Evaluating the Impact of E-Bike Purchase Incentives on Vehicle Travel via a Randomized Rebate Program

Rubina Singh (corresponding author)
Department of Civil and Environmental Engineering
University of Washington, Seattle, USA, 98195
Email: rs49742@uw.edu

Daniel Malarkey
Department of Civil and Environmental Engineering
University of Washington, Seattle, USA, 98195
Email: djmalark@uw.edu

Don MacKenzie
Department of Civil and Environmental Engineering
University of Washington, Seattle, USA, 98195
Email: dwhm@uw.edu

ABSTRACT

This study evaluates the impact of Washington State's 2025 electric bike (e-bike) rebate program on vehicle travel. The program offered $1,200 rebates to income-qualified participants and $300 rebates to others, with recipients randomly selected from the pool of applicants. Leveraging this randomized assignment, we estimate the causal effects of both receiving a rebate offer and purchasing an e-bike on daily vehicle miles traveled. Using GPS-based travel data, a pretest-posttest control design, and instrumental variable methods to account for selection into e-bike adoption, we find no statistically significant decrease in mean daily vehicle miles traveled resulting from either intervention within the first three months following rebate offer. These findings suggest that e-bike rebates may have limited ability to reduce vehicle travel and emissions in the US.

1. INTRODUCTION

Cities and states across the US have adopted policies to increase bicycling mode shares as a strategy to reduce transportation greenhouse gas emissions, alleviate congestion, and improve public health (*1*, *2*). While conventional bicycles are a low-cost, low-emissions alternative to car travel, their utility is often limited by trip distance, topography, and physical exertion (*3*, *4*). Electric bicycles (e-bikes) help overcome these barriers by bridging the gap between conventional cycling and motorized transport, expanding the range and types of cycling trips that can replace motor vehicle trips (*5*).

In addition to their potential to induce mode shift, e-bikes can also improve physical health, lower transportation costs, reduce traffic congestion, and improve air quality (*1*, *6–9*). Recognizing these benefits and the barrier to adoption posed by e-bikes' high upfront cost, many cities, states, and organizations have introduced incentive programs to promote e-bike adoption (*1*, *10–12*). Several of the government-administered initiatives are funded by climate improvement legislation, in the belief that e-bike adoption will reduce vehicle use and lower transportation-related greenhouse gas emissions (*1*, *13–15*).

Despite growing interest by policymakers in promoting e-bikes as a sustainable mobility option, the extent to which financial incentives for e-bike adoption reduce transportation emissions in the US remains unclear. Most causal evidence on this topic comes from Northern Europe, where cycling norms and infrastructure differ substantially. To date, no studies in North America have combined robust experimental methods with GPS-based travel diaries to evaluate the impact of incentives on e-bike adoption and changes in travel behavior or emissions.

This study examines two key questions among applicants to Washington State's e-bike rebate program: (1) What is the effect of being offered an e-bike rebate on motor vehicle miles traveled (VMT)? and (2) What is the effect of purchasing an e-bike on changes in VMT? To answer these questions, we leverage the randomized assignment of rebate offers and analyze changes in vehicle use over a three-month period using GPS travel data collected via participants' smartphones. We find that neither being offered a $300 or $1200 rebate, nor purchasing an e-bike, leads to a statistically significant decrease in daily VMT.

2. LITERATURE REVIEW

A growing body of research over the past decade has examined the effects of e-bikes on emissions and travel behavior, yielding mixed results. While some studies focus on substitution effects and overall mode share, others assess how e-bike acquisition influences motorized vehicle use, including reductions in VMT. These studies vary in design, with some employing a cross-sectional research design with retrospective questions on travel behavior, while others use an experimental approach. Even among studies using experimental or quasi-experimental designs, there is substantial variation in the type of intervention (natural acquisition, loan programs, or incentive programs), data collection techniques (self reported or passively collected GPS data), and the geographic context.

2.1. Effect of E-Bikes on Mode Share and Vehicle Use

Many studies have examined the substitution effects and mode share impacts of e-bikes using longitudinal panel data collected before and after adoption. For example, research in the Netherlands found that while e-bikes most often replace trips made by conventional bikes, they also substitute trips by car, public transport, and walking (*16*, *17*). De Haas et al. (2022) further showed that the substitution effects vary by trip purpose; e-bikes used for commuting are more likely to replace car trips than those used for leisure (*16*). Kroesen (2017) highlighted that while e-bike owners reduce car usage more than conventional bike owners, they do not forgo vehicle purchases (*17*). In Switzerland, Rérat et al. (2024)

found that e-bikes predominantly replace public transport trips, but can also substitute walking, car, and cycling trips (*18*).

In terms of mode share, most of these studies report that e-bike adoption leads to a significant increase in the share of cycling trips (*17*, *19–22*), and several suggest reductions in vehicle trips (*17*, *23–25*), though the degree of change varies widely. For instance, a review by Bourne et al. (2020) found that e-bikes replaced 20-86% of car journeys, with a median of 24% mode substitution of vehicle trips found by Bigazzi & Wong (2020) (*19*, *26*). Many of these studies note that the degree of substitution is dependent on trip purpose, with stronger effects observed for commuting (*3*, *16*, *23*).

Focusing solely on substitution effects and mode share provides an incomplete picture. Replacing specific vehicle trips with e-bike trips does not necessarily imply a net reduction in total vehicle use (*3*), though it could still yield non-emissions related benefits. Thus, some studies have explicitly examined the effect of e-bike acquisition on overall motorized travel, measured through vehicle miles traveled (VMT) or vehicle kilometers traveled (VKT) (*3*, *13*, *27–29*). Here, the reported effect sizes also varied, with reductions in VMT ranging from 0% to 20% (*27*) .

Much of this heterogeneity in outcome may be attributable to differences in context. All three outcomes– substitution effects, mode share, and vehicle use– vary with baseline travel patterns, land use characteristics, transportation infrastructure, and prevailing mobility norms (*3*, *17*, *19*, *23*, *26*). For example, studies have shown that the substitution effects tend to be greater in contexts where the car mode share is higher prior to e-bike adoption (*3*, *29*). Sun et al. (2020) finds that shifts from private cars to e-bikes are more successful in low-density areas with limited public transport options, since when there are many mode options, e-bikes may displace trips that would have otherwise been made by conventional bikes or public transport, leading to ambiguous or even adverse sustainability outcomes (*3*, *18*, *23*).

2.2. Research Designs of E-Bike Emissions Studies

Several of the studies discussed above rely on cross-sectional data, and/or ask study participants to retroactively report on their travel behavior rather than collecting data prior to the intervention (*18*, *20*, *28*). While such cross-sectional studies can offer valuable descriptive insights, they are inherently limited in their ability to support causal inference (*3*, *16*, *30*). In the context of e-bike research, at least one study has demonstrated that omitting a control group can lead to biased estimates of treatment effects (*31*). Moreover, recall-based estimates are sensitive to small differences in question framing (*32*), further underscoring the importance of rigorous research designs.

A recent review evaluated all studies evaluating the impact of e-bikes on travel behavior using quasi-experimental or experimental design, defined as data collection before and after the intervention, with or without a control group (*3*). The review found only found ten studies, and only four of those evaluated the total change in vehicle use. Table 1 summarizes the experimental or quasi-experimental studies found in their review (*22–24*, *29*) and in our own review (*13*, *27*) that evaluated the impact of e-bike adoption on VMT or VKT.

TABLE 1 Experimental and Quasi-Experimental Studies Assessing the Impact of E-Bikes Adoption on Total Vehicle Use (Adapted from (*3*))

Citation	Study Location	Intervention Type	GPS data used?	Randomization of Treatment?	Sample Size > 100 in the Intervention Group?	Change in VMT or VKT
Söderberg F.K.A. Andersson et al., 2021	Sweden	Loan Program	Yes	Yes	No	Car use decreased by 14 km/person/day
Sundfør et al., 2024	Norway	Incentive Program	No	Yes	Yes	Vehicle mode share by VKT decreased by 10.1%
Sundfør & Fyhri, 2022	Norway	Incentive Program	Yes	No	Yes	No significant change
Sun et al., 2020	Netherlands	Natural Acquisition	No	No	Yes	Vehicle mode share by VKT decreased by 9.6%
Cairns et al., 2017	United Kingdom	Loan Program	No	No	No	Car mileage decreased by 20%
Bigazzi et al., 2025	Canada	Incentive Program	No	No	Yes	Car use decreased by 49 km/recipient/week

As shown in Table 1, the majority of the studies rely on self-reported data, with only two studies using GPS-based data collection (*22*, *29*). Self-reported travel data are subject to recall and social desirability biases, which can reduce the accuracy. In contrast, GPS data allow for more continuous measurement of travel behavior, enabling researchers to capture seasonal variation and assess longer-term changes in vehicle use and emissions (*3*, *22*, *33*).

Randomization is particularly important in evaluations because changes in VMT or VKT are likely to be endogenous with the decision to acquire an e-bike. While quasi-experimental designs can address some of these concerns, random assignment remains the most robust method for ensuring that unobserved confounders (such as environmental attitudes, or access to cycling infrastructure) are equal in treatment and control groups. This is essential for isolating the causal effect of e-bike acquisition on vehicle use.

Most of these studies were conducted in Europe with transportation systems that differ substantially from those found in the US. Findings from countries such as the Netherlands, where there is a large bicycling culture, should not be generalized to other settings (*16*). In the US, where baseline cycling rates are low and automobile dependence is high, the impact of e-bike adoption may differ substantially from those observed in high-cycling European contexts. Yet, to date, only one study with a quasi-experimental design has examined this effect in North America (*13*). Their study reports a decrease in car use following an incentive program, but it relies on self-reported travel diaries and does not employ randomization of the treatment (*13*). Thus, further research is needed to rigorously evaluate the effects of e-bike interventions in the US.

Finally, the existing literature varies widely in the type of e-bike interventions studied. Some studies examine natural adoption, with individuals independently choosing to purchase an e-bike without external incentives (*23*), while others evaluate outcomes under structured e-bike loan programs (*27*, *29*). Such loan programs often operate as short-term pilots, so their results may not reflect outcomes under more permanent, user-driven adoption models. In contrast, e-bike purchase subsidies are being adopted by many jurisdictions in North America (*15*). Thus, there is a growing need to evaluate whether these initiatives are leading to sustained reductions in vehicle use and emissions (*3*, *34*).

2.3. Study Contributions

There remains a lack of rigorous evidence on the causal impacts of e-bike rebate programs in North America on policy-relevant outcomes (*3*, *34*). This study addresses these gaps by evaluating a randomized e-bike rebate program in Washington State, using a pre-post design with treatment and control groups. Rebate recipients were randomly selected, and travel behavior was measured using GPS-based data collection. The minimum sample size was determined based on a power analysis to ensure effects were detectable.

By combining random assignment, high-frequency passively collected travel data, and a policy-relevant intervention, this study contributes novel empirical evidence on the behavioral impacts of e-bike rebate programs in the US context.

3. STUDY DESIGN

3.1. Participant Recruitment

3.1.1. WSDOT Rebate Program

In April 2025, the Washington State Department of Transportation (WSDOT) launched a statewide e-bike rebate program as a part of its broader climate and mobility agenda. The program was funded through a $5 million allocation from the Washington Climate Commitment Act, and aimed to promote e-bike adoption by reducing purchase costs for residents across the state (*8*). The University of Washington (UW) was contracted to evaluate the program's impact.

The program allocated 60% of rebate funds for income-qualified participants, defined as individuals with household incomes below 80% of their county's area median income, and 40% to non-income qualified applicants. Income-qualified individuals were eligible for $1,200 rebates, and non-income qualified individuals were eligible for $300 rebates. The rebates were redeemable exclusively at participating local bike shops, and all purchases were required to be made in person.

The application portal opened on April 9, 2025, and remained active for 14 days. The application process consisted of two stages. In the first stage, applicants provided basic demographic and contact information, indicated whether they wished to be considered for the $1,200 rebate, and selected their preferred e-bike type. Applicants who expressed interest in the $1,200 rebate were prompted to report their approximate household income to assess likely eligibility. After completing this stage, all applicants received a confirmation email with a link to the second stage.

The second stage of the application asked for additional demographic information and responses to four survey questions:

1. What is your primary mode of transportation?
2. Do you think you will buy an e-bike in the next year even if you do not receive a rebate?
3. How did you first find out about this program?
4. Can UW contact you about paid participation in a research project to evaluate this program?

After the application period closed on April 23, the WSDOT team randomly selected rebate recipients from applicants in both income categories. Selected individuals were notified and given 96 hours to submit documentation of eligibility. Income-qualified applicants (for the $1,200 rebate) were required to provide proof of income and Washington residency, and non-income-qualified applicants (for the $300 rebate) only needed to verify residency. Once authenticated by the WSDOT team, the participants received digital vouchers, which could be redeemed at participating bike shops through June 30, 2025.

Applicants who were not initially selected were notified on April 23 and placed on a waitlist. As some individuals did not submit their required documentation or did not meet the eligibility criteria, WSDOT conducted subsequent randomized drawings to fill unclaimed rebate slots. The dates and counts of these follow-up selections are summarized in Figure 1, aggregated by week.

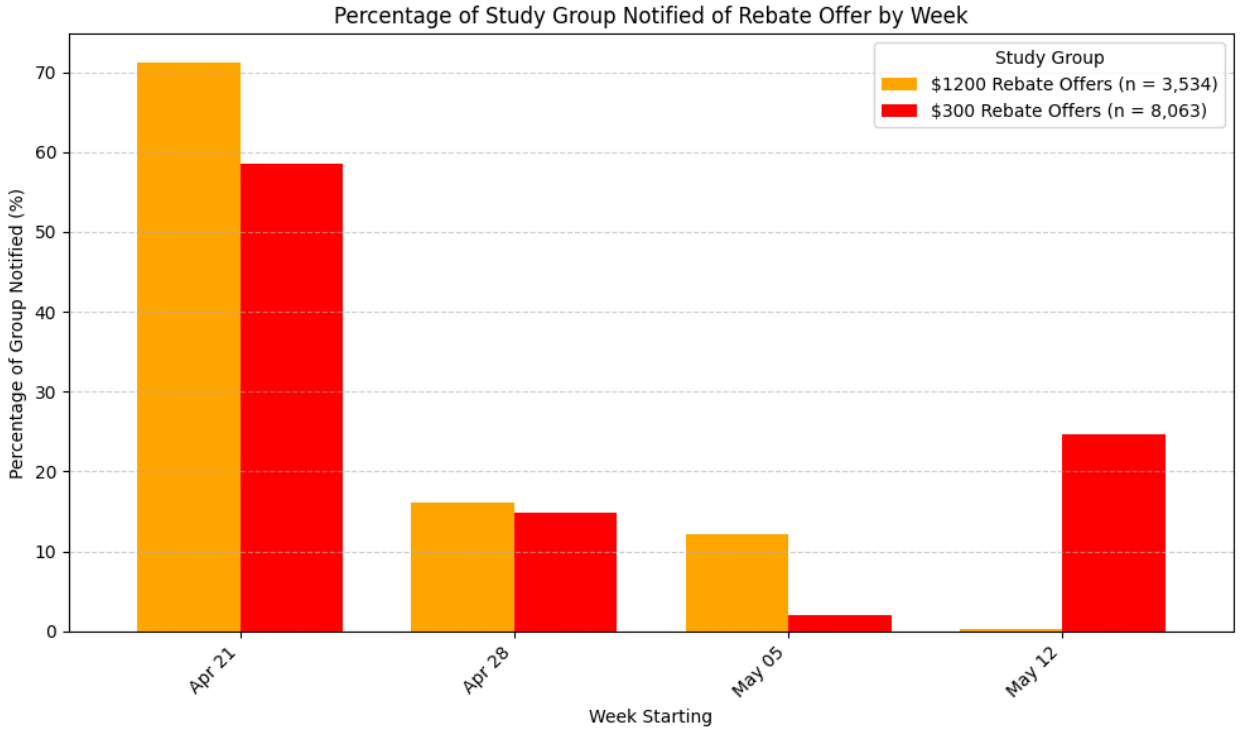


Figure 1 Percentage of study group notified of rebate offer by week

Figure 2 provides an overview of the e-bike rebate program and illustrates how the present study was integrated into its implementation.

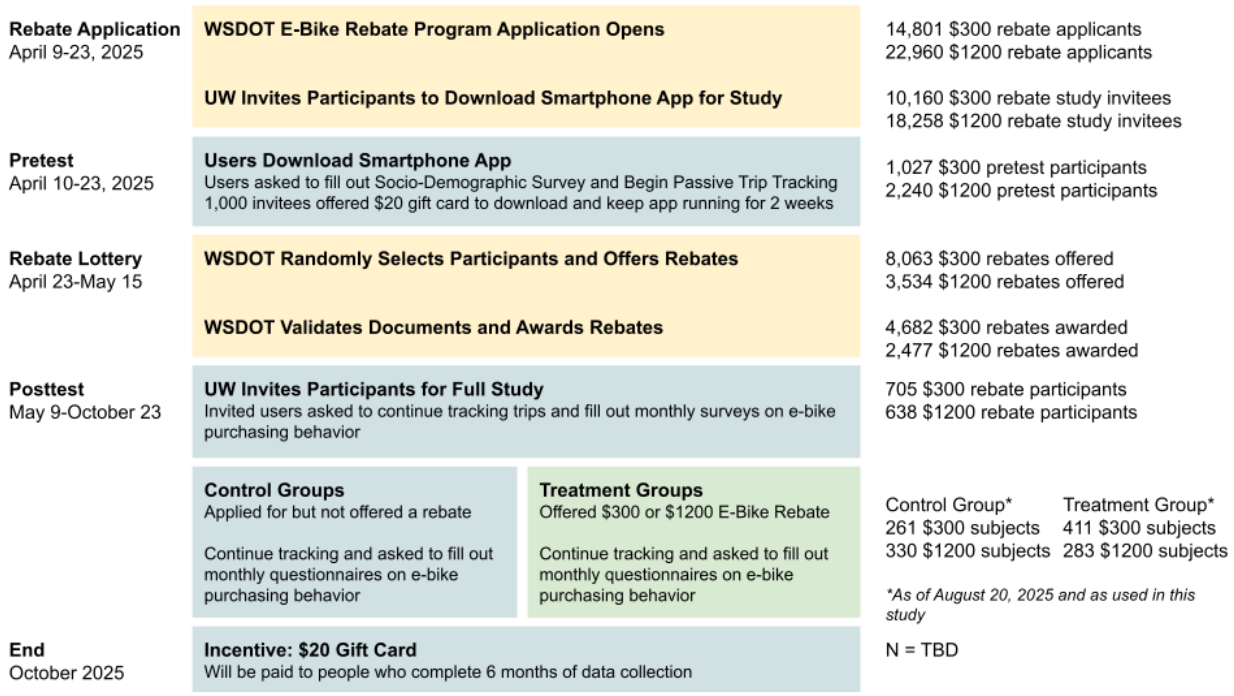


Figure 2 Timeline of the WSDOT e-bike rebate program and evaluation study

3.1.2. Recruitment of Pretest Study Participants

Pretest participants were recruited on a rolling basis during the rebate application window, after applicants had submitted both parts of the application but before rebate recipients were selected. Participants were contacted according to their response to the survey question asking if they were open to being contacted by the UW.

Eligible individuals were contacted via email and invited to participate in the pretest phase. The email explained that their contact information had been shared by WSDOT and invited them to download a smartphone app for passive trip tracking. The message included a download link, a unique token to access the app, and the research consent form. Participants were informed that, if selected and upon completion of the full study, they would be eligible to receive a $20 Tango gift card, redeemable at over 100 vendors (*35*). Figure 3 provides a sample of this recruitment email.

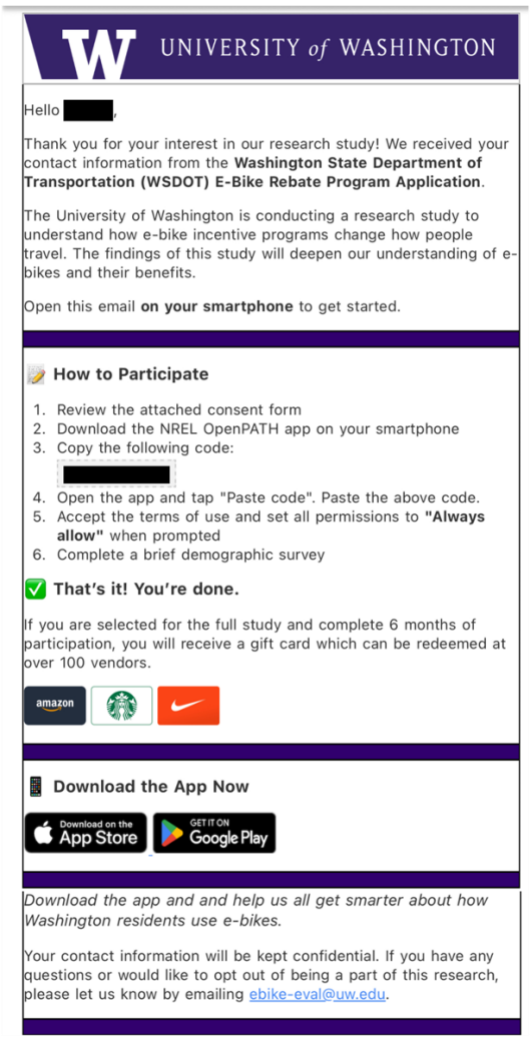


Figure 3 Sample recruitment email for pretest phase

Given the recruitment challenges associated with smartphone-based studies documented in prior research (*36*), 1,000 individuals invited on the first day of recruitment were randomly selected to receive a $20 Tango gift card as an upfront incentive. However, download rates among those who did not receive the upfront incentive were sufficiently high, and no further pretest incentives were offered.

3.1.3. Full Study Selections

Two weeks after the application closed and rebate selections were finalized, 705 applicants from the $300 rebate and 638 applicants from the $1,200 rebate were invited to participate in the full study. Target sample sizes were informed by power calculations using expected changes in VMT from Johnson et al. (2023) and accounting for 70% attrition in each group (*28*).

Full study invitees were randomly selected from the pretest pool after applying the following criteria:

1. They had downloaded and activated the smartphone tracking app during the pretest period.
2. They had not requested removal from the study.
3. Their app usage continued beyond the end of the application period (April 23).

All selected participants were asked to keep the app running for six months. As of August 20, 277 participants in the $300 group and 253 in the $1,200 group remain active in the study. Those who

complete the full study period (through October 2025) will be eligible for a $20 gift card. Table 2 presents a comparison of the study sample with the broader applicant pool and the Washington State population.

3.2. Comparison of Study, Program, and State Populations

TABLE 2 Summary statistics for study sample, program applicants, and state population

Question Statement[1]	Categories	Full Study Participants	All Rebate Applicants	Washington State Population (*37–39*)
How old are you?	Age	Median: 40	Median: 40	Median: 39
What is your gender?	Female	45%	42%	50%
	Male	51%	52%	50%
	Non-binary	3%	3%	Not provided as an option
	Other	0%	0%	Not provided as an option
	Prefer Not to Say	1%	3%	Not provided as an option
What is your race?	White	63%	59%	65%
	Black or African American	6%	4%	4%
	American Indian or Alaska Native	2%	2%	1%
	Asian	9%	13%	10%
	Native Hawaiian or Other Pacific Islander	1%	1%	1%
	Another	5%	4%	6%
	2 or more races	9%	8%	13%
	Prefer not to say	4%	9%	Not provided as an option
What is the highest degree or level of school you have completed?	Less than bachelor's degree	49%	Not Collected	41%
	Bachelor's degree or higher	51%		59%
Which of the following best describes your current employment status?	Employed	70%	Not Collected	61%
	Not employed	30%		39%
Which category best describes your household income before taxes from the last calendar year?	Under $50,000	44%	Not Collected	26%
	$50,000-$74,999	16%		14%
	$75,000-$99,999	10%		13%
	$100,000-$199,999	19%		30%
	≥ $200,000	6%		17%
	Prefer not to answer	4%		Not provided as an option
How many passenger vehicles are owned, leased, or available for regular use by the people who live in your household?	0	17%	Not Collected	4%
	1	37%		22%
	2	31%		39%
	3	10%		20%
	4+	4%		15%
County (Top 5, Based on Question	King County	37%	40%	30%
	Pierce County	13%	11%	11%
	Snohomish County	9%	10%	12%

[1] Question wording reflects the phrasing used in the smartphone app demographic survey.

'What is your ZIP code?')	Spokane County	8%	7%	7%
	Clark County	5%	5%	7%
Total Count		1,257[2]	37,761	7,642,355

Table 2 shows that full study participants closely resemble the broader pool of rebate applicants in age, gender, race, and vehicle ownership, indicating that selection into the study was not systematically biased. However, both the study sample and the applicant pool differ from the state population: they have lower household incomes, fewer vehicles, and are more likely to live in urban counties. These differences reflect the study's focus on individuals who applied for an e-bike rebate and completed multiple stages of the application process. Because of this, the findings may not generalize to the broader population. Section 8 discusses the implications for external validity in more detail.

3.2. Smartphone Tracking App

To measure respondents' travel behavior, we used the National Renewable Energy Laboratory's OpenPATH smartphone app. Most studies in this domain have primarily relied on self-reported travel diaries (Table 1), which can be limited in accuracy and completeness, especially for short-duration trips (*40*). In response to these limitations, several reviews on the environmental impacts of e-bikes have called for greater use of GPS-based data in evaluation studies (*3*, *41*).

Furthermore, recent advances in GPS-based data collection have improved the applicability of these methods for transportation mobility research (*42*). Unlike traditional surveys that rely on "active" data collection, GPS-based tools passively generate longitudinal travel data, improving accuracy while reducing respondent burden (*43*). Although early adoption of these methods raised concerns about sampling bias, due to the underrepresentation of older and lower-income individuals who may not have access to a smartphone, these concerns have lessened as 91% of Americans now own a smartphone (*44*). Moreover, any residual disparities in smartphone ownership are expected to be consistent within the randomly assigned treatment and control groups, minimizing threats to internal validity.

The OpenPATH app is an open-source platform designed to collect continuous travel diary data using GPS-based tracking. To preserve confidentiality, it relies on unique user tokens and prompts participants to complete a brief demographic survey upon entry. The app then passively records trips and uses a mode-detection algorithm to classify them by travel mode. OpenPATH supports multimodal data collection, including car, walking, bus, bicycling, air travel, and train.

The app has been validated in prior studies and demonstrates accuracy in detecting vehicle-based travel, with reported F-scores between 0.6 and 0.7 (*45*). Given this level of accuracy, and this study's focus on vehicle trips, participants were not asked to manually label trips or report trip purposes. To avoid influencing participants' behavior, we disabled the app's built-in dashboard that visualizes estimated greenhouse gas emissions based on trip data (see discussion in Section 8).

Figure 4 provides screenshots of the participant interface.

[2] As discussed in Section 4, sample sizes vary depending on the data used. This table includes all posttest invitees who recorded at least one trip using the tracking app.

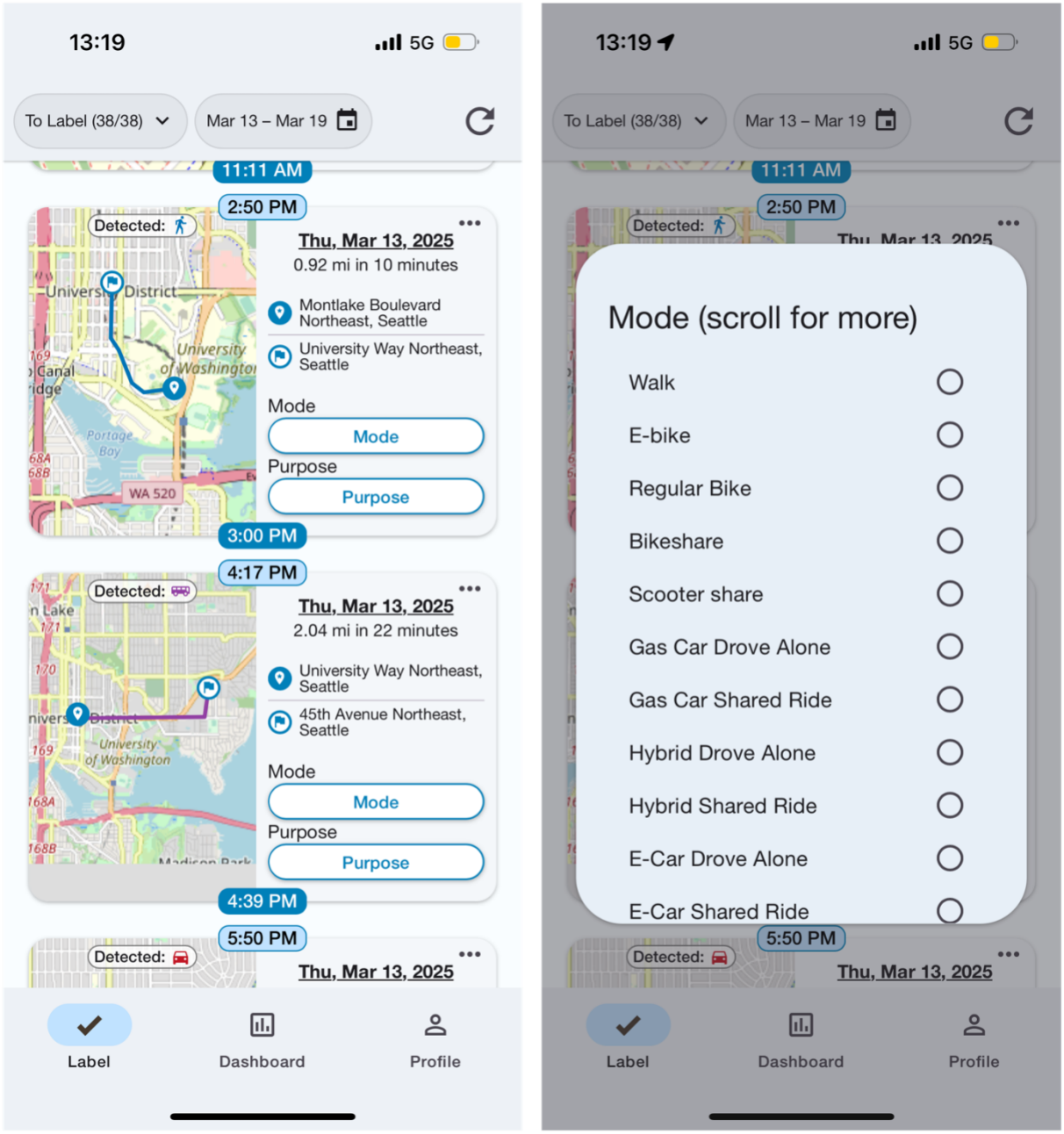


Figure 4 App interface with detected modes (left) and optional mode correction (right)

3.3. Monthly Surveys

To supplement the smartphone-based data collection, participants in the full study were also asked to complete five monthly surveys with the following questions:

1. "Did you own an electric bike before the start of the WSDOT e-bike rebate program (April 9, 2025)?"
2. "Regardless of whether you received an e-bike rebate or NOT, have you purchased an electric bike in the last month?".

If participants answered yes to the second question, they were asked to approximate the date of purchase.

Survey completion was required to remain eligible for the study incentive. Responses to these questions are presented in Section 4.1.

4. DATA

4.1. Survey Data

Participants responded to several survey questions at the time of application and in monthly follow-ups about their transportation habits and e-bike purchasing behavior. In expectation, randomization should produce balance across treatment and control groups within each rebate level. However, we examine whether this holds for selected observed covariates. Figures 5 and 6 presents the distribution of responses across study groups and reports results from chi-squared tests assessing whether any differences are statistically significant.

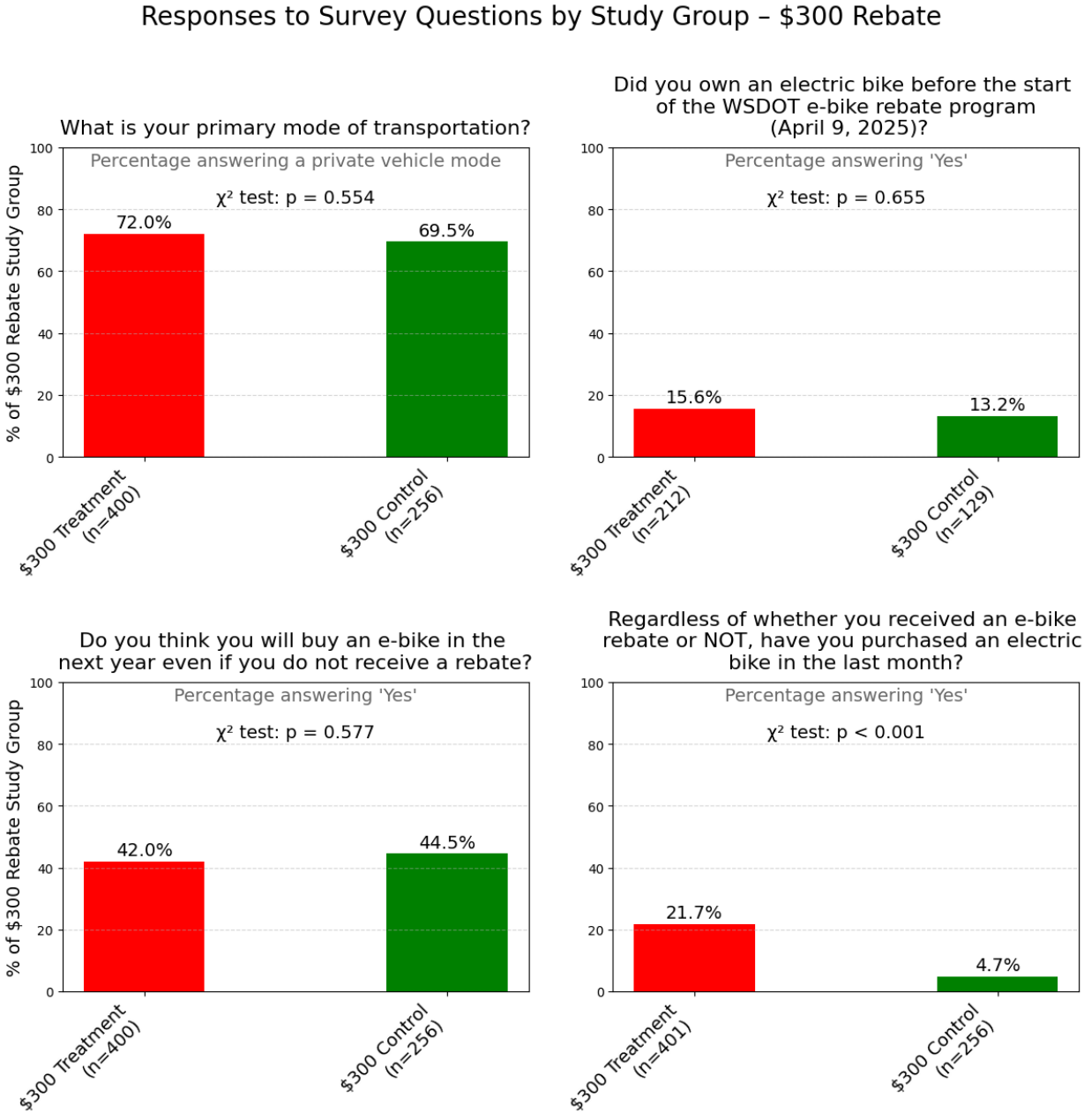


Figure 5 Distribution of Survey Responses by Treatment Status for $300 Rebate Group

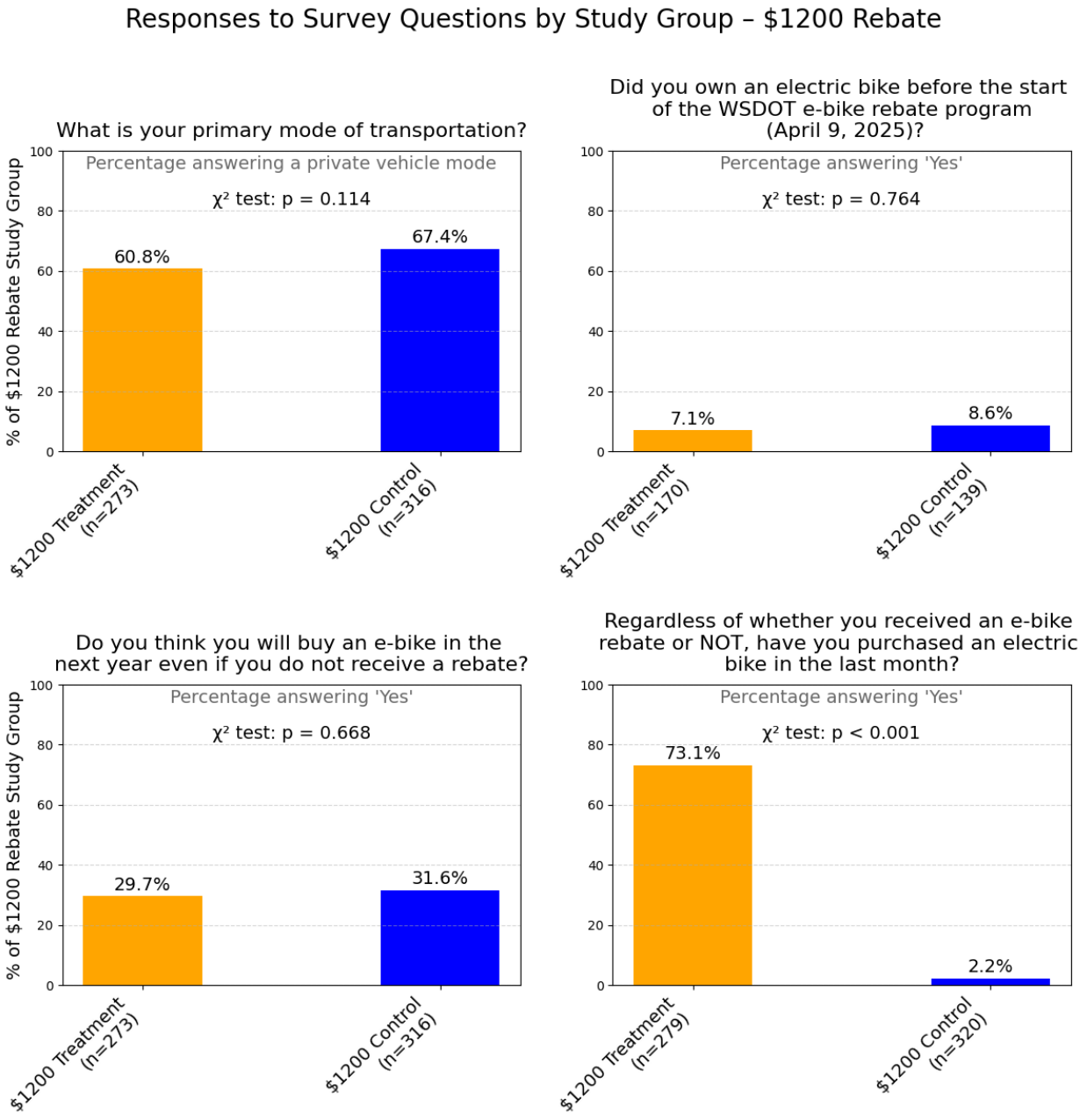


Figure 6 Distribution of Survey Responses by Treatment Status for $1,200 Rebate Group

As expected, most survey responses do not differ significantly between treatment and control groups at the $\alpha = 0.1$ level, indicating that randomization successfully balanced observable characteristics relating to e-bikes and prior transportation behavior. The exception is e-bike purchasing behavior, where significantly more individuals in the treatment group reported having purchased an e-bike. This suggests that offering a rebate is associated with increased e-bike adoption, a finding discussed further in Section 6.

The figures also highlight that a larger share of participants in the $1,200 treatment group purchased an e-bike compared to those in the $300 group, suggesting that the higher-value incentive was more effective at encouraging purchase.

4.2. App Data

Figure 7 shows the number of users generating trip data each day on the OpenPATH app. Participation peaked around the end of the application period, coinciding with the first round of rebate selections. Because part our analysis evaluates changes in VMT, the sample size for each study group depends on how the before and after periods are defined. For example, defining the pretest period based on the first rebate selection date yields fewer participants than using the last selection date. We discuss the implications of this timing choice further in Section 6.

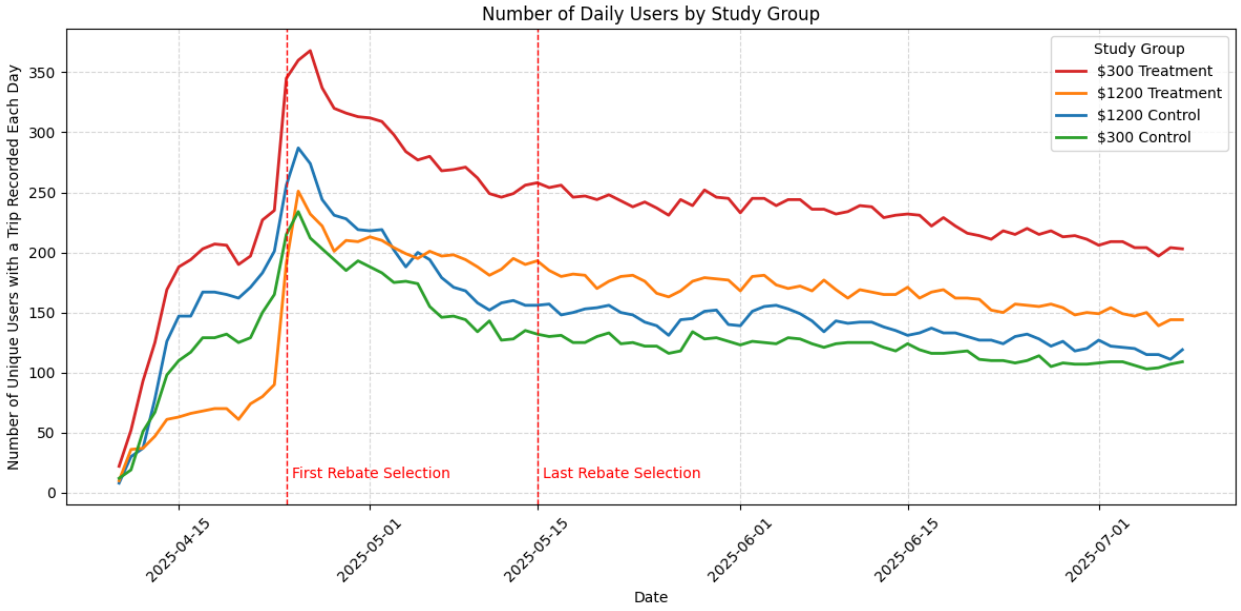


Figure 7 Daily number of active app users, as measured by the unique users with a trip recorded

Across the full study period and across our study participants, the OpenPATH app recorded a total of 991,271 trips over 140 days of data collection. 249,902 of these trips were predicted by OpenPATH's built-in classifier as the "car" mode, which is the primary data used in this study.

To improve the data quality of these vehicle trips, we applied a speed-based filter. The maximum posted speed limit in Washington State is 70 mph, with excessive speeding defined as 10 mph or more over that limit (*46*, *47*). Accordingly, we excluded all trips with an average speed greater than 80 mph, calculated as total trip distance divided by duration, reducing the number of trips by 55.

5. METHODS

We conduct two principal analyses to address our two research questions. First, we estimate the degree to which offering applicants an e-bike rebate affects VMT. Second, we estimate the amount by which purchasing an e-bike affects VMT.

5.1. Estimating the Effect of E-Bike Rebate Offers on VMT

To evaluate the impact of e-bike rebate offers on VMT, we use a linear regression framework to compare outcomes between the treatment group and the control group.

The treatment group is defined as individuals who were offered a rebate, regardless of whether they ultimately received it. This definition preserves the randomized assignment generated by the lottery selection. In contrast, actual voucher awards were conditional on eligibility verification and documentation, which may introduce endogeneity. For example, individuals who were offered a $300 rebate may have declined it due to lower motivation, which may also be correlated with vehicle use. By focusing on rebate offers, we retain the exogenous variation generated by the random selection process.

The effect of rebate offers on VMT is estimated separately for each rebate group using the following panel regression specification:

$$VMT_{it} = \alpha_i + \lambda_t + \beta \times DiD_{it} + \varepsilon_{it}, \quad \text{Eq. 1}$$

where the dependent variable, VMT_{it}, is the vehicle-miles traveled for individual $i \in N$ on calendar day $t \in T$. The key independent variable, DiD_{it}, is an interaction term equal to 1 if individual is in the treatment group and the trip date is after rebate notification, and 0 otherwise. ε_{it} is the error term that captures the omitted variables.

To control for unobserved heterogeneity, we include α_i to account for individual fixed effects and λ_t to account for calendar day fixed effects, which captures changes due to seasonality or holidays that could affect travel across the full study sample.

5.2. Identification of the Effect of Purchasing an E-Bike on VMT

To identify the effect of purchasing an e-bike on VMT, we use an instrumental variable, or two-stage least squares (2SLS) approach. The treatment of interest (e-bike purchasing) is considered endogenous with the outcome (change in VMT) since unobserved covariates may be correlated with both e-bike purchasing behavior and change in VMT (e.g., environmental attitudes). Thus, the instrumental variable approach allows us to understand this behavior, leveraging a randomized intervention. Our instrument is being offered an e-bike rebate (i.e., selection in the lottery) and the treatment is e-bike purchase. The 2SLS equations are shown below:

$$\overline{\Delta VMT_i} = \beta_0 + \beta_1 D_i + \varepsilon_2 \quad \text{Eq. 2}$$

$$D_i = \pi_0 + \pi_1 Z_i + \varepsilon_1 \quad \text{Eq. 3}$$

where D_i is the e-bike purchasing behavior for person $i \in N$, Z is the selection in the rebate lottery for person $i \in N$, and $\overline{\Delta VMT_i} =$ is the outcome of interest, calculated as follows:

$$\overline{\Delta VMT_i} = \frac{\sum_{t \in After} d_{it}}{N_{i,After}} - \frac{\sum_{t \in Before} d_{it}}{N_{i,Before}} \quad \text{Eq. 4}$$

$\overline{\Delta VMT_i}$ is the change in average daily VMT for individual i, d_{it} is the total vehicle distance for individual i on day t, and $N_{i,After}$ and $N_{i,Before}$ are the number of valid observation days in the before and after periods, respectively. The before period starts at the participant's enrollment in the study and continues until the the treatment is applied, defined by an intervention date; the after period spans from the intervention date to their last observed trip (of any mode). This measure is sensitive to how the intervention date is defined, since rebate offers were distributed in multiple waves.

For the instrumental variable analysis to hold, the following must be met:

$$Cov[\varepsilon_1, Z] = 0 \quad \text{Eq. 5}$$
$$Cov[\varepsilon_2, Z] = 0 \quad \text{Eq. 6}$$
$$\pi_1 \neq 0 \quad \text{Eq. 7}$$

In other words, Eq. 5 requires that the instrument is not correlated with any omitted variables that influence D. Since the instrument is truly randomized, this assumption is expected to hold. Eq. 6 requires that the instrument only affects the outcome through the effect on the treatment. It is unlikely that being selected for an e-bike rebate offer would affect trip making or car ownership, except by affecting e-bike ownership, as discussed further in Section 7. Finally, Eq. 7 requires requires that the instrument has a sufficiently strong (non-zero) effect on e-bike purchasing behavior.

6. RESULTS

6.1. Effect of E-Bike Rebate Offer on VMT

To evaluate the impact of offering an e-bike rebate on daily VMT, we analyze separate panel regression models for the $300 and $1,200 rebate groups. These models, reported in Table 3, estimate the average treatment effect of being offered an e-bike rebate on daily VMT with two outcomes: (1) total daily VMT, and (2) daily VMT among participants who reported "car" as their primary mode of transportation. Days with no trips are treated as missing, while days with trips using non-car modes are treated as having zero daily VMT. Trips occurring on the day of the intervention (rebate notification) are excluded from the analysis.

TABLE 3 Estimated effects and standard errors of e-bike rebate offers on VMT

Model Type	Effect of Rebate Offer on Daily VMT: Panel Regression			
Model Outcome	Daily VMT		Daily VMT For Car as "Primary Mode"	
Rebate Group	$300	$1200	$300	$1200
Intercept	28.972***	30.668***	42.798***	41.100***
(Std. Error)	(0.753)	(1.102)	(1.102)	(1.566)
Rebate Offer	2.720**	-1.801	0.892	2.374
(Std. Error)	(1.274)	(1.993)	(1.868)	(3.168)
R^2	< 0.000	< 0.000	< 0.000	< 0.000
Treatment Group Size	411	283	287	165
Control Group Size	261	330	178	213

***: 2-tail significance at α=0.10. **: 2-tail significance at α=0.05. ***: 2-tail significance at α=0.01.**

Table 3 shows that for three of the models, the estimated effect of being offered an e-bike rebate is not statistically significant at conventional levels (α = 0.10). The exception is a slight increase in VMT for the $300 rebate group in the daily VMT specification; however, this effect does not persist in robustness checks. These results suggest that, within approximately three months of the rebate offer, there is no detectable causal effect of the rebate on reducing total daily VMT.

6.2. Effect of E-Bike Purchase on VMT

To evaluate the impact of e-bike purchases on changes in daily VMT, we first calculate the average change in daily VMT per person. This change is defined as differences in travel behavior in the "before" and "after" period, and the results are sensitive to how the intervention date (the point separating these periods) is chosen.

All applicants were informed of their initial rebate offer status on April 23, 2025, and those who were not offered a rebate were placed on a waitlist. As shown in Figure 1, some waitlisted applicants were subsequently removed from the waitlist and offered a rebate, with the final notification of this type occurring on May 15, 2025. Rebate redemption was nominally allowed for 45 days from the date of the rebate was sent, but extensions were granted to most participants. The final date that any rebate could be redeemed was June 30, 2025.

The selection of the intervention date for the analysis has empirical consequences because participants did not all receive the treatment on a single date. For example, if the analysis uses only the purchase date as the intervention, changes in travel behavior that occur following rebate notification may be misclassified as a part of the "before" period. To address this, we vary the intervention date and examine how estimates change across different specifications.

Table 4 presents the 2SLS estimates of the impact of e-bike purchases on average daily VMT. We report results for three specifications: (1) using the initial notification date as the intervention date, (2) using the final notification date, (3) excluding trips that occurred between the start of the rebate notification period and the last day to redeem a rebate. For all model specifications, we exclude trips on the date of the intervention. Estimates are reported separately for the $300 and $1,200 rebate groups. Sample sizes vary depending on the availability of valid trip data in the before and after periods.

TABLE 4 Estimated effects and standard errors of e-bike rebate offers and purchases on VMT

Model Type	Effect of E-Bike Purchase on Change in Average Daily VMT: 2SLS Analysis					
Intervention Date Description	Single Intervention Date for All Participants		Individualized Intervention Date for Each Participant		Single Intervention Date for All Participants, Excluding Trips between April 23 and June 30	
Before Period	All trips prior to May 15		*For e-bike purchasers:* All trips prior to e-bike purchase *For non-purchasers:* All trips prior to May 15		All trips prior to April 23	
After Period	All trips after May 15		*For e-bike purchasers:* All trips after e-bike purchase *For non-purchasers:* All trips after May 15		All trips after June 30	
Rebate Group	$300	$1200	$300	$1200	$300	$1200
Intercept	1.05	4.523***	1.529	6.079***	1.44	4.944*
(Std. Error)	(2.135)	(1.626)	(2.13)	(2.258)	(3.418)	(2.735)
E-Bike Purchase	0.283	-2.114	2.074	-2.137	10.658	1.882
(Std. Error)	(10.237)	(2.762)	(10.49)	(3.495)	(16.790)	(8.722)
R^2	< 0.000	0.006	< 0.000	0.005	< 0.000	< 0.000
Treatment Group Size	266	203	261	199	127	48
Control Group Size	139	175	138	175	72	88
F-statistic for first-stage regression	23.4	563.3	22.5	548.8	14.1	362.6

***: 2-tail significance at α=0.10. **: 2-tail significance at α=0.05. ***: 2-tail significance at α=0.01.**

Across all 2SLS models, the instrument (rebate offer) is strong, with first-stage F-statistics exceeding 10 (Table 4). These results support the validity of the 2SLS design and confirm that both rebate offers

effectively induced variation in e-bike purchases, though the effect is much stronger with the $1,200 rebate.

The coefficients for e-bike purchase in the models show no statistically significant effects on total daily VMT. This suggests that while the randomized rebate offers successfully induced e-bike purchases, those purchases did not translate into reductions in VMT within the first three months of the rebate offer for either group.

7. INTERNAL AND EXTERNAL VALIDITY

7.1. Internal Validity

Several factors pose potential threats to the internal validity of this study, particularly those related to the accuracy of the app-based measurement and the assumptions underlying our causal identification strategy.

First, while the NREL OpenPATH app is a scalable and efficient way to collect high-resolution travel data, its validity depends on users consistently carrying their smartphones while traveling. Some participants may have installed the app on secondary devices, or did not carry their phones during travel, but our analysis assumes that days without recorded tracking data represent days with no trips, which may lead to an underestimation of the true VMT.

Second, the estimation of the effect of e-bike purchases on VMT relies on the instrumental variable approach, where selection for a rebate offer serves as the instrument. As discussed in Section 5.2, valid causal inference using IV requires that the instrument satisfy the exclusion restriction such that it only affects the outcome through the treatment (i.e., e-bike purchase). However, this assumption may be violated if individuals in the control group chose to purchase a vehicle they had previously deferred buying, due to the prospect of receiving an e-bike rebate. We do not test for this behavior directly, so it remains a potential source of bias.

Third, while rebate assignment was randomized, observability of outcomes was not. Participants could uninstall or disable the app at any time, and we observe that attrition was higher in the control group than in the treatment group. Although incentives are only provided at the end of the study to encourage continued participation, differences in dropout behavior may bias estimates of the treatment effect, however we offer no guess as to the size or direction of any such effect.

7.2. External Validity

The main threat to external validity stems from the self-selected nature of the study population. Participants applied to a program specifically aimed at e-bike adoption, likely overrepresenting individuals already interested in reducing vehicle use or exploring alternative modes.

As shown in Table 2, participants also differ from the broader Washington population: they are more likely to live in urban areas, have lower incomes, and own fewer vehicles, all of which are factors that may make e-bikes more appealing. While treatment and control groups are balanced within rebate levels, the sample as a whole is not representative of the general population, and the results should not be generalized to individuals without prior interest in e-bikes.

8. CONCLUSION AND IMPLICATIONS

This study examined the impact of Washington State's e-bike rebate program on participants' vehicle miles traveled (VMT). Using panel regression and two-stage least squares (2SLS) models, we evaluated the effects of both receiving a rebate offer and purchasing an e-bike.

Our findings indicate that neither the offer of an e-bike rebate nor the purchase of an e-bike led to statistically significant decrease in mean daily VMT within the first three months after rebate offer. These null results are consistent across model specifications and robust to different definitions of the intervention date.

These findings align with a broader body of literature reporting null effects of e-bike adoption on vehicle use, even in Northern European contexts. For example, a recent meta-analysis of experimental studies in Europe concluded that e-bike use does not significantly reduce car use (*3*), despite mixed evidence in individual studies (*13*, *22–24*, *27*, *29*). The findings of this study, and the lack of consistency across different settings, suggests that the effectiveness of e-bike incentives in reducing vehicle use may be limited in the US setting where this study took place.

Many prior studies finding reductions in VMT focus on e-bike loan programs, which may prompt different behavioral responses than subsidized purchases. Loan programs offer short-term access and may encourage immediate changes in travel behavior. In contrast, a rebate requires a larger upfront commitment, and behavior may shift more gradually as participants integrate the e-bike into their routines. Our analysis captures only short-term effects–within four months of the rebate offer–when some participants may still be adjusting their travel habits. The full impact may take longer to appear, and longer-term follow-up is needed to assess whether VMT reductions show up over time.

A key contribution of this study is the separate evaluation of the effect of being offered a rebate and the effect of purchasing an e-bike. This distinction is important for policy design, as public agencies can offer incentives but do not control subsequent purchasing behavior. While rebate offers successfully induced e-bike purchases, neither the $300 nor the $1,200 rebate offer produced a statistically significant reduction in VMT, indicating that financial incentives for e-bikes may have limited ability to shift travel behavior and reduce emissions.

Nevertheless, the observed uptake of e-bikes might still point to other meaningful benefits of e-bike adoption. Even if total daily VMT does not decline, e-bike use may improve mobility, promote physical health, and increase access. Further research could help policymakers better understand the impact of e-bike purchasing subsidies on these other outcomes.

ACKNOWLEDGMENTS

This work was supported by the Washington State Department of Transportation and the Pacific Northwest Transportation Consortium.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: D. MacKenzie, R. Singh, D. Malarkey; data collection: R. Singh, D. MacKenzie, D. Malarkey; analysis and interpretation of results: R. Singh, D. MacKenzie, D. Malarkey; draft manuscript preparation: R. Singh, D. MacKenzie, D. Malarkey. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. C. Bennett, J. MacArthur, C. R. Cherry, L. R. Jones, Using e-bike purchase incentive programs to expand the market–North American trends and recommended practices. (2022).

2. Mode Shift | ACEEE. https://database.aceee.org/city/mode-shift.

3. G. Chevance, J. Bourne, L. Foley, J. Green, H. B. Sundfør, A. Fyhri, P. Bernard, E-bikes and travel behaviour change: systematic review of experimental studies with meta-analyses. *Transport Reviews* **45**, 433–454 (2025).

4. B. C. Langford, C. R. Cherry, D. R. Bassett Jr, E. C. Fitzhugh, N. Dhakal, Comparing physical activity of pedal-assist electric bikes with walking and conventional bicycles. *Journal of Transport & Health* **6**, 463–473 (2017).

5. H. B. Bjørnarå, S. Berntsen, S. J. te Velde, L. Fegran, A. Fyhri, B. Deforche, L. B. Andersen, E. Bere, From cars to bikes – the feasibility and effect of using e-bikes, longtail bikes and traditional bikes for transportation among parents of children attending kindergarten: design of a randomized cross-over trial. *BMC Public Health* **17**, 981 (2017).

6. J. E. Bourne, S. Sauchelli, R. Perry, A. Page, S. Leary, C. England, A. R. Cooper, Health benefits of electrically-assisted cycling: a systematic review. *International Journal of Behavioral Nutrition and Physical Activity* **15**, 116 (2018).

7. E. Fishman, C. Cherry, E-bikes in the Mainstream: Reviewing a Decade of Research. *Transport Reviews* **36**, 72–91 (2016).

8. D. Malarkey, D. Prendez, D. MacKenzie, "Policy Brief on Designing and Evaluating Electric Bicycle Incentive Programs" (University of Washington, Active Transportation Division Washington State Department of Transportation, 2024).

9. A. Riiser, E. Bere, L. B. Andersen, S. Nordengen, E-cycling and health benefits: A systematic literature review with meta-analyses. *Front. Sports Act. Living* **4** (2022).

10. A. Saki, A. Bigazzi, Industry Stakeholder Perspectives on the Adoption of Electric Bicycles in British Columbia. *Transportation research record* **2673**, 1–11 (2019).

11. J. MacArthur, J. Miller, I. Swain, E-bike Lending Libraries: Trends and Practices in The United States. (2025).

12. R. Rossi, E-Bike Rebates and Vouchers in the US (November 2024), *Upway United States* (2024). https://upway.co/blogs/news/what-ebike-rebates-and-vouchers-nov2024.

13. A. Bigazzi, A. Hassanpour, E. Bardutz, Travel behaviour and greenhouse gas impacts of income-conditioned e-bike purchase incentives. *Transportation Research Part D: Transport and Environment* **138**, 104519 (2025).

14. City and County of Denver, PeopleForBikes, Bicycle Colorado, Ride Report, Rocky Mountain Institute, "Denver's 2022 Ebike Incentive Program: Results and Recommendations" (2023); https://5891093.fs1.hubspotusercontent-na1.net/hubfs/5891093/Denvers%202022%20Ebike%20Incentive%20Program%20Results%20and%20Recommendations.pdf?__hstc=137334191.fc3bb347ecd265673c5b31dc2f210b38.1693353186

243.1693353186243.1693353186243.1&__hssc=137334191.1.1693353186243&__hsfp=1538425095&hsCtaTracking=f6c129d8-5739-4033-ae8d-38d8a4d7d52b%7C4d3304a1-3f00-438b-b2bd-bd69b50cfdb9.

15. E-Bike Research | TREC. https://trec.pdx.edu/e-bike-research.

16. M. De Haas, M. Kroesen, C. Chorus, S. Hoogendoorn-Lanser, S. Hoogendoorn, E-bike user groups and substitution effects: evidence from longitudinal travel data in the Netherlands. *Transportation* **49**, 815–840 (2022).

17. M. Kroesen, To what extent do e-bikes substitute travel by other modes? Evidence from the Netherlands. *Transportation Research Part D: Transport and Environment* **53**, 377–387 (2017).

18. P. Rérat, D. Marincek, E. Ravalet, How do e-bikes compete with the other modes of transport? Investigating multiple dimensions of a modal shift. *Applied Mobilities*, 1–14 (2024).

19. J. E. Bourne, A. R. Cooper, P. Kelly, F. J. Kinnear, C. England, S. Leary, A. Page, The impact of e-cycling on travel behaviour: A scoping review. *Journal of Transport & Health* **19**, 100910 (2020).

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

21. A. Fyhri, N. Fearnley, Effects of e-bikes on bicycle use and mode share. *Transportation Research Part D: Transport and Environment* **36**, 45–52 (2015).

22. H. Sundfør, A. Fyhri, The effects of a subvention scheme for e-bikes on mode share and active mobility. *Journal of Transport & Health* **26**, 101403 (2022).

23. Q. Sun, T. Feng, A. Kemperman, A. Spahn, Modal shift implications of e-bike use in the Netherlands: Moving towards sustainability? *Transportation Research Part D: Transport and Environment* **78**, 102202 (2020).

24. H. B. Sundfør, S. Berntsen, E. T. Bere, A. Fyhri, The effects of subsidising e-bikes on mode share and physical activity - A natural experiment. *Journal of Transport & Health* **35**, 101752 (2024).

25. D. Ton, D. Duives, Understanding long-term changes in commuter mode use of a pilot featuring free e-bike trials. *Transport Policy* **105**, 134–144 (2021).

26. A. Bigazzi, K. Wong, Electric bicycle mode substitution for driving, public transit, conventional cycling, and walking. *Transportation Research Part D: Transport and Environment* **85**, 102412 (2020).

27. S. Cairns, F. Behrendt, D. Raffo, C. Beaumont, C. Kiefer, Electrically-assisted bikes: Potential impacts on travel behaviour. *Transportation Research Part A: Policy and Practice* **103**, 327–342 (2017).

28. N. Johnson, D. T. Fitch-Polse, S. L. Handy, Impacts of e-bike ownership on travel behavior: Evidence from three northern California rebate programs. *Transport Policy* **140**, 163–174 (2023).

29. A. Söderberg F.K.A. Andersson, E. Adell, L. Winslott Hiselius, What is the substitution effect of e-bikes? A randomised controlled trial. *Transportation Research Part D: Transport and Environment* **90**, 102648 (2021).

30. D. B. Rubin, For objective causal inference, design trumps analysis. *The Annals of Applied Statistics* **2**, 808–840 (2008).

31. A. Fyhri, H. Beate Sundfør, Do people who buy e-bikes cycle more? *Transportation Research Part D: Transport and Environment* **86**, 102422 (2020).

32. J. Gao, A. Ranjbari, D. MacKenzie, Would being driven by others affect the value of travel time? Ridehailing as an analogy for automated vehicles. *Transportation* **46**, 2103–2116 (2019).

33. S. Handy, B. van Wee, M. Kroesen, Promoting Cycling for Transport: Research Needs and Challenges. *Transport Reviews* (2014).

34. H. Nosratzadeh, D. Bhowmick, A. B. Ríos Carmona, L. Pearson, J. Thompson, T. Thai, B. Beck, Implementing Without Evaluating: The Missing Link in Understanding the Effectiveness of Financial Incentive Programs for E-Bikes. Social Science Research Network 4950963 [Preprint] (2024). https://doi.org/10.2139/ssrn.4950963.

35. Gift Card Rewards and Services | Tango. https://www.tangocard.com/.

36. A. Meister, N. F. Bashan, R. Basu, X. Shen, R. Q. Wang, A. Sevtsuk, The BostonWalks study: a longitudinal travel survey using smartphone tracking. *Transportation*, 1–31 (2025).

37. Washington State Office of Financial Management, "April 1 Population of Cities, Towns, and Counties" (2025).

38. Washington State Transportation Commission, "Washington State Transportation Commission Road Usage Charge Assessment" (2014); https://wstc.wa.gov/wp-content/uploads/2019/10/STS-2014-RUC-June-Novsurvey-Report-final.pdf.

39. Washington - Census Bureau Profile. https://data.census.gov/profile/Washington?g=040XX00US53#populations-and-people.

40. B. Blanc, M. Figliozzi, K. Clifton, How Representative of Bicycling Populations Are Smartphone Application Surveys of Travel Behavior? *Transportation Research Record* **2587**, 78–89 (2016).

41. J. MacArthur, N. Kobel, J. Dill, Z. Mummuni, "Evaluation of an Electric Bike Pilot Project at Three Employment Campuses in Portland, Oregon" (Portland State University, 2017; http://archives.pdx.edu/ds/psu/19469).

42. C. Chen, J. Ma, Y. Susilo, Y. Liu, M. Wang, The promises of big data and small data for travel behavior (aka human mobility) analysis. *Transportation Research Part C: Emerging Technologies* **68**, 285–299 (2016).

43. C. Harding, "From Smartphone Apps to In-person Data Collection: Modern and Cost-effective Multimodal Travel Data Collection for Evidence-based Planning," thesis, University of Toronto (Canada), Canada -- Ontario, CA (2019).

44. Pew Research Center, “Mobile Fact Sheet” (2024); https://www.pewresearch.org/internet/fact-sheet/mobile/.

45. G. Kosmacher, K. Shankari, Evaluating the interplay between trajectory segmentation and mode inference error. *Transportation research record* **2678**, 32–49 (2024).

46. J. Goldstein-Street, Washington to rein in fast drivers with speed limiters • Washington State Standard, *Washington State Standard* (2025). https://washingtonstatestandard.com/2025/05/12/washington-to-rein-in-fast-drivers-with-speed-limiters/.

47. Washington Spatial Data, WSDOT - Roadway Data Speed Limits, (2025); https://geo.wa.gov/datasets/WSDOT::wsdot-roadway-data-speed-limits/about.