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Modeling the impacts of electric bicycle purchase incentive program designs

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ABSTRACT

Governments are interested in incentivizing e-bike adoption, due to potential benefits from displacing travel by private automobile. To inform the development of e-bike purchase incentive programs, the objective of this paper is to determine how key elements of program design (particularly rebate amounts and structure) are expected to affect new e-bike purchases. An aggregate demand model is developed and applied to rebate scenarios to examine incentive effectiveness. Results show that rebate programs are expected to be bound by available rebates, not e-bike demand, and additional bike shop revenues exceed rebate costs. At a fixed program budget, fewer, larger rebates yield fewer additional sales, but a larger share of rebates go to low-income and new (marginal) purchasers. Flat and proportional rebate structures yield similar sales, although flat rebates are more income-equitable. Flat rebates are recommended for new e-bike incentive programs, with robust program evaluations to inform future program designs.

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Electric bicycle; e-bike; incentive program; aggregate demand model; rebates; case study

1. Introduction

The growing literature on electric bicycles (e-bikes) indicates that e-bike use (and interest in e-bikes) is steadily growing worldwide, with uptake in North America and Europe lagging uptake in Asia (Fishman and Cherry 2016). Many governments are interested in incentivizing further e-bike adoption, due to potential benefits from increasing physical activity in the population and displacing travel by private automobile. Commonly cited motivators of e-bike adoption are some of the same factors motivating other forms of active travel (e.g. exercise-related health benefits, environmental concerns) coupled with the greater ease of cycling with motor assistance (e.g. traveling with less time and/or longer distances, mitigating effects of hills, and reducing perspiration during travel). Commonly cited deterrents are price and fear of theft, in addition to the deterrents of cycling in general such as fear of injury and exposure to weather (Fishman and Cherry 2016; Fyhri et al. 2017; Leger et al. 2019; Rose 2012).

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Incentive programs for e-bikes take various forms, often targeting the known barriers to adoption (McQueen, MacArthur, and Cherry 2019). Some program strategies are similar to general cycling promotion (in particular infrastructure improvements), while others target particular issues of concern for e-bikes (secure parking with electric power, for example). As e-bikes are a relatively novel option for many travelers, many incentive programs (particularly those run by companies in the e-bike industry) use free or discounted e-bike rentals or loans. To address the issue of purchase cost directly, a common e-bike adoption incentive program type is purchase incentives through monetary rebates to consumers (sometimes coupled with other incentive elements such as training or rentals).

Although e-bike incentive programs have increased in recent years, to date there has been limited evaluation of program impacts on e-bike adoption or usage (McQueen, MacArthur, and Cherry 2019). Several studies in northern Europe and the US have found positive perception and behavior changes from interventions in the form of short-term e-bike loans of 1–10 weeks (Fyhri et al. 2017; MacArthur et al. 2017; Moser, Blumer, and Hille 2018; Wikstrøm and Böcker 2020). Moser, Blumer, and Hille (2018) reported that a two-week loan program 'had a long-term effect on participants' habitual associations with car use, regardless of whether they would go on to purchase an e-bike' after the intervention. Fyhri et al. (2017) reported an increased willingness to pay for e-bikes after such a first-hand experience, and suggested price reductions as an incentive strategy. de Kruijf et al. (2018) found direct financial incentives (per km cycled) to be effective for increasing e-bike travel, but did not investigate purchase decisions or incentives.

Developing a purchase incentive program involves many design elements including eligibility, administration, and rebate amounts. A key design question is how to use available resources most effectively with respect to program goals. For example, a fixed program budget could be distributed as many small incentives or fewer, larger incentives. If the goal is to encourage mode shift toward cycling, a key program performance indicator is the incentivized amount of new e-bike adoption. It cannot be reasonably assumed that all purchase incentives are going toward new (marginal) purchasers; some purchases would have been made without the incentive. So incentive program design relies on an understanding of how incentives influence purchase behavior.

A variety of methods have been used to model the impacts of incentives on vehicle sales or travel mode adoption, depending on the context, objectives, and available data and resources. Past research on e-bike adoption scenarios has used sales and adoption assumptions, due to a lack of available information and models (Bucher et al. 2019; McQueen, MacArthur, and Cherry 2020). For example, in Mason, Fulton, and McDonald (2015) the impacts of e-bike uptake are estimated by *a priori* assumed adoption levels. No known research estimates e-bike sales or adoption based on a behavioral model of responses to price incentives or rebates.

More research has been done on electric vehicle (automobile) sales and adoption in the context of price incentives (rebates and tax breaks). Chandra, Gulati, and Kandlikar (2010) assumed that rebates have no effect on the aggregate number of new cars sold, and hence only modeled the effects of price incentives on the hybrid electric vehicle (HEV) market share of new car sales. They estimated that 26% of new HEV sales were attributed to a US$1000 rebate. DeShazo, Sheldon, and Carson (2017) similarly modeled the effect of an electric vehicle (EV) rebate program based on the market share of EV, using a utility-based demand model estimated from stated preference (survey) data. Diamond (2009) estimated a similar HEV market-share model using empirical sales data from the United States.

Hence, models of EV purchase subsidies estimate the share of auto sales that will be EV, assuming that the incentives have a negligible effect on total auto ownership. This approach would poorly transfer to e-bike incentives because they are *per se* intended to increase total bicycle ownership and usage, not incentivize a shift away from conventional bicycles. Such an effect is supported by a recent meta-analysis that suggested just around ¼ of e-bike use displaces travel by conventional bicycles, varying widely by context (Bigazzi and Wong 2020). Thus, it is unreasonable to assume that anywhere near all of the incentivized e-bike adoption is from a fixed market of bicycle ownership, and an alternative approach is needed to estimate the effects of e-bike purchase incentives on e-bike adoption.

Given the lack of information in the literature, those seeking to develop e-bike purchase incentive programs have little basis for making decisions about program design elements. This paper aims to help address that gap and inform the design of e-bike purchase incentive programs. The objective is to determine how key elements of program design (in particular the role of rebate amounts and structure) are expected to affect new e-bike purchases. Related impacts of the program such as additional bike shop revenues are also examined. A mathematical model is developed to estimate the effects of e-bike purchase incentives from microeconomic principles, and then the model is applied to several rebate scenarios to examine incentive effectiveness in different contexts.

2. Method

An aggregate demand model is used to estimate increased e-bike purchases resulting from a rebate program, and further adoption impacts are estimated from values in the relevant literature. Additional e-bike sales due to rebate incentives are estimated from program parameters (number and size of rebates), market information (baseline e-bike price and sales estimates), and representative elasticity values from the literature. The model is applied to case study market characteristics from two Canadian cities, one small and the other large, with otherwise comparable characteristics: Victoria and Vancouver, British Columbia.

2.1. e-bike demand model

The aggregate demand model is based on extensive literature in transport economics (Ortuzar and Willumsen 2011; Small and Verhoef 2007). Individuals have a likelihood of purchasing an e-bike in a given year that is dependent on e-bike price p, e-bike characteristics, individual preferences and characteristics, opportunity costs of purchasing, and other factors. Aggregate demand d for e-bikes is a function of the same set of factors and the size of the population. Two common forms for the aggregate demand functional relationship to price are linear, $d = f(p)$, and power, $d = f(p^k)$. Price elasticity of e-bike demand ε represents the effect of e-bike price on aggregate e-bike demand:

$$\varepsilon = \frac{p}{d}\frac{\partial d}{\partial p}.$$

A rebate r will reduce the effective consumer e-bike price from p to $p - r$, assuming a relatively flat e-bike market supply curve so that the rebate program does not affect e-bike retail prices. Using a linear demand function, the new total demand with a rebate is $d = d_b\left(1 - \frac{\varepsilon r}{p}\right)$ where d_b is the baseline demand without a rebate. The change in demand as a result of the rebate is $\Delta d = d - d_b = -d_b \varepsilon \frac{r}{p}$. Alternatively, using a power demand function the new demand level is $d = d_b\left(1 - \frac{r}{p}\right)^{\varepsilon}$ and the change indemand is $\Delta d = d_b\left[\left(1 - \frac{r}{p}\right)^{\varepsilon} - 1\right]$.

The change in demand, Δd, represents the additional potential EB sales with the rebate, but the sales may not be realized if there are a limited number of rebates, n_r, available within the incentive program (due to budget constraints). If $d \le n_r$, there are enough rebates to satisfy all demand (baseline plus rebate-induced), and there will be $s = \Delta d$ additional sales and $s + d_b$ total rebates issued. If $d > n_r$, there are not enough rebates available for all demand with the rebates. In that case, it is assumed that it is effectively impossible to only provide rebates to the marginal (rebate-induced) purchases, and an individual's opportunity to receive a rebate is independent of their likelihood of purchasing. It is also assumed that purchasers would know about the availability of a rebate before purchasing. Hence, the n_r available rebates are distributed proportionally to baseline and marginal demand such that:

- $\frac{d_b}{d} n_r$ go to baseline individuals who would have purchased without the rebate, and

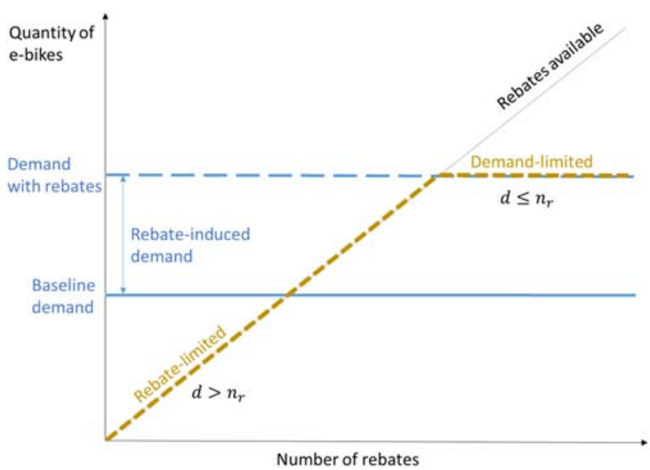

Figure 1. Illustration of rebate- and demand-limited conditions.

Table 1. Summary of demand functions.

	Linear demand function		Power demand function	
	Demand-limited ($d \le n_r$)	Rebate-limited ($d > n_r$)	Demand -limited ($d \le n_r$)	Rebate-limited ($d > n_r$)
Rebate-limited test condition	$d_b\left(1-\frac{\varepsilon r}{p}\right) > n_r$		$d_b\left(1-\frac{r}{p}\right)^{\varepsilon} > n_r$	
Total demand with rebate, d	$d_b\left(1-\frac{\varepsilon r}{p}\right)$		$d_b\left(1-\frac{r}{p}\right)^{\varepsilon}$	
Additional demand with rebate, Δd	$-d_b \varepsilon \frac{r}{p}$		$d_b\left(\left(1-\frac{r}{p}\right)^{\varepsilon}-1\right)$	
Additional sales, s	$-d_b \varepsilon \frac{r}{p}$	$\frac{n_r \varepsilon r}{\varepsilon r - p}$	$d_b\left(\left(1-\frac{r}{p}\right)^{\varepsilon}-1\right)$	$n_r\left(1-\left(1-\frac{r}{p}\right)^{-\varepsilon}\right)$
Rebates issued	$d_b\left(1-\frac{\varepsilon r}{p}\right)$	n_r	$d_b\left(1-\frac{r}{p}\right)^{\varepsilon}$	n_r
Portion of rebates to new purchasers	$\frac{\varepsilon r}{\varepsilon r - p}$		$\left(1-\left(1-\frac{r}{p}\right)^{-\varepsilon}\right)$	

- $\frac{\Delta d}{d} n_r$ go to induced (marginal) purchasers, resulting in $s = \frac{\Delta d}{d} n_r$ additional sales (which equates to $s = \Delta d$ at the limiting case $d = n_r$).

Rebate-limited and demand-limited additional sales are illustrated in Figure 1. The minimum budget to satisfy demand and reach the demand-limited (not rebate-limited) condition is $n_r r = dr$ (i.e. where $n_r = d$).

Applying the linear and power demand functions, expressions for additional sales and relevant program impacts are given in Table 1. In summary, to estimate the additional sales from a rebate program, the following model inputs are needed:

- Market information: baseline price (p) and demand (d_b) without rebates
- Program design variables: rebate amount (r) and number available (n_r)
- Consumer attributes: price elasticity of e-bike demand (ε)

The selection of these variables is discussed in the next section. There are several major assumptions in the method which are noted above and discussed at the end of the paper, but warrant repetition here. The first is that e-bike market prices are assumed to be unaffected by the introduction of the rebate program (i.e. bike shops do not adjust their prices in response to the rebates or the induced demand). The second is that rebates are arbitrarily allocated to purchasers so that a marginal/induced purchaser (who would only purchase with the rebate) and a baseline demand purchaser (those who would have purchased without the rebate) have an equal likelihood of receiving a rebate.

2.2. Input data and assumptions

2.2.1. Case study locations

The model is applied for a case study of two similar cities of different sizes, but similar contexts: Victoria and Vancouver, British Columbia, Canada. Both cities have strong sustainable transportation policy agendas, with robust cycling networks (for North America), and various cycling supports from advocacy organizations and all levels of government. Neither currently has an e-bike purchase incentive program. The province of British Columbia does have a vehicle scrappage program with the option of a C$1050 rebate on an e-bike of at least C$1200, among other options including C$6000 toward a new electric car or C$200 cash (where C$1000=US$800). However, informal information from both bike shops and the SCRAP-IT program indicates the e-bike incentive is rarely used. Estimates are made for both the municipalities and regions of Victoria and Vancouver, with the regions encompassing suburban areas with less cycling infrastructure and activity.

2.2.2. e-bike sales

E-bike sales and ownership numbers are difficult to obtain, particularly at fine spatial scales. E-bike sales estimates at the national level are typically made through customs records, which itself is challenging due to a lack of clarity in filing categories (Benjamin and Poynter 2014; Wild and Woodward 2018). There is no known large-scale survey that collects e-bike ownership data, and the closest spatial sales data available are for the entire USA. Due to a lack of market data, baseline e-bike demand (d_b) for the case study geographies is estimated by scaling US annual sales by population and bicycle commute mode share.

The core assumption behind the sales estimate is that *per capita* e-bike sales are proportional to bicycle commute mode shares. Local annual e-bike sales, S_L, are estimated from annual US national sales, S_U, the population of each geography, P_L and P_U, and the bicycle commute mode share of each geography, M_L and M_U. The core assumption can be written $\frac{S_L}{P_L M_L} = \frac{S_U}{P_U M_U}$, and rearranged to solve for $S_L = S_U \frac{P_L M_L}{P_U M_U}$.

Base year (2016) data are given in Table 2. Population and bicycle commute data and 5-year growth estimates are taken from the US and Canadian Censuses (Statistics Canada 2012, 2017; U.S. Census Bureau 2018). US e-bike sales estimates are compiled from the eight sources: (Benjamin and Poynter 2014; Citron and Gartner 2016; Fishman and Cherry 2016; MacArthur, Dill, and Person 2014; McFarland 2018; Sutton 2017; Takiff 2017; The NDP Group, Inc. 2017). Compiled sales estimates from all eight sources yield 13 observations over the years 2012 through 2017. A linear trend-line through these data is estimated as $S_U = 101,500 + 28,500(Year - 2012)$, with an R^2 of 0.45, indicating 2016 sales of 215,500 and annual growth of 28,500.

Table 2. Baseline e-bike sales data estimates.

	Victoria city	Victoria metro	Vancouver city	Vancouver metro	USA
2016 Population (annual growth)	85,792 (1.40%)	367,770 (1.31%)	631,486 (0.91%)	2,463,431 (1.27%)	324,310,011 (0.77%)
2016 Bicycle commute mode share (annual growth)	11.11% (0.88%)	6.58% (2.24%)	6.14% (7.08%)	2.35% (5.44%)	0.69% (2.50%)
2016 Annual e-bike sales (annual growth)	unknown	unknown	unknown	unknown	215,500 (28,500)
2020 baseline demand (±20%)	1375 (±275)	3671 (±734)	6960 (±1,392)	9913 (±1983)	329,500 (±65,900)
2030 baseline demand (±20%)	2329 (±466)	7045 (±1409)	20,388 (±4078)	25,786 (±5157)	614,500 (±122,900)

Table 2 also gives 2020 and 2030 estimates for baseline demand d_b, based on the 2016 data and growth rates, and the core assumption equation (i.e. per capita e-bike sales are proportional to bike commute mode share), along with an assumed ±20% margin of error to account for the large uncertainty. Sales of e-bikes are estimated at 4–28 per 1000 population for Victoria and Vancouver (varying by geography and year) and at 1–2 per 1000 population for the US; for comparison, the US and Europe are estimated to purchase non-electric bicycles at a rate of about 50 and 30 per 1000 persons per year, respectively (Benjamin and Poynter 2014). The projected e-bike sales growth rate in Victoria and Vancouver is 5% to 11% per year. The e-bike market size is difficult to estimate at this scale, but note that if program is rebate-limited, then the additional sales (s) are independent of d_b. Hence, the results will not be sensitive to this variable in a market of sufficient size to satisfy the rebate scarcity constraint: $d > n_r$.

2.2.3. e-bike prices

Sales prices for e-bikes were obtained through a survey of nine local e-bike retailers in 2018. Prices were categorized according to style (mountain, cargo, road, etc.), and motor assist type (pedal-assist, throttle-assist, etc.). Across all e-bikes, prices ranged from C$590 to C$12,370. By several different weightings by type and model, overall median prices were in the range of C$3700 to C$4900.

Based on these data, representative low, medium, and high e-bike prices are given as C $2500, C$4500, and C$6500, respectively (in CAD). Baseline demand is assumed to be uniformly distributed across these price levels. For comparison, industry information suggests average US sales prices (in C$) of C$3200, with 40% of US sales from e-bikes over C$4000, 30% from e-bikes in the range C$3300 to C$4000, and 30% from e-bikes below C$3300 (The NDP Group, Inc. 2017). Also, as mentioned above, a recent report for the Victoria region suggested a regional e-bike price range of C$2000 to C$8000 (WATT Consulting Group 2018).

Price changes over time are difficult to predict. As a new technology, e-bike prices may fall as battery technology advances. At the same time, prices are rising in the bicycle market in general, and the future trend for e-bike prices is unknown. Given this uncertainty, scenarios are estimated with price trends ranging ±5% annually.

2.2.4. Price elasticity of e-bike demand

Due to limited information on e-bike demand and price sensitivity, values are derived from the broader literature on bicycles and electric cars. Five relevant studies report the following values for price elasticity of demand: −1.3 for bicycles in the Netherlands (Derksen and Rombouts 1937), −2.7 for bicycles in the US (Kerr 1987), and −0.9 to −2.3 for electric vehicles in the US (DeShazo, Sheldon, and Carson 2017; Glerum et al. 2014; Mabit and Fosgerau 2011). Based on these studies, a broad range of elasticity values is applied, with a central value of −2.0, but ranging from −1.0 to −3.0.

2.2.5. Income effects on e-bike demand

Lower-income individuals tend to have higher marginal utilities of income, and hence be more sensitive to price and rebates (DeShazo, Sheldon, and Carson 2017). Thus, rebates are more cost-effective if targeted to lower-income consumers, and equity and efficiency outcomes can align. Potential price effects are estimated by segmenting the potential e-bike market into three income categories (low/medium/high), and applying 20% changes to price elasticities across segments, informed by DeShazo, Sheldon, and Carson (2017) and Small and Verhoef (2007). The baseline demand is also distributed disproportionally across the income segments, to account for the high income of early e-bike adopters reported in the literature (Fishman and Cherry 2016; MacArthur, Dill, and Person 2014). The assumed baseline demand is equal across income tertiles for low-priced e-bikes, two times higher from high-income versus low-income tertiles for medium-priced e-bikes, and 3 times higher for high-income versus low-income tertiles for high-priced e-bikes.

2.3. Rebate program scenarios

Modeled program characteristics and rebate amounts are based on a review of existing e-bike incentives programs. To focus on municipal-led programs, the review was limited to rebate programs that targeted residents of a specified area rather than employees of companies or business-oriented programs. Examples included programs in Edmonton, Austin, and Oslo (Austin Energy 2018; City of Edmonton 2020; Weller 2017), in addition to those in a recent white paper on e-bike incentive programs (McQueen, MacArthur, and Cherry 2019). Typical incentive amounts range from C$260 to C$1600, although amounts over C$1000 are rare. Based on these observations, the suggested ranges for representative rebates is as follows: Low (C$200 to C$400), Medium (C$400 to C $1000), and High (C$1000 to C$1600).

As an alternative to flat rebate amounts, tiered rebate structures offer rebate amounts that vary, usually based on the price of the e-bike. For example, rebate amounts can increase by C$100–200 with incremental C$1000 e-bike price tiers. A similar approach is rebate amounts at a fixed percentage of e-bike prices, often capped at a maximum amount. Typical amounts are 20%–30% of e-bike price, capped anywhere in the range of flat rebate amounts, from C$300 to C$1600.

The modeled programs begin in 2020, and a 10-year horizon is included to model demand out to 2030 with varying demand and prices. Program effects are estimated using a linear demand function and representative annual program budgets of C $50,000 to C$1,300,000 – roughly half of the relevant population. Two types of rebate structures are modeled with varying rebate amounts, based on the review of existing programs: flat rebates of C$200 to C$1600, and proportional rebates of 10% to 30% of e-bike price. For e-bike prices ranging from C$2500 to C$6500, the 10% to 30% proportional rebates translate to rebate amounts of C$250 to C$1950. A tiered rebate structure was not modeled separately because it is essentially a discrete equivalent to the proportional rebates, and yields similar results. Rebates are equally available across all e-bike price levels and distributed randomly; hence, consistent with above, in rebate-limited conditions rebates are distributed proportionally to total demand at each e-bike price level.

3. Results

3.1. Program design factors

The upper 8 rows of Table 3 give the estimated effects in 2020 of a flat rebate program in Vancouver with an annual budget of C$300,000 and fixed rebates of C$200 to C$1600.

Table 3. Estimated impacts of a flat rebate program in Vancouver (in C$)[1].

Rebate amount [2]	Number of rebates available	Total e-bike demand	Induced e-bike demand	Additional sales	New bike shop revenue	Rebates to additional purchasers	
$200	1500	7680	720	141	$543,700	$28,100	9%
$400	750	8400	1440	129	$497,100	$51,400	17%
$600	500	9120	2160	118	$457,900	$71,100	24%
$800	375	9840	2880	110	$424,400	$87,800	29%
$1000	300	10,560	3600	102	$395,400	$102,300	34%
$1200	250	11,280	4320	96	$370,200	$114,900	38%
$1400	214	12,000	5040	90	$348,000	$126,000	42%
$1600	188	12,720	5760	85	$328,300	$135,900	45%
10%	776	8350	1390	129	$500,000	$50,000	17%
20%	388	9740	2780	111	$428,600	$85,700	29%
30%	259	11,140	4180	97	$375,000	$112,500	38%

[1]$300,000 annual budget, base demand of 6960 for 2020, demand elasticity of −2.0, and linear demand function.
[2]Average rebate amounts of $387, $773, and $1160 for 10%, 20%, and 30% rebate programs, respectively.

The number of available rebates decreases with higher per-rebate values. At the same time, higher rebate amounts increase total and induced (marginal) e-bike demand.

These are all rebate-limited cases (i.e. all available rebates are used), and so the additional sales are limited by the number of rebates available to marginal purchasers (those who will only purchase with the rebates). At higher rebate amounts, the induced demand increases, as does the portion of rebates going to marginal purchasers. However, the additional e-bike sales fall somewhat with rebate amount, as fewer rebates are available. New revenue to bike shops falls as well with fewer additional sales. Still, because induced demand is a higher share of total e-bike demand at higher rebate levels, the amount and share of rebates going to marginal purchasers increase with rebate amount.

In short, there is a general trade-off, where higher rebate amounts yield fewer additional e-bike sales (because fewer rebates are available at a fixed program budget), but a higher proportion of the rebate funds go to marginal purchasers. Also, note that the new bike shop revenue (induced by the rebates) exceeds the program costs in all cases.

The lower three rows of Table 3 also give the estimated effects of a proportional rebate program (but otherwise the same), with rebates of 10% to 30% of e-bike prices. These are again rebate-limited cases, with all available rebates used. The estimated effects are similar to the flat rebate program, where higher rebate levels yield slightly fewer additional purchases, but a greater share of rebates going to marginal purchasers. In addition, the magnitude of the effects is similar, if comparing flat and proportional rebates in Table 3.

The effects scale linearly with the budget, so doubling the budget essentially doubles the impact of the program. The linear relationship with the budget is due to the consistent rebate-limited state of the program (i.e. there is ample demand to take up all the available rebates). With small rebates and a large budget, the effects could become demand-limited, which would cap the program effects. For the example program in Vancouver above, this would not happen until the annual budget exceeded C$1.5 million.

3.2. Context

Table 4 compares flat rebate program effects across the four geographies described above: municipal and regional Victoria and Vancouver. For comparison across scales, annual

Table 4. Comparison of flat C$800 rebate across geographies.

	Victoria city	Victoria metro	Vancouver city	Vancouver metro
Population	90,700	387,400	654,800	2,590,500
Baseline demand	1380	3670	6960	9910
Program budget	$50,000	$200,000	$300,000	$1,300,000
Number of rebates	63	250	375	1625
Total (induced) e-bike demand	1950 (570)	5190 (1520)	9840 (2880)	14,010 (4100)
New sales (revenue)	18 ($70,700)	73 ($282,900)	110 ($424,400)	476 ($1,838,900)
Minimum budget to satisfy demand ($800 rebates)	$1,560,000	$4,150,000	$7,870,000	$11,210,000
Minimum budget to satisfy demand ($200 rebates)	$300,000	$810,000	$1,540,000	$2,190,000

program budgets are set at around half of the relevant population. Rebate levels and other parameters are set at medium values: $800 flat rebates, demand elasticity of −2.0 with a linear demand function. The incentive program impacts are rebate-limited in all cases, yielding proportionally similar effects across geographies. In all cases, 29% of the rebates go to marginal purchasers, because that only depends on the rebate amount, e-bike prices, and demand elasticity – see Table 1. New bike shop revenue is 41% higher than the budget in all cases, and additional sales are proportional to budgets. The bottom two rows in Table 4 give the minimum program budgets in each geography to satisfy all demand (and reach the demand-limited condition), which are much higher than the proposed (and typical) amounts. Smaller rebates (e.g. C$200 instead of C $800) induce less demand and provide more rebates at a fixed budget, and so yield a demand-limited condition at a lower budget. Comparing geographies, regional settings are closer to a demand-limited condition because they have less e-bike demand as a ratio to the population; but even then, program budgets would have to be very large to satisfy all demand.

3.3. Forecast impacts

Forecasting program impacts out to 2030 based on growth in baseline demand and changing prices, the baseline demand growth for e-bikes has no impact on the estimated program effects because, as described above, the programs are rebate-limited and not demand-limited. This includes the analysis of uncertainty of ±20% in the base and forecasted e-bike demand. This result is favorable for the modeling approach, given the large uncertainty in estimating e-bike demand at a local scale.

The results are, however, sensitive to potential e-bike price changes over time. Rising prices reduce the program effects, while falling prices amplify program effects, due to changes in the size of the rebates relative to e-bike prices. Modeling the same flat-rebate programs as in Table 4, e-bike price growth of 5% annual yields 30% lower new e-bike sales due to the incentive program in 2030 across all geographies, while annual 5% price reductions yields 40% higher new e-bike sales due to the programs. Thus, if e-bike prices fall (due to market growth and improvements in battery technology, for example), then that will enhance the program outcomes. A proportional (versus flat) rebate program design would produce effects insensitive to e-bike market price changes, as long as the total program budget were adjusted accordingly.

Table 5. Share of rebates by purchaser income and e-bike price level (in C$).

Rebate amount	Low income	Medium income	High income	Low price	Medium price	High price
$200	25%	33%	42%	35%	33%	32%
$800	27%	34%	40%	39%	32%	29%
$1600	28%	34%	38%	42%	31%	27%
10%	25%	34%	41%	34%	33%	33%
20%	26%	34%	41%	34%	33%	33%
30%	26%	34%	40%	34%	33%	33%
Reference share of baseline demand	24%	33%	43%	33%	33%	33%

3.4. Distribution by income and price

Table 5 gives the distribution of rebates by income and price tertiles for flat rebate programs of C$200 to C$1600 and percentage rebates of 10% to 30% (using the same program parameters as above). The income-based estimates assume higher price elasticity for lower-income purchasers, and baseline e-bike demand disproportionately from higher-income purchasers, particularly for higher-priced e-bikes, as described in the Methodology section. The resulting distributions of rebates are similar across geographies.

The results show that the incentive program overall can be considered somewhat progressive with respect to income, with higher proportions of rebates going to lower-income purchasers compared to the baseline shares of demand. The effect is amplified with higher rebate amounts because lower-income purchasers tend to have higher price elasticities, which means they are more responsive to price incentives. Higher flat rebates also increase demand more for lower-priced e-bikes, for which the flat rebate is a greater proportion of the total cost – and which are more often purchased by lower-income purchasers. On the other hand, proportional rebates reduce the progressiveness of the rebates because a larger share of the total rebates available goes to higher-priced e-bikes, which are more often purchased by higher-income purchasers.

Although the program tends to increase rebates to lower-income purchasers relative to baseline demand, with the assumption that the baseline demand is skewed toward higher-income purchasers, a larger share of rebates will likely still go to the high-income segment, despite the program helping to shift the distribution toward lower-income purchasers. Overall, a flat rebate program is expected to make e-bikes more affordable for low-income purchasers, although it may not cancel out disparities in baseline demand by income.

3.5. Parameter sensitivity

The results reported above are not sensitive to baseline demand assumptions because the program effects are rebate-limited, not demand-limited. As shown above, program budgets would have to be very large to meet the demand-limited condition, particularly with medium or large rebate amounts.

The results are, however, highly sensitive to the assumed price elasticity of e-bike demand. For the example programs above, the induced demand varies by a factor of three with elasticity ranging from −1.0 to −3.0, leading to additional e-bike sales that vary by a factor of two. For similar reasons, the results are also moderately sensitive to the assumption of a linear versus power form demand model. The power model implies a more dynamic response, generating greater induced demand and additional e-bike sales, by about 30% compared to the linear model estimates. Hence, estimates reported above are conservative, and program impacts could be higher, depending on the true demand response to price incentives. Given the uncertainty of the true elasticity value and its greater impact on the results, the true demand functional form is likely of less importance.

4. Limitations

The demand modeling approach applied here has several important uncertainties and sensitivities. Estimated incentive program impacts are highly sensitive to demand elasticity and moderately sensitive to price trends and demand functional form. However, results are not sensitive to baseline demand or demand trends because incentive programs are likely to be rebate-limited. This assumption and finding is supported by a recent e-bike incentive program in Edmonton, Canada, with a C$50,000 rebate program (rebates of 30% up to C$750) that ran out of rebates in just days.

A substantial assumption in the method is that e-bike market prices are assumed to be unaffected by the introduction of the rebate program. In other words, bike shops do not adjust their prices in response to the rebates or the induced demand. This assumption is supported by the relatively small portion of e-bike demand receiving a rebate: 3% to 12% for the programs in Table 4. At that scale, the rebate is unlikely to substantially distort the local market e-bike price.

Another assumption is that rebates are arbitrarily allocated to potential purchasers, so that there is an equal likelihood of a marginal purchaser (who would only purchase with the rebate) obtaining a rebate as a baseline purchaser (who would have purchased without the rebate). It would be nearly impossible to selectively provide incentives to marginal purchasers, and so this is a reasonable assumption given the lack of information about strategic actions that baseline or marginal purchasers may take to obtain a refund. If marginal purchasers are more motivated and effective in obtaining rebates than baseline purchasers, that would increase the program effectiveness; but the opposite may also be true (marginal purchasers may be less motivated, decreasing program effectiveness).

The analysis is conservative in neglecting potential positive spill-over effects of additional e-bike sales due to the incentive program. For example, each new e-bike purchaser may increase the likelihood of acquaintances purchasing an e-bike through social network effects; or they may increase the general likelihood of e-bike purchases through familiarity and norming. Such effects have been reported but not sufficiently quantified to include in the analysis (Fyhri et al. 2017; Simsekoglu and Klöckner 2019). Similarly, the effects of an initial e-bike purchase induced by the incentive program on the likelihood of future e-bike purchases by the same person are not modeled.

The model applied in this paper is built on well-established microeconomic principles, but not empirically validated. It is difficult to empirically discriminate between marginal and baseline purchasers; self-reported survey instruments are vulnerable to response biases (hypothetical, strategic, etc.) undermining their internal validity, samples of e-bike purchasers are biased through self-selection, and a relevant control population can be difficult to identify and recruit. As e-bike incentive programs more frequently emerge, it is imperative to couple them with robust evaluation studies, which can help to improve understanding of key factors such as the price elasticity of e-bike demand conditioned on socio-demographics.

This analysis considers e-bike purchases but not actual usage. If purchases correspond to usage, then program impacts can be extended to outcomes such as displaced driving, emissions reductions, and increased physical activity – e.g. in the order of 500 kg CO_2e per year per e-bike (Bigazzi and Berjisian 2019). However, it is uncertain how e-bike usage by new purchasers may differ from that of existing early adopters, particularly – and crucially – how marginal (induced) purchasers differ from baseline purchasers. If an e-bike purchase is only made with the inducement of a substantial price reduction, will the purchaser be less motivated to use it? Mode substitution patterns may also differ between marginal and baseline adopters – and by other relevant factors such as income. If higher-income purchasers are more likely to substitute for driving, then program equity and environmental impact goals may come into conflict. These questions need to be answered with robust before-and-after evaluation including both immediate and long-term travel behavior changes.

5. Conclusions

While the precise impact estimates of this analysis should be interpreted with caution, the modeling provides several insights about e-bike incentive programs. These include: e-bike rebate incentive programs are expected to be rebate-limited (not demand-limited) at typical rebate and budget amounts – in other words, all available rebates will be used; program impacts increase proportionally with the budget, but are otherwise consistent across geographies; additional bike shop revenue is expected to exceed rebate costs, even allowing for administrative costs; incentive programs *improve* access to e-bikes for lower-income residents, but may not overcome disparities in baseline demand; higher rebate amounts (at a fixed budget) generally yield fewer additional sales and lower additional bike shop revenues, but a larger share of rebates goes to low-income and new (marginal) purchasers; flat and proportional rebate structures yield similar results, although flat (or capped) rebates yield better income equity; and estimated effects are robust to uncertainty in current and future baseline e-bike demand, but flat rebate effects will be amplified if e-bike prices fall over time, and diminished if they rise.

Based on these findings, flat rebates of C$400 to C$800 are recommended as a reasonable starting point for initiating an e-bike rebate incentive program. A flat rebate program is simpler than proportional or tiered rebates, which reduces administrative costs and can also be good for adoption because program simplicity is an important factor for the effectiveness of incentives (DeShazo, Sheldon, and Carson 2017). Flat rebates also are preferable from an equity perspective, to avoid larger rebates going to higher-priced e-bikes (which are more likely to be purchased by higher-income individuals). Flat rebates (with respect to e-bike price) can be tiered by income level to further improve program equity. Other considerations in rebate program design beyond rebate structure include: rebate eligibility requirements (e-bike type and price, purchase location, residency, income thresholds), administration (application process, allocation of scarce rebates), and co-requirements (education/training program). The relatively simple model presented and applied in this paper can be used in the program design process in other locations, to examine trade-offs in rebate size and structure.

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