Impacts of E-bike Ownership on Travel Behavior: Evidence from three Northern California rebate programs

January 2023

A Research Report from the National Center for Sustainable Transportation

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16. Abstract
E-bike incentive programs are being utilized across the United States to encourage the adoption of active transportation. This study assesses the impacts of three e-bike rebate programs in Northern California using survey results gathered by each agency. Three research questions are answered through this study: "How has e-bike ownership impacted the mode choices, trip purpose, and travel frequency of our sample?", "How much do e-bike rebate recipients reduce their mobile greenhouse gases (GHGs)?", and "How did the design of each program impact who was able to participate and the program outcomes?". To answer these, the research team merged and cleaned the survey data from the three programs, explored descriptive statistics, and undertook an estimation of GHG emissions reductions. This analysis highlighted changes in travel behavior, car travel replacement, the impact of program designs, and various equity impacts. E-bike recipients reported more regular bike use after getting their e-bike, although their frequency of bike travel began to decline in the long-term. Respondents also reported high rates of occasional car trip replacement (1-3 times per week and 1-3 times per month). The vast majority of e-bike use in the sample was for recreational travel. Although the GHG reductions analysis estimated a monthly diversion of 12-44 kilograms of CO_2 per rebate participant. The authors conclude with an equity analysis that explores how program design influenced who participated in these rebate programs. This found that low-income requirements are successful at targeting those with the most need for financial assistance, though these requirements do not help meet other equity metrics by association.

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NCST

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EXECUTIVE SUMMARY

Benefits of e-bicycling have motivated many cities and countries in Europe to incentivize e-bicycling through a wide variety of intervention programs. Until recently, similar incentives have been scant in the United States. Local e-bike incentive programs have emerged across the country, mostly notably three programs starting in 2020 and 2021 in California by Contra Costa County, Redwood Coast Energy Authority, and Peninsula Clean Energy. These programs include a wide variety of approaches that can be used to inform other local programs, but also help understand more widespread programs being proposed at the state and federal levels.

Given the increase in demand and incentives for e-bicycling; this project evaluates the behavioral effects (change in bicycling, driving, use of transit) of these incentives to help guide future policy interventions for e-bicycling. We examine these changes based on survey data and propose future study designs for more in-depth analyses and evaluations of e-bike incentives. Through this research we hope to answer three research questions: "How has e-bike ownership impacted the mode choices, trip purpose, and travel frequency of our sample?", "How much do e-bike rebate recipients reduce their mobile GHGs?", and "How did the design of each program impact who was able to participate and the program outcomes?". To answer these, we explored survey responses through descriptive statistics and undertook an estimation of GHG emissions reductions. We decided against more complex data analysis given data quality issues that arose during the cleaning process. Despite that, our analysis revealed changes in travel behavior, car travel replacement, the impact of program designs, and various equity impacts.

E-bike recipients reported more regular bike use after getting their e-bike, although their frequency of bicycle use began to decline in the long-term while still remaining above previous rates. Respondents also reported high rates of occasional car trip replacement (1-3 times per week and 1-3 times per month), indicating that e-bikes were substituting occasional car trips. While there was evidence of regular car trip replacement, the vast majority of e-bike use in our sample was for recreational travel. Given that this data was collected during the COVID-19 pandemic as many restrictions were still in place these high rates of reported recreational travel was unsurprising but created concern surrounding emissions benefits. Our GHG reductions analysis estimated a monthly diversion of 12-44 kilograms of CO_2 per rebate participant, which was similar to the GHG emissions reductions observed in other research. We conclude with an equity analysis that explores how program design influenced who participated in these rebate programs. This found that the program requirements are successful at targeting those with low incomes, though these requirements did not seem to result in very large participation from Black, Indigenous, and People of Color.

Introduction

Public and private agencies across North America have been experimenting with promoting micromobility through financial incentive programs. Specifically, electric bike (e-bike) rebate programs have been used as tools to address climate, urban development, and public health goals. These programs provide financial assistance for the purchase of e-bikes, often through a post-purchase payment or discount at the point of purchase. This research explores how several e-bike rebate programs in Northern California have impacted the travel behavior of their participants. By better understanding the impacts of e-bike ownership, we can better understand the viability of these incentive programs as a tool to combat climate change, promote public health, and encourage equity in cycling.

Why E-bikes?

E-bikes are electronically assisted bicycles that utilize an electric motor to either add power to the user's pedal or propel the bike via a throttle that the rider can control. These battery-powered motors are rechargeable and allow riders to reach speeds that average around 20-30 mph, helping riders up hills and in reaching farther destinations. There are many varieties of e-bikes, including standard, recreational, cargo, and conversion kits that can add electric assist to non-electric bikes. However, in California, all are regulated using a 3-class system. Class 1 and 2 e-bikes have speeds limited to 20 mph, while class 3 e-bikes are able to reach speeds of 28 mph. Class 2 e-bikes are unique in that they have throttles allowing the user to power the bike without use of the pedals. Certain states and localities may restrict the use or sale of specific e-bikes based on perceived safety concerns or other factors (Bennett et al., 2022).

E-bikes have been widely celebrated for improving the accessibility of biking by decreasing the physical barrier to bicycling and improving rider enjoyment. This enjoyment has been referred to as the "fun factor" of e-bikes or "e-bike excitement". Studies have shown that riders feel that the experience is fun, and this fun factor may even contribute to reduced car dependence (Bennett et al., 2022; Jones et al., 2016; MacArthur et al., 2018; Popovich et al., 2014). Additionally, there is a wealth of evidence that e-bikes allow users to travel greater distances with ease, especially when compared with non-electric bicycles (Jones et al., 2016; MacArthur et al., 2018). Considering that nearly half of all car trips in the United States are less than three miles, the opportunity for e-bikes to replace car travel is substantial (Reed & INRIX, 2019).

Why are financial incentive programs supporting the purchase of e-bikes rather than non-electric bikes? This is, in part, because evidence from many studies has indicated that e-bikes, more so than non-electric bikes, replace car travel (Fitch, 2019). However, e-bikes have also been promoted by financial incentive programs as they can be used by more people for more trips than regular bikes. In this way, incentives are utilized to reduce the high costs of e-bike purchases and promote bike use among those who would increase their active travel with access to an e-bike. The potential benefits of wider e-bike use are substantial. E-bikes have the potential to reduce congestion, positively impact public health, improve air quality, mitigate GHG emissions, benefit local economies, and reduce car dependence (Bennett et al., 2022; Fyhri et al., 2017). The characteristics of e-bikes, in combination with broader trends in the

United States, have created an interest in the mode amongst the general population. This latent demand for e-bikes and bicycle-friendly infrastructure in U.S. cities has had significant impacts on the bicycle industry.

E-bike Market

As California moves forward towards what may be the end of the COVID-19 pandemic as we know it, active transportation continues to be desirable for many who discovered the joy of walking and biking during periods of lockdown. Between 2009 and early 2020, rates of bicycling in the United States have been relatively stable, but in 2020 with the onset of the pandemic, the U.S. saw a jump in bicycling across all demographics (PeopleForBikes, 2021). During the first year of the pandemic, 10% of American adults engaged with bicycling in a new way, whether this was picking up a bike for the first time in years or choosing to use their bike for a new type of trip. This growth in bicycling rates seemed to converge perfectly with the growing demand for e-bikes in the United States. According to research from the NPD Group, e-bike sales grew 145 percent between 2019 and 2020, more than double the growth in traditional bike sales (Surico, 2021). In 2021, the number of e-bikes purchased in the United States solidly outpaced the sale of electric vehicles (EV) (Carnes, 2022). This reflects a growing demand for active travel and the relative affordability of e-bikes when compared with EVs. Figure 1 below shows the quarterly expenditure on bicycles and accessories in the United States from 2019 to 2021 (Bureau of Economic Analysis, 2022).

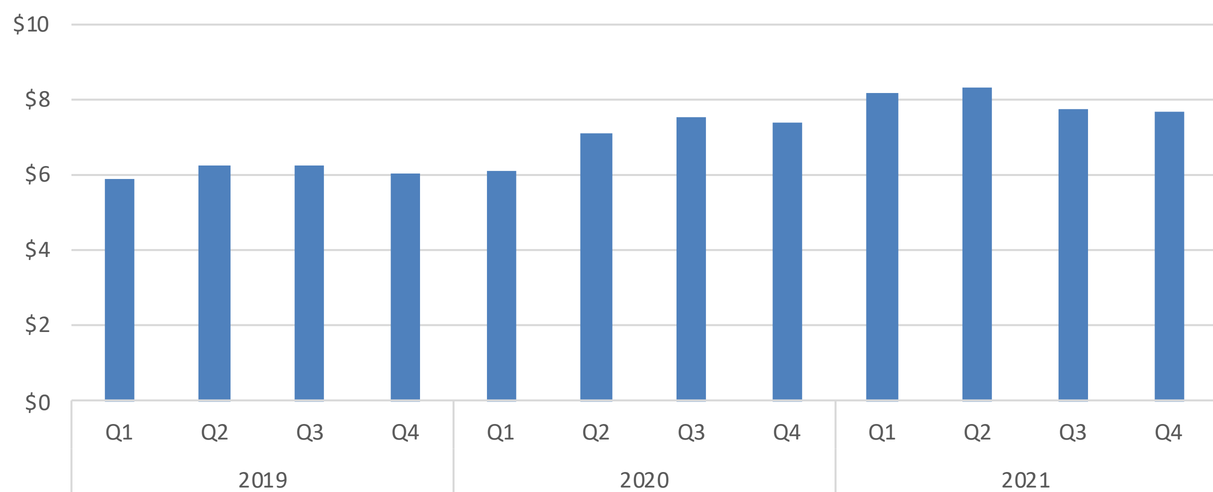

Figure 1. Growth in United States bicycle sales from 2019 to 2021. Expenditure on bicycles and accessories in the U.S. in billions of USD.

Total expenditure began to rise from Quarter 1 to Quarter 2 in 2020, just as pandemic restrictions began to hit communities across the United States. Sales peaked in quarter 2 of 2021 with just over eight billion dollars spent on bicycles. Since then, bicycle sales have steadily declined while remaining above the pre-pandemic normal. To better understand specific e-bike market changes during this same period, we used two different data sources. The first, a dataset from the NPD group, captured the business-to-consumer (B2C) e-bike sales in the

United States (The NPD Group, 2022). B2C for bicycles includes bike shops and any other retailer that sells bikes they do not manufacture. It is important to note that most e-bikes are currently sold through direct-to-consumer (DTC) channels because many e-bike manufacturers operate their own highly successful online stores. Therefore, the NPD data likely only represents 25-50% of real-world e-bike sales. In contrast, with traditional non-electric bikes, the B2C channel is roughly 75% of the market share, which means that this data is skewed to show more non-electric bike sales than e-bike sales (Patrick Hogan, personal communication, 2022). Regardless of the bias, this data still reveals some clear trends. While non-electric bicycle sales fell in 2021, e-bike sales continued to grow. This suggests that the total market potential of e-bikes has yet to be achieved. While e-bikes make up a substantial proportion of bicycle sales in the United States, they represent a much smaller proportion of the number of bicycle units sold. According to additional data from the NPD group, e-bikes make up less than 3% of all bicycle units sold in the U.S. Of course, this discrepancy can, in part, be attributed to the far higher cost of purchasing an e-bike than non-electric bikes. To clarify these findings, we sourced additional e-bike sales data from the Light Electric Vehicle Association (Figure 2).

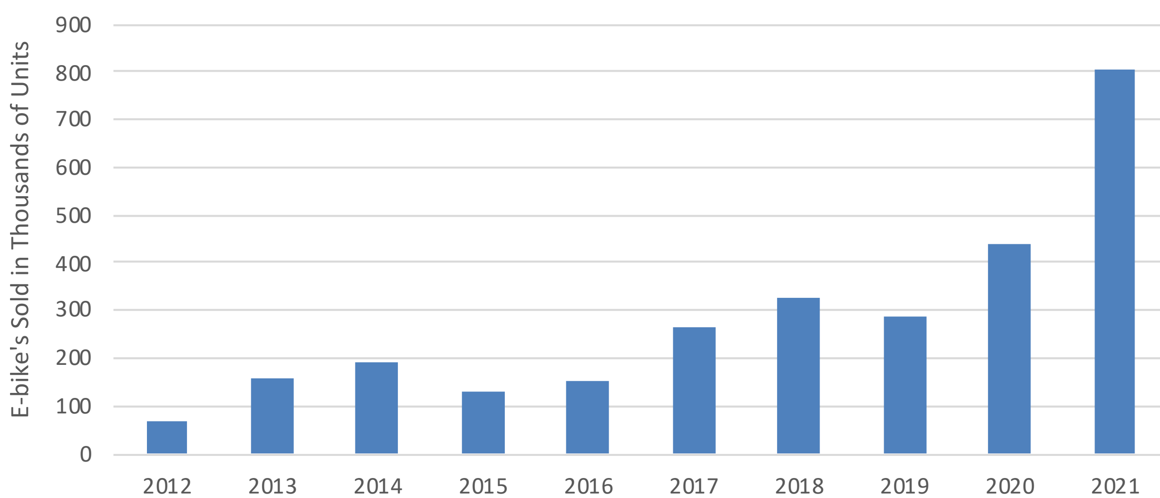

Figure 2. U.S. e-bike sales from 2012 to 2021

The data above shows U.S. market consumption for e-bikes from 2012 to 2021 through e-bike imports, meaning that both DTC and B2C sales are included (Benjamin, 2022). This provides additional context to the previous data with a wider time scale and more accurate data. In Figure 2, we observe several small increases in consumption followed by a year or two of decline. However, the number of e-bike units sold in 2020, and particularly 2021, jumped dramatically.

Benefits and Barriers

E-bikes play a unique role in overcoming barriers to bicycle use. Their primary benefits are that they can maintain higher speeds with less effort and reduce physical exertion (Fishman & Cherry, 2016). This makes bicycling far more comfortable and allows users to limit the physical burden of active travel. For bicycle commuting, topography, distance, and time act as significant barriers and e-bikes can mitigate each of these (Fishman & Cherry, 2016). These benefits, amongst many others, are a key reason e-bikes have grown in popularity and are often used in place of car travel.

Despite the ability of e-bikes to help overcome the physical barriers to increased biking, e-bikes still face many challenges reaching non-bicycle users. In a Norwegian study on the e-bike's role in overcoming barriers to bicycle use, researchers found that perceived barriers to bicycling were mostly related to factors that e-bikes could not alleviate such as poor infrastructure and safety concerns (Fyhri et al., 2017). However, this same research suggested that e-bikes are more likely to reduce car use and increase mobility because of high levels of interest amongst those who bike the least. Of the many barriers to e-bike adoption, the most common of these appear to be a lack of quality bicycle infrastructure, lack of familiarity with bicycles, and environmental factors (Fyhri et al., 2017; Simsekoglu & Klöckner, 2019).

One of the most critical barriers to the broader adoption of e-bikes is the upfront purchase cost. Most e-bikes are purchased new from a manufacturer or other retailer as the second-hand market has not fully developed. E-bikes range dramatically in cost based on the type of e-bike, the manufacturer, and its quality. However, as of 2022, the majority of models on the market cost between $1000 and $3000, with the cheapest models being offered at around $600 and the most expensive reaching prices over $10,000 (Speciale, 2022). Conventional bikes also have a wide range of costs though most are substantially less than the average price of an e-bike. While the cost of an e-bike may be less than many other vehicles, it is still a significant expenditure many people simply cannot afford. For this reason, among others, many of the early adopters of e-bikes tend to be male, older, wealthier, white, highly educated, and residents of neighborhoods with better bicycle infrastructure (MacArthur et al., 2018). Given this disparity in adoption, financial incentives can be powerful tools to make e-bikes a viable option for people without the means to purchase an e-bike. Typically, these incentives come in the form of a rebate or tax break for consumers, each of which eases the burden of the purchase by offering a reduction in price, a later refund, or a reduction in taxes owed.

Many expect the growth in bicycle sales to continue throughout the decade, particularly as funds become available for bicycle infrastructure improvement projects via the Infrastructure Investment and Jobs Act (Sorenson, 2021). In combination with infrastructure investment, e-bike financial incentive programs lessen barriers by significantly reducing the cost of purchasing an e-bike. In 2021, California Representative Jimmy Panetta introduced a bill named the E-BIKE Act that would have allowed for a refundable tax credit for 30% of the cost of a qualified electric bicycle (117th Congress, 2021). This was later merged with the Build Back Better (BBB) Act that, at the time of this writing, has been transformed into the Inflation Reduction Act of 2022, with the e-bike tax credit completely removed. While some political efforts, such as the BBB Act, have failed, others show promise. Calbike and the California Air Resources Board (CARB) have dedicated $10 million to develop a statewide program for e-bike purchase incentives (Calbike, 2022). This funding will be used to develop a statewide e-bike voucher program that will likely prioritize low-income California residents. California's efforts, along with the many e-bike incentive programs led by government agencies and utility providers, show a significant political will to make e-bikes more accessible to average Americans. As interest in e-bikes has grown during the pandemic, this is a crucial time for governments to decide if investing in e-bike ownership is cost-effective strategy for meeting climate and equity goals.

Incentive Strategies

E-bike incentive programs differ in many program parameters. Outside of direct financial incentives, governments have used numerous other methods to encourage e-bike use. These have included shared e-bike services, lending libraries, employer-sponsored programs, low-interest loans, and even the distribution of free e-bikes. However, the most typical type of e-bike incentive is a rebate. A rebate is a type of financial incentive that may either be a partial repayment after purchase or a point-of-purchase discount through a voucher. Even within rebate programs, because the programs are largely untested in the US, program parameters have varied widely. Once the goals of a rebate program have been defined program designers can begin to identify a target population, define the types of e-bikes to include, determine the types of retailers to include, select purchase incentive amounts, define internal and external processes, and identify strategic partners (Bennett et al., 2022).

At the time of this writing, thirty-nine active e-bike incentive programs have been established in North America, nine of which are in California (Bennett & MacArthur, 2022). Out of these nine programs, seven have offered a partial purchase rebate. Providing financial incentives such as rebates will help with adoption, but other research suggests parallel strategies are needed for more widespread increases in bicycling. Particularly infrastructure investment and programs to increase experience and knowledge of e-bicycling are important for promoting e-bikes (Fitch, 2019). In this way, e-bikeshare services can be particularly valuable for giving people the chance to try e-bikes before deciding whether to purchase one (Handy & Fitch, 2022). The flexibility of rebate strategies and the variety of tools available to aid in their success allows for the customization of any program to meet the specific needs of a community. For example, if a program hopes to encourage the adoption of e-bikes amongst families with children they might consider including e-bike types better suited to the needs of those family units.

E-bikes and Travel Behavior

While research on e-bike ownership in Europe is prevalent, studies exploring the impacts of ownership in the United States are sparse. However, despite the geographic and cultural differences inherent to European e-bike research, this work has helped guide the design of this study. For example, studies in Oslo have found that respondents who use non-electric bicycles the least are most likely to be interested in purchasing an e-bike (Fyhri et al., 2017). E-bikes often serve the role of enabling those who could not or would not make the same trip by a traditional non-electric bicycle (Dill et al., 2012). These results suggest that electronic assistance reduces the barriers to bicycle adoption, especially amongst those who previously found the bicycle to be an unappealing transportation mode.

Many of the potential benefits of e-bike ownership rely on the mode of transportation that it replaces. Given that many non-bicycle users show interest in e-bikes, we would expect a greater mode shift from cars and public transportation. A great deal of research has found that e-bike ownership reduces car trips far more than non-electric bicycles (Bourne et al., 2020; Cairns et al., 2017; Söderberg f.k.a. Andersson et al., 2021). However, several studies have shown that e-bike ownership strongly reduces the use of non-electric bicycles, and also, to a lesser degree, cars and public transportation (Kroesen, 2017; MacArthur et al., 2018). Whether or not e-bike ownership increases or decreases non-electric bike trips, it is clear their availability increases the number of total bicycle trips and distance traveled across all age groups (Fyhri & Fearnley, 2015; MacArthur et al., 2018). Existing research identifies a clear reduction in car travel use after purchasing an e-bike. However, interestingly, it is primarily single-purpose trips that are being substituted by e-bikes (Söderberg f.k.a. Andersson et al., 2021). This indicates that e-bike users still rely on personal vehicles for trip-chaining and the transportation of passengers and goods.

Findings from MacArthur's work are from early e-bike adopters who did not receive incentives, meaning that the behavior described below comes from a unique population. One of the goals of our research is to understand the behavior of the later adopters who needed a financial incentive to access the mode. While keeping this in mind, MacArthur's work suggests that utilitarian e-bike use is more common amongst younger e-bike users while older users tend to use their e-bikes primarily for recreation and social outings (Bourne et al., 2020; MacArthur et al., 2018). Additionally, those with less bicycle experience are more likely to report recreational travel as their primary e-bike travel purpose (MacArthur et al., 2018). Despite these discrepancies, overall bicycle use for both commuting and recreational travel increases after the purchase of an e-bike (Fyhri & Fearnley, 2015). People also appear to perceive e-bikes as safer than non-electric bikes. Many users have reported that their e-bikes have helped them avoid a collision, either through quick acceleration or by making safer routes more accessible (MacArthur et al., 2018). Though not all road users share the same feelings. Three quarters of participants in a panel of Amsterdam residents reported that e-bikes were making bike lanes less safe because of their speed (NL Times, 2022). These findings highlight that there may be challenges with facilitating safe interactions between e-bikes and other active transportation uses. Despite this, e-bikes appear to encourage users to explore new trip types by reducing the barriers to exploratory use.

A primary motivation for the majority of e-bike incentive programs in North America is the need to meet climate goals. By replacing car travel, e-bike ownership is able to reduce total transportation emissions. While e-bikes do have greater energy intensity than some modes they may replace, such as walking and non-electric biking, the energy loss from replacement is low, and thus overall impacts are beneficial (Shankari et al., 2021). Estimates predict e-bike ownership is likely to result in a GHG reduction between 10-12%, which translates to roughly 225-394 kg CO_2 per year (McQueen et al., 2020).

Besides the early e-bike adopters of in MacArthur's work, we know little about how e-bikes are used in the United States. European studies have primarily focused on the commuting behavior of e-bike users which leaves gaps in our understanding of other types of travel. Additionally, low-income rebate recipients have been especially understudied in past research. Therefore, to better understand how e-bike ownership impacts travel behavior our study seeks to address these gaps. Our study seeks to understand how e-bike ownership changes bicycle use, with an emphasis on exploring longitudinal changes in the frequency of mode use, car replacement, and trip purpose. In addition, the income qualifications found in several of these rebate programs will allow for an equity-centered analysis of the impacts of e-bike ownership. Given that California is on the brink of launching a statewide e-bike incentive program, exploring the impact of three smaller-scale programs can help inform best practices. Our analysis will add additional context to understands of how e-bike ownership can change travel behavior.

Research Questions

- How has e-bike ownership impacted the mode choices, trip purpose, and travel frequency of our sample? Does our sample report different behavior from what previous research has observed?
- How much do e-bike rebate recipients reduce their mobile GHGs?
- How did the design of each program impact who was able to participate and the program outcomes?

Methods

E-bike Rebate Programs in Northern California

This analysis will focus on the travel behavior of participants in three e-bike rebate programs across Northern California shown in Figure 3 below. The Redwood Coast Energy Authority (RCEA), Peninsula Clean Energy (PCE), and Contra Costa County (CC) rebate programs all offer similar rebate programs with some key differences. Table 1 below explores five broad parameters of these programs' structures. Two strategies were used between these programs, an after-purchase rebate and a point-of-sale discount. An after-purchase rebate refers to a rebate application that must be submitted for approval after the transaction, while a point-of-sale discount accounts for the rebate payment during the transaction. The program's incentive strategy also includes the outreach strategy for each program. The incentive amount offered also varies between programs, with some programs determining payment based on a percentage of e-bike price and others providing a set payment. Two of the programs set a maximum allowed e-bike price, likely to prevent the purchase of luxury e-bikes. However, this may have the unintended consequence of restricting the purchase of cargo or specialty e-bikes. Finally, there are a variety of eligibility requirements for the would-be rebate participant, such as residential status and low-income status. The design of each of these programs fall into the spectrum of parameters suggested in Canadian research on the impacts of incentive program designs. In particular, the incentive amounts offered by RCEA, PCE, and CC are very similar to the suggest range of $310-620 recommended in the only research available in North America focused on identifying the most cost effective e-bike rebate amount (Bigazzi & Berjisian, 2021).

Figure 3. Jurisdiction of rebate programs

Table 1. Rebate Program Structure

Program Parameters	Redwood Coast Energy Authority	Peninsula Clean Energy	Contra Costa County
Incentive and Outreach strategy	• After purchase rebate • Website, press release, flyers, social media, etc.	• Point-of-sale discount or after purchase rebate • Email distribution	• After purchase rebate • Email distribution, newsletter, advertisements, social media
Incentive amount	50% of e-bike price up to $500 maximum	80% of e-bike price up to $800 maximum	$150 or $300
Maximum bike price	N/A	$1,800	$5,000
E-bike types	• List of pre-approved e-bikes	• All new class 1, 2, and 3 e-bikes with motors of 750 watts or less.	• All new class 1, 2, and 3 e-bikes, • e-bike conversion kits, • e-mopeds (max speed < 30 mph) (with pedals)
Eligibility	• Energy customer • Limit one rebate per electric account	• Low-income status (400% federal poverty level) • Resident of San Mateo County	• Low-income status • Resident of Contra Costa County • Older than 18 • One rebate per household

The structures employed in these programs influence where the resources are distributed and whom they will inevitably benefit. As an example, the Redwood Coast Energy Authority has no low-income eligibility requirements and no set maximum e-bike price. Therefore, the program opened up to would-be e-bike buyers who already planned on purchasing an e-bike and do not need assistance to afford one. Contrast this with the Peninsula Clean Energy program that requires participants to be designated as low-income and sets a maximum price cap of $1,800 that prevents participants from purchasing higher-end e-bikes. However, this price cap does prevent the purchase of specialty e-bikes that may be a necessity for participants who need unique features. Examples of this might be cargo bikes for hauling goods or children, specialty e-bikes for those with mobility disadvantages, or electric mountain bikes for rural travel. Sitting in the middle of these two is the Contra Costa County program which has a low-income requirement yet only offers rebates of $150 or $300. This rebate amount is only a small discount when compared with typical e-bike prices.

Each element of the program design determines what type of person the program is able to serve. These rebate program elements can thus be conceptualized as a filter that sifts the population of would-be e-bike rebate participants and only allows those through whom the program wishes to serve access to the rebate resources. A simplistic representation of this is shown below (Figure 4).

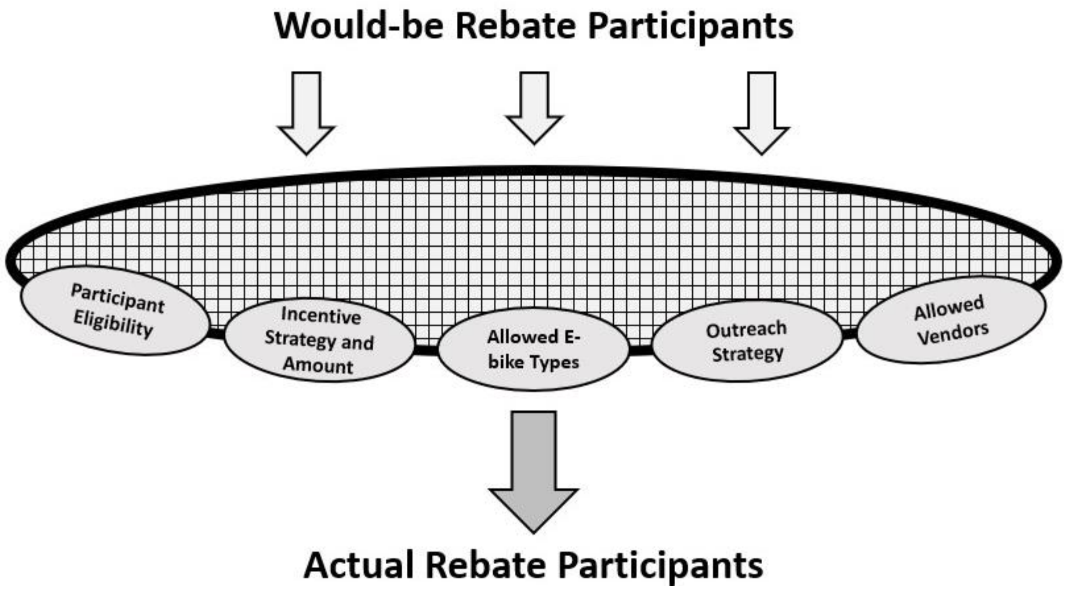

Figure 4. Conceptualization of rebate structures as a filter of potential participants.

Through using the data from these Northern California e-bike rebate programs we seek to understand the effectiveness of these programs and their impact on participants' travel behavior. A better understanding of the outcomes of e-bike rebate programs will help inform the design of future programs. To do this we need to better understand how ownership of an e-bike impacts short and long-term travel behavior.

Data Collection and Survey Design

Participants in these three rebate programs were asked to complete a follow-up survey after receiving their rebate. Each program distributed an online survey using Google Forms that was designed by Contra Costa County and UC Davis. This survey was then distributed through each partner agency. The distribution timeline varied for each program. PCE sent their follow up survey out one month after participants received their e-bike while RCEA distributed theirs one year after reception of the rebate. CC was unique in that they distributed both a two month follow-up and a one-year follow-up, allowing for longitudinal data. Survey response rates varied significantly, with RCEA having 72% of recipients participate, PCE seeing 19%, and CC getting an 87% response rate. These surveys asked the respondent to report information about their demographics, travel behavior, and attitudes about their e-bike. In total, we received 41 responses from RCEA, 67 from PCE, and 509 from Contra Costa County.

Study Sites

Most of the responses are from Contra Costa County, with roughly 82% of our sample having participated in that program. Contra Costa County had far more responses than the other programs, which can be attributed to the county's substantially larger population compared to San Mateo and Humboldt County. The lower incentive for this rebate program allowed Contra Costa County to offer a greater number of rebate payments than the other agencies. Within Contra Costa County, we break down the number of people who received rebates by their city of residence (Figure 5).

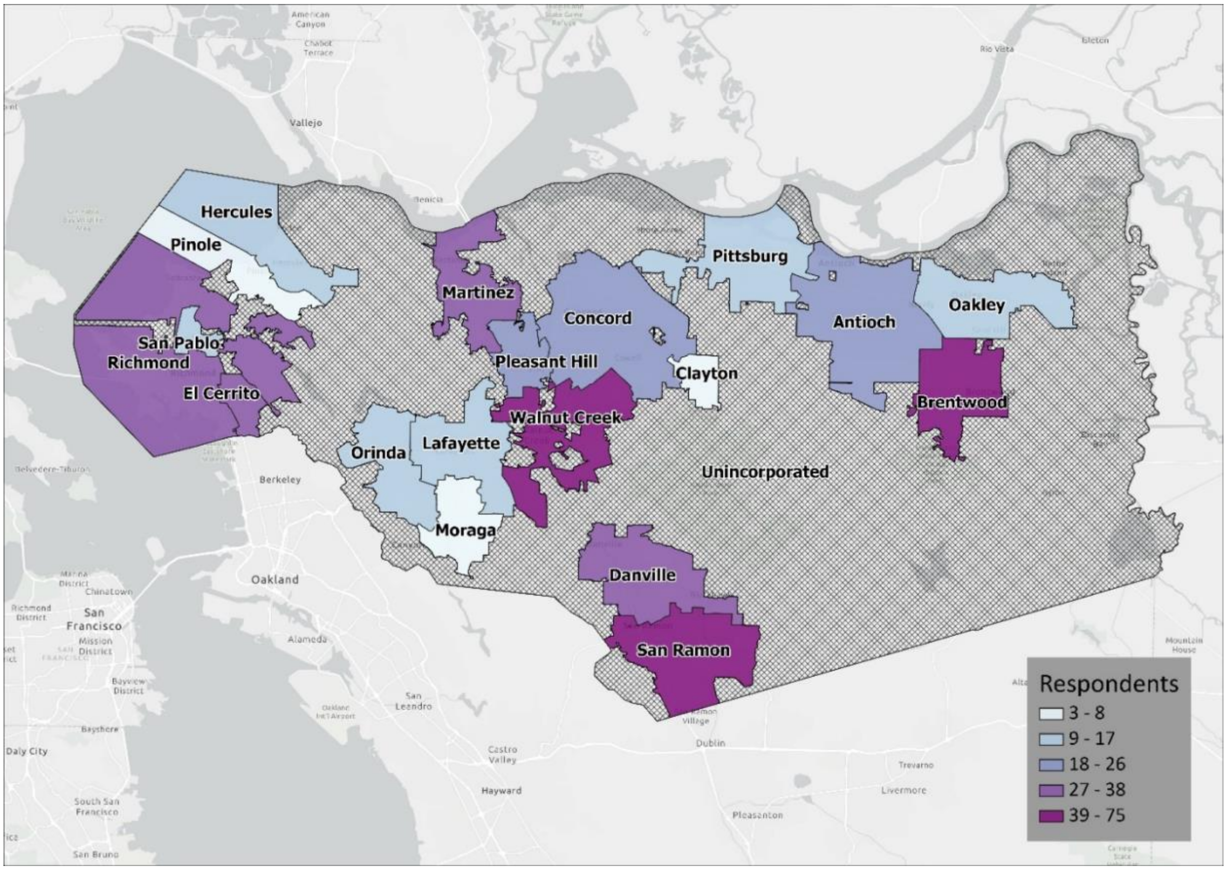

Figure 5. Rebate Distribution in Contra Costa County.

Figure 5 shows that Walnut Creek (75 approved rebates), Brentwood (51), and San Ramon (48) received most of the rebates. Other cities like Moraga, Pinole, and Clayton received far fewer rebates. Generally, the number of rebates per city follows the population size, with some notable exceptions. Specifically, Concord and Antioch have very few rebates, considering that they are some of the largest cities in Contra Costa County. After a review of the demographic differences between these cities we were unable to identify any notable differences. For now, we are unsure why Concord and Antioch received fewer rebates than other comparable cities.

The datasets from Contra Costa County, RCEA, and PCE were merged into a single dataset using a script in R that automated the process. Using this automated data cleaning script, we were able to take the raw datasets we received from our partner agencies and quickly merge them as we received updated survey data. Specific issues with data quality were discovered during this process, such as an error in the Contra Costa survey, which skipped respondents past several critical questions. This resulted in significantly reduced sample sizes for several variables. In particular, the data on the frequency of travel by mode was impacted, leaving very few responses for travel frequency prior to receiving an e-bike and in the months shortly after having received theirs. Any results affected by this error are identified in our analysis. Additionally, several questions were removed from the RCEA survey by our partner agency, resulting in fewer responses for reported odometer readings and several other key variables. Given these challenges with data quality, we chose to rely on descriptive statistics and not undertake complex statistical modeling. To better understand how e-bike ownership impacted travel behavior we explore univariate and bivariate statistics to examine how these rebate recipients traveled after receiving their e-bike. We sought to understand trip purposes, frequency of travel, car trip replacement, and the key barriers to greater e-bike use.

Characteristics of Sample

To explore the impact of the program design on participants, we summarized household income, educational achievement, household size, age, gender, race, ethnicity, and current employment status. Understanding the characteristics of participants of these rebate programs was necessary to better interpret the results of our analysis. This examination is important specifically because the sociodemographics of our sample differ from the study areas in critical ways that are explored below. These demographic differences do not lessen the quality of this analysis but offer insight into who benefitted from these programs and if equity goals were successful.

Table 2. Demographics of Sample

Demographics		Count	%
Gender	Man	346	60.2%
	Woman	228	39.7%
	Non-binary	1	0.2%
Age	18-34	71	12.3%
	35-44	114	19.8%
	45-54	126	21.9%
	55-64	135	23.5%
	65+	129	22.4%
Race	Asian	47	n/a
	Black	14	n/a
	American Indian or Alaska Native	7	n/a
	Native Hawaiian or other Pacific Islander	7	n/a
	White	173	n/a
Ethnicity	Hispanic or Latinx	34	n/a
Household Income Level	<$25,000	40	9.9%
	$25,000 to $50,000	72	17.9%
	$50,000 to $75,000	54	13.4%
	$75,000 to $100,000	51	12.7%
	$100,000 to $125,000	2	0.5%
	$125,000 to $150,000	62	15.4%
	$150,000 to $175,000	16	4.0%
	$175,000 to $200,000	52	12.9%
	$200,000+	54	13.4%
Education Level	HS Diploma	33	6.0%
	Some College	78	14.2%
	Associates	39	7.1%
	Bachelors	230	41.7%
	Masters	132	24.0%
	Trade School	7	1.3%
	PhD or Higher	32	5.8%
Household Size	1	74	17.4%
	2	266	62.6%
	3	47	11.1%
	4+	38	8.9%
Employment Status	Full-time	253	48.8%
	Part-time	37	7.1%
	Unemployment	32	6.2%
	Student	16	3.1%
	Retired	104	20.1%
	Homemaker	12	2.3%
	Self Employed	64	12.4%

On average, these programs attracted participants who are on average older, whiter, and more highly-educated than each region's demographics (Table 3). Respondents were allowed to skip any question they felt uncomfortable or unprepared to answer. This means that certain demographic questions received more limited responses. However, from these self-reported demographics, most of the sample were men with far fewer respondents being women and only one participant identifying as a non-binary gender. The age distribution was more varied, though nearly half of the sample was above the age of 55 with just 12.3% below the age of 34. This implies that younger populations are underrepresented in our study. Respondents were able to select multiple races and whether or not they were Hispanic or Latinx. The majority of respondents reported that they were white with the next highest racial category being Asian. From the self-reported data, our sample is overrepresented by white people with comparatively few Black, Asian, Native Hawaiian, Pacific Islander, American Indian, or Alaskan Native respondents. Similarly, only 34 respondents in our sample reported being Hispanic or Latinx, which is very low given that Hispanic and Latinx people make up an average of 21.2% of the population in the study area (US Census Bureau, 2021). We observed a generally even income distribution across our sample, with our sample's mean household income of $101,749 being just above the study area mean of $93,774 (US Census Bureau, 2021). Also, 26% of the pooled (all programs) sample were eligible for the low-income qualification for each rebate program. Most of the sample had a Bachelor's degree or higher with many also having obtained a graduate degree, meaning these respondents are more highly educated than their regions average, with only 42.1% of the study areas population having a bachelor's degree or higher. Additionally, household sizes in our sample also tended to be smaller than the average for our study areas. Finally, just about half of our sample are employed full-time with another 20% being retired. In short, this sample is not entirely representative of these study areas. So our results and discussion should be interpreted with this in mind. Table 3 below explores the differences between our sample and the demographics of each study area in greater detail.

Table 3. Demographics of Sample Compared with Study Area Demographics

		Sample			ACS Estimates			Percent Difference		
Demographics		RCEA	PCE	CC	RCEA	PCE	CC	RCEA	PCE	CC
Gender	Man	60%	68%	61%	50%	50%	49%	10%	19%	12%
	Woman	40%	30%	39%	50%	50%	51%	10%	20%	12%
	Non-binary	0%	2%	0%	-	-	-	-	-	-
Age	18-34	-	11%	13%	26%	23%	22%	-	13%	9%
	35-44	-	17%	20%	13%	14%	14%	-	2%	7%
	45-54	-	17%	23%	11%	14%	14%	-	3%	9%
	55-64	-	23%	24%	13%	13%	13%	-	10%	10%
	65+	-	37%	24%	18%	16%	16%	-	21%	8%
Race	Asian	8%	17%	21%	3%	32%	19%	5%	15%	2%
	Black	0%	6%	7%	2%	3%	10%	2%	3%	3%
	American Indian or Alaska Native	0%	6%	3%	6%	1%	1%	6%	5%	2%
	Native Hawaiian or other Pacific Islander	0%	0%	4%	0%	1%	1%	0%	1%	3%
	White	92%	72%	65%	83%	58%	64%	10%	14%	1%
Ethnicity	Hispanic or Latinx	0%	28%	15%	13%	24%	27%	13%	4%	12%
Household Income Level	<$25,000	5%	27%	7%	26%	9%	11%	20%	18%	4%
	$25,000 to $50,000	19%	43%	12%	25%	10%	13%	6%	33%	0%
	$50,000 to $75,000	19%	16%	12%	17%	10%	13%	2%	6%	1%
	$75,000 to $100,000	30%	10%	11%	11%	10%	12%	19%	0%	1%
	$100,000 to $150,000	14%	3%	19%	12%	17%	19%	1%	14%	0%
	$150,000 to $200,000	8%	0%	22%	5%	13%	13%	3%	13%	9%
	$200,000+	5%	0%	17%	5%	30%	21%	1%	30%	3%
Household Size	1	44%	45%	11%	33%	22%	22%	12%	23%	11%
	2	44%	19%	70%	37%	32%	32%	8%	13%	39%
	3	11%	12%	12%	13%	19%	18%	2%	7%	6%
	4+	0%	24%	7%	18%	27%	29%	18%	3%	22%

This sociodemographic data was gathered from a variety of census tables this adds further context to many of the observed differences we discussed above and highlights some differences in the allocation of rebate resources between these programs (US Census Bureau, 2022). For example, PCE, with its much stricter program qualifications had no high-income participants and thus a higher proportion of low-income participants than the others. However, these qualifications did not seem to impact other equity metrics such as the racial and ethnic diversity of participants or gender diversity. For example, PCE had, by far, the highest proportion of both male and 65+ respondents, indicating that rebate programs designed to reach low-income participants may not necessarily meet other equity metrics by association.

Travel Behavior and GHG Reductions

One of the primary motivations for e-bike incentive programs is to reduce GHG emissions by offsetting car travel. Therefore, to help understand how successful these programs were, we need to understand how travel behavior changes impacted emissions. Respondents were asked to report information about their behavior including travel frequency by mode, odometer readings, alternative travel modes, trip purposes, average trip distances, and much more. Despite some issues with data quality, which will be expanded on in a later section, this captured the travel behavior of the rebate program participants. Using this information, we were able to better understand the influence of e-bike ownership on travel behavior and create an analysis to estimate GHG reductions.

To better understand the effectiveness of these programs for addressing climate change and reducing car-dependence, we estimated vehicle-miles traveled (VMT) and greenhouse gas emissions (GHG) before and after respondents received their e-bikes. Due to limited data for certain questions, we developed two methods to account for the lack of complete information. Method 1 utilized a sub-sample of the 75 participants with a response to each of the necessary questions. Using these responses, we created an estimation of the number of monthly trips by car and by e-bike when replacing a car trip based on reported travel frequencies. These were then multiplied by the average distance when replacing a vehicle trip with an e-bike to create a rough estimation of VMT. Using the average distance when replacing a vehicle trip may bias the estimation, as we expect that these trips would be shorter than the average vehicle trip. However, the other distance variables in our study received too few responses to be used in our estimation. With data on regional fleet mixes and GHG emissions from the EMFAC emissions inventory tool provided by CARB, we were able to estimate the total CO_2 equivalent emissions (CARB, 2022). Method 2 followed the same general process but instead took an average of the reported frequency of travel, frequency of car trip replacement, and distance when replacing a car trip and applied that to each response to maximize the sample size. Method 1 benefitted from high quality data but had a small sample size (n = 75), whereas Method 2 had a far higher sample size (n = 577), but generalized VMT and car trip replacement frequency.

Limitations

The results of this study were primarily limited by issues with data quality created during the survey design and distribution process. As briefly discussed earlier, each program made edits to their survey and often removed, added, or changed the language of key questions. This significantly lowered the sample sizes for several questions and made the data joining and cleaning processes complex and time intensive. Additionally, a skip logic was accidently applied to a question early in the CC survey that skipped the vast majority of respondents (n = 345, 68%) past a critical section of the survey which explored travel frequency by mode. Fortunately, the error was found before the conclusion of the data collection though the sample size was far smaller than expected. The gaps in each dataset made more sophisticated analysis unreliable. For this reason, the analysis was primarily done with simple descriptive statistics.

Findings

Analysis was broken into subsections related to research themes. This exploratory analysis led to some analyses that were unplanned yet revealed unexpected travel behavior impacts. In the sections below many dimensions of the program participants survey responses are examined, all of which will help answer our research questions and provide additional context on the impacts of e-bike ownership.

E-bike Selection and Cost

The vast majority of respondents already had access to a working bicycle, with only 22.5% not having access to one at the time of their application. Given this data we assume that most of our respondents already had familiarity with biking. This familiarity likely informed their e-bike selection. Through self-reported values, the average bike price in our sample was $1,553, with a median of $1305.50. This average is consistent with other estimates of the average cost of an e-bike (Speciale, 2022). However, e-bikes can be much more expensive, especially folding, cargo, or off-road bikes. The lowest cost bike purchased in our sample was $160, likely a conversion kit, and the most expensive was $7,455. Additionally, our sample had a wide variety of bike brands, with bikes purchased from over 80 unique brands. Figure 6 below shows the most common e-bike brands with greater than ten reported purchases, Rad and Jetson are the most popular of these. All the Jetson bikes are from the CC sample. Jetson offers several e-bikes with price points between $300-$400, which suggests that CC rebate recipients may have used their rebate to pay for a significant portion (or the entire price) of their e-bike even with the smaller payments offered by CC. This likely made Jetson bikes desirable for participants in CC's program who clearly preferred to pay as little as possible rather than a nicer e-bike with a discount. However, it was unsurprising to see Rad Power taking the position of the second most popular brand as Rad is one of the largest e-bike manufacturers with a wide variety of models.

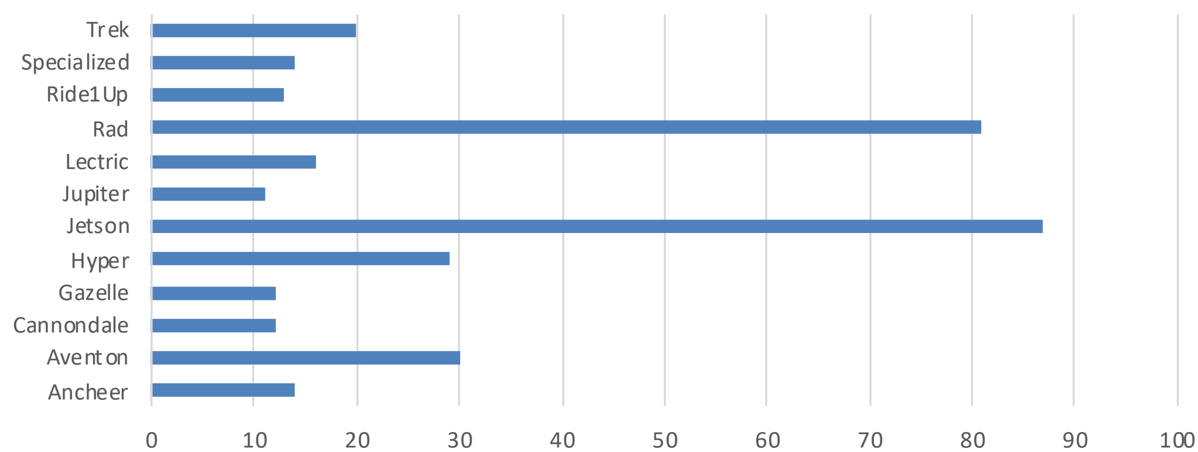

Figure 6. Most popular e-bike brands (n>10) in the sample.

Information on the specific models these participants purchased is muddled, primarily due to both PCE and RCEA omitting this question as well as data quality issues with the self-reported data. Though from the available data there appears to be a wide variety of e-bike models. The Jetson bikes were primarily the Bolt model (n = 79), which is more similar to an electric scooter. Many of these Jetson Bolts likely had pegs instead of pedals, with only the Bolt Pro having pedals. Fortunately, the rest of the bikes in the sample appeared to be more utilitarian. Though we were not able to identify any e-cargo bikes, e-mountain bikes, or other specialty models in this sample.

Primary Travel Modes

Respondents reported their primary transportation mode after they received their e-bike. In total, 77.9% of the sample reported a car or motorcycle as their primary transportation mode, with 21.5% having an electric or hybrid car as a primary mode. Interestingly, 13.8% of respondents listed their e-bike as their primary transportation mode, with another 1.2% reporting a non-electric bike as their primary mode. Although not a direct apples-to-apples comparison, this primary mode use is far higher than the typical bicycle mode share in these regions, with Contra Costa seeing a less than 2% bicycle mode share in 2018 and San Mateo County seeing less than 3.6% (MTC, 2022). Other modes did not break a 5% share, with walking coming the closest at 3.3% of the mode share. Additionally, our sample has very few transit users, with just 1.7% reporting some form of public transit as their primary mode. Generally, this resembles the wider mode share for the region except for transit use, which is roughly 10% lower than the regional averages (MTC, 2022).

Travel Frequency by Mode

Unfortunately, the data quality issues referenced earlier in this document affected one of the key variables, namely, the frequency of travel by mode before and after respondents received their e-bikes. Because of this, the results in this section only contain a few of the responses from CC and are essentially all made up of PCE respondents (all low-income qualified recipients in San Mateo County). When comparing travel frequency before and after receiving their e-bike, respondents primarily increased their bicycling in the first two months, but that increase was not sustained by 1 year (Figure 7). In addition, Figure 7 shows a significant drop in the number of people reporting they never use a bike and a decline in infrequent bike travel. Frequent (daily and 1-3 times a week) bicycle use increased substantially, indicating that people are using their new bikes. In contrast, personal vehicle use changed very little for respondents who were already not using their car. Despite the small change in the number of people not using their cars there was a large reduction in daily car use. It was common for daily car use to turn to weekly or monthly car use after receiving their e-bike. This suggests e-bikes are replacing occasional personal vehicle trips with daily car trips decline despite respondents still driving a lot.

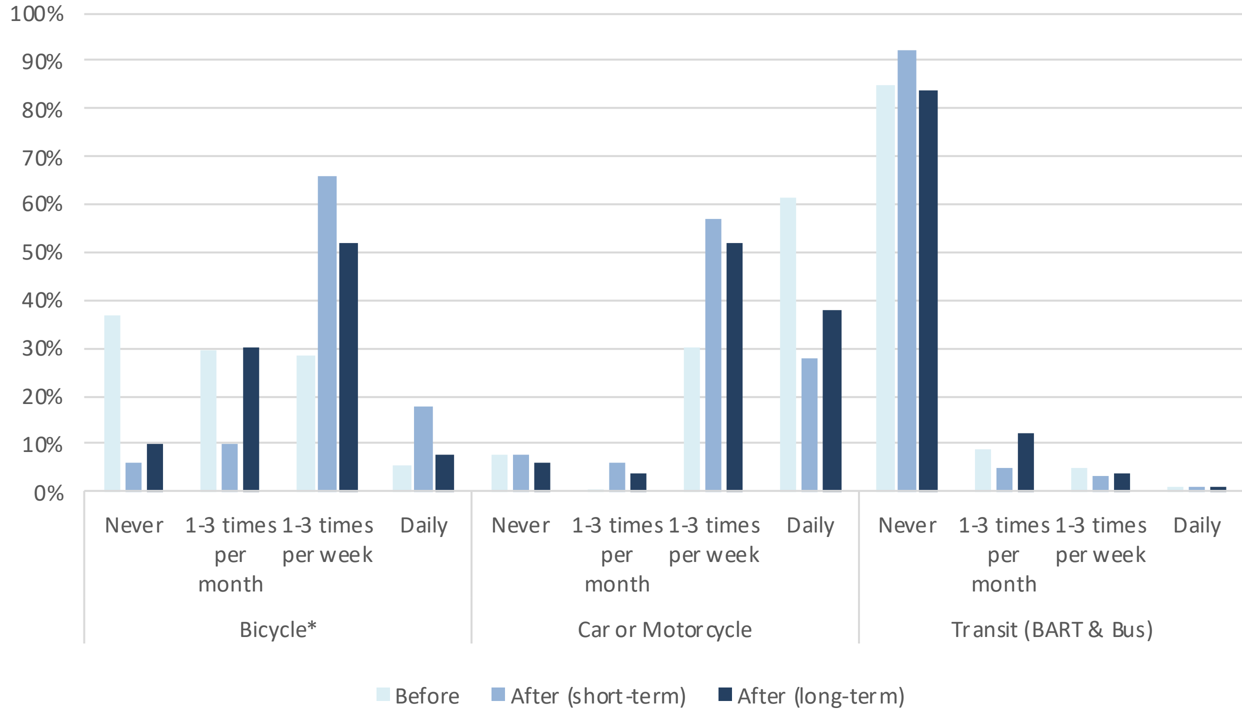

Figure 7. Frequency of travel by mode before and after receiving their e-bike. (before: n = 113, short-term: n = 115, long-term: n = 247). We group all bicycle and e-bicycle trip making.

Figure 7 shows a significant drop in the number of people reporting they never use a bike and a decline in infrequent bike travel. Frequent (daily and 1-3 times a week) bicycle use increased substantially, indicating that people are using their new bikes. In contrast, personal vehicle use changed very little for respondents who were already not using their car. Despite the small change in the number of people not using their cars there was a large reduction in *daily* car use. It was common for daily car use to turn to weekly or monthly car use after receiving their e-bike. This suggests e-bikes are replacing occasional personal vehicle trips with daily car trips decline despite respondents still driving a lot.

Public Transit and E-bike Ownership

In Figure 7 above, there are very few transit users and once they received e-bikes, there are even fewer. This lack of transit users may be in part due to these surveys being distributed while many travel restrictions were in place and during times of peaking COVID-19 case counts. Given the few transit users in this sample, it is difficult to understand the impact of e-bike ownership on transit use. There is concern that e-bike ownership may lead to less public transit use, particularly in the "post-pandemic" stage where public transportation can still be perceived as dangerous. Unfortunately, we have too few transit users (n = 26) to make a strong claim about this relationship.

Bicycle Use and Car Trip Replacement

In the year follow-up survey from CC and PCE we observed a drop in reported e-bike use (daily and 1-3 times per week), with more respondents reporting they never use their e-bikes. This suggests that over longer periods participants are using their e-bikes more infrequently. In comparison, the long-term respondents reported using their personal vehicle more regularly than they had in the short-term. Interestingly, frequency of transit use also saw a small growth in the longer-term responses, which may be due to an increasing comfort with public transportation as pandemic-risks diminish.

As discussed earlier, one of the primary motivators of these programs was to reduce GHG emissions by encouraging participants to replace car trips with active travel. In total, 82% of our sample reported having replaced at least one car trip with their e-bike. Figure 8 shows that in the short-term most of our sample reports replacing car trips 1-3 times per week and 1-3 times per month, with less than 10% of the sample reporting daily replacement. In the long term, we observe fewer car trip replacements. Still, nearly 40% of the sample replaces at least a weekly trip even though we see a sharp decline in daily replacement and significant growth in the number of people reporting that they never replace a trip. This is consistent with the observations made earlier about the frequency of mode use.

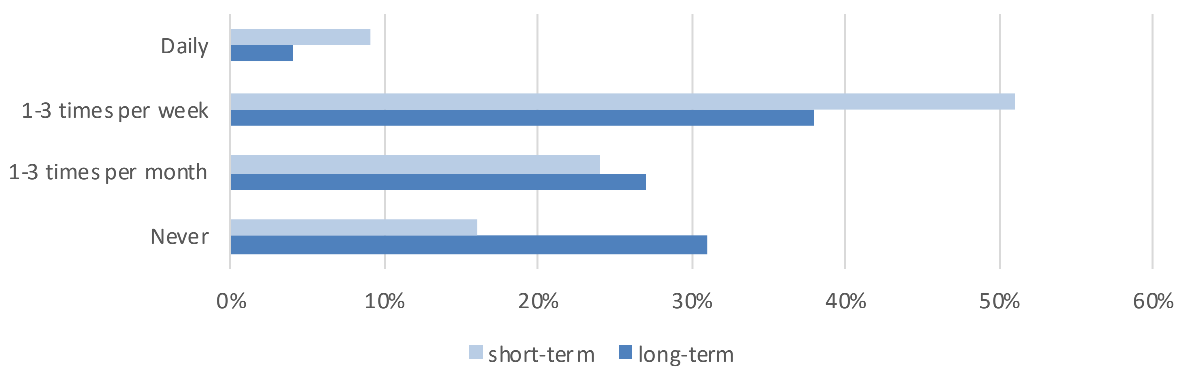

Figure 8. Frequency of replacing car trip with an e-bike. (short-term: n = 449, long-term: n = 247)

Figure 9 below shows the frequency of replacing a car trip with an e-bike by income group. Generally, as respondents' income increases, they replace car trips less frequently. However, respondents with household incomes over $150,000 reported higher rates of daily car replacement than most of the other income groups. This finding suggests that there is a subgroup of high-income participants who frequently use their e-bike to replace most of their car trips. Interestingly the lowest rates of replacement appear to come from the middle-income households in our study. This may be because middle-income households do not have the flexibility of higher-income households, yet they have a car and do not have to rely on their bike for as much of their travel as lower-income households might. We also looked at differences in car replacement amongst reported genders and found that men, on average, replaced car travel slightly more often than women. Additionally, Figure 10 represents the differences in car replacement between reported age groups. Here we found some clear differences between age groups. For example, younger respondents reported more regular replacement than older respondents. In particular, daily replacement falls dramatically as the age category increases.

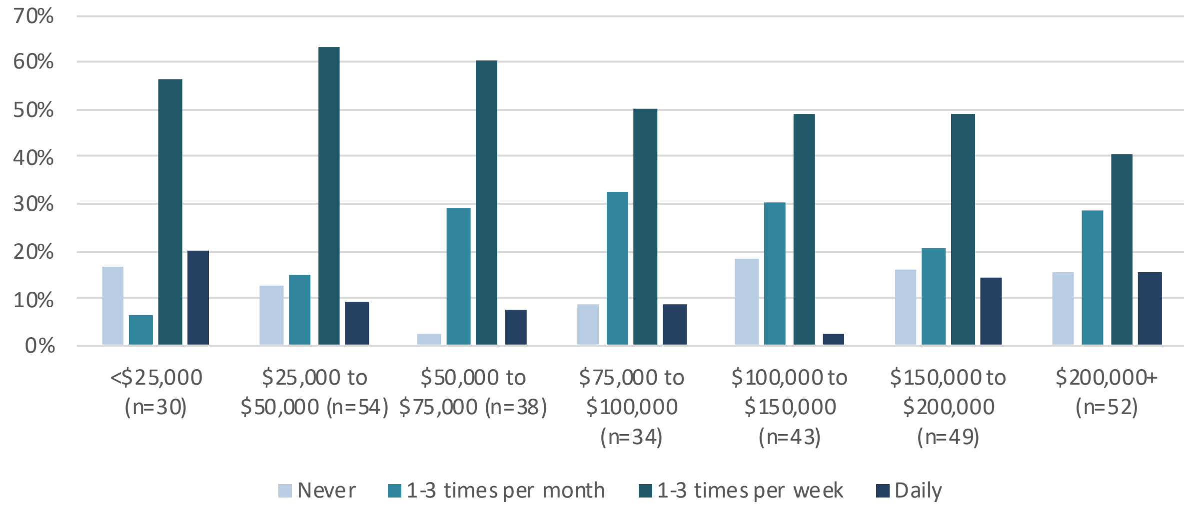

Figure 9. Frequency of replacing car trips with e-bike by income category. (short-term: n = 300)

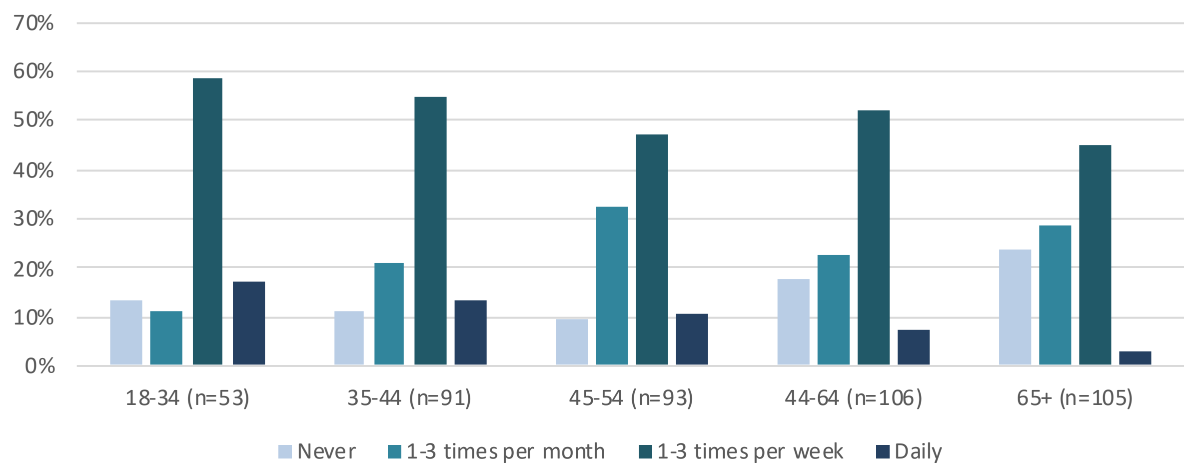

Figure 10. Frequency of replacing car trips with e-bike by age group. (short-term: n = 448)

Trip Purpose and Reported Destinations

The survey examined travel purposes by asking respondents to report destinations they have traveled to and the purpose of their last e-bike trip. While the survey asked respondents to report the destinations they had traveled to, in practice the options listed were trip purposes. In the discussion below the responses to both will be referred to as trip purposes. As shown in Figure 11 below, the most commonly reported trip purposes are recreational travel without a specific destination, shopping or errands, and social outings. The reported purpose of the respondents last e-bike trip, shown in Figure 12, are similar to those from the previous question with a few key differences. In particular, the frequency of recreational travel is far higher in Figure 12. This may indicate that recreational travel is happening more frequently than travel for other purposes. Additionally, reported travel for social outings is at levels more similar to trips to work, volunteer, shop, or run errands, indicating that frequency of travel is similar for these modes. There are few differences between the short-term and long-term responses with the most significant shifts happening with travel for social outings increasing and travel for work decreasing.

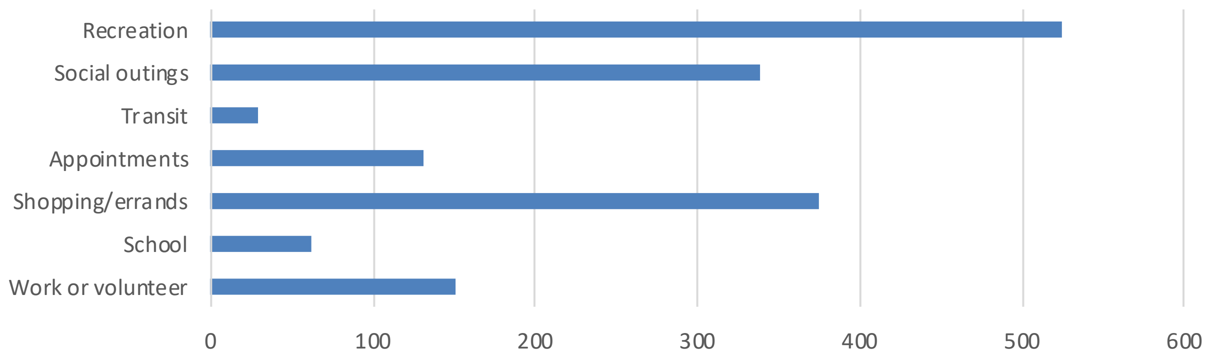

Figure 11. Reported destinations traveled to on e-bike. (short-term: n = 556)

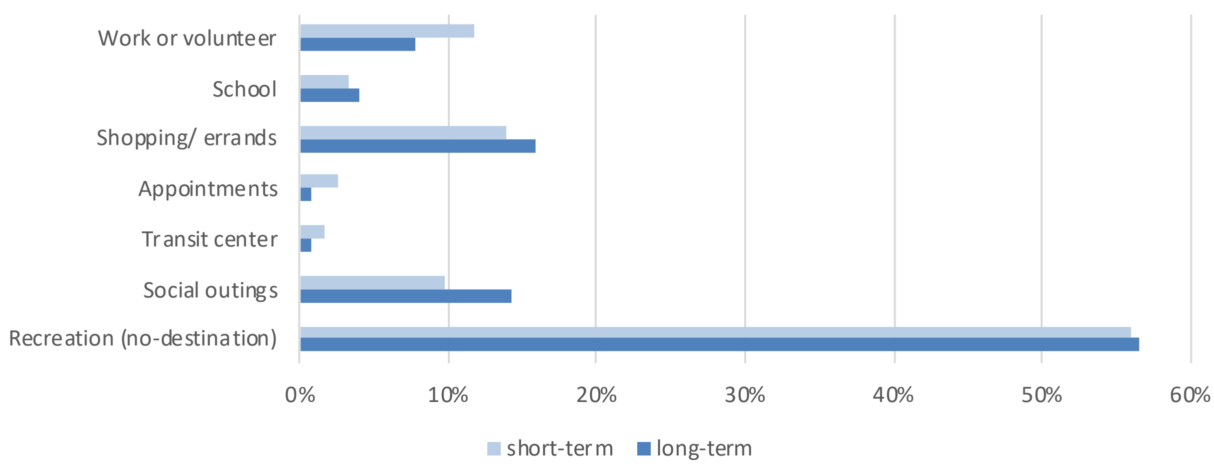

Figure 12. Reported purpose of last e-bike trip. (short-term: n = 457, long-term: n = 250)

Distance Traveled and Odometer Readings

Respondents were asked to report the average travel distances for their regular e-bike trips and for trips when replacing a car. The option to skip these questions was offered, and most chose to do so. For both questions over 90% of respondents skipped the question or answered, “I don’t know”. This indicates that the respondents do not know how far they travel or find it difficult to try to estimate. Fortunately, travel distance could be gauged using reported e-bike odometer readings, the results of which are shown in Figure 13 below. In the first several months, nearly 50% of participants had less than 200 miles on their e-bike odometer, which is roughly 3.5 miles or less of daily e-bike travel. Another 24% of the sample reported between 200 and 400 miles on their odometer, which translates to somewhere between 3.5 and 7 miles of daily e-bike travel. The long-term responses, as expected, have much higher odometer readings.

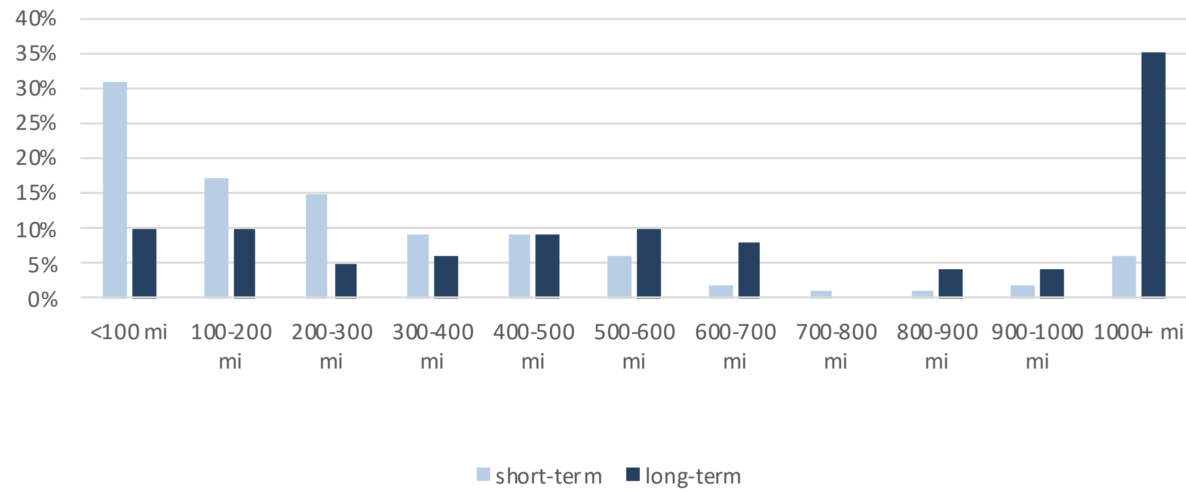

Figure 13. E-bike odometer readings. (short-term: n = 324, long-term: n = 80)

When these long-term readings are broken down into monthly rates, as shown in Figure 14, it appears that participants are traveling less by e-bike one year after receiving their e-bike than they were in the months immediately after getting their bike. This is best demonstrated by the 20% jump in the proportion of respondents reporting less than 50 miles of e-bike travel a month.

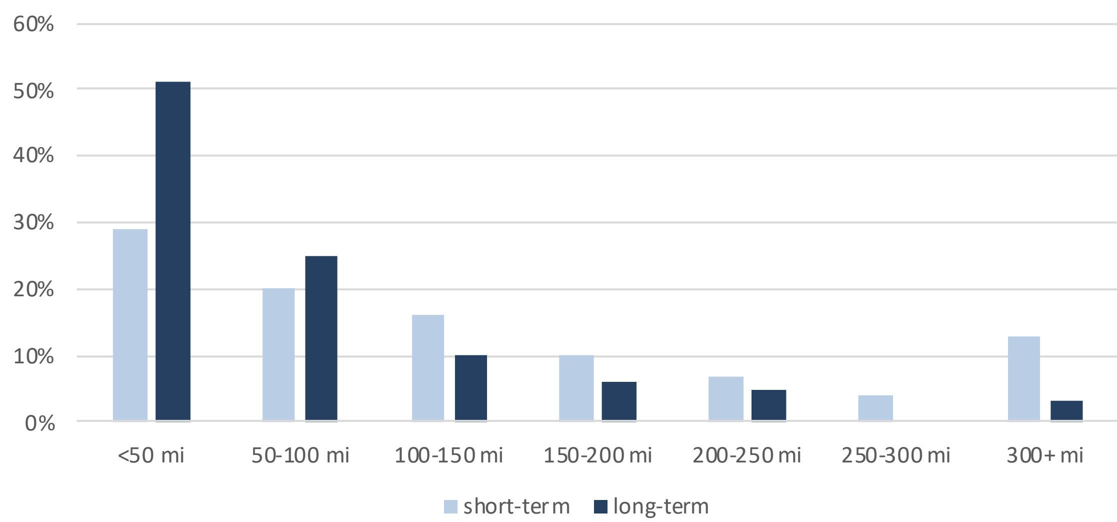

Figure 14. E-bike odometer monthly rates. (short-term: n = 324, long-term: n = 80)

Figure 15 demonstrates the variation in average odometer readings between cities in CC. Figure 15 reveals that participants are traveling by e-bike more in the communities just north of Berkeley, perhaps suggesting that connectivity to Berkeley's bike infrastructure promotes e-bike use. Other communities such as Lafayette, Orinda, Walnut Creek, and Concord see comparatively less travel by bike. This difference is potentially due to variations in topography, land use, bicycle infrastructure, and culture between these communities. When compared with Figure 5 there appears to be some correlation between the number of rebates distributed and the average odometer readings. It appears that communities with a higher number of rebates have, on average, greater odometer readings.

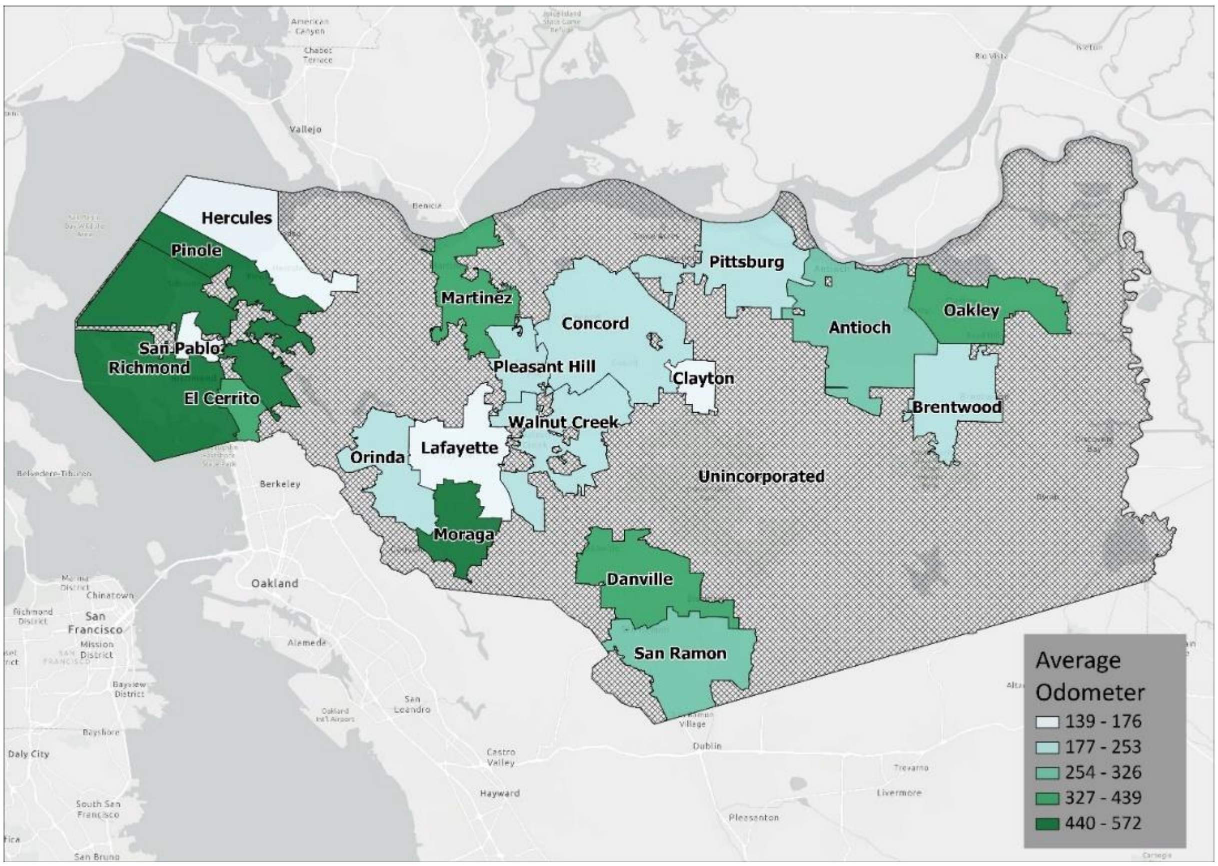

Figure 15. Average e-bike odometer readings by city of residence (in miles).

Charging Behavior

Understanding the charging behavior of respondents helps to better understand their e-biking behavior, particularly their frequency of use and distance traveled. Given that data quality issues affected both the travel frequency and odometer reading responses, this information is especially valuable. Figure 16 below shows that the majority of respondents either charge their battery when it falls between 20 and 60% or after every use. Additionally, Figure 17 reveals that participants primarily charge their e-bikes 1-3 times per week or 1-3 times per month, reinforcing the earlier findings that these respondents primarily reported occasional e-bike use.

Very few respondents reported daily charging, which suggests that not many participants were traveling far enough each day to warrant that behavior.

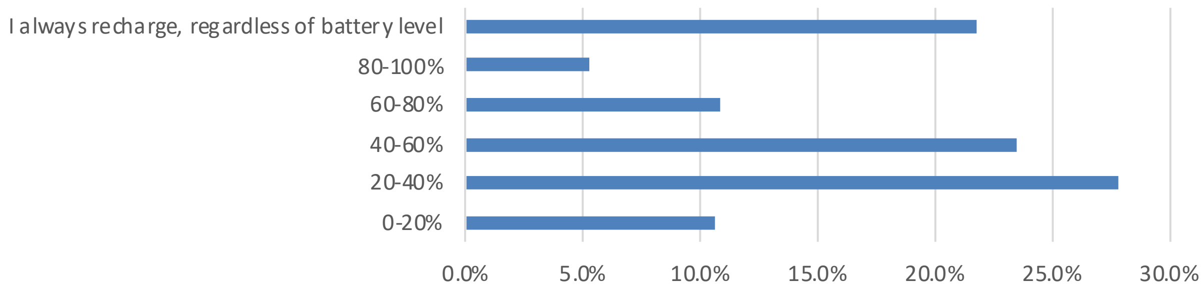

Figure 16. Battery level at time of recharge. (short-term: n = 459)

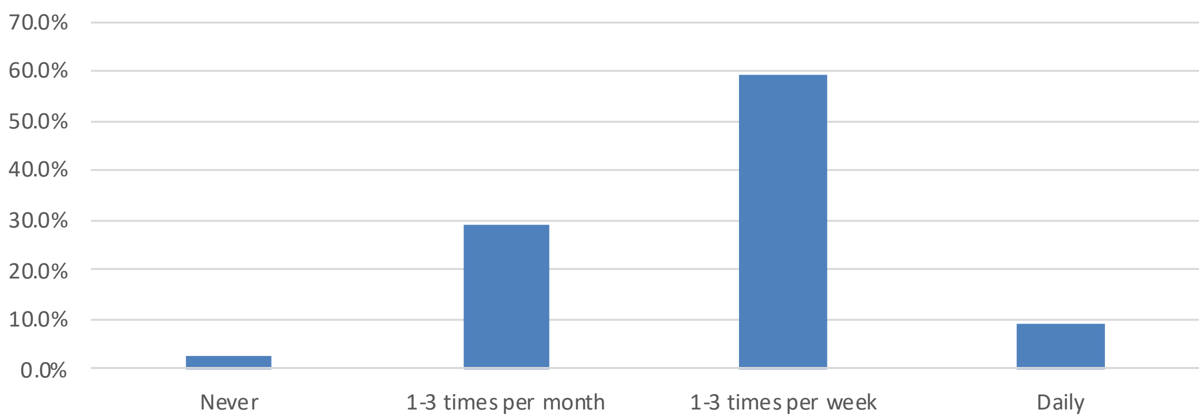

Figure 17. Frequency of e-bike charging. (short-term: n = 458)

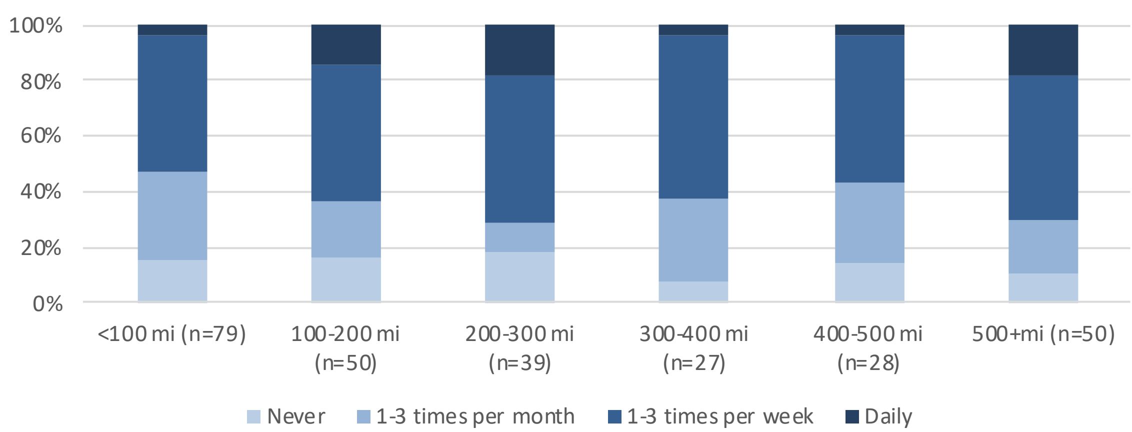

Figure 18. Reported odometer readings by charging frequency. (short-term: n = 280)

Because we do not know the battery capacity and/or range of each e-bike, we could not use charging behavior to estimate milage. However, we compared e-bike charging frequency with reported e-bike odometer readings in Figure 18 to explore the relationship. However, Figure 18 is largely inconclusive. For example, respondents with very high odometer readings (300-500 miles) reported less daily charging than many of the respondents with far lower odometer readings. This is likely due to differences in battery capacity, not behavior. Ignoring e-bike range, the fact that more than 50% of respondents report charging once or more a week no matter how far they were riding indicates more evidence for regular e-bike use by the majority of e-bike recipients.

Benefits and Barriers

From a set list, respondents selected the benefits of owning an e-bike and the barriers to using their e-bike more (Figure 19 and Figure 20). The most popular benefits were that e-bikes were good for recreational use, a good alternative to a car for some trips, able to travel further than non-electric bikes, and less effort than a non-electric bike. Interestingly, environmental gains were not seen as a major benefit of e-bike use. This suggests that environmental consciousness is not a significant factor in our sample's decision-making.

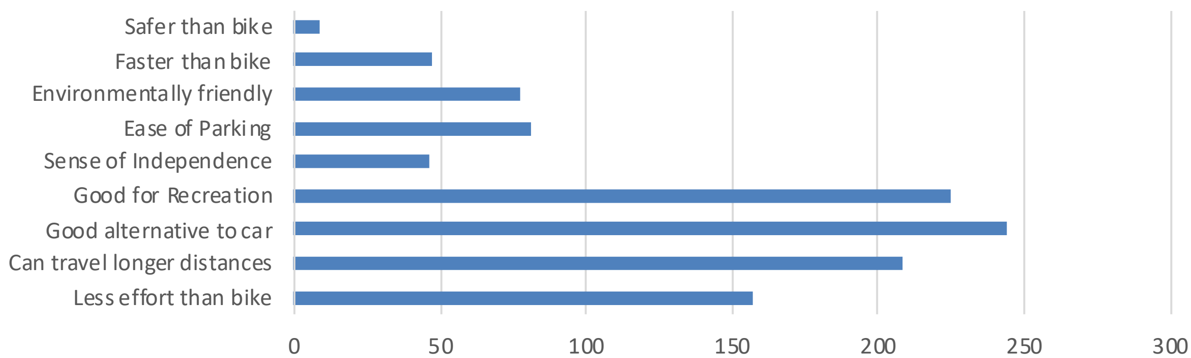

Figure 19. Reported benefits of an e-bike

The reported barriers to increased use of e-bikes were more varied than the benefits, though one clear barrier is a fear of vandalism and theft. This reflects the high cost of these e-bikes and challenges with bike security, especially in urban spaces with poor bike parking facilities. Both the lack of parking space and quality bike lanes were identified as other critical barriers. Adverse weather conditions was the second most common barrier, which was surprising, particularly given the relatively temperate climates of the Bay Area and the Northern Coast of California. Interestingly, very few respondents reported the risk of injury or battery capacity as barriers to increased biking. Existing safety features and battery life seems to be sufficient for most of our sample. Only one respondent reported that they did not like using their e-bike, which reinforces the understanding that e-bikes make active travel fun and exciting.

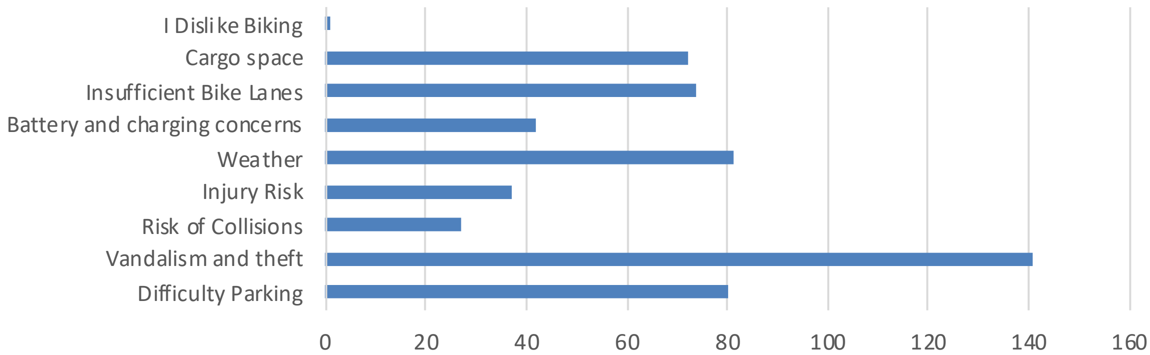

Figure 20. Reported barriers to using an e-bike more.

E-bike ownership may also break down barriers to adoption by simply exposing family, friends, and strangers to e-bikes. Near the end of the survey respondents what people had asked about their e-bike and whether they had influenced anyone to purchase an e-bike. It appeared to be quite common for friends, neighbors, family, and strangers to ask about their new e-bike with over half of the respondents reporting that they had influenced someone to buy an e-bike.

GHG Reductions

Using two methods we estimated that in the short-term our respondents replaced about 35-44% of their car VMT with a reduction in 12-44 kilograms of CO_2 equivalent emissions per person each month. On average, PCE had more VMT and thus greater estimated GHG emissions. Method 2 generally estimated greater GHG emissions though the proportions remain similar to the results of method 1. Given the expectation of declining e-bike use over time, GHG benefits are expected to decrease in the long-term.

Table 4. Short-Term VMT and Total CO_2 Equivalent Emissions by Time and Jurisdiction – Method 1

	Before	Short-Term	Car Replacing E-bike Trips
Sum VMT (per respondent)	**175.01**	**103.59**	**82.03**
PCE	*171.90*	*107.03*	*87.70*
CC	*159.93*	*89.79*	*68.38*
Total CO_2 Equivalent Emissions (metric tons)	**0.084**	**0.052**	**0.044**
PCE	*0.135*	*0.085*	*0.074*
CC	*0.044*	*0.025*	*0.020*

Table 5. Short-Term VMT and Total CO_2 Equivalent Emissions by Time and Jurisdiction – Method 2

	Before	Short-Term	Car Replacing E-bike Trips
Sum VMT (per respondent)	**133.13**	**82.68**	**45.41**
PCE	-	-	-
CC	-	-	-
Total CO_2 Equivalent Emissions (metric tons)	**0.041**	**0.026**	**0.012**
PCE	*0.093*	*0.058*	*0.027*
CC	*0.035*	*0.021*	*0.010*

Discussion

Travel Behavior, Car Replacement, and Trip Purpose

After receiving their e-bikes, participants in this study began to travel in ways that many had not previously. In particular, our survey results show an increase in bike use followed by a decrease, although bicycling one year post e-bike was still above baseline. Though bike use has diminished since the initial months after receiving their e-bike, our sample is still biking far more often than they had previously. Though the sample uses their e-bikes primarily for recreational travel, they are still reported fairly regular car trip replacement. The frequency of recreational travel is likely so significant in part due to the ongoing pandemic and variety of restrictions that were in place when this data was collected. Similar to previous research on this topic, our sample reported replacing, on average, over a third of their VMT. This suggests that respondents are partaking in more utilitarian travel than is being captured in the trip purpose responses, or our sample has been using their cars for recreational trips. This is perhaps due to the design of the survey where trip purposes and the reported travel destinations were captured at one or two timepoints. Approaches like continuous travel behavior data collection using travel diaries may be more appropriate for accurately capturing trip purposes and their frequencies. Fortunately, research from a Colorado e-bike pilot project has been using that exact method to explore longitudinal travel behavior. This work found a more uniform distribution of trip purposes with the top seven purposes being in the 8%-20% range (Shankari et al., 2021). During the early stages of the COVID-19 pandemic there was reporting of a resurgence in “pleasure driving” or recreational car travel (Wilson, 2020). Given that this data was collected throughout the pandemic, recreational car travel may not have been quite as unusual as expected. The high rates of reported recreational travel may also be explained through the age distribution of our sample. As stated previously, existing research suggests that older respondents are much more likely to use their e-bikes for recreational purposes. Given that we had very few respondents under the age of 34, it was unsurprising to see recreation being the dominant trip purpose. These high rates of recreational travel may also indicate that bicycle infrastructure fails to facilitate regular utilitarian use. This is reinforced by lack of available parking, insufficient bike lanes, and difficulty transporting cargo or passengers all being reported as barriers to increased e-bike use.

Earlier research suggests that there are high levels of interest in e-bike adoption from those who bike the least (Fyhri et al., 2017). This implies potential for substantial GHG emissions reductions as non-frequent bicyclists embrace e-biking. Almost every participant in our sample had access to a working bicycle before participating in a rebate program but very few reported regular bicycle travel prior to receiving their e-bike. Further research should be done to explore differences in travel behavior and attitudes amongst participants with varied bicycle familiarity.

From the self-reported travel behavior questions, it is clear that there is some discrepancy between the respondents’ real world travel and their reported behavior. In short, it is difficult to discern whether people are overstating their car replacement, understating their total travel, overstating their recreational travel, or some combination of the possibilities discussed above.

Further research should use different survey instruments to explore the trip purposes of e-bike owners in greater detail.

Barriers and Bicycle Accessibility

The self-reported barriers to increased use of an e-bike help to inform areas for improvement in the design of e-bike incentive programs and the need for other strategies to improve bicycle mobility. As an example, difficulty transporting cargo and passengers could be partially solved by adding caveats to e-bike rebate programs to support the purchase of specialty e-bikes. This could include additional financial incentives or support for participants who aim to purchase a cargo e-bike, passenger e-bike, or other specialty e-bike. Another commonly reported barrier was the poor quality or lack of bicycle infrastructure. The absence of quality bicycle infrastructure is a larger issue that must be addressed outside of rebate programs. The presence of this as a common barrier is a reminder that rebate programs alone cannot promote the broader adoption of active travel. To improve bicycling comfort traffic speeds must be slow and bike facilities must be available and of high quality (Fitch et al., 2022). Additionally, these infrastructure efforts should promote an interconnected network of bikeways that offer direct paths to key destinations. Physical separation from motor vehicle traffic and improved intersection design would mitigate conflicts and encourage more bicycle travel (Pucher & Buehler, 2016). To generate a significant mode shift, communities would need to see improvements in infrastructure and dramatic changes in urban land use. Without these efforts, financial incentives to change travel behavior will likely only serve communities with access to quality urban spaces.

The interaction between e-bikes and public transportation is one area that is particularly understudied, with only a few publications that explore this in depth. Research on Chinese e-bike owners has shown that people in areas underserved by public transportation are more likely to shift from transit to e-bikes (Cherry et al., 2016). Additionally, there are many challenges with integrating e-bikes as a feeder mode for public transportation systems as users report difficulty with transit access trips (Cherry et al., 2016; MacArthur et al., 2018). Bicycle users can experience challenges carrying heavy bikes onto transit and difficulty findings space to store their bike while on board. In addition, bike parking at transit stations may be perceived as a risky place to store a bike. These findings highlight both the potential of e-bikes to improve mobility in areas with poor transit service and the need to bridge gaps between active transportation and public transit.

One of the clear takeaways from the survey results was that lower-income participants replaced car trips more regularly and therefore had greater emissions reductions than the rest of the sample. However, our highest income respondents were reporting more daily replacement than the rest of the sample despite less frequent overall replacement. This suggests that they may have better access to quality bicycle infrastructure or have lifestyles that better accommodate frequent bicycle use. Generally, e-bikes have mitigated some of physical barriers to bicycling and improved the accessibility of active transportation. Though, from the reported barriers in this survey it is apparent that improvements in bicycle design alone cannot solve all the barriers that prevent people from using active transportation. More research is needed to understand how e-bike incentive programs interact with other strategies to improve the accessibility of bicycling in U.S. cities.

Program Costs and GHG Reductions

By using data collected on participant travel frequency, car trip replacement frequency, and average distance of their trips we were able to estimate the individual GHG reductions caused by e-bike ownership. To better understand the effectiveness of e-bike rebate programs as an investment to reduce GHG emissions we received rough estimates of the costs of implementing each program. Unfortunately, each agency did not track administrative costs so the budget for rebate payments had to be used to calculate the investment-to-GHG reduction ratios for each program. RCEA invested roughly $702 per participant while PCE spent $796 and CC spent $191. For PCE, on average, this translates to an investment of $796 to achieve a short-term GHG reduction of 44 kilograms of CO_2 equivalent emissions per month per participant. For CC their $191 investment generated a short-term reduction of 20 kilograms per month. These estimates are similar to those found in earlier research in Portland, Oregon examining the impacts of e-bikes loaner programs on GHG emissions (McQueen et al., 2020).

To evaluate the cost-effectiveness of transportation programs CARB has developed some general benchmarks for GHG cost-effectiveness (CARB, 2020). However, as of the time of this writing, these do not include any micromobility or active transportation programs, making project comparison difficult. Further work must be done to understand and fill this regulatory gap to establish guidelines for cost-effective micromobility incentive programs. The benefits of active travel go far beyond emissions reductions. Increased active travel has numerous positive impacts on health and wellbeing and greatly mitigate the negative effects of car travel (Mulley et al., 2013). For e-bike incentive programs it will likely be years before their benefits are fully realized.

Program Design and Equity

To achieve an equitable distribution of resources it is advised that rebate programs utilize income qualifications, flat-rate incentives, graded incentive levels, and mitigate participant burden through streamlined application processes and point-of-sale discounts (Bennett et al., 2022). Importantly, e-bike rebate programs are likely to be rebate-limited rather than demand-limited. This means that all available rebates are likely to be claimed and impacts will presumably scale with the programs budget (Bigazzi & Berjisian, 2021). To reach lower-income residents it is recommended to offer higher rebate amounts with a flat-rate incentive, that meaning a payment that does not scale with the cost of the e-bike. This strategy will improve access to e-bikes for low-income individuals but is unlikely to overcome disparities in baseline demand (Bigazzi & Berjisian, 2021). Flat rebates also reduce administrative burdens and helps to avoid larger rebate payments going to higher priced e-bikes that are likely only financially feasible for high-income participants. The three programs in our study each had a unique program design that was, in part, informed by the research summarized above.

RCEA had the least restrictive approach to participant eligibility and therefore had fewer low-income participants than the other programs resulting in fewer car replacing trips. CC utilized some of the recommended strategies such as flat-rate rebates and graded incentive levels but they did not have upper-income thresholds and offered small rebate payments. While the program technically targeted low-income participants with slightly higher rebate payments for income-qualifying individuals, in practice only 26% of their sample was low-income, meaning that a large number of rebates likely went to individuals who would have been able to purchase an e-bike without a rebate payment. Finally, PCE had a program design that only allowed low-income participants through the use of income-qualifications and was successful in only distributing rebates to low-income individuals. However, PCE, similar to the other programs, had issues with its representativeness in other demographic categories. Namely, PCE respondents were older and whiter than the general population of San Mateo County. This may mean that other strategies are needed to improve equity outcomes. A potential solution could be targeted program outreach in underrepresented communities utilizing a variety of communication channels including partnerships with community organizations. Using income qualified programs that are known to have large numbers of BIPOC people to streamline the income verification processes may also be useful. Additionally, rebate programs may try to target specific Census blocks or tracts with greater proportions of BIPOC residents. Future research should explore how these methods, amongst others, could be employed to better achieve equity goals in rebate distribution.

Improving accessibility in the distribution of financial incentives for e-bikes is a complex problem with no one-size-fits-all solution. Public agencies must put effort into better curating their programs to reach the underserved populations in their community. Strategies to achieve this could include the ones discussed above or other creative approaches. Continued and improved assessment of these programs will help to inform best practices for achieving desirable equity outcomes in future programs.

Conclusion

The results of each program's survey have shown that ownership of an e-bike leads to significant changes in travel behavior. Particularly, e-bikes have been shown to replace many car trips, principally in the early months after the purchase of an e-bike. While many dimensions of long-term travel behavior impacts are less clear, there is evidence that respondents continue to replace car trips, albeit at lower frequencies. Still needed is research that looks beyond a year of e-bike use and research that looks beyond VMT reduction toward all the other benefits an e-bike affords people. For example, in this study e-bikes appear to induce recreational travel, both in the short-term and long-term. This recreational travel could be providing important physical and emotional health benefits.

A primary focus of this research has been exploring the effects of these programs on car trip substitution and GHG reductions. We found differences in e-bike use between household income groups, genders, and age categories. Particularly, lower-income and high-income groups reported the most frequent car trip replacement, though overall the frequency was greater for low-income participants. Additionally, younger respondents tended to use their e-bikes to replace car trips more often than older respondents. However, most of our sample reported at least semi-regular replacement.

This research has revealed the limitations and success of e-bike incentive programs. As California is prepared to introduce a statewide e-bike voucher program it becomes increasingly important to understand the variety of impacts that wider e-bike ownership will have on communities across the state. Future research should investigate the long-term impacts of e-bike ownership, travel behavior by e-bike type and price, and alternatives to e-bike ownership for achieving the same results. Additionally, the potential for incentive programs for non-electric bikes should be explored. The evidence that e-bikes replace more VMT than non-electric bikes is largely from European countries where there are substantial land use and cultural differences. Incentives for non-electric bikes may be more helpful for the lowest income families by allowing for them to cover the full cost of a bike purchase with a comparatively small rebate. More detailed research should also be done to better understand differences in bike use in different geographic contexts and over longer periods. In particular, examining behavior based on where the respondent lives and works on the rural-to-urban gradient and how behavior changes past a year of ownership.

These three programs show that e-bikes have a place in California communities. They have been able to bridge barriers to active transportation that many previous efforts and services have not. E-bikes offer a fun and exciting alternative to the traditional bicycle, public transportation, and private vehicle while showing promise as a strategy to address climate change. Changes in travel behavior associated with e-bike ownership could have positive and lasting feedbacks for sustainability and equity. E-bikes may offer individuals the freedom to shed cars, access better jobs, improve their health, and reach more destinations. We hope that with the wide availability of incentives there will be continued growth in the use of this mode. Though if uncoupled with other strategies to promote active travel, incentive programs alone will likely not be enough to promote a sustained and widespread mode shift.

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Data Summary

Products of Research

Participants in the three rebate programs were asked to complete a follow-up survey after receiving their rebate. These surveys asked the respondent to report information about their demographics, travel behavior, and attitudes about their e-bike. In total, we received 41 responses from the Redwood Coast Energy Authority, 67 from Peninsula Clean Energy, and 509 from Contra Costa County.

Data Format and Content

The datasets accompanying this project are separated by the time at which the survey was administered. Peninsula Clean Energy (PCE) and Contra Costa County (CC) distributed a survey 1-2 months after respondents received their rebate and CC also distributed a 1-year follow-up survey. Redwood Coast Energy Authority (RCEA) distributed their survey 1-year afterwards. The "short-term" dataset includes responses from the surveys distributed 1-2 months while the "long-term" dataset has responses to the 1-year follow-up. The raw data was partially cleaned in R using the script available with the archived data, though additional manual cleaning in Excel was still needed. Details on each variable are included in a separate lookup file.

Data Access and Sharing

The final data of this project is available upon request from the Principal Investigator, Dillon Fitch-Polse (dtfitch@ucdavis.edu).

Reuse and Redistribution

There are no restrictions on the use of the data. Data can be reused with credit to this report and the authors of the research.