $\mathrm{MET}-1$, which is sometimes called marginal MET). Weekly non-sedentary MET-minutes are calculated as the product of self-reported minutes per day and days per week by mode (in the travel matrix data), and the modal non-sedentary MET increment (third column in Table 4).

Table 4. Representative MET values by mode

Mode	MET	Non-sedentary MET increment
Walking	3	2
Cycling	7	6
E-cycling	5	4
Auto	1.3	0.3
Transit	2	1
Other	2	1

Common adult physical activity guidance recommends at least 150 minutes of moderate or vigorous physical activity per week, which means activity at a MET of at least 3 (Bull et al., 2020; Canadian Society for Exercise Physiology, 2021; Department of Health, Physical Activity, Health Improvement and Protection, 2011). Most travel by active modes (walking and cycling on a conventional or electric bicycle) achieves a moderate physical activity level, as does active portions of transit trips (walking to a transit stop, for example). More intense activity is associated with greater health benefits (Bull et al., 2020); assuming benefits scale with intensity, the 150 minute threshold translates to an increment of at least 300 non-sedentary MET-minutes per week.

2.9 Regression analysis

Regression analysis was used to examine relationships between study outcomes (marginal purchases, mode substitution, etc.) and bicycle purchase and purchaser attributes (e-assist, incentive, income, gender, age, etc.), while controlling for potentially confounding and time-varying external factors (weather, fuel price, COVID restrictions, etc.). All statistical tests used a significance threshold of $p<0.05$ (i.e., 95% confidence of avoiding Type I error or a false positive). Because this is explanatory rather than predictive modelling, we did not re-estimate models with non-significant independent variables removed. Sample weights (see Section 2.5) were used in all regression model estimates.

In addition to the data collected in the survey about the bicycle purchase and purchaser, additional independent variables were drawn from other sources and used to control for time-varying exogenous factors that might have influenced the reported travel behaviour. These variables are listed in Table 5. Other household contextual variables such as terrain, cycling facilities and transit access were considered, but not included due to the limited variation within the sample, and limited number of explanatory variables that could be included in the model with the available sample size.

Table 5. External control variables used in regression analysis

Variable	Definition	Source
Fuel price	Average monthly retail gasoline prices in cents per litre for Victoria, BC	Statistics Canada (Statistics Canada, 2024)
Temperature	4-week average daily temperature in degrees C	Data from University of Victoria weather station, downloaded from the Government of Canada (Environment Canada, 2024)
Precipitation	4-week average daily precipitation in mm	Same as temperature
COVID restrictions	Binary, indicating survey response within the period during which BC was in a pandemic-related state of emergency (March 18, 2020 through June 30, 2021)	Province of BC (Province of British Columbia, 2022)

2.9.1 E-bike purchase decisions

The likelihood of four alternative behaviours without the purchase incentives (i.e. making the same purchase, no purchase, or purchasing a conventional bicycle or different e-bike) were modeled at the person level, dependent on personal, bicycle, incentive, and contextual factors. Dirichlet regression was used to incorporate the self-reported probability of each alternative (avoiding the need of assuming a single choice), and to allow for independent effects for each alternative (Douma and Weedon, 2019; Maier, 2014). Dirichlet regression models the probability at each level of a categorical dependent variable, while addressing the challenges of compositional data (comprising proportions of a constrained total), such as multicolinearity. For modelling, the the two options of no purchase and other conventional bicycle purchase were combined to create a three-level dependent variable (no e-bike purchase, purchase other e-bike, or purchase same bicycle).

An ordered logit regression model was also estimated, to apply a more common choice modelling technique. For the ordered logit model, a three-level ordered factor dependent variable (no e-bike purchase < purchase other e-bike < purchase same bicycle) was created, transformed to discrete choices as the highest-likelihood alternative selected by each respondent. Because the results were substantially the same as the Dirichlet regression model, only the Dirichlet regression results are presented in this report.

2.9.2 Mode shift and GHG reductions

Changes in automobile PKT and weekly GHG by each participant were modelled using an approach that is appropriate for panel data (repeated measurements from the same participants over time) and the non-normal distribution of these variables (which are truncated at zero and have substantial positive skew). For this purpose we applied a weighted negative binomial mixed-effects regression model, estimated in the statistical software R with the package 'glmmTMB' (Brooks et al., 2017; R Core Team, 2019). This model includes random effects for each participant (to account for intra-subject error correlation), and a set of fixed effects for personal, bicycle, and contextual factors. The dependent variables for each model are weekly automobile PKT and weekly GHG from all travel.

The estimated parameters on a dummy variable for post-purchase observations indicate the reduction in each outcome associated with a bicycle purchase (controlling for all other factors). Group fixed effects were included for the three study groups (Saanich program, e-bike control, and conventional bicycle control). The group variables were interacted with the post-purchase variable to measure differences in purchase effects between the groups. Saanich rebate amount was also interacted to test for moderating effects on pre- and post-purchase behaviours.

Responses in each wave were spread over time (see Figure 9 below), and so we used time-varying contextual variables (fuel price, weather, and COVID restrictions) rather than time fixed effects to account for external factors. Random effects were used to control for correlated participant error rather than fixed effects due to the data structure (few observations over many individuals), the ability to include time-invariant personal factors in the model, the desire to make inferences beyond the studied sample, and the expectation that the few non-personal, time-varying independent variables in the model are uncorrelated with the individual error (Greene, 2008).

3 RESULTS

3.1 Data Overview

3.1.1 Responses

The number of responses at each step of data cleaning is given in Table 6. We examined the potential impacts of using a completion threshold below 100%, but found that it would not substantially increase the sample size, because most incomplete responses were less than 10% complete.

Table 6. Number of responses through data cleaning

Type of responses	Wave 1	Wave 2	Wave 3
Raw (post-consent)	655	233	130
Complete (100%)	450	214	120
Cleaned	402	213	116

Numbers of participants at each step of the survey process are shown in Table 7, segmented by sub-sample. As a reminder, the sample was partitioned into a Study group (Saanich incentive recipients) and a Control group (all other participants). The Saanich program distributed 389 incentives within the recruitment period, resulting in a Wave 1 Study group response rate of 42%. The cleaned dataset contained complete responses from 402 participants at Wave 1 (41% from the Study group and 59% from Control group), 116 of which also completed Waves 2 and 3. Of the complete Wave 1 responses, 85% agreed to be re-contacted for Wave 2, of whom 63% actually completed Wave 2, resulting in a 53% retention rate between Waves 1 and 2. Of the complete Wave 2 responses, 98% agreed to be re-contacted for Wave 3, of whom 56% actually completed Wave 2, resulting in a 54% retention rate between Waves 1 and 2, and a 29% retention rate between Waves 1 and 3. These rates were highly consistent between the Study and Control groups, as illustrated in Figure 8.

Table 7. Number of participants at each step of the survey process

	Study group			Control group			Total sample		
Stage	N*	% of previous	% of Wave 1	N	% of previous	% of Wave 1	N	% of previous	% of Wave 1
Complete Wave 1	164	NA	100%	238	NA	100%	402	NA	100%
Consent to recontact	141	86%	86%	199	84%	84%	340	85%	85%
Complete Wave 2	92	65%	56%	121	61%	51%	213	63%	53%
Consent to recontact	89	97%	54%	119	98%	50%	208	98%	52%
Complete Wave 3	48	54%	29%	68	57%	29%	116	56%	29%

* Number, Percent of previous, Percent of Wave 1

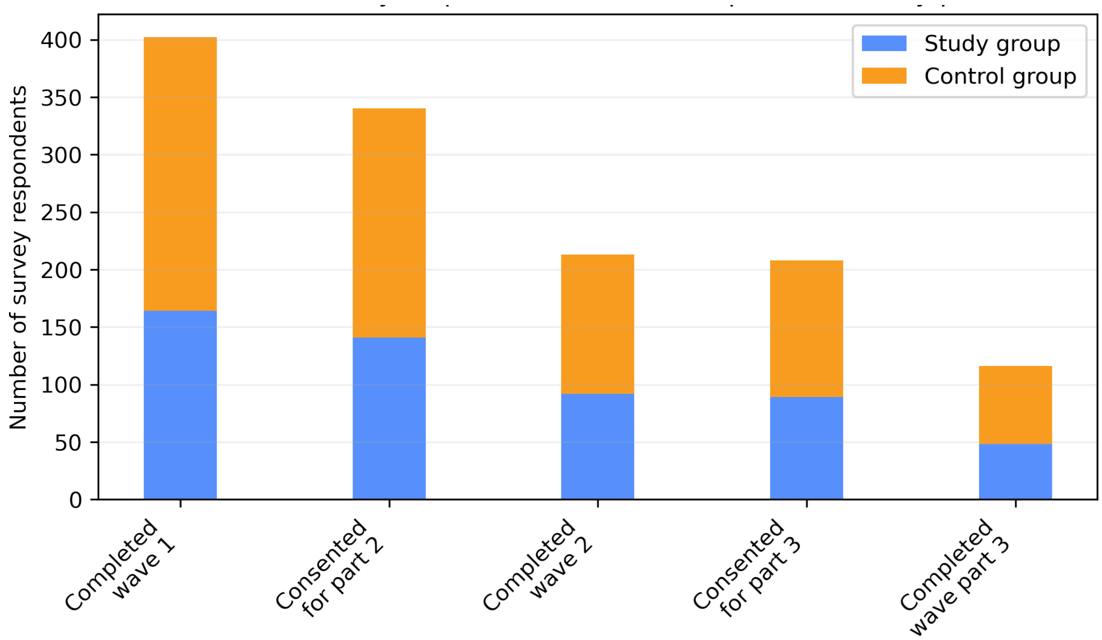


Figure 8. Number of participants at each step of the survey process

The survey responses over time are shown in Figure 9 (excluding participants who declined to be re-contacted for subsequent waves). The total sample at each wave is comprised of approximately 40% Study and 60% Control groups. The Study group participants joined steadily over the first year of data collection as incentives were distributed by Saanich, while the Control group participants were mostly recruited during online advertising in January and February 2022.

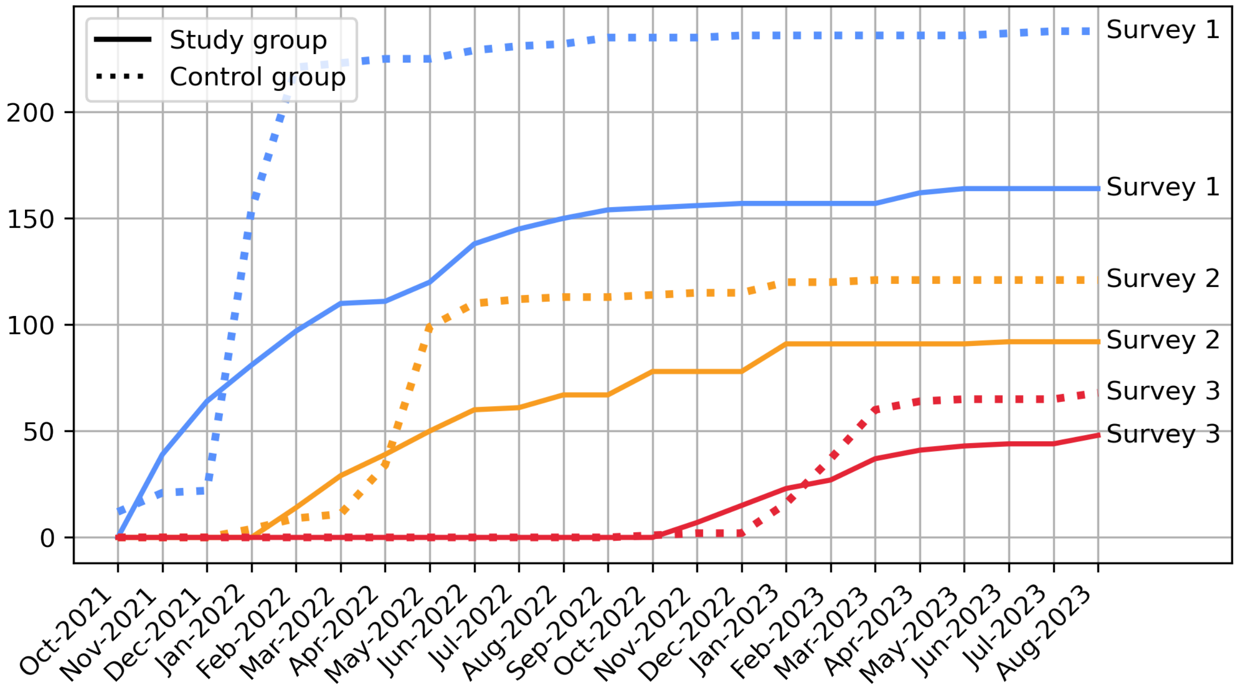


Figure 9. Cumulative complete responses over the course of data collection (excluding those who did not consent to re-contact at each wave)

3.1.2 Sample characteristics

The Wave 1 sample demographic characteristics are shown in Table 8, along with summary demographics of all Saanich e-bike incentive recipients and local, regional, and provincial demographic data from the 2021 Census (Statistics Canada, 2022) and the 2022 Capital Regional District household travel survey (R.A. Malatest & Associates Ltd. and David Kriger Consultants Inc., 2023). The sample compares well to the incentive recipients and local population over most demographic features. The sample is lower-income than the population, which is expected for an income-conditioned incentive. The travel habits were measured using different prompts, which yielded higher rates of at least weekly use for all modes in the sample than the Saanich program; however, the ordering of modal popularity is the same (automobile > walk > conventional bicycle > public transit > electric bicycle). The sample had lower automobile and higher bicycle and transit commute rates than the regional population (note that the sample reported current primary commute mode in all waves, which was post-purchase for most respondents in Wave 1).

Table 8. Sample characteristics in Wave 1 compared to all incentive recipients and regional population

Attribute	Wave 1 Sample	Saanich program	District of Saanich	Greater Victoria	British Columbia
Gender: not cis-man	52%	51%	51%	52%	51%
Age: >=55 years	41%	45%	37%	38%	35%
Age: >=65 years	20%	21%	23%	24%	20%
Physical disability	5%	8%	Unk[1]	Unk	Unk
Indigenous	2%	3%	3%	5%	6%
Visible minority	22%	13%	25%	16%	34%
Completed at least college/university certificate/diploma	86%	Unk	84%	87%	82%
Household size (mean)	2.7	Unk	2.4	2.2	2.4
Households with children	33%	Unk	32%	27%	34%
Annual household income over $100k	30%	Unk	46%	41%	42%
Annual household income over $150k	13%	Unk	25%	21%	21%
Household motor vehicles (mean)	1.48	1.91	1.72	1.56	1.62
Household conventional adult bicycles (mean)	1.83	Unk	1.49	1.31	Unk
Household electric bicycles (mean)	0.73	Unk	0.20	0.17	Unk
Travel habits: at least weekly trips by each mode (pre-purchase)					
Walk	83%	46%	Unk	Unk	Unk
Conventional bicycle	47%	37%	Unk	Unk	Unk
Electric bicycle	14%	7%	Unk	Unk	Unk
Automobile	87%	84%	Unk	Unk	Unk
Public transit	30%	18%	Unk	Unk	Unk
Primary commute mode (for those who commute)					
Walk	9%	Unk	6%	10%	6%
Bicycle (conventional or electric)	34%	Unk	5%	5%	2%
Automobile	43%	Unk	77%	74%	80%
Public transit	13%	Unk	9%	8%	9%

[1] Unk: Unknown

Table 9 breaks down the sample demographic characteristics by group (Study versus Control) and Wave (to examine changes with sample attrition). The Study group was older than the Control group, with lower household income (as expected for the income-conditioned e-bike incentive program). Pre-purchase, the Study group took transit and cycled less (conventional or electric), and used automobiles more, than the Control group (this changed in subsequent waves, as expected and examined below). Some demographic features changed between waves due to attrition, although few of the changes were markedly monotonic (increasing or decreasing in both intervals) and the final Wave 3 samples still compared well to the Saanich program and population characteristics.

Table 9. Sample characteristics by group and wave

Attribute	Wave 1		Wave 2		Wave 3	
	Study	Control	Study	Control	Study	Control
Gender: not cis-man	52%	53%	55%	53%	47%	54%
Age: >55 years	50%	34%	51%	40%	52%	39%
Age: >65 years	25%	17%	27%	20%	27%	16%
Physical disability	7%	4%	9%	6%	2%	4%
Indigenous	3%	2%	1%	2%	0%	2%
Visible minority	24%	20%	19%	16%	17%	18%
Completed at least college/university certificate/diploma	82%	88%	81%	88%	87%	87%
Household size (mean)	2.5	2.9	2.4	2.6	2.4	2.6
Households with children	31%	35%	28%	27%	29%	26%
Household motor vehicles (mean)	1.55	1.43	1.51	1.44	1.52	1.34
Household conventional adult bicycles (mean)	1.65	1.95	1.70	1.88	2.02	1.78
Household electric bicycles (mean)	1.05	0.51	1.21	0.65	1.21	0.75
Annual household income over $100k	18%	37%	19%	42%	21%	41%
Travel habits: at least weekly trips by each mode						
Walk	83%	83%	82%	87%	83%	82%
Conventional bicycle	40%	52%	15%	44%	4%	24%
Electric bicycle	7%	18%	76%	42%	67%	50%
Automobile	94%	83%	92%	88%	98%	87%
Public transit	19%	37%	15%	34%	17%	38%

The Study group demographics by incentive tier are illustrated in Figure 10. Substantially larger shares of higher-income households received smaller rebate amounts, indicating the core of the program design was successfully executed. Due to interrelationships among demographic attributes, rebate amounts also systematically varied with age (older recipients received smaller rebate amounts) and the number of household motor vehicles (households with more motor vehicles received smaller rebate amounts).

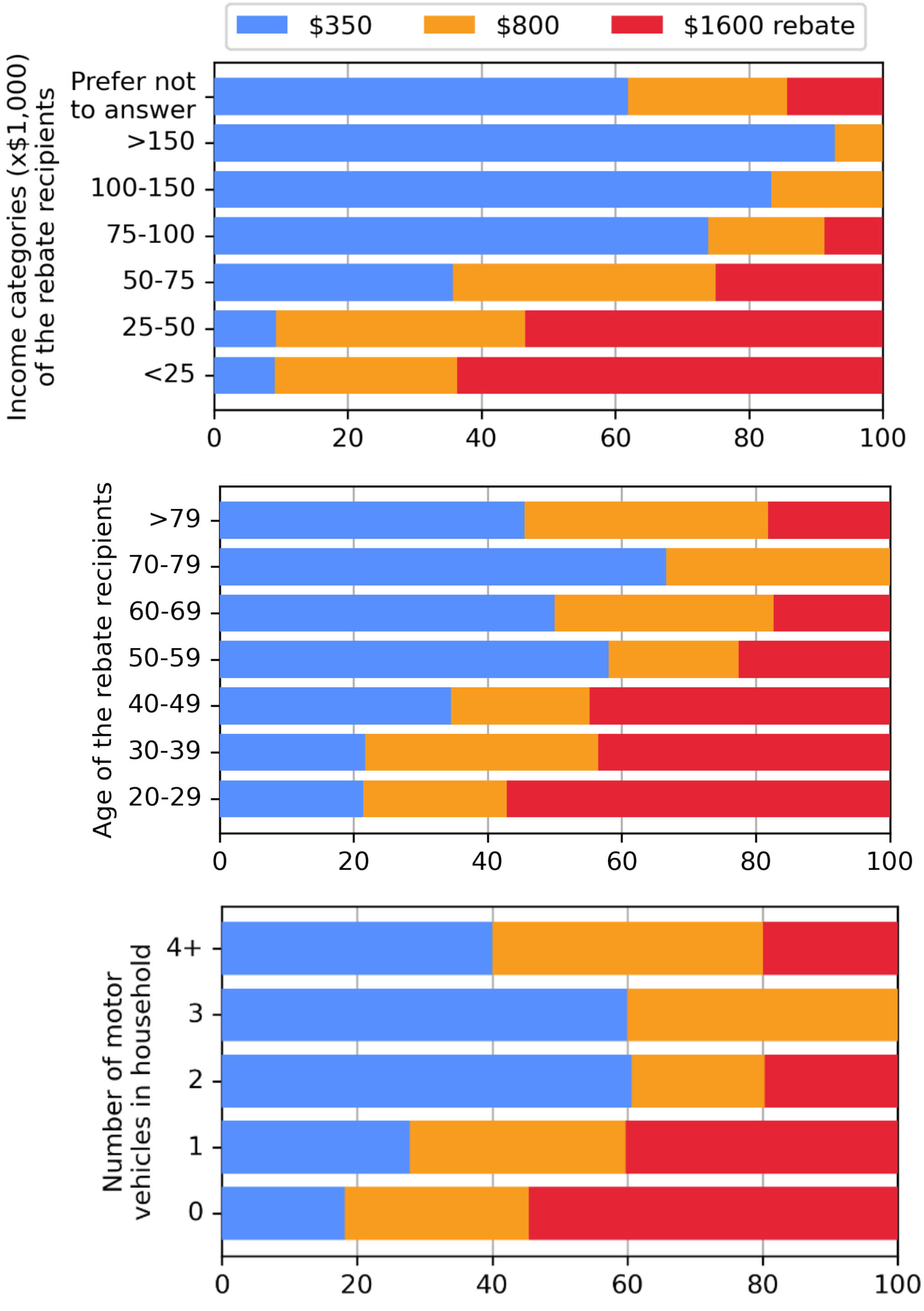


Figure 10. Age, household income, and household vehicles by rebate tier

Self-reported comfort cycling on different types of facilities (at Wave 1) is shown in Figure 11 for the Study and Control groups, which did not differ substantially in their responses, although the Control group expressed slightly more confidence cycling in bike lanes.

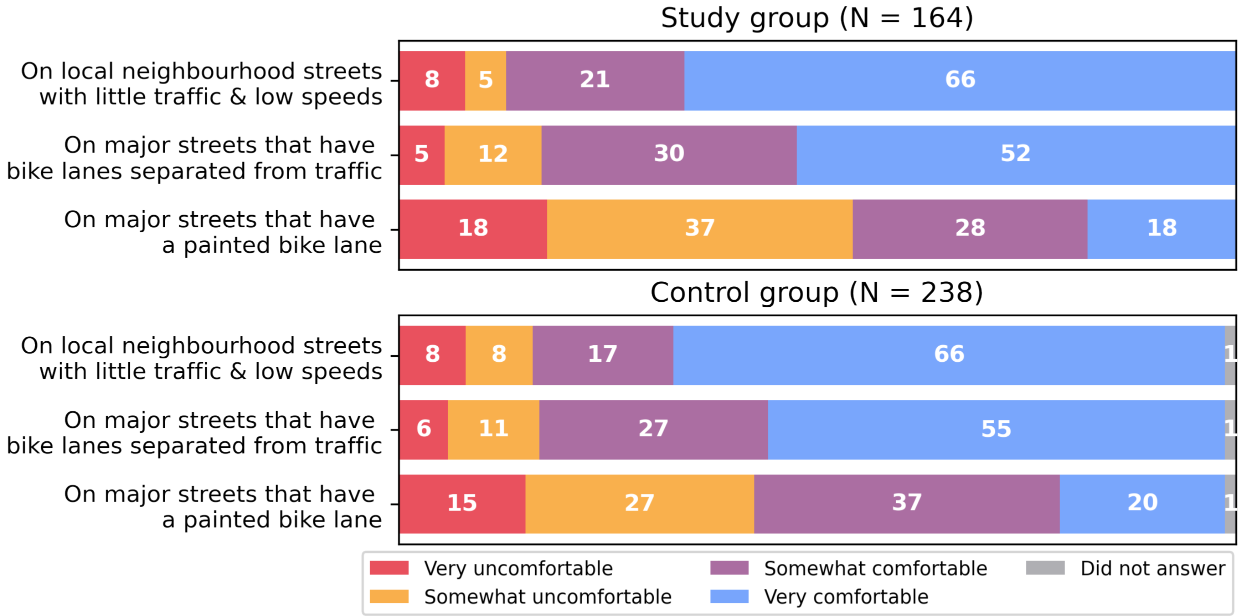


Figure 11. Self-reported comfort cycling on different facility types at Wave 1 (percentages indicated on the charts)

Figure 12 shows vehicle and bicycle ownership in each survey wave, for the sub-set of 116 participants who completed all three survey waves. The question measured status at the time of response, and 84% of respondents had already purchased their bicycle at Wave 1. However, there is still a decrease in motor vehicle ownership and increase in bicycle ownership between Waves 1 and 2, which remains unchanged in Wave 3.

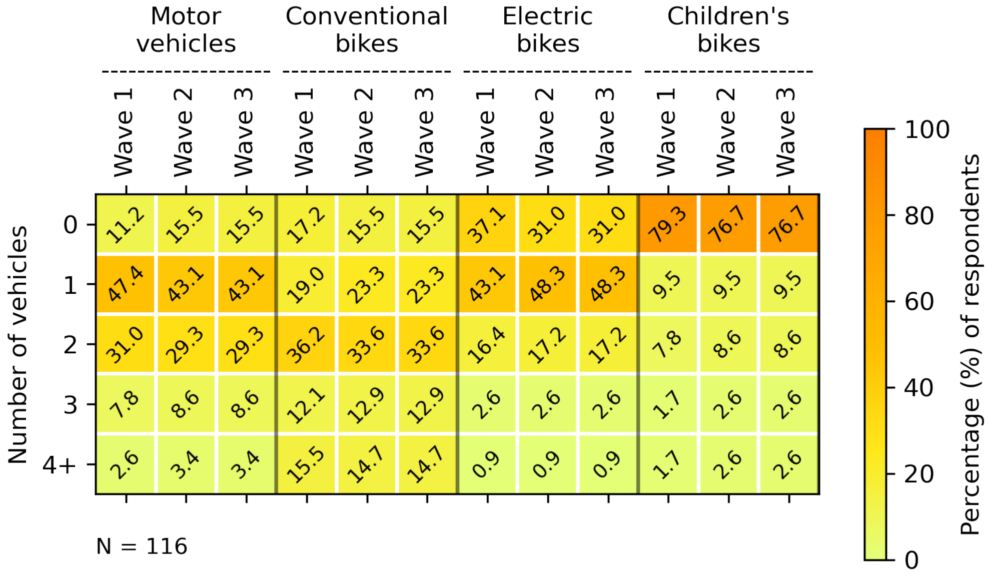


Figure 12. Vehicle and bicycle ownership in each wave

3.1.3 Panel attrition model

A binary logit regression model was estimated to examine potential sample bias introduced through attrition in the panel between waves. The estimated model results are shown in Table 10. The dependent variable was completion of Wave 3, and so positive parameter estimates indicate variables that increased likelihood of retention in the panel, while negative parameter estimates indicate variables associated with people more likely to leave the study before Wave 3. Results show that we disproportionately lost Wave 1 participants who received larger Saanich rebates, had a physical disability, had more cars in the household, were less comfortable cycling, and who cycled more.

Table 10. Binary logit model of panel retention

Variable [1]	Estimate	p-value
Intercept	0.148	0.83
E-assist bicycle purchased	0.681	0.12
Saanich rebate ($100)	**-0.093**	**<0.01**
Cis-man	0.489	0.12
>50 years old	0.253	0.43
Physical disability	**-1.619**	**0.01**
College degree	0.242	0.56
High income (>$100k)	0.215	0.58
Visible minority	0.168	0.67
<3 adults in HH	0.262	0.51
No children in HH	-0.114	0.75
<2 cars in HH	**0.712**	**0.04**
COVID restrictions	-0.046	0.93
Very uncomfortable on painted bike lanes	**-0.980**	**0.02**
(Pre-purchase) weekly cycling (100 km)	**-0.547**	**0.05**

[1] Variables values as reported in Wave 1

Non-random sample attrition can introduce bias if it is associated with the outcomes of interest (such as travel mode shift and GHG changes). Looking at the significant variables in Table 10, some could be associated with increased or decreased use of purchased bicycles. For example, losing uncomfortable cyclists and people with physical disabilities would suggest the sample retained people who might have cycled more, while losing people already cycling more and with fewer household vehicles would suggest the sample retained people who might have cycled less. Fortunately, while attrition was non-random, the factors associated with attrition are not consistently pointing to bias in one direction.

Including the significant variables in Table 10 in the regression analysis limits the potential impact of sample attrition on the results, because it controls for those relationships with studied outcome variables. We include all except Wave 1 weekly cycling in the regression models below, because that variable would be endogenous to travel behaviour change.

3.1.4 Sample weights

Sample weights were created for regression analysis to represent the greater Victoria, BC population over 6 key variables (transformed to binary classifiers for practicability):

1. Gender (cis-man)
2. Income (higher than $100,000)
3. Education (college certificate or more)
4. Race (visible minority)
5. Commuter (commutes to work or school)
6. Automobile commuter (primary commute mode)

Sample weights were created by raking the respondent data (from Wave 1) to match the marginal distributions in the population for all six weighting variables. Weights were trimmed (strictly) at lower and upper bounds of 0.3 and 3.0 times the median weight, respectively (0.248 and 2.48). The resulting weights had a mean of 0.92, median of 0.83, and interquartile range of 0.43 to 0.96.

3.2 Purchased bicycles

3.2.1 Overview of bicycle purchases

Bicycle purchase and ownership information for the complete sample (Study and Control groups) are illustrated in Figure 13. Of 402 Wave 1 completions, 85% had recently purchased a bicycle (conventional or electric), which increased to 89% of Wave 2 completions due to additional purchasers. By Wave 3, 5% of respondents (all in the Control group) had not purchased a bicycle, while 3% no longer owned a previously-purchased bicycle. The reported reasons for no longer having the bicycle were:

- "Bicycle is still on back order so it has not yet been received.",
- "I moved out of province",
- "Battery problems. Had to return",
- "It was bulky / slow",
- "My neighbourhood has very heavy traffic and I didn't feel safe.", and
- "Felt unsafe.".

Theft does not appear to have been a major factor for the program impacts, although we cannot be certain due to a possible relationship with sample attrition.

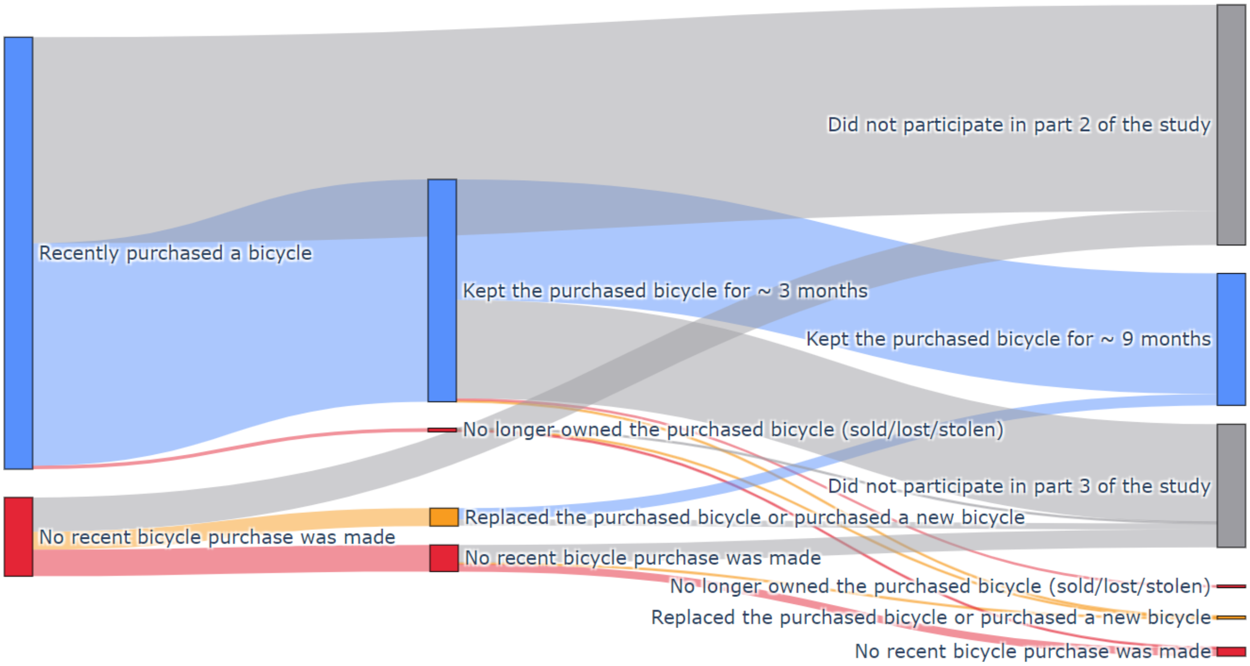


Figure 13. Illustration of bicycle purchase and ownership status for the sample at Wave 1 (left), Wave 2 (center), and Wave 3 (right)

Based on the reported purchase information, the Control group was further divided into those who purchased an e-bike, conventional bicycle, or no bicycle. Information about the purchased bicycles is given in Table 11. Of the Control group purchasers, 49% purchased a conventional bicycle and 51% purchased an e-bike, mostly with no reported rebates. Respondents reported on average 80% to 94% of personal use of the new bicycle (versus others in their household), higher for conventional than electric bicycles in the Control group, and higher in the Study than Control groups for e-bikes. The distribution across the full sample is shown in Figure 14. Mean purchase prices in the Study group were similar to the Saanich program data, which were both substantially lower than non-incentivized e-bike purchases and higher than conventional bicycle purchases in the Control group. Rebate amounts for the 9% of e-bike purchasers in the Control group who received a rebate were similar to the Saanich rebate amounts.

Table 11. Bicycle purchase information

Variable	Saanich program	Study sub-sample	Control sub-sample Conventional bicycle	Control sub-sample Electric bicycle
Number of purchasers	389	164	86	90
Has odometer	NA[4]	84%	17%	74%
Mean expected percentage of bicycle use by respondent	NA	85%	94%	80%
Received a rebate[1]	100%	100%	2%	9%
Rebate value (all purchasers)[1,2]	$796 ($515)	$887 ($535)[3]	$7 ($46)	$38 ($197)
Rebate value (those receiving)[1,2]	$796 ($515)	$887 ($535)	$300 ($0)	$862 ($450)
Total cost after rebates[2]	$2,133 ($565)	$2,120 ($1,444)	$1,460 ($1,444)	$2,925 ($2,882)

[1] Excludes Provincial 12% sales tax exemption available to all e-bike purchasers

[2] Mean (standard deviation)

[3] Mean value of the Saanich rebate alone was $847 (standard deviation $526)

[4] Not Available

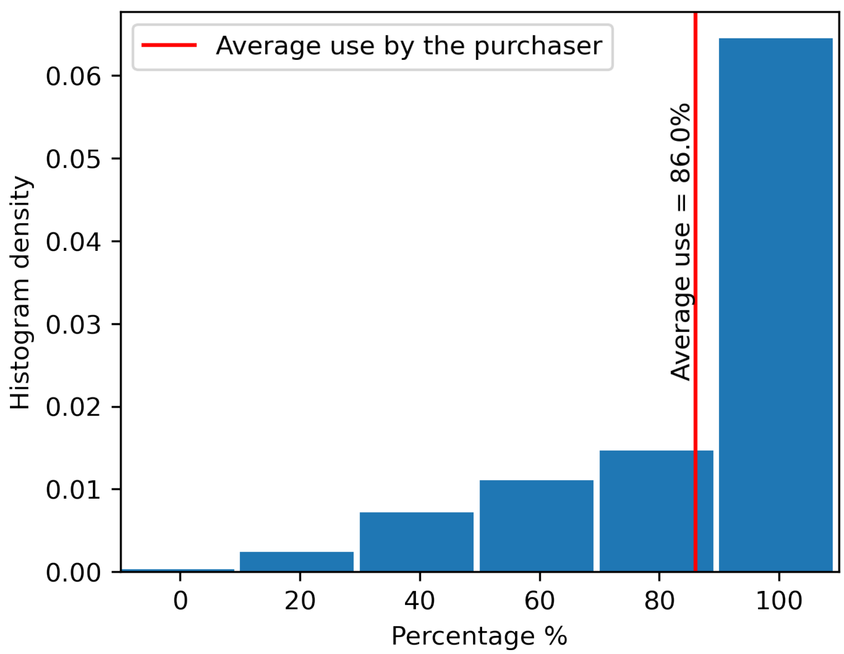


Figure 14. Distribution of expected percentage use of the purchased bicycle by the respondent (versus by others)

The rebate and mean bicycle purchase amounts in each incentive tier for the Saanich program participants are illustrated in Figure 15. Total bicycle cost was similar across incentive tiers, and so the amount paid by the purchasers essentially declined by the rebate amount.

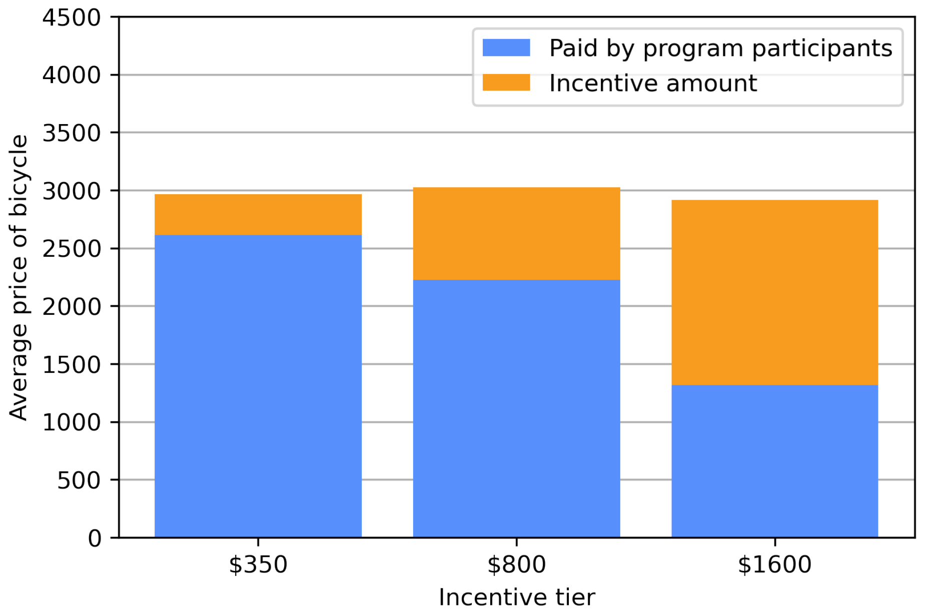


Figure 15. Average bicycle purchase prices by incentive tier

Respondents were also asked to rank the top three considerations in making their bicycle purchase. Assigning 3 points to the first factor, 2 to the second factor, and 1 to the third factor, Figure 16 shows the mean points for each factor within the samples. Purchase cost is consistently the top factor, highest ranked for conventional bicycle purchasers followed by the Study group and then non-Saanich e-bike purchasers. Study group participants were also more motivated by the intention to shift travel modes. Conventional bicycle purchasers were much more focussed on "fun" (their second-ranked factor), while e-bike purchasers were more focussed on "physical effort" and "appearance/style".

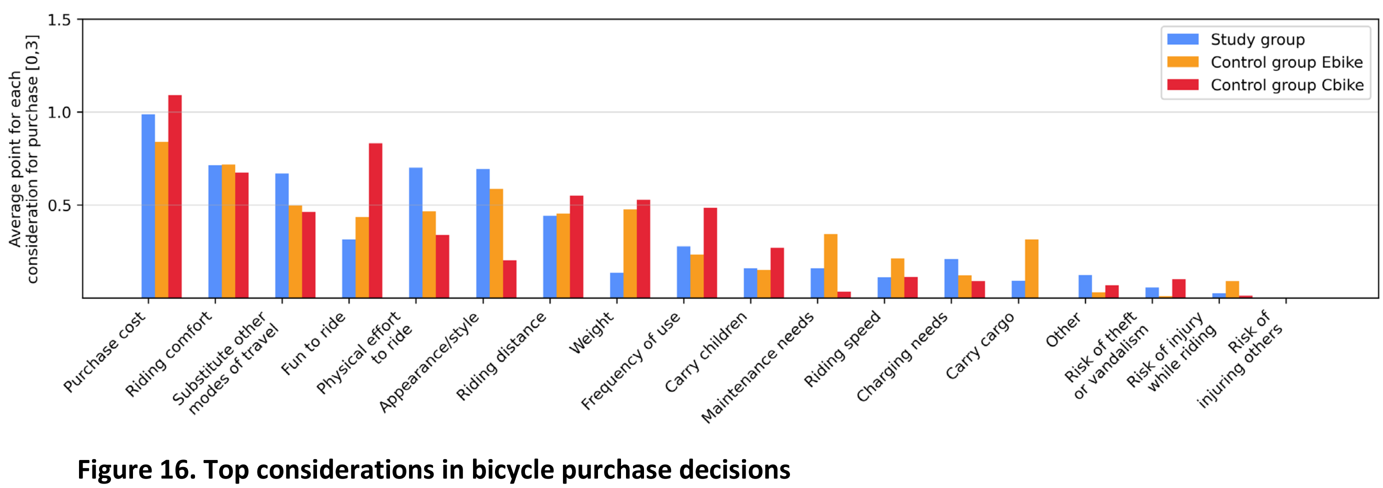


Figure 16. Top considerations in bicycle purchase decisions

3.2.2 What would have happened without the incentives

To quantify the marginality of purchases, respondents were asked to self-report on "If the incentives described above were not available for this purchase, what is the likelihood each of the following would have happened?" The mean self-reported likelihoods of each alternative for the Study and Control groups are shown in Figure 17. Note that most Control group purchasers received no rebate (Table 11).

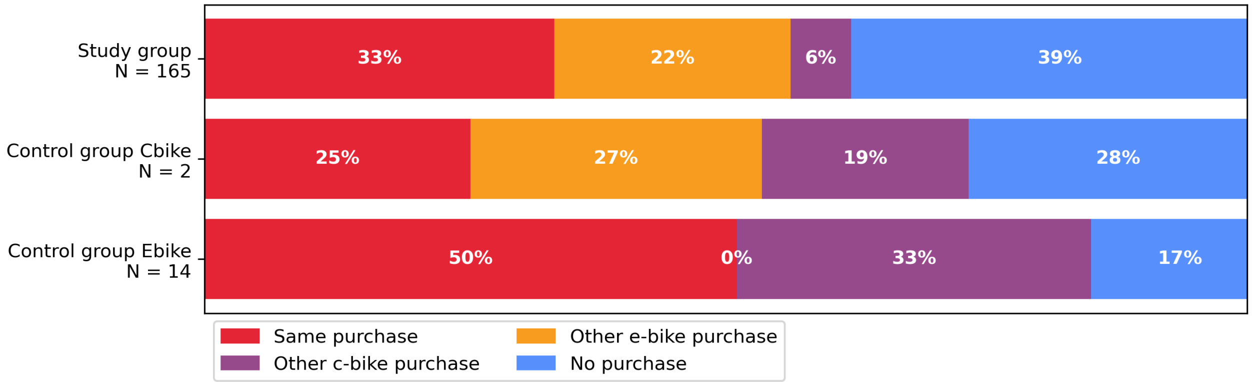


Figure 17. Mean self-reported likelihood of alternative behaviours without incentive by group

The mean self-reported likelihoods of each alternative for the Study group (receiving Saanich rebates) is shown in Figure 18, separated by incentive/rebate tier. At increasing rebate levels, the proportion of people making the same purchase without the incentive falls from 56% to 7%, while the proportion of people who would have purchased no bicycle at all increases from 20% to 65%. The other 24% to 37% of respondents would have purchased some other (presumably less desirable and/or lower quality) bicycle, with uncertain effects on usage. These results provide strong evidence that larger incentives attracted a higher proportion of marginal purchasers, as expected.

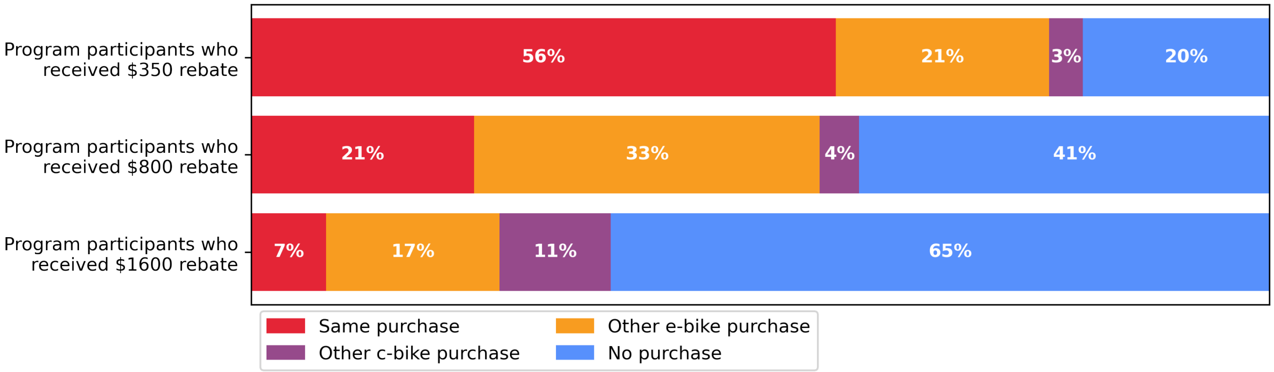


Figure 18. Mean self-reported likelihood of alternative behaviours without incentive by rebate amount

These alternatives can be used to infer the price elasticity of e-bike purchasers in the Saanich program. As described in Bigazzi and Berjisian (2021), the share of marginal purchasers in the rebate program can be estimated as $1-\left(1-\frac{r}{p}\right)^{-\varepsilon}$, where r is the rebate amount, p is the pre-rebate purchase price, and ε is the price elasticity of e-bike demand (assuming a power demand function). Rearranging, the elasticity can be calculated from rebate, price, and share of marginal purchasers m as: $\varepsilon=\frac{-\ln(1-m)}{\ln\left(1-\frac{r}{p}\right)}$. Alternatively using a linear power demand function, the share of marginal purchasers is $\frac{\varepsilon r}{\varepsilon r-p}$, which rearranges to $\varepsilon=\frac{mp}{r(m-1)}$.

These parameters for the Study group are given in Table 12, segmented by Saanich rebate amount, using the no-purchase alternative, and the no-purchase and conventional bicycle purchase alternatives together as the proportions of marginal purchases. The calculated elasticity ranges from -1.3 to -5.8, with most values in the range of -1.8 to -3.1. Median elasticity for the linear and power models is -2.9 and -1.8, respectively. These results align well with the suggested range of -1.0 to -3.0, and applied assumption of -2.0, in Bigazzi and Berjisian (2021), which was based on the limited available literature. The elasticity is higher for the lower-income (higher amount) rebate tiers using the linear demand model, but not the power model.

Table 12. Inferred elasticity from marginal purchases

Variable	\$350 rebate	\$800 rebate	\$1600 rebate
Pre-rebate price	\$2,965	\$3,025	\$2,915
Post-rebate price	\$2,615	\$2,225	\$1,315
Share marginal purchases			
Marginal: no purchase[1]	0.20	0.41	0.65
Marginal: no purchase or conventional bicycle[2]	0.23	0.45	0.76
Implied elasticity (linear model)			
Marginal: no purchase[1]	-2.12	-2.63	-3.38
Marginal: no purchase or conventional bicycle[2]	-2.53	-3.09	-5.77
Implied elasticity (power model)			
Marginal: no purchase[1]	-1.78	-1.72	-1.32
Marginal: no purchase or conventional bicycle[2]	-2.08	-1.95	-1.79

[1] Likelihood of no purchase alternative without rebate treated as marginal
[2] Likelihood of no purchase or conventional bicycle purchase alternatives without rebate treated as marginal

3.2.3 Regression models of marginal purchases

The estimated Dirichlet model results for the likelihood of alternative behaviours for each Saanich incentive recipient if the incentives had not been available are given in Table 13. This model is estimated for the Saanich incentives only (153 observations with complete data), but a similar model for the total amount of purchase incentives self-reported by each purchaser yields similar results. Table 13 gives odds ratios for two alternatives: making the same purchase or purchasing a different e-bike, in comparison to the reference alternative of making no purchase or purchasing a conventional bicycle (i.e., being a marginal purchaser). Odds ratios greater than one indicate variables that increase the likelihood of that alternative, while odds ratios less than one indicate variables that decrease the likelihood of that alternative. In this model, lower odds ratios indicate more marginal purchasers.

Table 13. Estimated Dirichlet model of likelihood of alternative behaviours without purchase incentive

Variable	Same purchase (odds ratios)	Other e-bike (odds ratios)
Intercept	**14.553**	2.916
Rebate amount ($100)	**0.878**	**0.928**
Cis-man	0.823	0.819
Age (years)	1.002	0.997
Physical disability	0.667	0.494
College degree	0.757	0.899
Visible minority	0.714	0.936
Household income ($10k)	1.035	1.020
<3 adults in household	0.797	0.735
No children in household	**0.567**	0.635
<2 cars in household	0.903	1.055
Fuel price (c/L)	0.994	0.999

Reference alternative: no purchase or conventional bicycle purchase
Bold indicates estimated parameters with p<0.05

The statistically significant variables in Table 13 are rebate amount (higher rebates make marginal purchases more likely) and households without children (which are more likely to make marginal purchases). Other variables that do not meet the 95% confidence threshold suggest that marginal purchases are more likely for cis-men, people with a physical disability or college degree, and people who are a visible minority. The results do not indicate a significant relationship between income and the marginality of purchases, although the odds ratios suggests that higher income purchasers are less likely to be marginal. A lack of significance for the income variable is likely due to the inverse correlation between income and rebate amount resulting from the Saanich program design. In addition to the relationship between income and incentive amount, recipients of larger rebates also tended to be younger and have fewer household vehicles (Figure 10).

The Dirichlet model results are illustrated in Figure 19 (for a purchaser with mean demographic attributes). Separate results are given for household incomes of $50,000 and $150,000. Each line shows how the expected likelihood of that alternative (if the incentive had not been available for the purchase) varies with rebate amount. Figure 19 shows that as rebate amount increases, the likelihood of making the same purchase falls and the likelihood of purchasing no e-bike increases, as expected. The likelihood of purchasing a different e-bike is not greatly affected by rebate amount, but falls slightly. At all rebate levels, lower-income purchasers are more likely than higher-income purchasers to make a marginal purchase. These results illustrate the greater sensitivity of low-income purchasers to e-bike prices, which makes e-bike rebates more effective in inducing new (marginal) purchases for this segment of the population (Bigazzi and Berjisian, 2021).

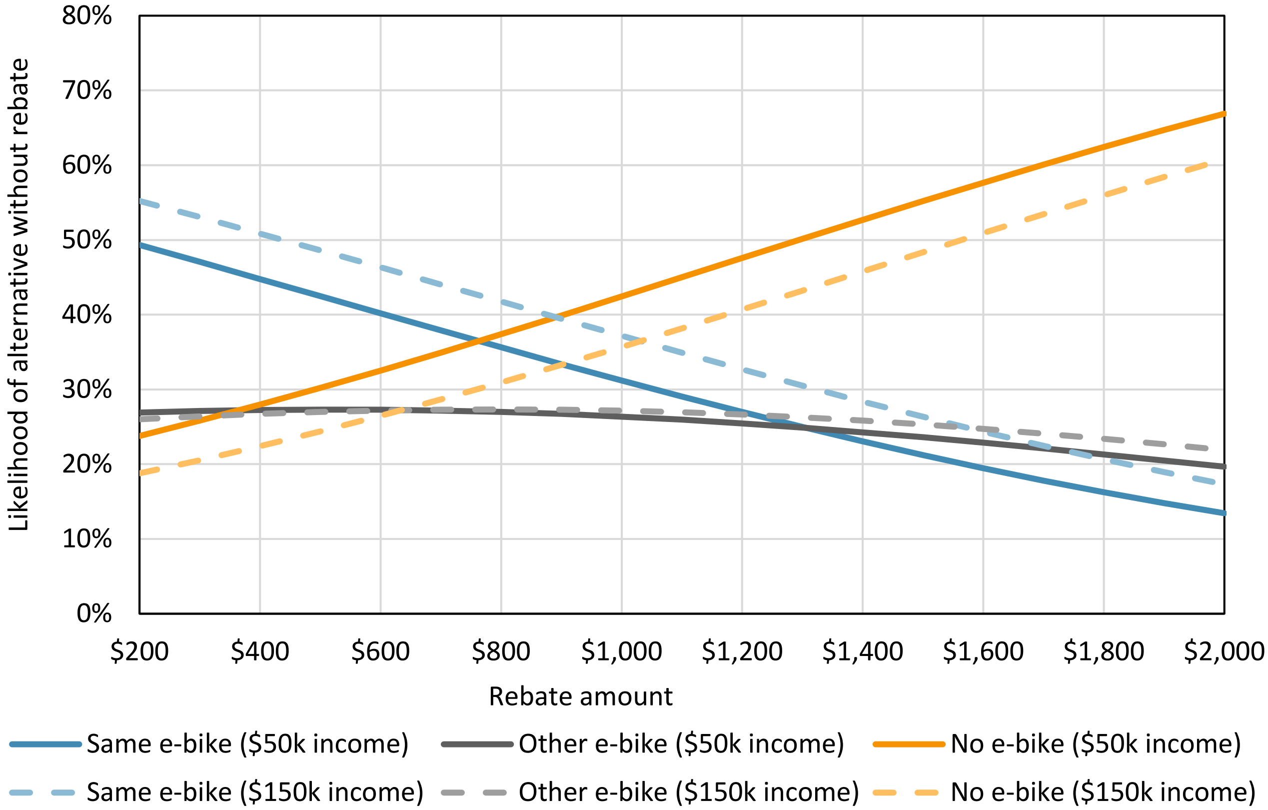


Figure 19. Illustration of modelled likelihood of alternative behaviours without Saanich purchase incentives

We can also interpret variables in Table 13 relative to rebate amounts, by comparing the parameter values. For example, households without children were more likely to be marginal purchasers, as mentioned above; the marginality of purchases by a no-child household is equivalent to purchases by a household with children receiving a $438 larger rebate. Applying this technique to income, for every additional $50,000 in income, a household would have to receive a $134 *larger* incentive to have the same likelihood of inducing a marginal purchase. Also, fuel prices being 10 cents/litre higher has the same effect on marginality of purchases as $49 higher rebate amounts.

3.3 Use of purchased bicycles

3.3.1 Overall experience

Overall, respondents' experience with their new bicycles, as reported in Waves 2 and 3, greatly exceeded their own pre-purchase expectations, as shown in Figure 20. These effects persisted beyond a year of ownership. In particular, respondents reported using their bicycles even more than expected, despite intended mode substitution already being a primary consideration in purchases (as shown in the next section).

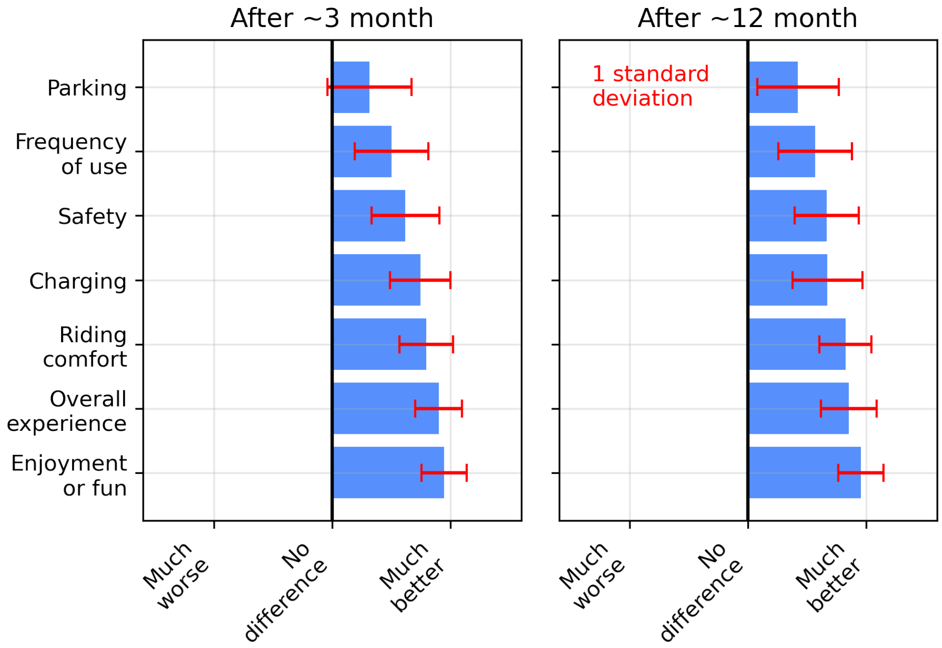


Figure 20. Experience with new bicycles, compared to pre-purchase expectations

3.3.2 Considerations in use

Self-reported "main considerations in deciding whether to use [their] new bicycle versus another mode of travel" are shown in Figure 21 for the Study and Control groups in each Wave, for participants who completed all 3 waves (using the same point weights as in Figure 16). The fundamental trip features of distance and time are top considerations, as are weather and safe riding facilities – commonly cited factors in cycling participation. No factor stands out as consistently more important for one group versus another, with the possible exception of bicycle parking for the Study group. Over the successive waves, there is a shift in focus from travel distance to travel time, particularly for the Study and conventional bicycle Control groups, and a decreased focus on factors such as exertion and parking.

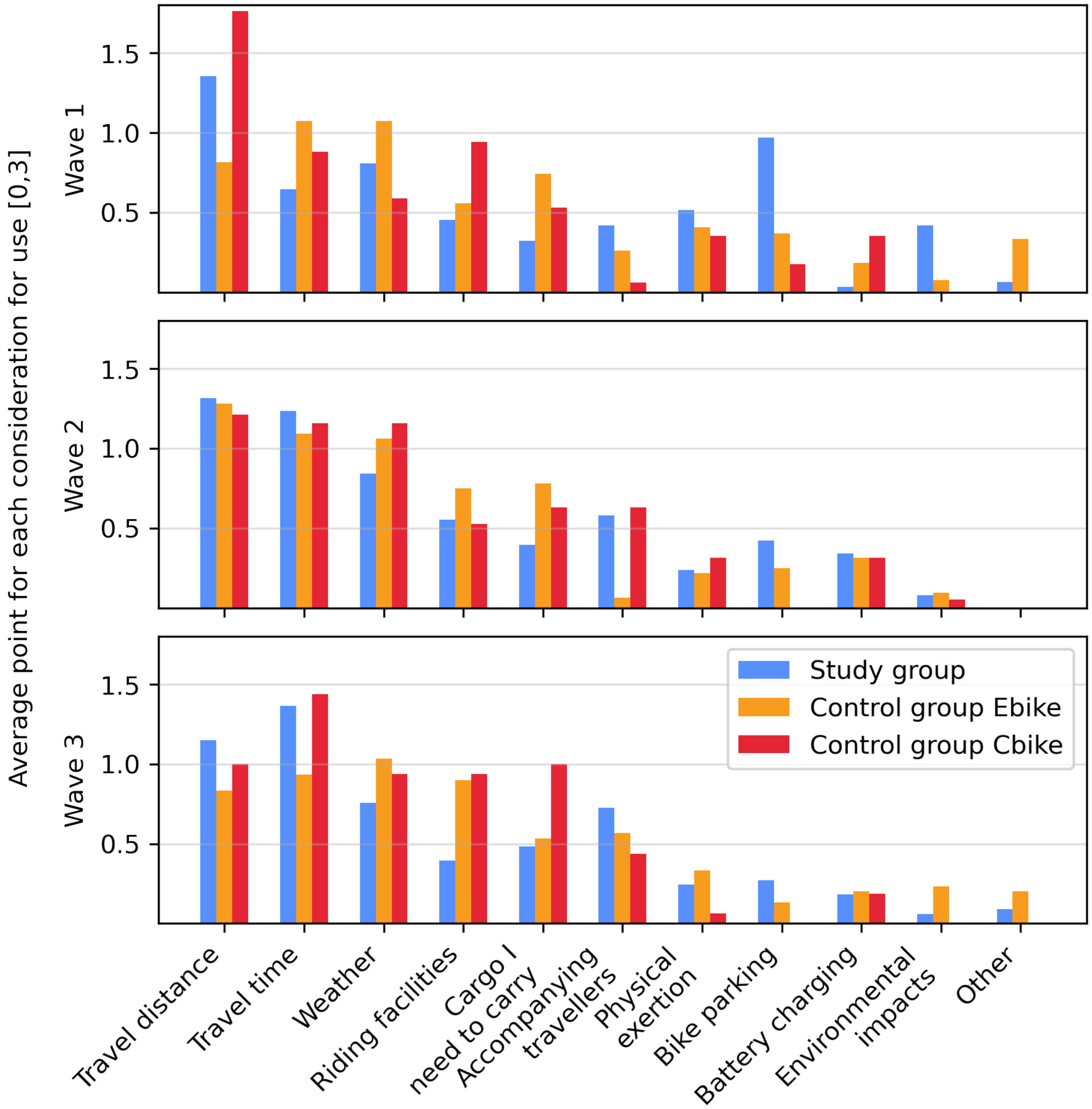


Figure 21. Top considerations in using the new bicycle (by participants who completed all three waves)

3.3.3 Recent trips

Participants in each wave were asked to report details of the last three round tips they took with their new bicycles ("leaving from home and returning again, with any number of stops along the way"). Table 14 summarizes the resulting usage characteristics. The implied trip speeds and frequencies are reasonable, increasing confidence in the self-reported data. Usage is also quite similar between the two e-bike groups.

Table 14. Characteristics of last 3 trips taken on new bicycle

Variable	Control group (conventional bicycle)	Control group (electric bicycle)	Study group
Observations	125	153	211
Mean trip length (km)	18.2	17.2	16.2
Mean trip duration (min)	49.7	44.5	43.0
Implied trip speed (km/hr)	22.6	23.6	23.5
Implied frequency (trips/week)	4.3	3.4	3.3
Implied usage (km/week)	79.2	55.3	54.3

The distribution of trip purposes for the last three trips is illustrated in Figure 22. Compared to the purchased conventional bicycles, the e-bikes were disproportionally used for commuting (work or school), and less often used for exercise or leisure. This pattern was consistent across study waves, although there was a general trend toward more utilitarian trip purposes in waves 2 and 3.

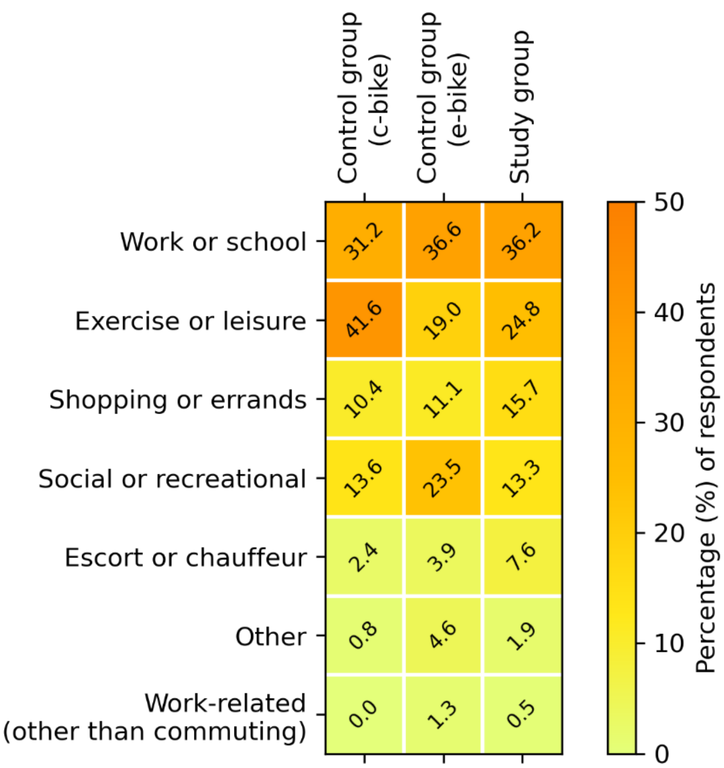


Figure 22. Trip purpose for last three trips with purchased bicycle

Figure 23 shows the average self-reported likelihood of using alternative modes for the reported recent trips, had the respondent not purchased the bicycle. Automobile was the travel mode most frequently replaced by e-bike trips, while conventional bicycle trips would more often have been made by a different conventional bicycle. Conventional bicycle trips were also more likely to replace walking and transit trips than e-bike trips. The alternative cycling mode for e-bike trips was also 2 to 3 times more likely to be a conventional than electric bicycle, indicating high availability of conventional bicycles. No trip alternative (i.e., induced travel) was reported for 10% to 19% of trips on purchased bicycles.

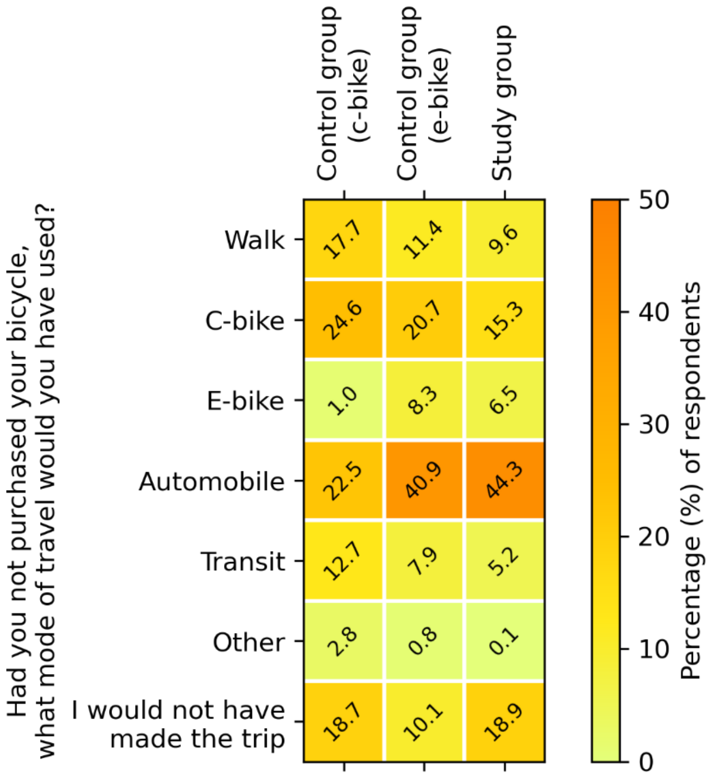


Figure 23. Mean self-reported likelihood of using alternative modes for the last three trips, if the recent bicycle purchase had not been made

3.3.4 Cycling comfort

Figure 24 shows the evolution of self-reported comfort on three different types of facilities for the panel of participants who answered this question in all three survey waves. Overall, the data suggest steady comfort over the three survey waves and between the Study and Control groups, with only small differentials that are not consistent or substantial.

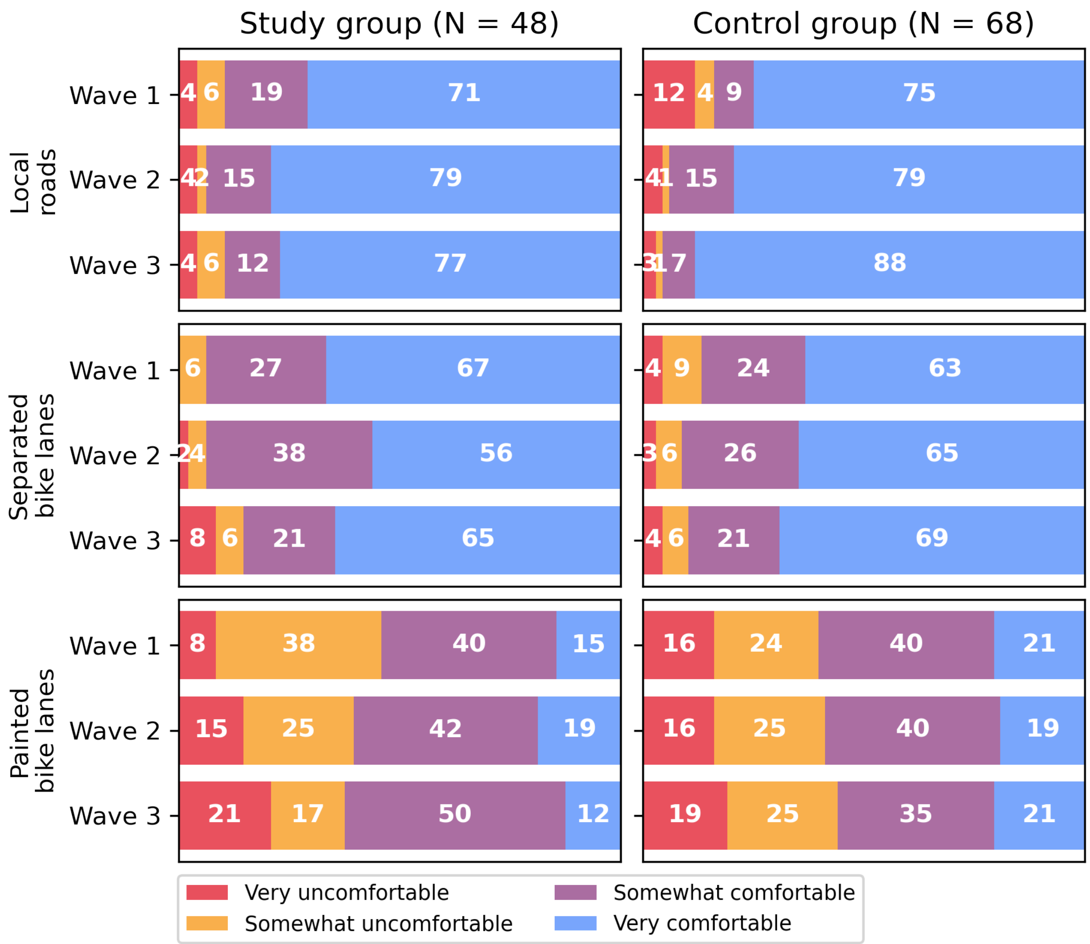


Figure 24. Changes in self-reported comfort cycling in different environments (numbers indicate percentage of the sample in each category)

3.3.5 Incidents

The survey included questions about incidents experienced using their new bicycle (since purchase), defined as “you fell to avoid contact, caused someone to fall, or made contact with another person or vehicle”. In Waves 2 and 3, <1% of respondents had had an incident with a pedestrian, cyclist, or someone using a micromobility device, while 4% had had an incident involving no one else (fall or fixed object), and 6% and 9%, respectively, had had an incident involving contact with a motor vehicle. The remaining 90% and 86% of respondents in Waves 2 and 3, respectively, had had no such incident.

The severity for the self-reported incidents (highest for each individual) is shown in Figure 25, separated by survey wave and incident type. No one reported the highest severity level in the survey: “Very serious (overnight hospital stay)”. Most incidents resulted in no or minor injuries, although a handful involved non-overnight hospital visit (all involving motor vehicles). Note that the number of observations here is small, and so the results should be interpreted with caution. In addition, these data are for all respondents, not only those who completed the Wave 3 (12 month) follow-up data collection, and so the differences include the effects of both new incidents between Waves 2 and 3 (i.e., in months 4-12) and attrition in the panel.

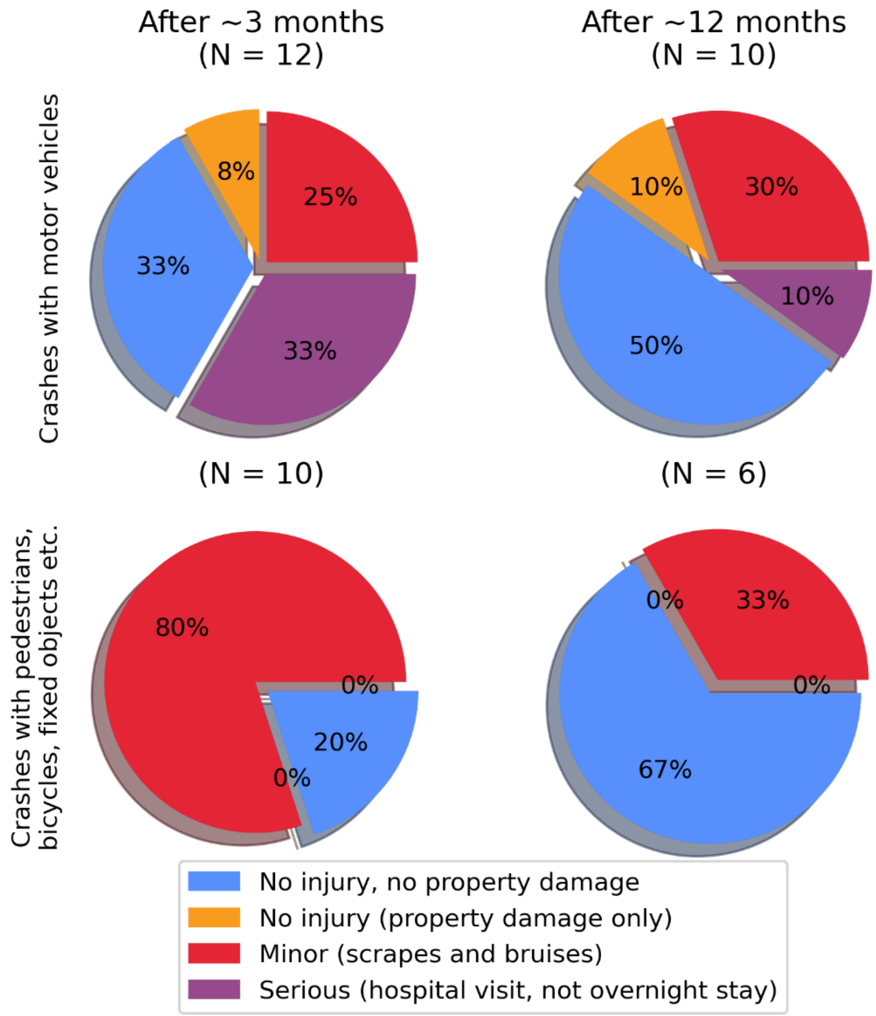
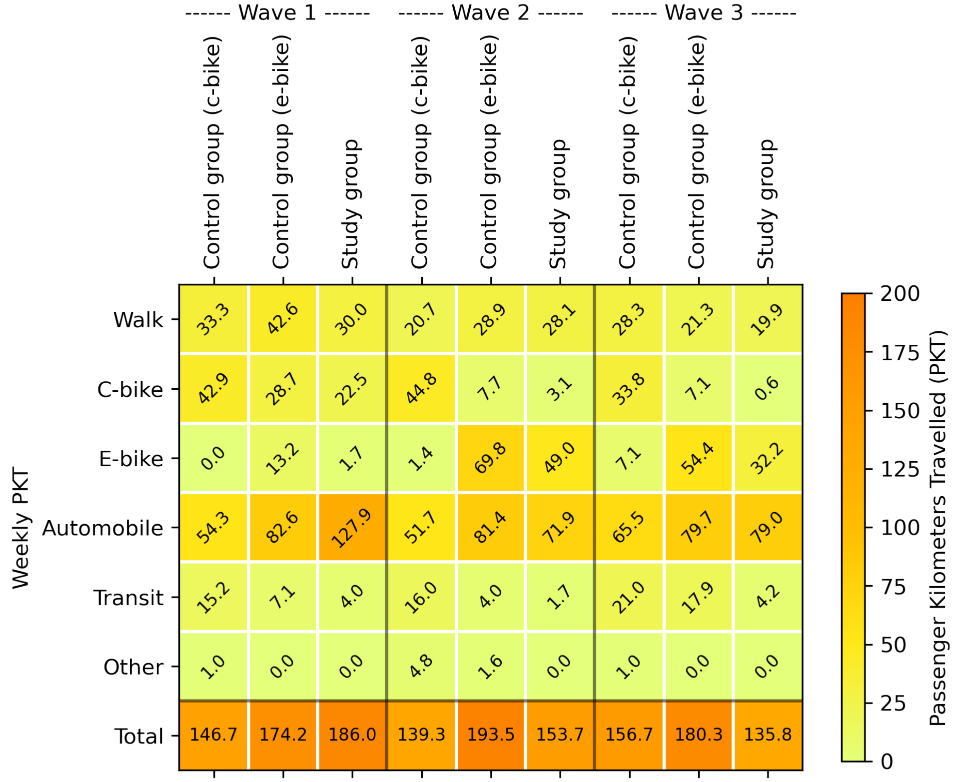


Figure 25. Severity for self-reported incidents while using new bicycle

3.4 Travel habits

The travel matrix data (days per week and km per day by each mode) yield the weekly PKT by mode for each sample group and survey wave shown in Figure 26 (see equations in Section 2.6). These results are restricted to the subset of respondents who completed all three waves, so that the sample is consistent across waves. For new bicycle purchasers, the travel matrix reflected travel in a typical week in the month preceding purchase; for others, it reflected travel in a typical week in the preceding month. For most respondents, Wave 1 represents pre-purchase behaviour, and Waves 2 and 3 represent short- and long-term post-purchase behaviour, respectively.



	Wave 1 Control group (c-bike)	Wave 1 Control group (e-bike)	Wave 1 Study group	Wave 2 Control group (c-bike)	Wave 2 Control group (e-bike)	Wave 2 Study group	Wave 3 Control group (c-bike)	Wave 3 Control group (e-bike)	Wave 3 Study group
Walk	33.3	42.6	30.0	20.7	28.9	28.1	28.3	21.3	19.9
C-bike	42.9	28.7	22.5	44.8	7.7	3.1	33.8	7.1	0.6
E-bike	0.0	13.2	1.7	1.4	69.8	49.0	7.1	54.4	32.2
Automobile	54.3	82.6	127.9	51.7	81.4	71.9	65.5	79.7	79.0
Transit	15.2	7.1	4.0	16.0	4.0	1.7	21.0	17.9	4.2
Other	1.0	0.0	0.0	4.8	1.6	0.0	1.0	0.0	0.0
Total	146.7	174.2	186.0	139.3	193.5	153.7	156.7	180.3	135.8

Figure 26. Weekly PKT by mode in previous month, as calculated from the self-reported travel matrix data

The travel matrix data suggest higher average e-bike usage before e-bike purchases in the Control than Study group (averaging 13 versus 2 km/week), and higher e-bike usage in Wave 2 than Wave 1 in both groups. Wave 1 (pre-purchase) conventional cycling was much higher in all three groups, especially for those who purchased a conventional bicycle. The e-bike purchasers had substantially higher pre-purchase automobile usage than the conventional bicycle purchasers. These differences reflect the fact that the treatment in this study (e-bike incentives) were not randomly assigned, and all three study groups had substantially different pre-purchase travel patterns.

The average PKT in each sample group and incentive tier, by survey wave, is illustrated in Figure 27 for walking, conventional bicycle (c-bike), electric bicycle (e-bike), automobile, and public transit travel modes. The data are essentially the same as those presented in Figure 26, but with the Study group broken out by incentive tier. Changes in weekly e-bike travel suggest that use of the purchased e-bikes was greater short-term (+3 months) than long-term (+12 months). The Control e-bike group had higher pre-purchase usage of both types of bicycles than the Study group, which persisted post-purchase in similar ratios. Some of the Control c-bike group took up e-cycling within the study period, which was not present pre-purchase. Pre-purchase auto usage was higher for the Study group than either Control group, but post-purchase auto usage was similar across all groups. Within the Study group, those who received larger incentives had substantially higher pre-purchase auto use, and so larger post-purchase reductions in auto use.

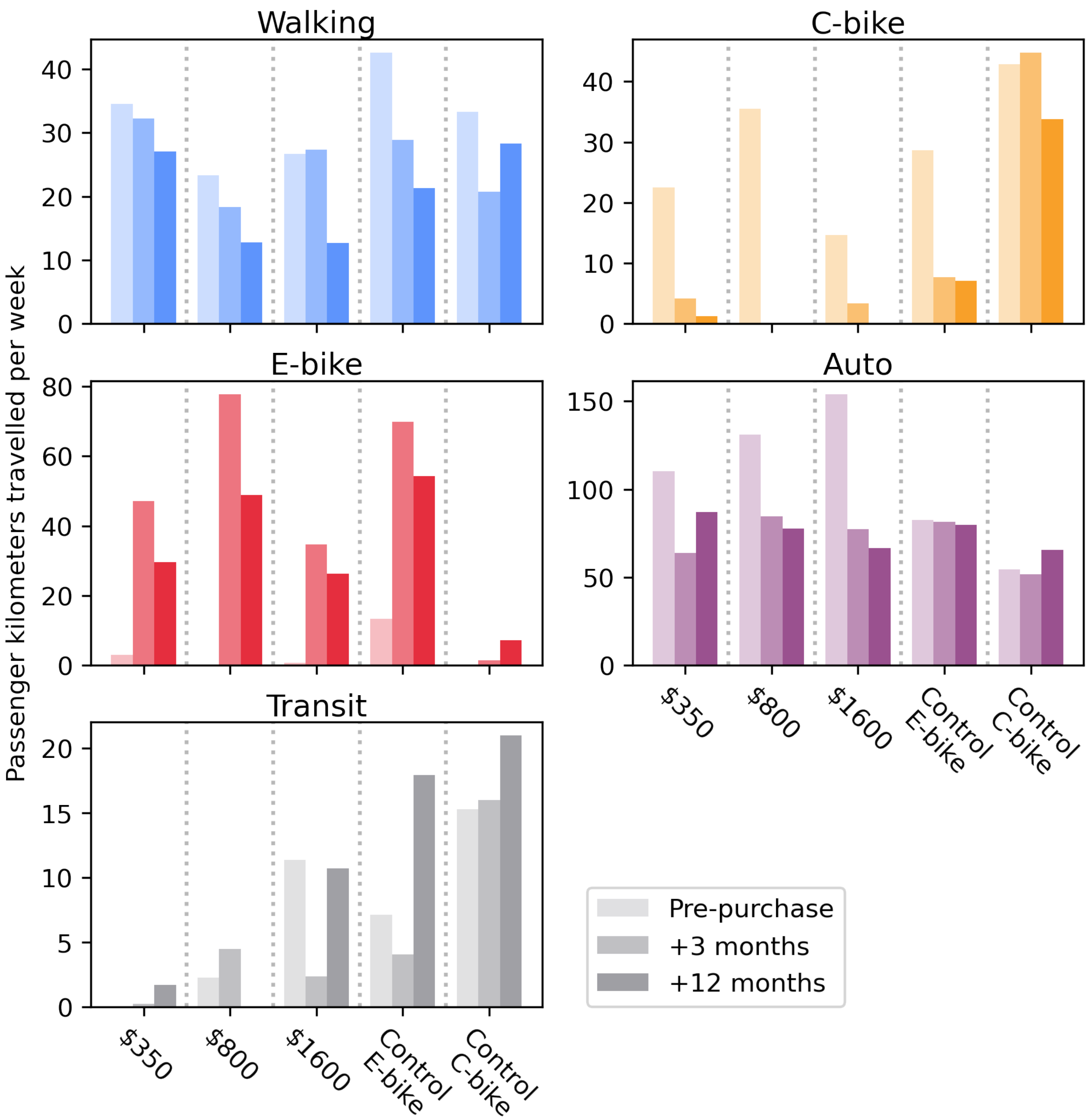


Figure 27. Illustration of average weekly PKT by travel mode for each sample group and incentive tier, by survey wave

Figure 28 shows ranked commute modes in each survey wave for the sub-set of participants who reported regularly commuting to work or school and completed all three survey waves. This question (unlike the travel matrix, which was retrospective) measured status at the time of response, and 84% of respondents had already purchased their bicycle at Wave 1.

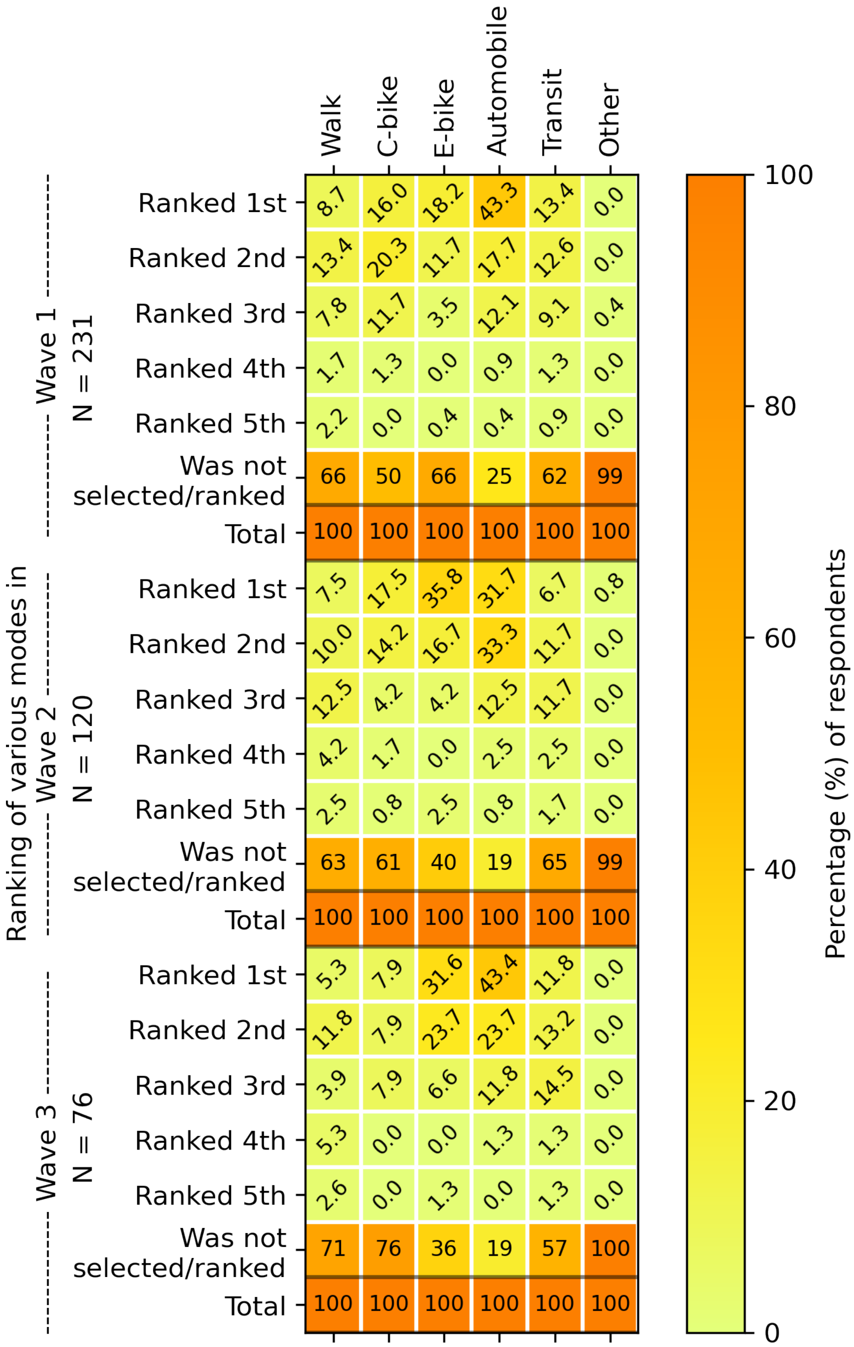


Figure 28. Ranked commute modes in each wave

3.5 Mode shift

3.5.1 Bicycle trip mode substitution

The alternative mode data for the last three trips reported using the purchased bicycle were used to calculate PKT changes for each mode due to mode substitution/displacement (see equations in Section 2.6). Figure 29 gives the mean PKT changes for each mode per trip and per PKT by the purchased bicycle for each sample group. These estimates combine the self-reported likelihood of each alternative mode (Figure 23), as well as self-reported change in trip distance for alternative modes. The changes per trip also depend on the distance of the reported trip. Cycling trips by conventional and electric bicycles increase PKT by those modes, respectively, but at a rate less than equivalence (i.e., <1 in Figure 29-b) due to intra-modal substitution (i.e., the likelihood that the trip would have been made using a different bicycle of the same type). The bottom row in the figure indicates a reduction in latent demand (i.e., induced or new VKT).

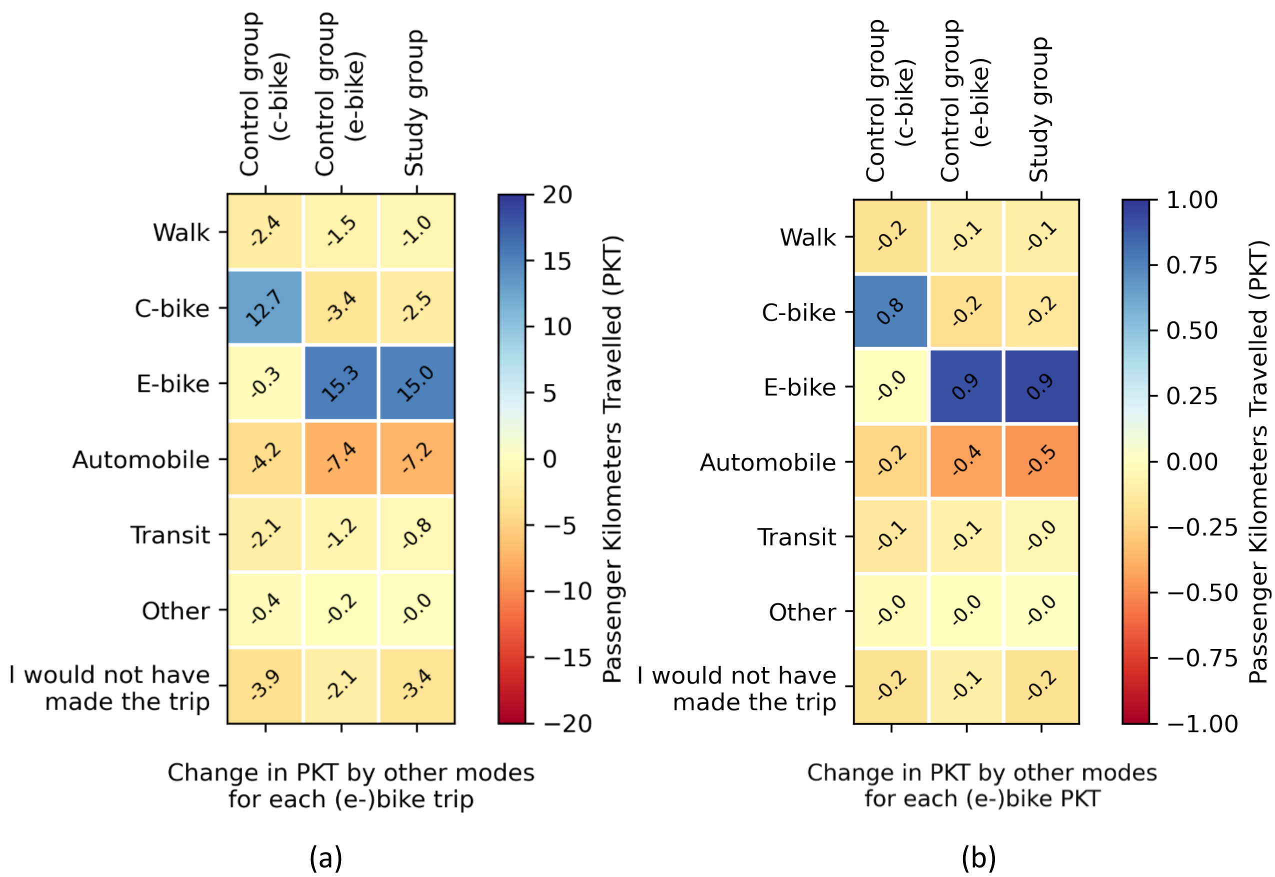


Figure 29. PKT changes due to mode substitution per trip (a) and per PKT (b) by the purchased bicycle

The means of individual changes in weekly PKT by each mode due use of the purchased bicycle are shown in Figure 30 for each sample group. These estimates extend the per-trip PKT change calculations using the individual implied weekly trip frequency using the purchased bicycles. The other modes decreased their weekly PKT proportional to the likelihood that those modes were substituted by the reported cycling trips (in addition to any reported changes in trip length by alternative modes). A large share of cycling displaced driving, with a smaller share substituting for travel by transit, walking, and other bicycles. Overall, compared to conventional cycling, e-bike purchasers displaced more weekly automobile travel and less transit or walking (as well as less new/induced travel).

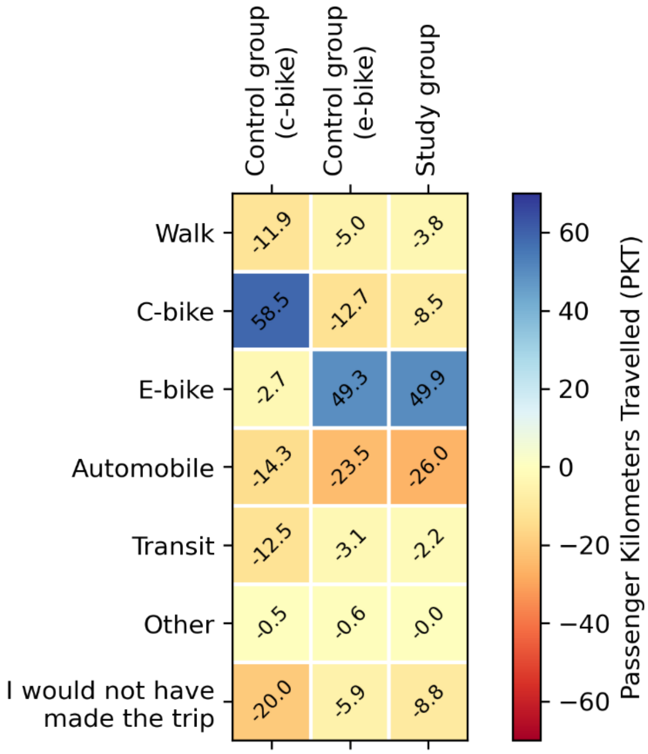


Figure 30. Weekly PKT changes due to substitution of trips by the purchased bicycle

3.5.2 Changes in travel habits

The mean PKT differentials between survey waves according to the self-reported travel matrix data are shown in Figure 31. Note that these data are not adjusted for the timing of individual bicycle purchases, although for most respondents Wave 1 represents pre-purchase behaviour, and Waves 2 and 3 represent short- and long-term follow-ups, respectively. The results indicate substantial increases in e-cycling, but not conventional cycling, in the first interval (Wave 1 to Wave 2), along with PKT reductions in most other modes. Waves 2 to 3 saw a moderation of these initial effects, with a reduction in cycling and small changes in most other modes. Combining these, the Wave 1 to Wave 3 values reflect the long-term changes in travel behaviour 12 months after bicycle purchase (not all of which can be attributed to the purchase). For example, the Study group reduced their auto PKT by 49 km/week in the long run (standard deviation 102). These long-term changes are smaller than the short-term changes observed at Wave 2, indicating less new cycling and smaller reductions in automobile use. Some conventional bicycle purchasers seem to have taken up e-bike use in this interval, as mean conventional cycling PKT fell in this group (though not by as much as the e-bike purchasers), while mean e-bike PKT increased.

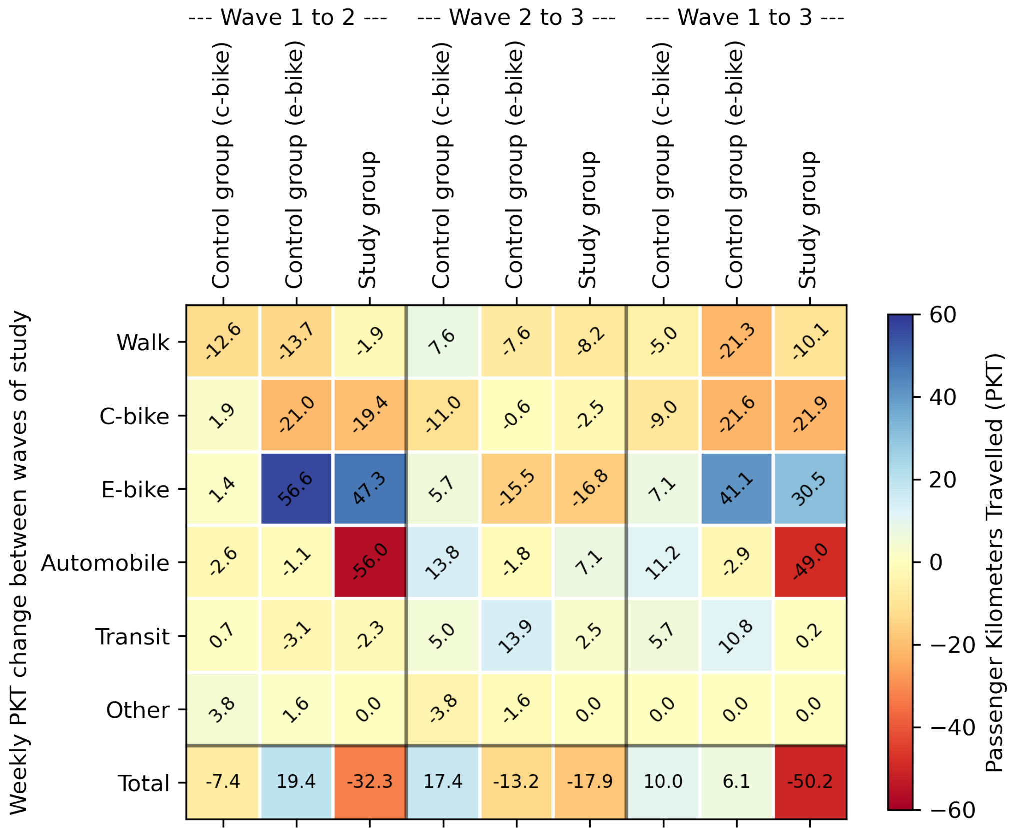


Figure 31. Change in weekly PKT by mode between survey waves, based on the self-reported travel matrix data

3.5.3 Regression model of automobile PKT changes across waves

The estimated negative binomial mixed regression model of weekly PKT by automobile is given in Table 15 (see model description in Section 2.9.2). The total number of observations in the model is 727, including data from 399 participants in at least 1 wave. The positive parameter estimates in Table 15 indicate variables that increase weekly automobile PKT, while negative parameter estimates indicate variables that decrease weekly automobile PKT. The odds ratios given in the last column indicate the proportional (factor) change in weekly automobile PKT with a unit change in each variable (values less than one indicate a decrease in PKT).

The key variables of interest for this analysis are the indicators for e-bike Control group and the Saanich Study group (which are in comparison to the reference conventional bicycle Control group), and the Saanich rebate amount. The parameter estimates for those three variables indicate[1] that pre-purchase auto use was 22% higher for the e-bike than conventional bicycle Control group, and 73% to 163% higher for the Saanich study group (at rebate amounts of $350 to $1600) than for the conventional bicycle Control group. The next four variables in Table 15

[1] Negative binomial model parameter estimates (β_i) can be used to calculate the modelled effects of changes in a set of corresponding independent variables X_i as: factor change $= \exp(\sum \beta_i \Delta X_i)$. Hence, being in the Study group ($\beta_1 = 0.43136$) with a $350 rebate ($\beta_2 = 0.03348$) is expected to change (pre-purchase) emissions by a factor of: $\exp(0.43136 + 0.03348 * 3.5) = 1.73$, or +73%.

indicate observations that were reported "after bicycle purchase", and so the odds ratios for these variables show the factor change in weekly PKT after bicycle purchase. People in the Control group who purchased a conventional bicycle subsequently increased their auto PKT by 30%. In contrast, post-purchase auto PKT for those in the Control group who purchased an e-bike increased by 7% (lower than the conventional bicycle group by a factor of 0.821). Post-purchase auto PKT for the Saanich study group fell by 33% to 41% for rebate amounts of $350 to $1600. Note that among these parameters, only the Saanich study group variables are statistically significant at p<0.05.

Table 15. Negative binomial mixed[1] regression model results for weekly automobile PKT

Variable	Parameter estimate	p-value	Odds ratio[2]
Intercept	**4.04113**	**<0.01**	**56.891**
E-bike control group[3]	0.20154	0.22	1.223
Saanich study group[3]	**0.43136**	**0.04**	**1.539**
Saanich rebate amount ($100)	0.03348	0.07	1.034
After bicycle purchase	0.26465	0.10	1.303
After bicycle purchase * E-bike control group[3,4]	-0.19694	0.29	0.821
After bicycle purchase * Saanich study group[3,4]	**-0.63432**	**<0.01**	**0.530**
After bicycle purchase * Saanich rebate amount ($100)[4]	-0.01019	0.51	0.990
Cis-man	0.18309	0.10	1.201
Age (years)	0.00499	0.22	1.005
Physical disability	-0.12319	0.63	0.884
College degree	0.30167	0.06	1.352
Visible minority	-0.17429	0.20	0.840
Household income ($10k)	0.01486	0.30	1.015
No children in household	**0.27109**	**0.03**	**1.311**
<2 cars in household	**-0.34881**	**<0.01**	**0.706**
Very uncomfortable on painted bike lanes[5]	0.22050	0.14	1.247
Experienced incident with injury	0.02108	0.91	1.021
Fuel price (c/L)	**-0.00472**	**0.05**	**0.995**
Mean daily temperature (C)	0.00803	0.41	1.008
Mean daily precipitation (mm)	-0.00804	0.65	0.992
COVID restrictions	-0.19336	0.33	0.824

[1] Random effects by participant
[2] Factor change in weekly auto PKT with a unit change in the variable
[3] Reference level: Control group participants who did not purchase an e-bike
[4] Interaction term
[5] Value as reported in Wave 1

Figure 32 illustrates the combined effects of the group and post-purchase variables on weekly auto PKT, with all other factors fixed, based on a reference pre-purchase weekly auto PKT of 54 km for the conventional bicycle Control group. The Control groups both increased to around 70 km per week post-purchase, with a larger change for the conventional bicycle purchasers. The

Saanich group greatly decreased auto PKT post-purchase; in absolute terms, the modelled reduction in auto PKT is twice as large for $1600 incentives versus $350 incentives.

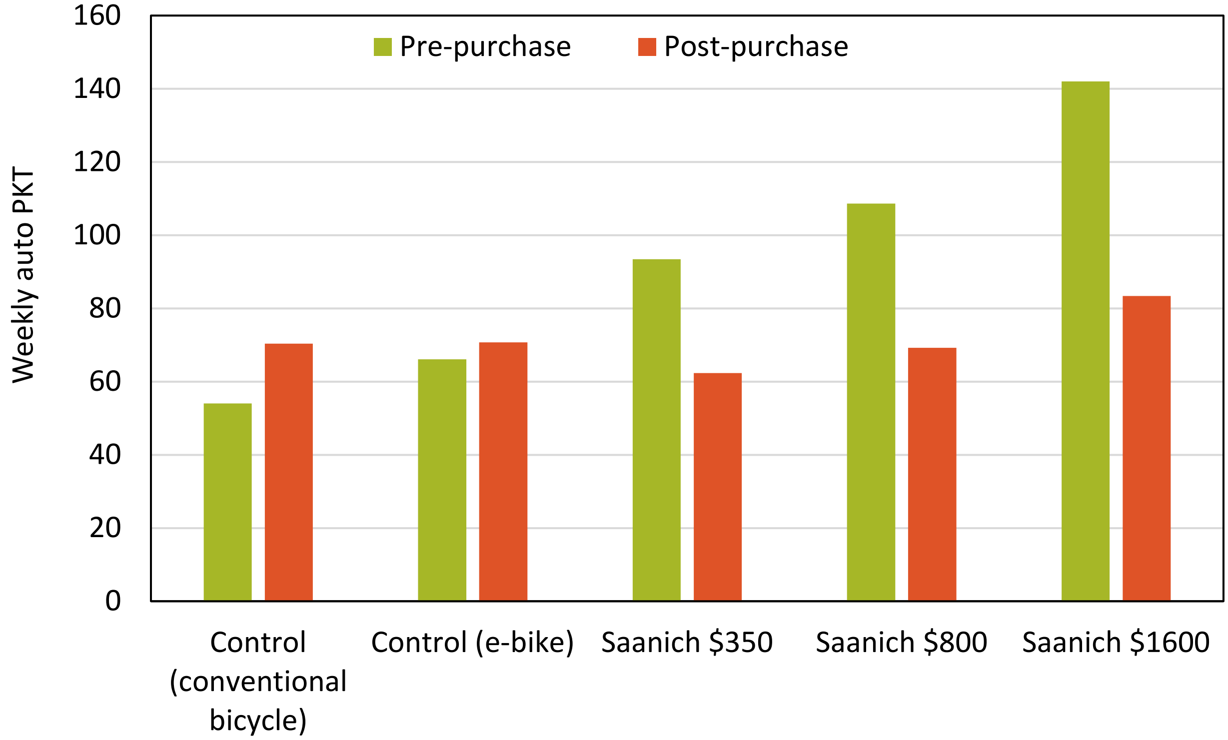


Figure 32. Illustration of modelled weekly auto PKT before and after purchase for each study group

In addition to the group and purchase variables, the other parameter estimates in Table 15 indicate that weekly auto PKT is 29% lower for households with fewer than 2 motor vehicles, 31% higher for households without children, and 5% lower with each 10 c/L in fuel price. Other variables that do not meet the 95% significance threshold indicate that weekly auto PKT is higher for cis-men versus non-cis-men, for people with at least a college degree, for people less comfortable cycling in bike lanes, and for higher-income households, and lower for people with a physical disability, for people who are a visible minority, and during the period of COVID restrictions.

Note that these model results isolate individual variable effects, if all other factors as fixed. The model results indicate the expected post-purchase effects if households in each study group and incentive tier have the same attributes for the other model variables. In reality, some of these variables are systematically related, which impedes our ability to distinguish independent variable effects – especially among income, study group, and rebate amount. Recipients of larger rebate amounts had lower household income, but also tended to be younger and have fewer household vehicles (Figure 10).

3.6 Greenhouse gas emissions

3.6.1 Estimated GHG based on weekly travel habits

The estimated GHG emissions attributable to the self-reported weekly travel habits are illustrated in Figure 33. These GHG changes are computed using PKT from the travel matrix data and representative lifecycle modal emissions factors (see calculation methods in Section 2.7). The vast majority of total emissions is generated from driving in all groups and waves. In Wave 1 (pre-purchase), the three groups have substantially different driving habits and hence emissions levels: non-incentivized e-bike purchasers had around 50% higher emissions than non-incentivized conventional bicycle purchasers, and incentivized e-bike purchasers had around 50% higher emissions than non-incentivized e-bike purchasers. All groups' emissions fell in Wave 2, but the changes were very small in both Control groups, while the Study group emissions fell by 43%. In Wave 3 we see the total emissions for all three groups become more similar, in the range of 23-27 kg CO_2e per week.

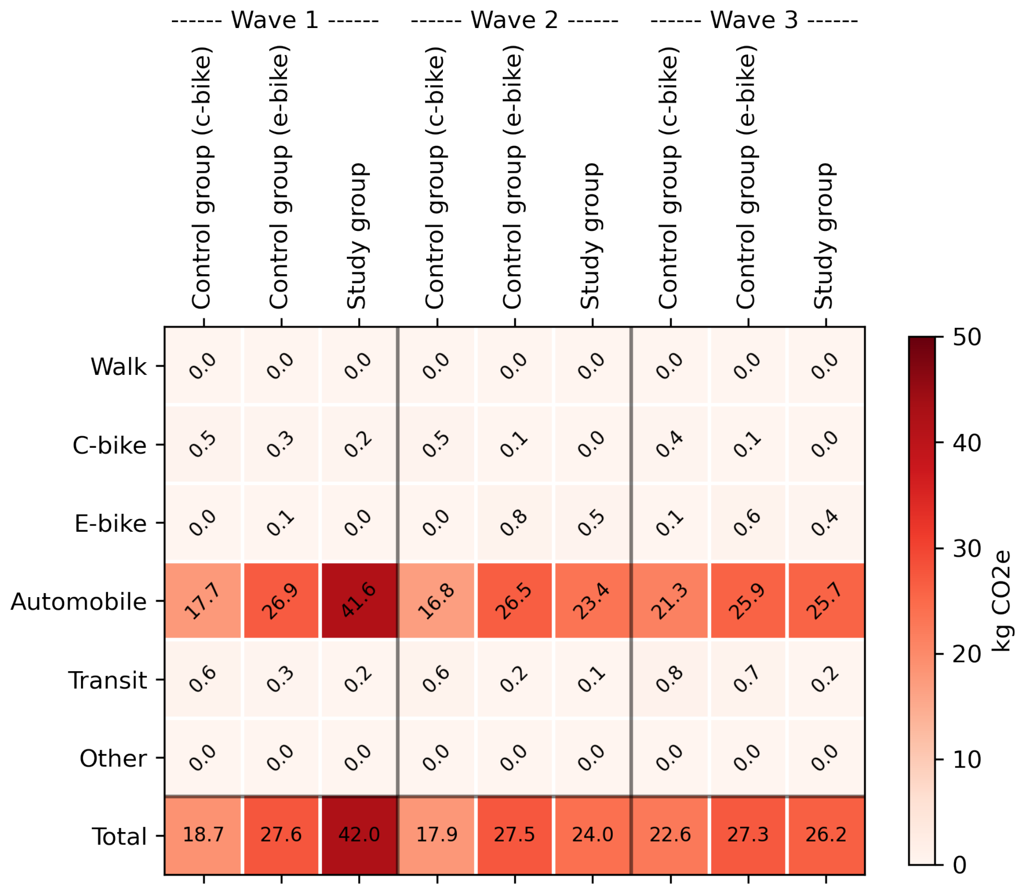
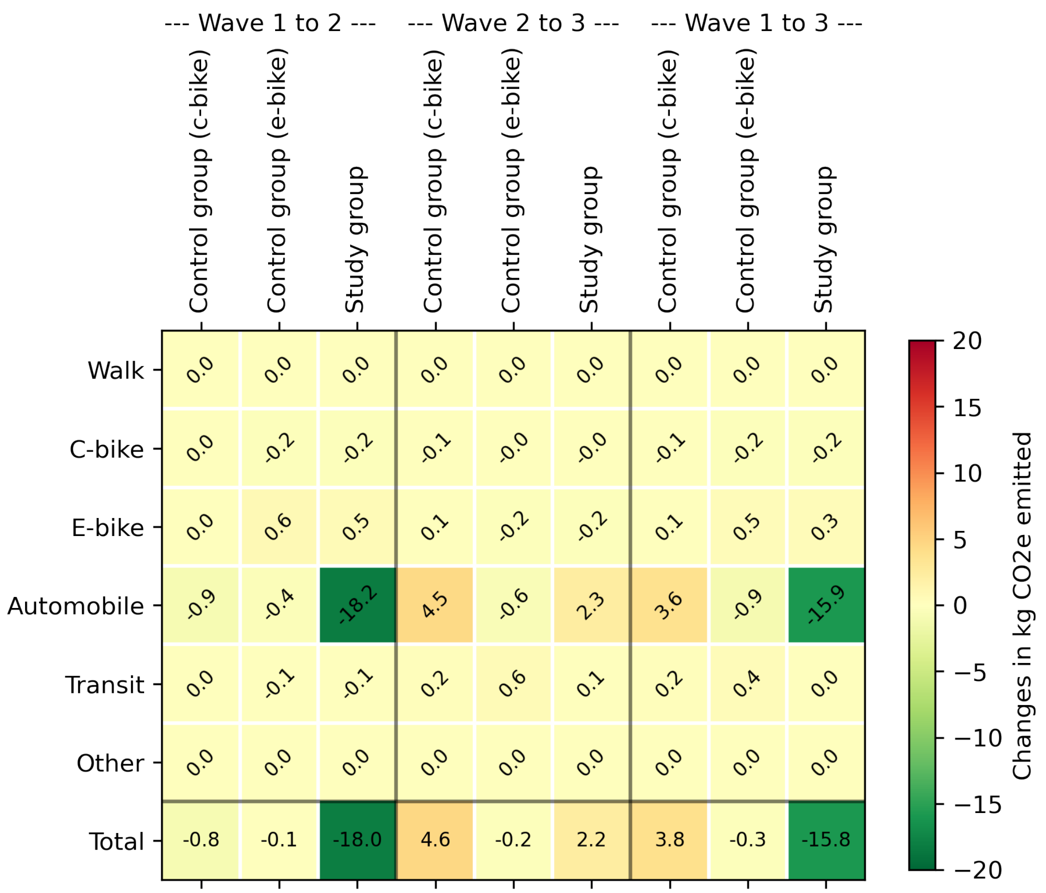


Figure 33. Weekly GHG from reported travel by each study group in each survey wave

Figure 34 shows the changes in weekly GHG from travel due to differencing the travel matrix data between survey waves. Note that these data are not adjusted for the timing of individual bicycle purchases, although for most respondents Wave 1 represents pre-purchase behaviour, and Waves 2 and 3 represent 3- and 12-month follow-ups, respectively. The results indicate large

GHG reductions due to reduced automobile PKT in the Study group in waves 2 and 3, which dominate the total GHG impacts of travel behaviour change in the sample. The long-term (Wave 3) driving reduction is 12% smaller than the short-term (Wave 2) change. It is notable that the Control groups exhibited small short-term GHG reductions and a long-term GHG increase due to increased driving for the conventional bicycle purchasers. As with PKT changes between waves, not all of the GHG changes can be attributed to the bicycle purchases. In summary, the Study group greatly reduced their emissions while the Control group did not, because they were already much lower pre-purchase.



	Wave 1 to 2: Control group (c-bike)	Wave 1 to 2: Control group (e-bike)	Wave 1 to 2: Study group	Wave 2 to 3: Control group (c-bike)	Wave 2 to 3: Control group (e-bike)	Wave 2 to 3: Study group	Wave 1 to 3: Control group (c-bike)	Wave 1 to 3: Control group (e-bike)	Wave 1 to 3: Study group
Walk	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
C-bike	0.0	-0.2	-0.2	-0.1	-0.0	-0.0	-0.1	-0.2	-0.2
E-bike	0.0	0.6	0.5	0.1	-0.2	-0.2	0.1	0.5	0.3
Automobile	-0.9	-0.4	-18.2	4.5	-0.6	2.3	3.6	-0.9	-15.9
Transit	0.0	-0.1	-0.1	0.2	0.6	0.1	0.2	0.4	0.0
Other	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total	-0.8	-0.1	-18.0	4.6	-0.2	2.2	3.8	-0.3	-15.8

Figure 34. Change in weekly GHG by mode between survey waves, based on the self-reported travel matrix data

3.6.2 Changes in GHG due to bicycle trip mode substitution

Figure 35 shows the estimated GHG impacts of the PKT changes inferred from self-reported mode substitution for recent trips made by the purchased bicycle (per trip, per PKT, and per week). Weekly effects are based on the frequency of trips made by the purchased bicycle. GHG changes are dominated by the effects of shifts in automobile use. Each e-bike trip displaced 2.4 kg CO_2e from driving, on average, which is the same in the incentive and non-incentive e-bike groups. Conventional bicycle trips displaced about half as much CO_2e as e-bike trips, although the relative effect increases for weekly travel. The implied weekly GHG reductions differ substantially between those estimated from travel habits (0-18 kg in Figure 34) versus those estimated from alternative modes for cycling trips (5-8 kg in Figure 35). There are several important differences between the scope and framing of these measures, as discussed below in Section 4. These estimates are analyzed using regression analysis in the next section, to control for contextual and confounding factors, and examine variation within the sample.

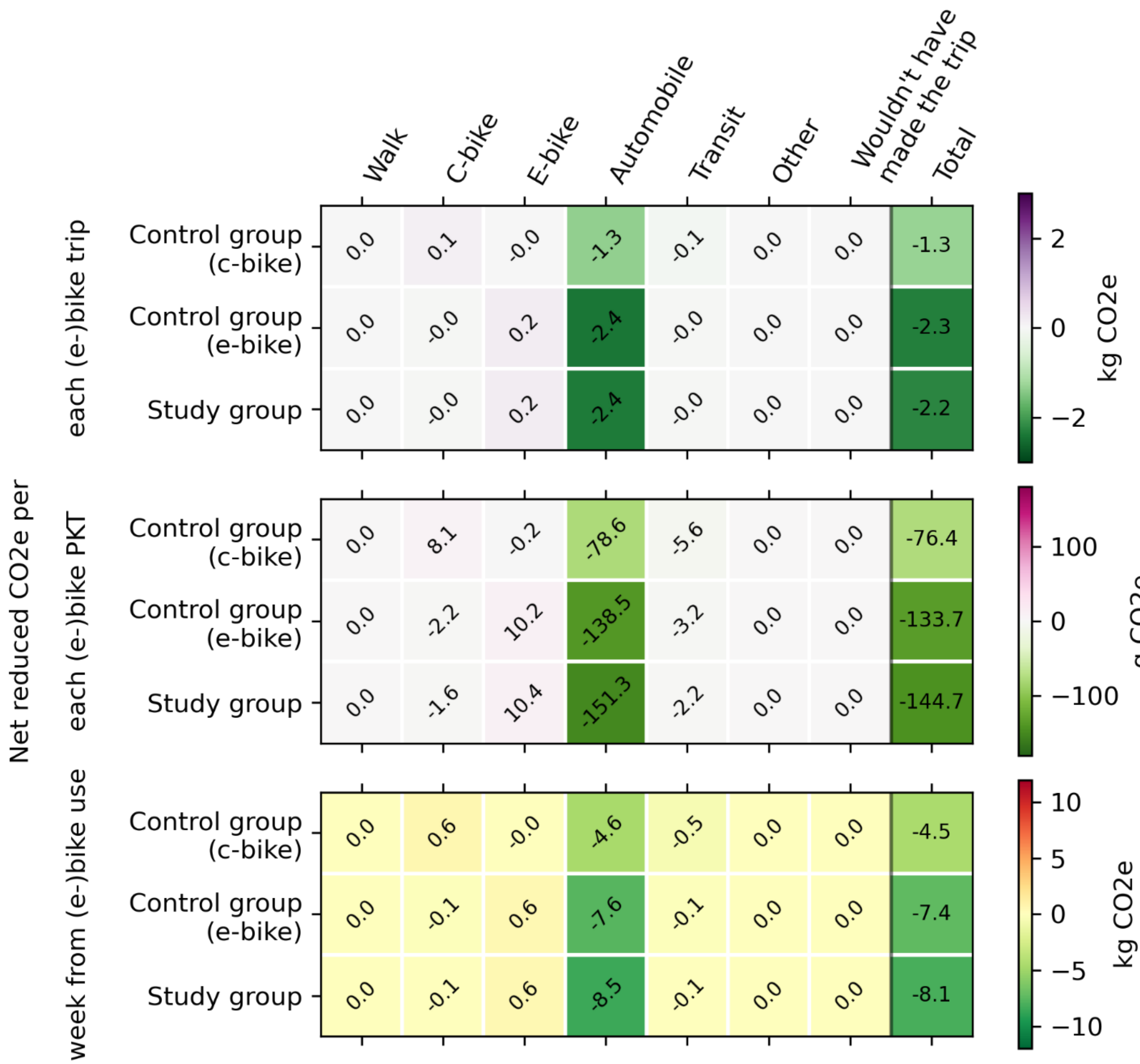


Figure 35. GHG changes due to mode substitution per trip (top), per PKT (middle), and per week of use (bottom) by the purchased bicycle

3.6.3 Regression model of total GHG from travel changes across waves

The estimated negative binomial mixed regression model of reduction in weekly GHG from travel is given in Table 16 (see model description in Section 2.9.2, and description of similar model for auto PKT in Section 3.5.3). The positive parameter estimates in Table 16 indicate variables that increase GHG, while negative parameter estimates indicate variables that decrease GHG. The odds ratios given in the last column indicate the proportional (factor) change in weekly GHG with a unit change in each variable (values less than one indicate a decrease in GHG).

The key variables of interest for this analysis are the indicators for e-bike Control group and the Saanich Study group (which are in comparison to the reference conventional bicycle Control group), and the Saanich rebate amount. The parameter estimates for those three variables indicate that pre-purchase GHG was 19% higher for the e-bike than conventional bicycle Control group, and 52% to 97% higher for the Saanich study group than the conventional bicycle Control group (for rebate amounts of $350 to $1600). The next four variables in Table 16 indicate observations that were reported "after bicycle purchase", and so the odds ratios for these variables show by 35% to 40% for rebate amounts of $350 to $1600. Note that among these parameters, only the Saanich study group variables are statistically significant at $p<0.05$.

Table 16. Negative binomial mixed[1] regression model results for weekly GHG from travel

Variable	Parameter estimate	p-value	Odds ratio[2]
Intercept	**3.20859**	**<0.01**	**24.744**
E-bike control group[3]	0.17321	0.21	1.189
Saanich study group[3]	**0.34330**	**0.05**	**1.410**
Saanich rebate amount ($100)	0.02124	0.17	1.021
After bicycle purchase	0.19123	0.17	1.211
After bicycle purchase * E-bike control group[3,4]	-0.16831	0.30	0.845
After bicycle purchase * Saanich study group[3,4]	**-0.59129**	**<0.01**	**0.554**
After bicycle purchase * Saanich rebate amount ($100)[4]	-0.00683	0.62	0.993
Cis-man	0.17025	0.06	1.186
Age (years)	0.00112	0.74	1.001
Physical disability	-0.08048	0.70	0.923
College degree	0.17548	0.19	1.192
Visible minority	-0.12160	0.29	0.886
Household income ($10k)	0.01041	0.38	1.010
No children in household	0.18630	0.08	1.205
<2 cars in household	**-0.23148**	**0.02**	**0.793**
Very uncomfortable on painted bike lanes[5]	0.17336	0.16	1.189
Experienced incident with injury	-0.00453	0.98	0.995
Fuel price (c/L)	-0.00322	0.11	0.997
Mean daily temperature (C)	0.00503	0.56	1.005
Mean daily precipitation (mm)	-0.00389	0.80	0.996
COVID restrictions	-0.13165	0.44	0.877

[1] Random effects by participant
[2] Factor change in weekly auto PKT with a unit change in the variable
[3] Reference level: Control group participants who did not purchase an e-bike
[4] Interaction term
[5] Value as reported in Wave 1

Figure 36 illustrates the combined effects of the group and post-purchase variables on weekly GHG, with all other factors fixed, based on a reference pre-purchase weekly GHG of 19 kg CO_2e for the conventional bicycle Control group. The Control groups both increase to around 23 kg CO_2e per week post-purchase, with a larger change for the conventional bicycle purchasers. The Saanich group greatly decreases GHG post-purchase, to levels similar to the Control groups.

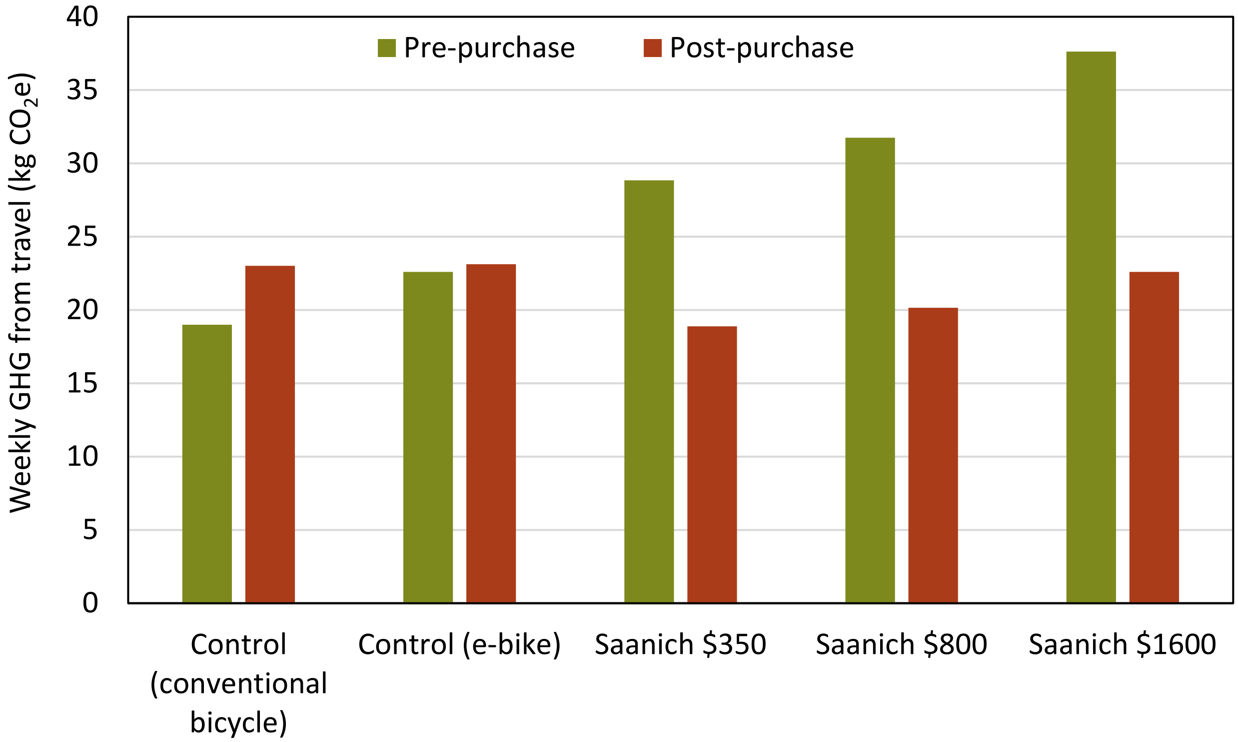


Figure 36. Illustration of modelled weekly GHG from travel before and after purchase for each study group

In addition to the group and purchase variables, the other parameter estimates in Table 16 indicate that GHG is 21% lower for households with fewer than 2 motor vehicles. Other variables that do not meet the 95% significance threshold indicate that GHG is higher for cis-men versus non-cis-men, for people with at least a college degree, for people less comfortable cycling in bike lanes, for households without children and for higher-income households, and lower for people with a physical disability, for people who are a visible minority, with lower fuel prices, and during the period of COVID restrictions.

3.7 Physical activity

Figure 37 shows the average estimated weekly non-sedentary MET-minutes during travel reported in each survey wave by each study group (see Section 2.8 for a description of this activity measure). Most travel MET-minutes are generated by walking, cycling, and e-cycling, with the e-bike purchase groups greatly increasing e-bike activity in the follow-up waves, and decreasing conventional cycling physical activity. Using 300 non-sedentary MET-minutes as an approximate threshold, average participants in all study groups far exceeded this physical activity level from travel in all three waves.

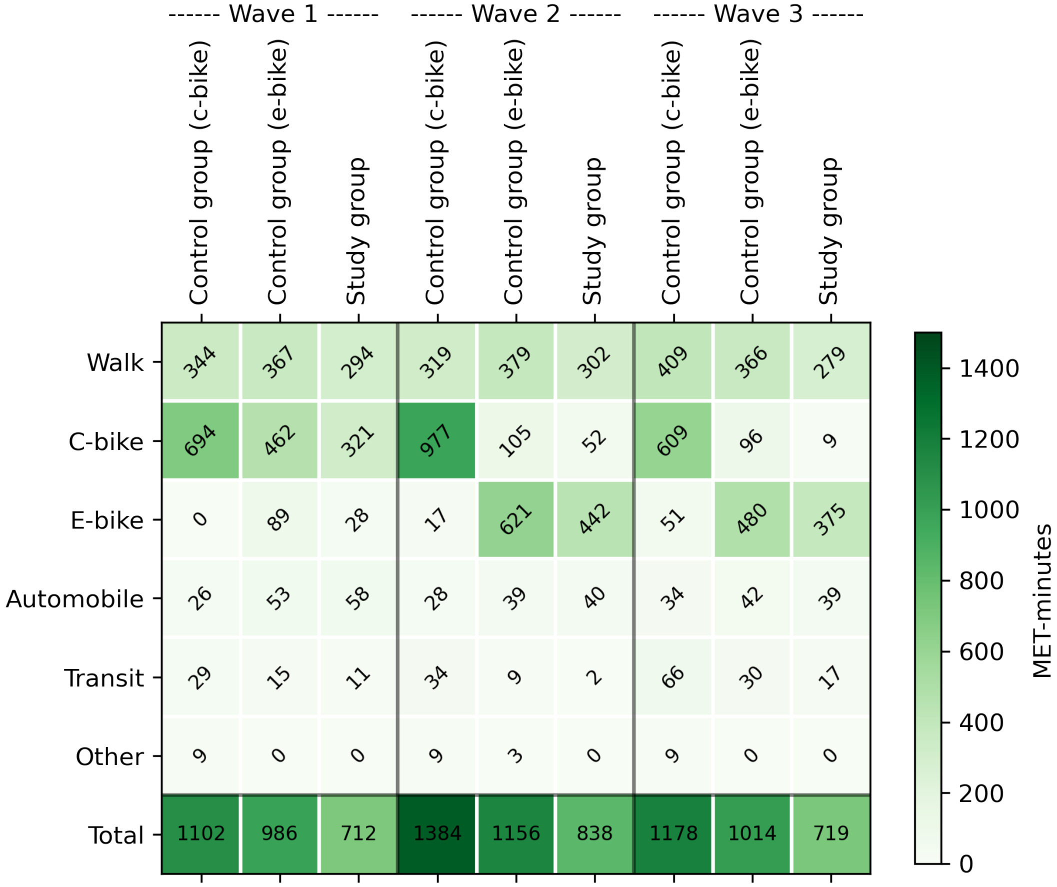


Figure 37. Mean weekly non-sedentary MET-minutes during reported travel by survey wave and study group

Changes in non-sedentary MET-minutes per week between survey waves are illustrated in Figure 38. The largest changes are the increases in physical activity during e-cycling by e-bike purchasers in Waves 2 and 3, which outweigh large decreases in physical activity during conventional cycling by the same groups. Conventional bicycle purchasers greatly increased their cycling physical activity in Wave 2, but fell back below pre-purchase levels by Wave 3 (while increasing walking, e-cycling, and transit activity, resulting in a net increase). All three study groups greatly increased total physical activity from Wave 1 to Wave 2, but fell back to slightly above Wave 1 levels in Wave 3. Note that these values are illustrative only, based on typical energy intensities by travel mode; an individual's physical activity during travel varies with many personal, bicycle, and trip-related factors that were not measured in this study.

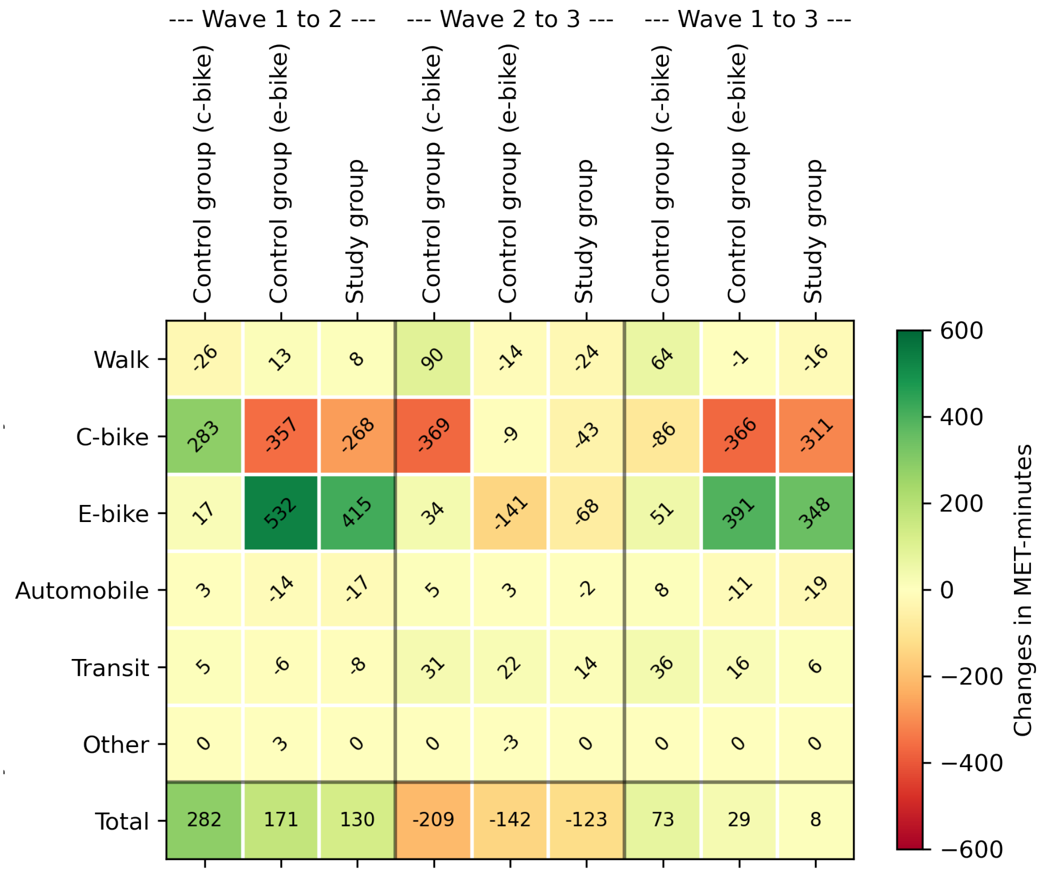


Figure 38. Change in weekly non-sedentary MET-minutes during travel between survey waves

3.8 Program impacts

3.8.1 GHG abatement cost

Calculated GHG abatement costs for the Study group are given in Table 17, along with other performance measures. These estimates use the individual long-term change in total weekly auto PKT and GHG from travel (from Wave 1 to Wave 3), and self-reported marginality of purchases (likelihood that they would have made no purchase or purchased a conventional bicycle without the incentive). The "marginal" values are the portions attributable to additional purchases (i.e., without "free-riding" purchases that would have been made without the incentive). The final abatement costs (last two rows) assume a 5-year e-bike lifespan, and apply the reported weekly reduction evenly across a year. The results are highly sensitive to the lifespan assumption. Applying a 10-year lifespan reduces abatement costs by half (e.g., brings the marginal and non-marginal abatement costs for all incentive recipients down to \$361 and \$95 per tonne, respectively). Note that the relationship between abatement cost and rebate amount is opposite for marginal (lower cost with higher rebates) versus non-marginal (higher cost with higher rebates) estimates. The differences across rebate levels are much higher for the marginal estimates, due to the sensitivity of marginality to rebate amount. The variation in auto PKT and GHG reduction across individuals was high, with coefficients of variation (standard deviation divided by mean) of 2.1 and 3.0 for non-marginal and marginal reductions, respectively. Abatement costs also had coefficients of variation around 3.

Table 17. Summary of reductions in GHG from travel for Saanich incentive recipients

Impact measure	$350 rebate	$800 rebate	$1600 rebate	All rebates[3]
Auto PKT reduction (PKT/week)	23.3	53.3	87.3	48.0
Marginal[1] auto PKT reduction (PKT/week)	4.0	17.4	64.4	23.3
GHG reduction (kg CO_2e/week)	7.45	17.27	28.30	15.51
Marginal GHG reduction (kg CO_2e/week)	1.27	5.65	20.96	7.56
GHG reduction per $100 of incentive (kg CO_2e/year/$100)	111	112	92	106
Marginal GHG reduction per $100 of incentive (kg CO_2e/year/$100)	19	37	68	36
GHG abatement cost[2] ($/tonne)	$181	$178	$217	$190
Marginal GHG abatement cost ($/tonne)	$1,060	$545	$294	$722

[1] Proportional to individual likelihood of not purchasing an e-bike without incentive
[2] Assumes a 5-year lifespan of the e-bike
[3] Weighted by proportion of the 389 program rebates distributed at each level

3.8.2 Bicycle retailer revenues

The bicycle purchase information in the study was used to calculate revenue implications for bicycle retailers and new spending. On average, spending by incentive recipients on their new e-bikes generated $2,968 in bicycle retailer revenue, of which $1,263 was marginal or additional because of the program (i.e., recipients would not have purchased an e-bike without the rebate). Subtracting the rebate amount, the program induced on average $813 in new consumer spending (per rebate). Table 18 shows the new spending and bicycle retailer revenue by incentive tier. Higher-tier rebates generated more new revenue and spending per incentive, but less new revenue and spending per incentive-dollar.

Table 18. New spending and bicycle retailer revenue

Variable	$350 rebates	$800 rebates	$1,600 rebates	All rebates[3]
Pre-rebate e-bike price	$2,965	$3,025	$2,915	$2,968
Post-rebate e-bike price	$2,615	$2,225	$1,315	$2,172
Share marginal purchases	0.23	0.45	0.76	0.43
New retailer revenue[1]	$682	$1,361	$2,215	$1,263
Induced spending[2]	$601	$1,001	$999	$813
New retailer revenue per rebate $	$1.95	$1.70	$1.38	$1.74
Induced spending per rebate $	$1.72	$1.25	$0.62	$1.31

[1] Due to marginal purchases, including rebate amount
[2] Due to marginal purchases, without rebate amount
[3] Weighted by proportion of the 389 program rebates distributed at each level

3.8.3 Total program impacts

Table 19 shows the aggregate program impacts, summing the preceding results across all incentives distributed. In addition, auto PKT is converted to VKT using an assumed automobile occupancy of 1.35 passengers from Capital Regional District data (R.A. Malatest & Associates Ltd. and David Kriger Consultants Inc., 2023). Incentive costs per additional (marginal) e-bike averaged $1864, increasing with rebate amount from $1522 to $2105. Hence, lower rebate amounts are more cost-effective in inducing marginal purchases (i.e., lower incentive cost per marginal bicycle), as expected from pre-program modelling and more recent research (Bigazzi and Berjisian, 2021; Jones et al., 2024). However, higher rebate amounts were more cost-effective in reducing GHG (i.e. lower incentive cost per tonne CO_2e), due to greater auto mode shift for the more incentivized purchases (Table 17). Note that the distinct effects of income versus rebate amount could not be fully separated in this study, due to the program design, and so the varying marginality and mode shift by rebate tier reflects the combined effects.

Table 19. Total program impacts

Variable	$350 rebates	$800 rebates	$1,600 rebates	All rebates[3]
Number of incentives	183	105	101	389
Total cost of incentives	$64,050	$84,000	$161,600	$309,650
Additional e-bikes[1]	42.1	47.3	76.8	166.1
Total cost per additional e-bike[1]	$1,522	$1,778	$2,105	$1,864
Annual VKT reduction	164,451	215,690	339,746	719,887
Annual marginal VKT reduction	28,407	70,454	250,462	349,323
Annual GHG reduction (tonnes CO_2e)	71	94	149	314
Annual marginal GHG reduction (tonnes CO_2e)	12	31	110	153
Lifespan[2] VKT reduction	822,253	1,078,451	1,698,730	3,599,434
Lifespan marginal VKT reduction	142,035	352,271	1,252,310	1,746,616
Lifespan GHG reduction (tonnes CO_2e)	354	471	743	1,569
Lifespan marginal GHG reduction (tonnes CO_2e)	60	154	550	765

[1] Due to marginal purchases

[2] Assumes a 5-year lifespan of the e-bike

[3] Weighted by proportion of the 389 program rebates distributed at each level

4 DISCUSSION

4.1 Sample composition and responses

The study recruitment achieved the target sample of at least 300 participants at Wave 1 and at least 100 participants at Wave 3. The sample demographic characteristics also compared well to the study population (Table 8). The Saanich program response rate of 42% is relatively high, although not as high as the study design target of 50%. Sample sizes for studies of this type are limited by the scope of the programs, and most studies of e-bike loan programs have sample sizes under 100 (Bjørnarå et al., 2019; Cairns et al., 2017; Fyhri and Fearnley, 2015; Ton and Duives, 2021), while larger programs can bring in larger samples (Johnson et al., 2023; Sundfør and Fyhri, 2022). A cross-sectional study of a national purchase incentive in Sweden that distributed nearly 97,000 incentives obtained 1,873 usable responses (reporting commute mode) from 10,500 invitations (an 18% usable response rate) (Anderson and Hong, 2022). Other recent studies of local programs have achieved response rates of 60% or more, with surveys distributed (and sometimes required) by the incentive program itself (Johnson et al., 2023; Sundfør and Fyhri, 2022). A three-wave panel study of an e-bike loan program in the Netherlands started with 400 participants and ended with 82 completing the 3-month wave 3 follow-up survey, a retention rate of 21% (compared to our 29% in the 12-month follow-up) (Ton and Duives, 2021).

The study population was potential and actual bicycle/e-bike purchasers in Saanich and greater Victoria, BC. Although the sample demographics compare well to the regional population, the Study group was lower-income than the region, due to the income-conditioning of the Saanich incentives. To contextualize the GHG intensity of the sample's travel, similar methods were recently applied to travel survey data from greater Vancouver, BC, yielding median daily GHG from travel of 5.5 kg CO_2e per person, respectively (Bigazzi et al., 2023). This scales to roughly 38 kg CO_2e per week, per person. In comparison, the sample's pre-purchase weekly GHG from travel was estimated as 19 (conventional bicycle Control group) to 42 (Study group) kg CO_2e per person, which fell to 23 to 27 kg CO_2e per week for all groups in Wave 3. This supports a finding that the Study group was more representative of typical travellers before purchasing their e-bikes, whereas the Control groups had a larger share of people who had already adopted cycling or low-auto-use travel habits.

4.2 Marginal e-bike purchasers

The study results indicate that the e-bike incentives were effective in increasing e-bike purchases, with 23% to 76% marginal purchasers, increasing substantially and significantly with rebate amount. The marginality of purchases suggests price elasticity of e-bike demand of -2.0 to -3.0. For comparison, our previous economic modelling assumed a price elasticity of -2.0 and estimated 17% to 45% marginal purchases for rebate amounts of $400 to $1600 in a hypothetical incentive program in Vancouver, increasing with rebate size (Bigazzi and Berjisian, 2021).

The only empirical estimation of marginal purchases from a real incentive program in the literature is based on the 2018 Swedish national incentive program, with rebates averaging CA$670 (Anderson and Hong, 2022). In that study, an estimate of 66% marginal purchases was made based simply on responses to the question "How important was the subsidy for your decision to buy the electric bike?” Purchase cost was consistently the highest-ranked purchase consideration in our sample (Figure 16), but we believe this measure is a comparatively poor indicator of marginality. Studies of motor vehicle subsidies in Canada have estimated that 26% to 35% of hybrid and electric vehicle sales were attributable to provincial purchase incentives (Azarafshar and Vermeulen, 2020; Chandra et al., 2010).

A recent USA study reported a lower rate of marginal purchases of 14% to 18%, based on responses to a hypothetical choice experiment with simulated e-bike incentives of US$400 to US$1200 (Jones et al., 2024). In addition to different study populations, the differences between the results may be due in part to hypothetical bias, which can lead to lower price sensitivity for study participants reporting hypothetical versus actual purchase behaviour, among other effects (Ash et al., 2004; Haghani et al., 2021; Hensher, 2010; Ryan and O, 2012). Their reported choice model parameters can be used to calculate price elasticity[2] of e-bike demand of -0.2 to -0.5, and incentive elasticity of e-bike demand of 0.5 to 0.7, both of which are well below values reported elsewhere for bicycles (Anderson and Hong, 2022; Derksen and Rombouts, 1937; Kerr, 1987) and electric vehicles (DeShazo et al., 2017; Glerum et al., 2013; Mabit and Fosgerau, 2011).

4.3 Use of purchased bicycles

The purchased e-bikes were used on average 3 to 4 days, or 32 to 70 km, per week (Table 14 and Figure 26). Around 40% to 44% of the reported e-bike use substituted for automobile travel, directly displacing automobile PKT by on average 7 km per e-bike (return) trip, or around 25 km per week (Figure 23, Figure 29, and Figure 30). These results comport well with existing literature on e-bike usage and mode substitution (Bigazzi and Berjisian, 2021, 2019; Bigazzi and Wong, 2020; Bucher et al., 2019; Cairns et al., 2017; Dekker, 2013; Hiselius and Svensson, 2017; Johnson et al., 2023; MacArthur et al., 2018; Sundfør and Fyhri, 2022). In comparison, around half as much conventional bicycle use (23%) substituted for automobile travel, displacing automobile PKT by on average 4 km per conventional bicycle (return) trip, or around 14 km per week. The purchased conventional bicycles were around twice as likely to be used for exercise or leisure trips as the purchased e-bikes (Figure 22).

The trip-level substitution data provide an incomplete picture of travel behaviour changes, because they do not capture the indirect effects of incorporating bicycles into a more multi-modal and less automobile-dependent travel pattern. They also do not account for the pre-purchase behaviour of the purchasers (incentivized e-bike purchasers had higher pre-purchase automobile PKT and lower cycling PKT than non-incentivized purchasers). Comparing weekly travel habits before and after purchase, we find that the e-bike purchasers increased their total weekly e-bike riding by 47 to 57 km in the short run and 31 to 41 in the long-run (more for non-incentivized than incentivized purchasers), with a concurrent 20 to 22 km reduction in weekly conventional cycling. In contrast, the conventional bicycle purchasers did not increase their

[2] Elasticity ε is calculated from the estimated choice model parameters on price and incentive variables as $\varepsilon = \text{Parameter} \times \text{Price} \times (1 - \text{ChoiceShare})$, with Price and ChoiceShare set at US$2190 and 0.90%, respectively, from the average values reported in the paper.

amount of weekly cycling, indicating they had already adopted regular cycling habits pre-purchase (Figure 31).

The largest changes in automobile use were for the incentivized e-bike purchasers, who reduced weekly auto PKT by 56 km in the short run and 49 km in the long run. In contrast, the non-incentivized purchasers of either type of bicycle had little to no reduction in their weekly auto PKT (Figure 31). The difference is almost entirely due to pre-purchase habits, as the incentivized purchasers had on average roughly twice the pre-purchase weekly auto PKT, and half the weekly cycling PKT as the non-incentivized purchasers (Figure 26). Regression analysis showed that, all else equal, increasing rebate amounts were associated with greater auto PKT reductions per e-bike purchased, again due to higher pre-purchase weekly auto PKT (Table 15 and Figure 32).

Together, the results show that larger incentives attracted e-bike purchasers with more potential auto PKT reduction due to higher pre-purchase auto usage. This result could be counterintuitive, because the larger incentives went to lower-income households, and higher income is generally associated with higher auto PKT (and in fact was in our regression model – see Table 15). This effect may be attributed to the desire of e-bike purchasers to use an e-bike rather than an automobile for some portion of their travel, and the greater ability of higher-income households to actualize that preference in their pre-purchase behaviour. Consequently, lower-income households had higher auto use pre-purchase, but not post-purchase. In this way, larger incentives enabled greater shifts for lower-income households.

4.4 Program impacts

Results of the analysis of GHG effects largely mirror those of the auto PKT effects, because auto PKT is the dominant source of weekly GHG from travel (Figure 33). The long-run weekly GHG reduction for the Saanich e-bike incentive recipients is estimated as 16 kg CO_2e on average, ranging from 7 to 28 kg CO_2e/week for the $350 and $1600 rebate levels, respectively (Figure 34 and Table 17). The modelled post-purchase GHG reduction of 35% to 40% leads to greater absolute reductions in the larger incentive tiers because of higher pre-purchase GHG intensity of travel (Figure 36). These GHG estimates based on changes in weekly travel by all modes between survey waves are larger than the direct GHG effects of mode substitution estimated from reported recent e-bike trips, which was about half as large, averaging 8 kg CO_2e/week (Figure 35).

Past modelling studies have calculated that widespread e-bike adoption could reduce GHG from passenger travel by 10 to 20% (Bucher et al., 2019; Hiselius and Svensson, 2017; Mason et al., 2015; McQueen et al., 2020). The incentivized e-bike purchasers in this study reduced their weekly GHG by much more than that (averaging 38%), although the non-incentivized purchasers only reduced their travel GHG by 1%, and the key factor is the pre-purchase GHG intensity of their travel. Anderson and Hong (2022) studied a 2018 national e-bike incentive program in Sweden that provided purchase rebates of 25% of the e-bike price, up to CA$1,500 (rebates averaged around CA$670). They estimated average annual reductions of 22 vehicle-kilometres travelled and 3.4 kg CO_2e per week, per purchaser, based only on changes in primary commute mode. Our estimated changes are larger, but include a broader scope of behavioural shifts. A study of local e-bike purchase incentives in California estimated weekly GHG reductions of 2.8 to

10.2 kg CO_2 per week for incentives of up to around $1080 (although most were much less) (Johnson et al., 2023).

Assuming a 5-year e-bike lifespan (a critical assumption), the approximate (non-marginal) GHG abatement costs in the Saanich program are $190 per tonne, increasing with rebate amount (Table 17). Limiting the estimated program impacts to marginal e-bike purchases (i.e., the self-reported likelihood that without the incentive the respondent would not have bought an e-bike), the GHG reductions are approximately half as large overall, and skewed toward the higher-value rebates (which yielded much higher likelihoods of marginal purchases). Thus, marginal GHG abatement costs increase to $722 per tonne, but decreasing rather than increasing with rebate amount. In comparison, the Swedish national incentive was estimated to "break even" at a carbon cost around CA$800 per tonne CO_2, assuming an 8-year e-bike lifespan (Anderson and Hong, 2022), while single-year GHG abatement costs for the California incentive programs were estimated at CA$5,850 per tonne CO_2, without considering the marginality of purchases (Johnson et al., 2023). Converting these values to a 5-year lifespan assumption yields abatement costs of $1,280 and $1,170 per tonne CO_2, respectively. Key differences among the studies include the type of incentives (amount and income-conditioning), the scope of travel changes accounted for, the assumed GHG intensity of car travel, and consideration of purchase marginality.

To contextualize these abatement costs, the social costs of CO_2e emissions in Canada for 2024 are estimated at $266 per tonne (Environment and Climate Change Canada, 2023). Abatement costs for transportation interventions such as electric vehicle purchase and vehicle scrappage subsidies have been reported[3] in the range of CA$300 to CA$1100 per tonne CO_2e (Azarafshar and Vermeulen, 2020; Chandra et al., 2010; Gillingham and Stock, 2018; Kok et al., 2011). More specifically, BC incentives for battery-electric and plug-in hybrid vehicle purchases were recently estimated to have abatement costs of $638 and $979 per tonne, respectively, in 2016 (Azarafshar and Vermeulen, 2020). In comparison, the current carbon price in BC is just CA$65 per tonne (Ministry of Environment and Climate Change Strategy, 2023), while the European carbon credit market price is CA$93 (CarbonCredits.com, 2023). Hence, the e-bike purchase incentives are cost-competitive with other types of transportation subsidies targeting GHG emission reductions, but unlikely to be cost effective on the international carbon market.

In addition to the GHG benefits, the e-bike purchasers increased their weekly physical activity during travel, despite a reduction in conventional cycling and walking (Figure 38). Also, the marginal incentivized e-bike purchases generated $1,263 in new bicycle retailer revenue, or $813 in new spending, on average per incentive.

[3] Critically, vehicle incentive impacts are usually calculated with the assumption that rebates incentivize shifts in the type of vehicle purchased, but do not affect the total amount of vehicles purchased (i.e., they do not account for induced vehicle ownership).

5 CONCLUSIONS

5.1 Program impacts

This study of the Saanich e-bike incentive recipients, along with comparison samples of non-incentivized conventional and electric bicycle purchasers from the region, has shown that the incentive program was effective in achieving its primary aims, and supports the pre-program analysis for program development and design. The program attracted a large portion of new or marginal purchasers (increasing from 23% to 76% with rebate amount). These purchasers were highly satisfied with their new e-bikes, and used them regularly (averaging 3 to 4 days and 30 to 70 km per week). The incentive recipients reduced their auto use by 49 km per week in the 12-month follow-up; approximately half of this reduction was due to direct substitution of e-bike trips, and the other half due to broader shifts in weekly travel habits (i.e., reduced auto dependence).

Larger incentives were associated with greater auto travel reduction due to higher pre-purchase auto usage. This was likely achieved due to income-conditioning the larger incentives, which directed them to more financially constrained households who were interested in shifting some of their auto use to cycling, but hindered by the cost of e-bikes. Although e-bikes reduce marginal travel costs, the initial purchase price is still a major barrier, especially for low-income households, which is reflected in the high reported marginality for e-bike purchases made with the largest incentives. In contrast, higher-income households were likely more able to actualize their travel mode preferences before the incentive program launched, which led to smaller behaviour changes.

The long-run reduction in GHG from personal travel for the Saanich e-bike incentive recipients averaged 16 kg CO_2e per week, increasing with rebate amount. The marginal and non-marginal GHG abatement costs are estimated to be $722 and $190 per tonne, respectively, which is cost-competitive with other types of transportation subsidies targeting GHG emission reductions (particularly those that can be applied at a local level), but unlikely to be cost effective on the international carbon market. These cost efficiency estimates are highly sensitive to key assumptions such as e-bike lifespan, in addition to the important distinction between marginal and non-marginal GHG reductions (which should be aligned with the methodology applied to comparator programs). Additionally, GHG reduction is one but not necessarily the primary benefit of increased e-bike adoption, which can also provide substantial social benefits through increased physical activity, reduced local air pollutant emissions, reduced travel costs, improved traveller well-being and accessibility, and other benefits. This analysis is also conservative in that it neglects further potential indirect benefits of the program through subsequent bicycle purchases by the incentive recipient and norming of e-bikes among the recipients' social networks and other travellers in the region (Marincek and Rérat, 2021; Simsekoglu and Klöckner, 2019).

5.2 Limitations

The analysis and results in this study have a range of limitations related to the data, assumptions, and inferences. Sample bias is concern in this study, as not all incentive recipients participated in the study, and not all participants completed all three survey waves. We used sample weights and panel regression methods to account for potential selection bias, but these techniques imperfectly mitigate the risk of bias in the results. The survey methods were selected by weighing concerns related to internal and external validity such as participant burden, measurement precision, and response bias. We applied two methods of measuring e-bike use and mode substitution, both relying on self-reporting and recall. Participant tracking techniques (most commonly a GPS-enable smartphone app) could have provided increased measurement precision in travel activity, but at a greater risk of sample bias. This was particularly a concern for low-income portions of the sample, given the structure of the incentive program.

Where we estimate secondary impacts from the travel data (i.e., GHG emissions and physical activity levels), uncertainty is introduced through the use of modal scaling factors. These modal factors are used to represent aggregate modal differences but neglect heterogeneity among individuals and trips. The GHG and MET estimates should be interpreted with caution, and assumed to have substantial uncertainty, in addition to the uncertainty of the travel behaviour changes underlying these secondary impacts.

The findings in this study will have limited applicability outside of the observed range of rebates. We find mostly monotonic effects across our three rebate tiers, but there may be threshold effects at rebate values outside this range (i.e., below \$350 or above \$1600). With only three rebate levels, we could not fully investigate non-linearity in rebate effects. The maximum rebate level in this program was approximately 50% of mean (pre-rebate) purchase price. Rebate effects likely change as the rebate amount approaches the purchase price, and we would not project our results to predict the impacts of an e-bike “give-away” program, for example. In addition, the study population was potential bicycle/e-bike purchasers – not all residents. Thus, the findings would not apply to e-bikes given to random people, who were not otherwise interested in or considering purchasing an e-bike.

Income variables in the analysis were not statistically significant, but the rebate amount variables were, and these two factors were difficult to separate analytically because of the program design (household income and rebate amount were strongly inversely correlated). We surmise that income was the key driver of the observed increased effectiveness of higher-value rebates, although it could not be proven here.

5.3 Recommendations and future work

We find that the Saanich e-bike incentives were effective in increasing e-bike adoption, displacing auto travel, and reducing travel-related GHG. Characterizing marginality is challenging but an essential component of quantifying the program impacts. The larger incentives were more effective, per rebate-dollar, in advancing GHG and VKT reduction goals, particularly when considering marginal impacts, although the smaller incentives induced more marginal purchases per rebate-dollar. The key to the effectiveness of the larger rebates was reaching more people who were interested but not already cycling (with higher average pre-purchase auto use). It appears that large, income-conditioned incentives enabled these low-income households to unlock latent preferences for less auto dependence. While income-conditioning the incentives was important, the larger incentive amounts for the income-conditioned incentives also likely played a role in attracting more marginal purchasers by overcoming the price barrier for low-income households. These two effects could not be separated in this analysis, and future studies of programs with other designs should aim to investigate the distinct effects of rebate amount from income restrictions.

Meanwhile, e-bike incentive program designers must consider the trade-offs of higher rebate amounts (assuming a fixed program budget): more incentives go to marginal purchasers, but each incentive costs more, with a net result of slightly fewer marginal purchases per program dollar. If the larger rebates also lead to greater mode shift by attracting purchasers with higher baseline auto use, then larger rebates are still more cost-effective in reducing VKT and GHG. We have shown that this can happen if the larger incentives are also income-conditioned, but the extent to which this will happen without income restrictions remains unknown (we believe it is unlikely). Hence, we recommend that future e-bike incentive programs condition the incentives on recipient income, which can provide equity benefits in addition to the expected increased effectiveness in VKT and GHG reductions.

Because all incentives were distributed to Saanich residents, this analysis was limited in the variety of contextual variables that could be included in the analysis. Future research on a wider-scale incentive program (provincial, national) could incorporate the moderating effects of inter-regional contextual factors expected to influence e-bike adoption and use such as cycling infrastructure, climate, topography, and transportation network characteristics. There may be a minimum viable cycling network for purchased e-bikes to effectively displace auto use.

Incentivizing e-bike purchases is demonstrably effective in spurring mode shift and reducing travel-related GHG, but questions remain over the most effective program design variables such as rebate structure and amount, and qualifying thresholds for income or other equity-related factors. In addition, the co-benefits of incentivized e-bike purchases (such as physical activity and travel cost) require further investigation. As interest in e-bike incentive programs at all levels of government has grown rapidly over the past several years, we look forward to new investigations of the effectiveness of these programs in various scales and settings.

6 REFERENCES

Ainsworth, B.E., Haskell, W.L., Herrmann, S.D., Meckes, N., Bassett, D.R., Tudor-Locke, C., Greer, J.L., Vezina, J., Whitt-Glover, M.C., Leon, A.S., 2011. 2011 compendium of physical activities: a second update of codes and MET values. Medicine and Science in Sports and Exercise 43, 1575–1581.

Anderson, A., Hong, H., 2022. Welfare Implications of Electric-Bike Subsidies: Evidence from Sweden (No. w29913). National Bureau of Economic Research. https://doi.org/10.3386/w29913

Andersson, A.S. f.k.a., Adell, E., Winslott Hiselius, L., 2021. What is the substitution effect of e-bikes? A randomised controlled trial. Transportation Research Part D: Transport and Environment 90, 102648. https://doi.org/10.1016/j.trd.2020.102648

Aono, S., Bigazzi, A.Y., 2019. Industry Stakeholder Perspectives on the Adoption of Electric Bicycles in British Columbia. Transportation Research Record: Journal of the Transportation Research Board 2673, 1–11. https://doi.org/10.1177/0361198119837158

Aono, S., Bigazzi, A.Y., Berjisian, E., 2019. Development of an Electric Bicycle Incentive Program for Victoria. (Prepared for City of Victoria). University of British Columbia.

Ash, M., Murphy, J.J., Stevens, T., 2004. Hypothetical Bias in Dichotomous Choice Contingent Valuation Studies. University of Massachusetts Resource Economics. https://doi.org/10.2139/ssrn.601364

Azarafshar, R., Vermeulen, W.N., 2020. Electric vehicle incentive policies in Canadian provinces. Energy Economics 91, 104902. https://doi.org/10.1016/j.eneco.2020.104902

Battaglia, M.P., Hoaglin, D.C., Frankel, M.R., 2009. Practical Considerations in Raking Survey Data. Survey Practice 2, 2953. https://doi.org/10.29115/SP-2009-0019

Berjisian, E., Bigazzi, A.Y., 2019. Summarizing the Impacts of Electric Bicycle Adoption on Vehicle Travel, Emissions, and Physical Activity. University of British Columbia, Vancouver, Canada.

Bigazzi, A., 2020. Marginal emission factors for public transit: Effects of urban scale and density. Transportation Research Part D: Transport and Environment 88, 102585. https://doi.org/10.1016/j.trd.2020.102585

Bigazzi, A., 2019. Comparison of marginal and average emission factors for passenger transportation modes. Applied Energy 242, 1460–1466. https://doi.org/10.1016/j.apenergy.2019.03.172

Bigazzi, A., Berjisian, E., 2021. Modeling the impacts of electric bicycle purchase incentive program designs. Transportation Planning and Technology 44, 679–694. https://doi.org/10.1080/03081060.2021.1956806

Bigazzi, A., Frank, L., Dummer, T., Berjisian, E., White, K., 2023. Transportation Emissions Estimates for Integrated Environment-Health Modelling.

Bigazzi, A., Wong, K., 2020. Electric bicycle mode substitution for driving, public transit, conventional cycling, and walking. Transportation Research Part D: Transport and Environment 85, 102412. https://doi.org/10.1016/j.trd.2020.102412

Bigazzi, A.Y., Berjisian, E., 2019. Electric bicycles: Can they reduce driving and emissions in Canada? Plan Canada Fall 2019, 39–42.

Bjørnarå, H.B., Berntsen, S., Velde, S.J. te, Fyhri, A., Deforche, B., Andersen, L.B., Bere, E., 2019. From cars to bikes – The effect of an intervention providing access to different bike types: A randomized controlled trial. PLOS ONE 14, e0219304. https://doi.org/10.1371/journal.pone.0219304

Bourne, J.E., Sauchelli, S., Perry, R., Page, A., Leary, S., England, C., Cooper, A.R., 2018. Health benefits of electrically-assisted cycling: a systematic review. International Journal of Behavioral Nutrition and Physical Activity 15, 116. https://doi.org/10.1186/s12966-018-0751-8

Brander, M., Ascui, F., 2015. The Attributional-Consequential Distinction and Its Applicability to Corporate Carbon Accounting, in: Schaltegger, S., Zvezdov, D., Alvarez Etxeberria, I., Csutora, M., Günther, E. (Eds.), Corporate Carbon and Climate Accounting. Springer International Publishing, Cham, pp. 99–120. https://doi.org/10.1007/978-3-319-27718-9_5

Brander, M., Burritt, R.L., Christ, K.L., 2019. Coupling attributional and consequential life cycle assessment: A matter of social responsibility. Journal of Cleaner Production 215, 514–521. https://doi.org/10.1016/j.jclepro.2019.01.066

Brooks, M.E., Kristensen, K., Benthem, K.J. van, Magnusson, A., Berg, C.W., Nielsen, A., Skaug, H.J., Mächler, M., Bolker, B.M., 2017. glmmTMB Balances Speed and Flexibility Among Packages for Zero-inflated Generalized Linear Mixed Modeling. The R Journal 9, 378–400.

Bucher, D., Buffat, R., Froemelt, A., Raubal, M., 2019. Energy and greenhouse gas emission reduction potentials resulting from different commuter electric bicycle adoption scenarios in Switzerland. Renewable and Sustainable Energy Reviews 114, 109298. https://doi.org/10.1016/j.rser.2019.109298

Bull, F.C., Al-Ansari, S.S., Biddle, S., Borodulin, K., Buman, M.P., Cardon, G., Carty, C., Chaput, J.-P., Chastin, S., Chou, R., Dempsey, P.C., DiPietro, L., Ekelund, U., Firth, J., Friedenreich, C.M., Garcia, L., Gichu, M., Jago, R., Katzmarzyk, P.T., Lambert, E., Leitzmann, M., Milton, K., Ortega, F.B., Ranasinghe, C., Stamatakis, E., Tiedemann, A., Troiano, R.P., van der Ploeg, H.P., Wari, V., Willumsen, J.F., 2020. World Health Organization 2020 guidelines on physical activity and sedentary behaviour. Br J Sports Med 54, 1451–1462. https://doi.org/10.1136/bjsports-2020-102955

Cairns, S., Behrendt, F., Raffo, D., Beaumont, C., Kiefer, C., 2017. Electrically-assisted bikes: Potential impacts on travel behaviour. Transportation Research Part A: Policy and Practice 103, 327–342. https://doi.org/10.1016/j.tra.2017.03.007

Canadian Society for Exercise Physiology, 2021. 24-Hour Movement Guidelines (No. Adults 18-64). Ottawa, Ontario, Canada.

CarbonCredits.com, 2023. Carbon Prices Today. Carbon Credits. URL https://carboncredits.com/carbon-prices-today/ (accessed 1.21.24).

Castro, A., Gaupp-Berghausen, M., Dons, E., Standaert, A., Laeremans, M., Clark, A., Anaya-Boig, E., Cole-Hunter, T., Avila-Palencia, I., Rojas-Rueda, D., Nieuwenhuijsen, M., Gerike, R., Panis, L.I., de Nazelle, A., Brand, C., Raser, E., Kahlmeier, S., Götschi, T., 2019. Physical activity of electric bicycle users compared to conventional bicycle users and non-cyclists: Insights based on health and transport data from an online survey in seven European cities. Transportation Research Interdisciplinary Perspectives 1, 100017. https://doi.org/10.1016/j.trip.2019.100017

Chandra, A., Gulati, S., Kandlikar, M., 2010. Green drivers or free riders? An analysis of tax rebates for hybrid vehicles. Journal of Environmental Economics and Management 60, 78–93. https://doi.org/10.1016/j.jeem.2010.04.003

de Kruijf, J., Ettema, D., Kamphuis, C.B.M., Dijst, M., 2018. Evaluation of an incentive program to stimulate the shift from car commuting to e-cycling in the Netherlands. Journal of Transport & Health 10, 74–83. https://doi.org/10.1016/j.jth.2018.06.003

Dekker, P., 2013. Electrification of road transport–An analysis of the economic performance of electric two-wheelers (Master's Thesis). Utrecht University, The Netherlands.

Department of Health, Physical Activity, Health Improvement and Protection, 2011. Start Active, Stay Active: A report on physical activity for health from the four home countries' Chief Medical Officers.

Derksen, J.B.D., Rombouts, A., 1937. The Demand for Bicycles in the Netherlands. Econometrica 5, 295–300. https://doi.org/10.2307/1905516

DeShazo, J.R., Sheldon, T.L., Carson, R.T., 2017. Designing policy incentives for cleaner technologies: Lessons from California's plug-in electric vehicle rebate program. Journal of Environmental Economics and Management 84, 18–43. https://doi.org/10.1016/j.jeem.2017.01.002

Douma, J.C., Weedon, J.T., 2019. Analysing continuous proportions in ecology and evolution: A practical introduction to beta and Dirichlet regression. Methods in Ecology and Evolution 10, 1412–1430. https://doi.org/10.1111/2041-210X.13234

Elder, S.J., Roberts, S.B., 2007. The Effects of Exercise on Food Intake and Body Fatness: a Summary of Published Studies. Nutrition Reviews 65, 1–19. https://doi.org/10.1111/j.1753-4887.2007.tb00263.x

Environment and Climate Change Canada, 2023. Social Cost of Greenhouse Gas Estimates – Interim Updated Guidance for the Government of Canada. Government of Canada, Ottawa, Ontario, Canada.

Environment and Climate Change Canada, 2021. Greenhouse gas sources and sinks in Canada. Government of Canada, Ottawa, Ontario, Canada.

Environment Canada, 2024. Weather Information [WWW Document]. URL https://weather.gc.ca/ (accessed 3.9.24).

Fishman, E., Cherry, C., 2016. E-bikes in the mainstream: Reviewing a decade of research. Transport Reviews 36, 72–91. https://doi.org/10.1080/01441647.2015.1069907

Fitch, D.T., Gao, Z., Noble, L., Mac, T., Mineta Transportation Institute, San Jose State University. College of Business, 2022. Examining the Effects of a Bike and E-bike Lending Program on Commuting Behavior (No. 22– 07). https://doi.org/10.31979/mti.2022.2051

Frank, L.D., Bigazzi, A., Hong, A., Minaker, L., Fisher, P., Raine, K.D., 2022. Built environment influences on healthy eating and active living: The NEWPATH study. Obesity 30, 424–434. https://doi.org/10.1002/oby.23352

Fyhri, A., Beate Sundfør, H., 2020. Do people who buy e-bikes cycle more? Transportation Research Part D: Transport and Environment 86, 102422. https://doi.org/10.1016/j.trd.2020.102422

Fyhri, A., Fearnley, N., 2015. Effects of e-bikes on bicycle use and mode share. Transportation Research Part D: Transport and Environment 36, 45–52. https://doi.org/10.1016/j.trd.2015.02.005

Gillingham, K., Stock, J.H., 2018. The Cost of Reducing Greenhouse Gas Emissions. Journal of Economic Perspectives 32, 53–72. https://doi.org/10.1257/jep.32.4.53

Glerum, A., Stankovikj, L., Thémans, M., Bierlaire, M., 2013. Forecasting the Demand for Electric Vehicles: Accounting for Attitudes and Perceptions. Transportation Science 48, 483–499. https://doi.org/10.1287/trsc.2013.0487

Gojanovic, B., Welker, J., Iglesias, K., Daucourt, C., Gremion, G., 2011. Electric Bicycles as a New Active Transportation Modality to Promote Health. Medicine & Science in Sports & exercise: Official Journal of the American College of Sports Medicine 43, 2204–2210.

Greene, W.H., 2008. Econometric Analysis. Pearson/Prentice Hall.

Haghani, M., Bliemer, M.C.J., Rose, J.M., Oppewal, H., Lancsar, E., 2021. Hypothetical bias in stated choice experiments: Part I. Macro-scale analysis of literature and integrative synthesis of empirical evidence from applied economics, experimental psychology and neuroimaging. Journal of Choice Modelling 41, 100309. https://doi.org/10.1016/j.jocm.2021.100309

Harris, C.R., Millman, K.J., van der Walt, S.J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N.J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M.H., Brett, M., Haldane, A., del Río, J.F., Wiebe, M., Peterson, P., Gérard-Marchant, P., Sheppard, K., Reddy, T., Weckesser, W., Abbasi, H., Gohlke, C., Oliphant, T.E., 2020. Array programming with NumPy. Nature 585, 357–362. https://doi.org/10.1038/s41586-020-2649-2

Hensher, D.A., 2010. Hypothetical bias, choice experiments and willingness to pay. Transportation Research Part B: Methodological, Methodological Advancements in Constructing Designs and Understanding Respondent Behaviour Related to Stated Preference Experiments 44, 735–752. https://doi.org/10.1016/j.trb.2009.12.012

Hiselius, L.W., Svensson, Å., 2017. E-bike use in Sweden – CO2 effects due to modal change and municipal promotion strategies. Journal of Cleaner Production 141, 818–824. https://doi.org/10.1016/j.jclepro.2016.09.141

Huang, Y., Jiang, L., Chen, H., Dave, K., Parry, T., 2022. Comparative life cycle assessment of electric bikes for commuting in the UK. Transportation Research Part D: Transport and Environment 105, 103213. https://doi.org/10.1016/j.trd.2022.103213

Hunter, J.D., 2007. Matplotlib: A 2D Graphics Environment. Computing in Science & Engineering 9, 90–95. https://doi.org/10.1109/MCSE.2007.55

Johnson, N., Fitch-Polse, D.T., Handy, S.L., 2023. Impacts of e-bike ownership on travel behavior: Evidence from three northern California rebate programs. Transport Policy 140, 163–174. https://doi.org/10.1016/j.tranpol.2023.06.014

Jones, L.R., Bennett, C., MacArthur, J.H., Cherry, C.R., 2024. Consumer Purchase Response to E-bike Incentives: Results from Nationwide Stated Preference Study. Transportation Research Part D: Transport and Environment Forthcoming.

Kerr, P.M., 1987. Demographic and Energy Effects on the U.S. Demand for Bicycles. Transportation Research Record 37–42.

Kok, R., Annema, J.A., van Wee, B., 2011. Cost-effectiveness of greenhouse gas mitigation in transport: A review of methodological approaches and their impact. Energy Policy, Clean Cooking Fuels and Technologies in Developing Economies 39, 7776–7793. https://doi.org/10.1016/j.enpol.2011.09.023

Mabit, S.L., Fosgerau, M., 2011. Demand for alternative-fuel vehicles when registration taxes are high. Transportation Research Part D: Transport and Environment 16, 225–231. https://doi.org/10.1016/j.trd.2010.11.001

MacArthur, J., Harpool, M., Scheppke, D., Cherry, C., 2018. A North American Survey of Electric Bicycle Owners (No. NITC-RR-1041). National Institute for Transportation and Communities, Portland, Oregon.

MacArthur, J., Kobel, N., Dill, J., Mumuni, Z., 2017. Evaluation of an Electric Bike Pilot Project at Three Employment Campuses in Portland, Oregon.

Mageau-Béland, J., Morency, C., 2021. Assessing Physical Activity Achievement by using Transit. Transportation Research Record 2675, 506–514. https://doi.org/10.1177/0361198121999057

Maier, M., 2014. DirichletReg: Dirichlet Regression for Compositional Data in R. DirichletReg: Dirichlet Regression for Compositional Data in R, Research Report Series / Department of Statistics and Mathematics. https://doi.org/10.57938/ad3142d3-2fcd-4c37-aec6-8e0bd7d077e1

Marincek, D., Rérat, P., 2021. From conventional to electrically-assisted cycling. A biographical approach to the adoption of the e-bike. International Journal of Sustainable Transportation 15, 768–777. https://doi.org/10.1080/15568318.2020.1799119

Mason, J., Fulton, L., McDonald, Z., 2015. A Global High Shift Cycling Scenario: The Potential for Dramatically Increasing Bicycle and E-bike Use in Cities Around the World, with Estimated Energy, CO2, and Cost Impacts. Institute for Transportation & Development Policy, Davis, California.

McQueen, M., MacArthur, J., Cherry, C., 2020. The E-Bike Potential: Estimating regional e-bike impacts on greenhouse gas emissions. Transportation Research Part D: Transport and Environment 87, 102482. https://doi.org/10.1016/j.trd.2020.102482

McQueen, M., MacArthur, J., Cherry, C., 2019. How e-bike incentive programs are used to expand the market (White Paper). Transportation Research and Education Center, Portland, Oregon.

Mendes, M., Duarte, G., Baptista, P., 2015. Introducing specific power to bicycles and motorcycles: Application to electric mobility. Transportation Research Part C: Emerging Technologies 51, 120–135. https://doi.org/10.1016/j.trc.2014.11.005

Mildestvedt, T., Hovland, O., Berntsen, S., Bere, E., Fegran, L., 2020. Getting Physically Active by E-Bike: An Active Commuting Intervention Study. Physical Activity and Health 4, 120–129. https://doi.org/10.5334/paah.63

Ministry of Environment and Climate Change Strategy, 2023. British Columbia's Carbon Tax. Province of British Columbia, Victoria, Canada.

Nordenstam, L., 2021. Attributional or consequential assessments in a cyclic greenhouse gas management process – Comparison of guidance on use and production of electricity and district heating. Journal of Cleaner Production 317, 128214. https://doi.org/10.1016/j.jclepro.2021.128214

Pierce, J.M.T., Nash, A.B., Clouter, C.A., 2013. The in-use annual energy and carbon saving by switching from a car to an electric bicycle in an urban UK general medical practice: the implication for NHS commuters. Environ Dev Sustain 15, 1645–1651. https://doi.org/10.1007/s10668-013-9454-0

Province of British Columbia, 2022. Gradual ending for COVID-19 orders and regulations [WWW Document]. URL https://www2.gov.bc.ca/gov/content/covid-19/info/state-of-emergency-ends (accessed 3.9.24).

R Core Team, 2019. R: A language and environment for statistical computing.

R.A. Malatest & Associates Ltd., David Kriger Consultants Inc., 2023. 2022 Capital Regional District Origin Destination Household Travel Survey (Final Report). Capital Regional District, Victoria, Canada.

Ryan, B., O, T.L., 2012. Hypothetical Bias in Choice Experiments: Is Cheap Talk Effective at Eliminating Bias on the Intensive and Extensive Margins of Choice? The B.E. Journal of Economic Analysis & Policy 12, 1–28.

Simsekoglu, Ö., Klöckner, C., 2019. Factors related to the intention to buy an e-bike: A survey study from Norway. Transportation Research Part F: Traffic Psychology and Behaviour 60, 573–581. https://doi.org/10.1016/j.trf.2018.11.008

Statistics Canada, 2024. Monthly average retail prices for gasoline and fuel oil, by geography. https://doi.org/10.25318/1810000101-eng

Statistics Canada, 2022. 2021 Census Profile. Ottawa, Ontario, Canada.

Sundfør, H.B., Fyhri, A., 2022. The effects of a subvention scheme for e-bikes on mode share and active mobility. Journal of Transport & Health 26, 101403. https://doi.org/10.1016/j.jth.2022.101403

Sundfør, H.B., Fyhri, A., 2017. A push for public health: the effect of e-bikes on physical activity levels. BMC Public Health 17. https://doi.org/10.1186/s12889-017-4817-3

The pandas development team, 2022. pandas-dev/pandas: Pandas. https://doi.org/10.5281/zenodo.7093122

Ton, D., Duives, D., 2021. Understanding long-term changes in commuter mode use of a pilot featuring free e-bike trials. Transport Policy 105, 134–144. https://doi.org/10.1016/j.tranpol.2021.03.010

Venables, W.N., Ripley, B.D., 2002. Modern Applied Statistics with S, Statistics and Computing. Springer, New York, NY. https://doi.org/10.1007/978-0-387-21706-2

Wolf, A., Seebauer, S., 2014. Technology adoption of electric bicycles: A survey among early adopters. Transportation Research Part A: Policy and Practice 69, 196–211. https://doi.org/10.1016/j.tra.2014.08.007

7 APPENDICES

7.1 Appendix A: Survey Instruments

7.1.1 Wave 1 Questionnaire

7.1.1.1 Consent form

THE UNIVERSITY OF BRITISH COLUMBIA

Effects of Bicycle Purchases on Travel Behaviour over Time

Thank you for considering participation in this study. The study is being conducted by Dr. Alex Bigazzi and the Research on Active Transportation (REACT) Lab at the University of British Columbia (UBC). We are investigating the effects of bicycle purchases on travel behaviour over time. *We seek study participants from the Capital Regional District who are considering purchasing or have recently purchased or acquired a new bicycle and are at least 16 years of age*. The study findings will help to inform programs and policies that facilitate bicycle adoption and promote sustainable transportation.

To measure long-term effects, we are using a three-part study design. In Part 1 (this survey), you will be asked to provide information about your travel habits, your household, any recent bicycle purchase you have made, and three recent trips made using that new bicycle. Then, at the end of the survey, you will be asked if you agree to be contacted in 3 months to participate in Part 2 of this study, which is a follow-up survey about changes to your travel habits and bicycle ownership, and recent cycling trips. Part 3 of the study will be a similar follow-up survey after 12 months.

Each of the three surveys should take around 10 minutes to complete. Participation is voluntary, and you can withdraw at any time. You may complete this survey and decline to be contacted about or participate in Part 2 or Part 3. Study data will be encrypted and your responses will remain confidential. No personally identifying information will be included when the study findings are presented or published.

You may enter a draw for one of five $25 gift cards and/or request to have the final study results sent to you by entering your email address below. Your email address will not be shared or used for any other purpose. Everyone who takes the survey and enters their email address will be considered in the prize draw (even those who withdraw or do not answer every question). Your chance of receiving a gift card is approximately 1 in 100; all gift cards will be distributed in the Capital Regional District.

If you have any questions about this study, please contact Dr. Alex Bigazzi at alex.bigazzi@ubc.ca. If you have accessibility needs to take the survey, including in another language, please email react.lab@ubc.ca or call 604-822-4426. If you have any concerns or complaints about your rights as a research participant and/or your experiences while participating in this study, contact the Research

Participant Complaint Line in the UBC Office of Research Ethics at 604-822-8598 or email RSIL@ors.ubc.ca or call toll free at 1-877-822-8598 (ethics ID: H21-02361).

Click on "I agree" below to indicate your consent to participate in this survey and proceed.

- I agree
- I disagree

Skip to section 7 If "I disagree" selected

1. Do you want to enter the draw for a gift card and/or hear about the results of the study? (*check all that apply*)

- I want to enter the draw for a gift card
- I want to hear about the results of this study
- I do not want to enter the draw for a gift card or hear about the results

Display this question if a participant checks first or second or both options from above

2. Please enter your email address.
(*Your email will not be shared or used for any other purposes*)
[Open text box]

7.1.1.2 Recent bike purchase info

Bicycle purchases

1. Did you recently purchase a bicycle (of any type, including electric bicycles), or have one purchased for you?
   a. Yes, one
   b. Yes, more than one [if checked: For the questions below, please tell us about your most recent e-bike purchase, or conventional bicycle purchase if no e-bike was purchased.]
   c. No [if checked, display "Are you considering purchasing a new bicycle or e-bike? [text box]" and then skip to Section 4]
2. On what date was the bicycle purchased? [date box]
3. What are the make and model of the bicycle? [text box]
4. Does the bicycle have (or will you add) motorized pedal assistance? In other words, is it an e-bike?
   a. Yes
   b. No
   c. I'm not sure __________
5. Did you (or do you expect to) receive any rebates or other financial incentives for this purchase?
   a. Yes [if checked, then display:]
      i. [Column – open text boxes] Amount of incentive
      ii. [Rows]
         1. Sales tax exemption
         2. Rebate/discount from manufacturer
         3. Rebate/discount from retailer

4. Rebate from Saanich
5. Rebate from BC SCRAP-IT
6. Other: _________

iii. What is the final amount paid for the bicycle, including taxes, after the rebates or incentives described above? Do not include accessories or other purchases made at the same time such as a helmet, lock, or lights.
[text box]

iv. If the incentives described above were not available for this purchase, what is the likelihood each of the following would have happened?
[slider group, summing to 100%, with "I don't know" opt-out option]

1. The same purchase would have been made
2. The purchase would have been delayed until the incentive(s) were available
3. A different e-bike would have been purchased ["different" conditional on purchased bike type]
4. A different conventional bike would have been purchased ["different" conditional on purchased bike type]
5. No bicycle purchase would have been made

b. No

i. What is the final amount paid for the bicycle, including taxes? Do not include accessories or other purchases made at the same time such as a helmet, lock, or lights. [text box]

6. What portion of the bicycle's use do you expect will be by you (versus others in your household)? [slider: 0-100%]
7. Does your bicycle have an odometer?
    a. No
    b. Yes
        i. Please enter the current number of kilometers on your bicycle's odometer.
8. What were the main considerations in purchasing this bicycle? (Select up to 3)
    a. Purchase cost
    b. Riding comfort
    c. Appearance/style
    d. Weight
    e. The physical effort required to ride it
    f. The speed I can go on it
    g. How far I can go with it
    h. How often I will ride it
    i. How fun it is to ride
    j. The children I can carry with it
    k. The cargo I can carry with it

l. The risk of theft or vandalism
m. The risk of injury to myself while riding it
n. The risk of injuring others while riding it
o. The desire to substitute other modes of travel
p. Maintenance requirements
q. Charging requirements [conditional on e-bike]

9. Now that you own it, what are your main considerations in deciding whether to use your new bicycle versus another mode of travel? (Select up to 3)
    a. Travel time
    b. Travel distance
    c. What I'll be doing at my destination
    d. Weather
    e. Safe riding facilities
    f. Cargo I need to carry
    g. Accompanying travelers
    h. Maintenance condition
    i. Clothing
    j. Physical exertion and/or perspiration
    k. Bike parking (convenience, security)
    l. Battery charge [conditional on e-bike]
    m. Environmental impacts
    n. The evaluation/judgement of others
    o. Cost/convenience of alternative modes of travel

7.1.1.3 Recent bike trips

[conditional on recent purchase – otherwise skip to Section 4]

Recent bicycle trips

1. Have you used your new bicycle at least 3 times?
    a. Yes
    b. No [skip rest of section]
2. We will next ask about the most recent 3 times that you used your new bicycle for a round trip (leaving from home and returning again, with any number of stops along the way).

    [Repeat 3 times, clearly indicating Trip #X]
    a. What date was this trip made?
    b. At what time did you begin your trip?
    c. What was the main purpose of this trip? [drop-down box]
        i. Travel to work or school (commuting)
        ii. Work-related travel (other than commuting)
        iii. Personal shopping or errands (store, bank, health appointments, etc.)

iv. Social, recreational, or dining (visiting friends/family, religious activity, etc.)
v. Exercise/leisure trip with no main destination
vi. Escort/chauffeur someone on their trip (to school, work, etc.)

d. About how many minutes did you spend riding the bicycle over the entire round trip?
e. About how many kilometres did you travel over the entire round trip?
f. Had you not acquired this new bicycle, what would you most likely have done?
    i. Made the same trip with a different, similar bicycle
    ii. Made the same trip with a different mode of travel
    iii. Made the trip to a different destination, using a different mode of travel
    iv. Not made the trip at all
g. [Conditional on the 'different mode' options]
What is the likelihood you would have used each of the following modes of travel?
[slider group, summing to 100%, with I don't know opt-out option]
[same mode options as rows in Q4.1]
h. [Conditional on the 'different destination' option]
How do you expect your trip distance would have changed, if made using the most likely travel mode indicated above? [slider from -100% to +100% with Other: _______]

7.1.1.4 Travel info

Travel habits

1. In the month before you acquired this bicycle, on average… [if did not recently purchase, then substitute "past month"]
    a. [Columns – responses are numerical boxes, with decimals OK]
        - How many days per week did you use each of the following modes of travel (for any purpose, including exercise or recreation)?
        - For approximately how many minutes per day, on days that you used it?
        - For approximately how many kilometres per day, on days that you used it?
    b. [Rows]
        - Walking or running
        - Conventional bicycle (non-motorized)
        - Motorized pedal-assist bicycle (e-bike)
        - Other wheeled device (skateboard, kick-scooter, skates, wheelchair, mobility scooter, etc.)
        - Motorcycle or scooter (that you do not pedal)
        - Driver or passenger in a car, truck, or van (private, shared, or taxi service)
        - Public transit (bus, rail, ferry, etc.)

2. What are the first 3 digits of your home postal code? (or other location identifier, if you prefer) [text box]
3. What are the first 3 digits of the postal code for the place to which you most often commute for work or school? (or other location identifier, if you prefer)
   a. I do not commute for work or school
   b. [text box]
4. [conditional on previous]
   What main mode of travel do you usually use to get to work or school?
   [same mode options as rows in Q4.1]
5. How comfortable would you feel cycling on your own in each of the following situations? [slider grid ranging from "Very uncomfortable to "Very comfortable", with "I don't know" check box]
   a. On local neighbourhood streets with little traffic and low speeds
   b. On major streets that have bike lanes separated from traffic with a physical barrier
   c. On major streets that have a painted bike lane with no physical barrier

7.1.1.5 Household & personal info

Household information

This last page of questions about you and your household will help us understand the context for bicycle adoption.

1. What is the total number of people living in your household, including yourself? A household is defined as a group of people who share a kitchen, and excludes visitors. [text box]
2. How many of the members of your household are:
   [2 columns: me (check box); other members of my household (number box)]
   d. At least 16 years of age
   e. Full-time workers (>30 hours/week)
   f. Part-time workers
   g. Full-time students
   h. Part-time students
   i. Licensed drivers
3. How many of each of the following working vehicles are currently available to the members of your household, including yourself? Include personal and business vehicles.
   j. Registered and insured motor vehicles (cars, trucks, vans, motorcycles)
   k. Bicycles & other non-registered wheeled vehicles
      i. Adult bicycles (non-motorized)
      ii. Children's bicycles (non-motorized)
      iii. Motorized pedal-assist bicycles (e-bikes)
   l. Other (please specify) _______________
4. What is your household dwelling type?
   m. Single-detached house

n. Semi-detached house (duplex, row house, townhouse)
o. Apartment or condominium
p. Other (please specify) __________

5. At home, where do you normally park your bicycles? [check all that apply] [conditional on ownership]
   q. On the street
   r. In a shared/common space (bike room, courtyard)
   s. In a private outdoor space (balcony, patio, yard)
   t. Inside my unit/house
   u. Other (please specify) ___________
6. What is your age in years?
   a. [text box]
   b. Prefer not to answer
7. What is your current gender?
   a. Man
   b. Woman
   c. Non-binary
   d. Not listed __________
   e. Prefer not to answer
8. What is your cultural background? (mark all that apply)
   f. African
   g. European
   h. East Asian (China, Mongolia, North Korea, South Korea, Japan, Hong Kong, Taiwan, Macau)
   i. South Asian (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka)
   j. South East Asian (Brunei, Myanmar, Cambodia, Timor-Leste, Indonesia, Laos, Malaysia, the Philippines, Singapore, Thailand, Vietnam)
   k. First Nations or Indigenous (please specify) ________
   l. Hispanic or Latinx
   m. Middle Eastern
   n. Other (please specify) _________
   o. Prefer not to answer
9. Do you have any difficulty walking, using stairs, or doing other physical activities?
   p. No
   q. Sometimes
   r. Often
   s. Always
10. What is the highest level of education you have completed?
    c. Some high school or less
    d. Completed high school/equivalency

e. College/university certificate or diploma
f. Bachelor's degree
g. Graduate degree (master's or doctorate)
h. Prefer not to answer

11. What is your gross (pre-tax) annual household income? (in CAD)
    i. <25k; 25-50k; 50-75k; 75-100k; 100-150k; >150k; Prefer not to answer

7.1.1.6 Closing

Thank you for participating. The survey is now complete.

1. Do you have any comments or clarifications about the information you provided in this survey? [open text box]
2. This survey was Part 1 of a 3-part study designed to investigate the effects of bicycle purchases on travel behaviour over time. The next two parts are follow-up surveys that will ask about changes from the responses you have given here after 3 and 12 months. Your continued participation in the next two parts of the study will be essential to the value of your responses. If you select "I agree" below, an invitation email for the next survey will be sent to you in 3 months, with up to 2 reminders. You will not be obligated to complete the survey, and can withdraw at any time. Your email address will not be shared or used for any other purpose.

   Do we have your permission to contact you for the follow-up survey in 3 months?
   a. I agree to be contacted
      i. Please enter your email address. (*Your email will not be shared or used for any other purposes*) [Open text box]
   b. Maybe – I want to know more before I agree
      i. You may contact us at react.lab@ubc.ca; or we will contact you to answer your questions if you enter your contact information here: [Open text box]
   c. I disagree – I do not wish to be contacted about the next part of the survey
3. Click submit to exit the survey.

7.1.1.7 Exit

Thank you very much for your participation!

Your survey answers have been saved. If you wish to change any of your answers, or if you have any questions or concerns about the survey, please contact react.lab@ubc.ca.

7.1.2 Wave 2 Questionnaire

Note: the Wave 3 questionnaire was materially the same as the Wave 2 questionnaire.

7.1.2.1 Consent form

THE UNIVERSITY OF BRITISH COLUMBIA

Effects of Bicycle Purchases on Travel Behaviour over Time – Part 2

Thank you for considering continued participation in this study, which will be essential to the value of your past responses. The study is being conducted by Dr. Alex Bigazzi and the Research on Active Transportation (REACT) Lab at the University of British Columbia (UBC). We are investigating the effects of bicycle purchases on travel behaviour over time. The study findings will help to inform programs and policies that facilitate bicycle adoption and promote sustainable transportation.

This is Part 2 of a 3-part study. You have been invited because you completed Part 1 and agreed to be contacted to participate in Part 2. If you did not complete Part 1, or have any questions or concerns about your invitation to participate in Part 2, please contact react.lab@ubc.ca.

This survey should take around 10 minutes to complete. You will be asked to provide updated information about your travel habits, your household, and three recent trips. At the end of the survey, you will be asked if you agree to be contacted in 9 months to participate in Part 3 of this study, which is a similar follow-up survey.

Participation is voluntary, and you can withdraw at any time. You may complete this survey and decline to be contacted about or participate in Part 3. Study data will be encrypted and your responses will remain confidential. No personally identifying information will be included when the study findings are presented or published.

You may enter a draw for one of five <u>$40 gift cards</u> and/or request to have the final study results sent to you by entering your email address below. Your email address will not be shared or used for any other purpose. Everyone who takes the survey and enters their email address will be considered in the prize draw (even those who withdraw or do not answer every question). Your chance of receiving a gift card is approximately 1 in 80; all gift cards will be distributed in the Capital Regional District.

If you have any questions about this study, please contact Dr. Alex Bigazzi at alex.bigazzi@ubc.ca. If you have accessibility needs to take the survey, including in another language, please email react.lab@ubc.ca or call 604-822-4426. If you have any concerns or complaints about your rights as a research participant and/or your experiences while participating in this study, contact the Research Participant Complaint Line in the UBC Office of Research Ethics at 604-822-8598 or email RSIL@ors.ubc.ca or call toll free at 1-877-822-8598 (ethics ID: H21-02361).

Click on “I agree” below to indicate your consent to participate in this survey and proceed.

- I agree
- I disagree

Skip to section 7 If “I disagree” selected

2. Do you want to enter the draw for a gift card and/or hear about the results of the study?
(*check all that apply*)

- I want to enter the draw for a gift card
- I want to hear about the results of this study
- I do not want to enter the draw for a gift card or hear about the results

Display this question if a participant checks first or second or both options from above

3. Please enter your email address.
(*Your email will not be shared or used for any other purposes*)
[Open text box]

7.1.2.2 A) Continued bike info

[If they **had** purchased a bicycle in the Part 1 survey]

Your new bicycle

1. Do you still own the new bicycle you previously told us about in the Part 1 survey?
    a. Yes
    b. No
        i. Why not? [text box]
        ii. Have you replaced the bicycle?
            1. Yes
                a. What are the make and model of the replacement bicycle?
                    [text box]
                b. For the questions below, please tell us about your use of this replacement bicycle.
            2. No
2. [conditional on them still owning it, and them giving us an odometer reading previously]
   Please enter the current number of kilometers on your bicycle's odometer. [text box]
3. [conditional on them owning an e-bike]
   When do you typically recharge your e-bike's battery?
    a. I charge it after every use, regardless of battery level
    b. When the battery level drops to...{0-20%, 20-40%...80-100%}

   How frequently do you charge your e-bike? (same response categories as the travel matrix question)
4. How has your experience been with the following aspects of your new bicycle, compared to your expectations?
   [slider scale from "much worse" to "much better"]
    a. Overall experience
    b. How often you use it
    c. Enjoyment/fun
    d. Riding comfort
    e. Safety
    f. Parking

g. Charging [conditional on e-bike]
h. Other [text box]

5. [conditional on still owning] What are your main considerations in deciding whether to use your new bicycle versus another mode of travel? (Select up to 3)
    a. Travel time
    b. Travel distance
    c. What I'll be doing at my destination
    d. Weather
    e. Safe riding facilities
    f. Cargo I need to carry
    g. Accompanying travelers
    h. Maintenance condition
    i. Clothing
    j. Physical exertion and/or perspiration
    k. Bike parking (convenience, security)
    l. Battery charge [conditional on e-bike]
    m. Environmental impacts
    n. The evaluation/judgement of others
    o. Cost/convenience of alternative modes of travel
6. Incidents
    a. While riding your new bicycle, have you had an incident where you fell to avoid contact, caused someone to fall, or made contact with another person or vehicle?
        i. No
        ii. Yes
    b. [if Yes] With which of the following other road users have you had an incident? (mark all that apply)
        i. Pedestrian
        ii. Cyclist or someone on a scooter, skates, or other wheeled device
        iii. Car, truck, van, motorcycle or other registered motor vehicle
        iv. Fixed object or other fall with no one else involved
    c. [if Yes] How serious was the most serious incident for you?
        i. Very serious (overnight hospital stay)
        ii. Serious (hospital visit, not overnight)
        iii. Minor (scrapes and bruises)
        iv. No injury (property damage only)
        v. No injury, no property damage

7.1.2.3 B) Recent bike purchase info

[If they **had not** purchased a bicycle in the Part 1 survey; questions the same as the Part 1 survey]

7.1.2.4 Recent bike trips

[do not show if they still have not purchased a bicycle, or lost it and did not replace it; questions the same as the Part 1 survey]

7.1.2.5 Travel info

[same as the Part 1 survey, but change "month before purchase" to "past month" if they have a new bicycle]

7.1.2.6 Household & personal info

Household information

This last page of questions about you and your household shows the responses you provided in the Part 1 survey. Please review and modify any responses to indicate changes to your household and bicycle/vehicle ownership.

Besides the questions below, have there been any other changes in your life situation that have significantly affected your travel habits? If so, please describe. [open text box]

[same questions as the Part 1 survey, pre-populated with Part 1 responses]

7.1.2.7 Closing

Thank you for participating. The survey is now complete.

4. Do you have any comments or clarifications about the information you provided in this survey? [open text box]
5. This survey was Part 2 of a 3-part study designed to investigate the effects of bicycle purchases on travel behaviour over time. Part 3 is another follow-up survey that will ask about changes from the responses you have given here 9 more months. Your continued participation in the last part of the study will be essential to the value of your responses. If you select "I agree" below, an invitation email for the next survey will be sent to you in 9 months, with up to 2 reminders. You will not be obligated to complete the survey, and can withdraw at any time. Your email address will not be shared or used for any other purpose.

   Do we have your permission to contact you for the follow-up survey in 9 months?
   a. I agree to be contacted
      i. Please enter your email address. (*Your email will not be shared or used for any other purposes*) [Open text box]
   b. Maybe – I want to know more before I agree
      i. You may contact us at react.lab@ubc.ca; or we will contact you to answer your questions if you enter your contact information here: [Open text box]
   c. I disagree – I do not wish to be contacted about the next part of the survey
6. Thank you for participating. The survey is now complete. Click submit to exit the survey.

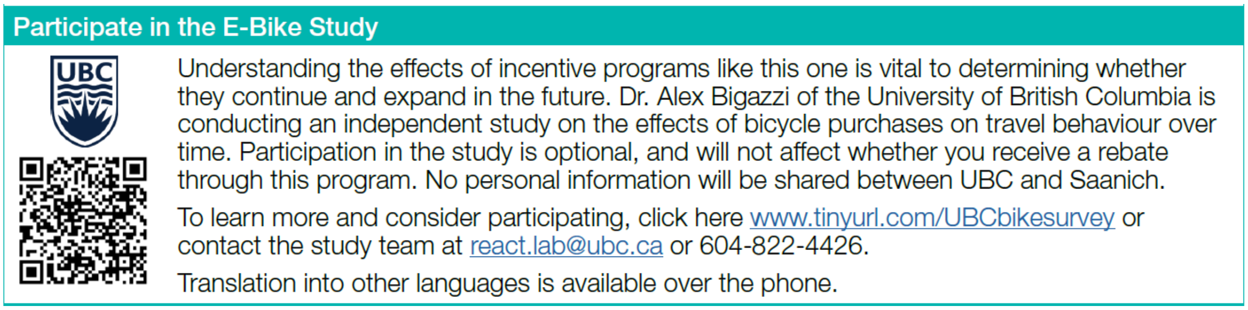
7.1.2.8 Exit

Thank you very much for your participation!

Your survey answers have been saved. If you wish to change any of your answers, or if you have any questions or concerns about the survey, please contact react.lab@ubc.ca.

7.2 Appendix B: Recruitment Materials

Saanich incentive program materials included the following text to recruit study participants (Figure 39). Figure 40 and Figure 41 show the card and flyer sent to bike shops in greater Victoria, BC for study recruitment.



Participate in the E-Bike Study

Understanding the effects of incentive programs like this one is vital to determining whether they continue and expand in the future. Dr. Alex Bigazzi of the University of British Columbia is conducting an independent study on the effects of bicycle purchases on travel behaviour over time. Participation in the study is optional, and will not affect whether you receive a rebate through this program. No personal information will be shared between UBC and Saanich.

To learn more and consider participating, click here www.tinyurl.com/UBCbikesurvey or contact the study team at react.lab@ubc.ca or 604-822-4426.

Translation into other languages is available over the phone.

Figure 39. Recruitment text in Saanich incentive program material

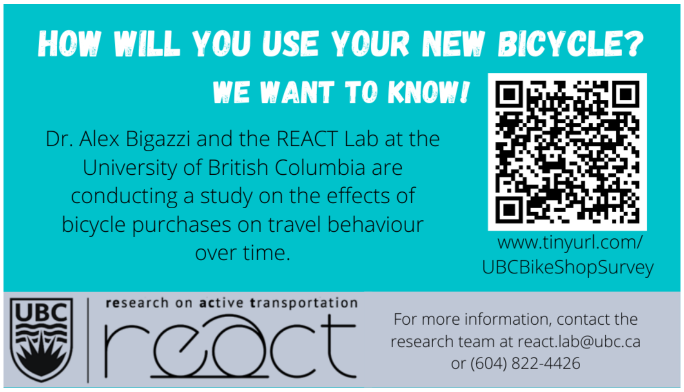


Figure 40. Recruitment card sent to greater Victoria bike shops for display

Figure 41. Recruitment flyer sent to greater Victoria bike shops for posting

The images used for online (Facebook and Instagram) ads are shown in Figure 42. The following text accompanied the images:

> "We are looking for residents of the Capital Regional District (greater Victoria, BC) who have recently purchased or are considering purchasing a new bicycle to take a survey about their travel habits. The survey should take 10 minutes to complete. All participants will have a chance to enter into a draw for one of five gift cards of $25 each. To participate, or for more information, please visit: www.tinyurl.com/UBCBikeShopSurvey. Note that if you like, follow, or comment on this post, others may associate your profile with this study."

Figure 42. Image used in online recruitment ads

The emailed invitation message to Wave 1 and 2 participants who consented to be re-contact for future waves is listed below.

Dear Survey Participant,

You previously participated in our study on **The effects of bicycle purchases on travel behaviour over time**. We are contacting you today to request your participation in the [2nd/3rd] part of this 3-part study being conducted by Dr. Alex Bigazzi and the Research on Active Transportation (REACT) Lab at the University of British Columbia (UBC).

The survey should take under 10 minutes to complete, and involves questions to provide updated information about your household, your travel habits, and three recent trips. Participation is voluntary, and you can withdraw at any time. Your continued participation in the study will be essential to the value of your responses. The study findings will help to inform programs and policies that facilitate bicycle adoption and promote sustainable transportation.

As recognition of the value of your time and input, participants may enter a draw for one of five gift cards of $[XX] each.

To learn more and consider participating, click here [survey link].

If you have any questions or accessibility needs to take the survey, including in another language, please contact the study team at react.lab@ubc.ca or 604-822-4426.

Thank you for your time and consideration,

Dr. Alex Bigazzi,
Associate Professor
Department of Civil Engineering and School of Community and Regional Planning
University of British Columbia

UBC | research on active transportation
react