How to design a zero-emissions vehicle mandate? Simulating impacts on sales, GHG emissions and cost-effectiveness using the AUtomaker-Consumer model (AUM)

Chandan Bhardwaj[a], Jonn Axsen[a], David McCollum [b]

HIGHLIGHTS

(1) Examine the impact of alternative ZEV mandate policy designs

(2) Use a novel which includes an endogenous automaker component, R&D effects and endogenous policy response.

(3) Compare policy design impacts on ZEV adoption, GHG emissions, profits and overall policy cost-effectiveness.

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ABSTRACT

Although numerous studies investigate the impacts of policy on zero-emissions vehicle (ZEV) sales, few address the impacts of a ZEV sales mandate and its particular design features. We use the AUtomaker-consumer Model (AUM) to simulate varying designs of a ZEV mandate in Canada's light-duty vehicle sector, requiring 30% ZEV sales by 2030. Design features include: different penalties for non-compliance, different allocations of credits per ZEV type, and the allowance of banking credits across years. For each policy design, we consider impacts on ZEV adoption, GHG emissions, consumer surplus, automaker profits, and overall policy cost-effectiveness. Results demonstrate trade-offs among the policy designs. Generally, ZEV mandate designs that are more effective at increasing ZEV adoption and decreasing GHG emissions also induce stronger reductions in consumer surplus and automaker profits. To achieve the ZEV sales goal, simulations show that a higher non-compliance penalty (CDN$ 10k per credit) is needed. ZEV adoption and GHG reductions are also improved by a "One credit per ZEV" scheme, rather than a "California-style" scheme that gives multiple credits per battery-electric vehicle. Further, allowing automakers to bank credit softens the policy impact on profits and increases automaker compliance in initial years. Across these different design combinations, we find that the most cost-effective design ($CDN/tonne mitigated, including consumer surplus and automaker profits impacts) utilizes a $10k non-compliance penalty and "One credit per ZEV" system that allows banking. Our analysis demonstrates the importance of various ZEV mandate design features, and the complex trade-offs involved among various policy goals.

Keywords: Climate policy; Zero-emission vehicle (ZEV), ZEV mandate; automaker model; technology adoption model, ZEV credit scheme

1 Introduction

Although there is a growing literature on the effects of different policies in inducing zero-emissions vehicle (ZEV) sales, relatively little research considers a ZEV sales mandate. The few studies that have examined ZEV mandates indicate that this policy has helped to channel automaker innovation activities towards ZEV development (Vergis and Mehta. 2010; Melton et al., 2016), and has helped to increase ZEV sales in regions with the policy (Slowik and Lutsey, 2017; Melton et al, 2017). Several forward-looking simulation models indicate that a ZEV mandate can help to further increase ZEV adoption (Axsen and Wolinetz, 2018), and could play an important role in helping a region to achieve deep GHG emissions mitigation targets for 2030 and 2050 (Sykes and Axsen, 2017; Lepitzki and Axsen, 2018; Greene et al., 2014). However, these studies do not consider the broader impacts of a ZEV mandate on consumer surplus, automaker profits or policy cost-effectiveness, nor do they consider the more subtle impacts of ZEV mandate design, such as credit systems for different types of ZEVs or the magnitude of penalties for non-compliance.

In this paper, we simulate the impacts of ZEV mandate policy in Canada’s light duty vehicle sector, including ZEV adoption, GHG emissions, consumer surplus, automaker profits, and overall policy cost-effectiveness. To the best of our knowledge, ours is the first study to compare the impacts of policy design, including: different penalties for non-compliance, different allocations of credits per ZEV type, and the allowance of banking credits across years. We use the AUtomaker-consumer model (AUM), to conduct our analysis, which is described in greater detail elsewhere (Bhardwaj et al, 2021). In this paper we use the term ZEV to refer to a vehicle that has zero tail-pipe emissions, namely plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) – we do not presently include hydrogen fuel cell vehicles in our analysis.

A ZEV mandate was first implemented by California in 1990 (and 10 other US states), and versions have more recently been implemented in China and the Canadian provinces of Quebec and British Columbia. The ZEV mandate requires automakers to sell a certain percentage of their total vehicle fleet annually to be ZEVs. Each sold ZEV earns credits which counts towards the ZEV requirement. For example, California has a ZEV credit requirement of 4% in 2020 rising up to 22% by 2025. The California system provides multiple credits per BEV sold (and potentially less than one credit per PHEV sold), which is expected to results in ZEV market share well below the 22% by 2025 target. In 2018, British Columbia introduced a ZEV mandate that follows California's requirements until 2025, but then requires 30% ZEV new market share in 2030 and 100% by 2040. This system intends to provide one credit per BEV or PHEV sold, meaning that later ZEV sales should match the credit allocation (if automakers choose to comply). More recently, numerous regions are planning to implement more ambitious ZEV mandates or internal combustion engine (ICE) bans – which can translate to a 100% ZEV sales requirement (Plotz et al., 2019). For example, California and Quebec are currently implementing ICE bans (or 100% ZEV requirements) to begin in 2035.

Despite the relatively long history of the California ZEV mandate, quantitative examination of ZEV mandates remains a small literature space (e.g., Sykes and Axsen, 2017; Greene et al, 2014;). Among the few modelling studies in this literature, most use technology adoption models that represent consumer behaviour in some detail, accounting for consumer preference heterogeneity and non-financial factors (e.g. LAVE-Trans model in Greene et al, 2014; ADOPT in Brooker et al, 2015; REPAC in Axsen and Wolinetz, 2018; FTT in Lam and Mercure, 2021). However, these models do not represent automaker decision-making endogenously, or in detail.

A second set of studies attempt to capture automaker behaviour, using system dynamics (e.g., Walther et al., 2010; Thies et al., 2016), technology adoption (e.g., Ou et al., 2018), or engineering optimization approaches (e.g., Jenn et al., 2019). However, important gaps remain in these modelling exercises. Thies et al. (2016) do not model the ZEV mandate (or other policies) and thus do not examine how automakers may endogenously respond to changes in the design features of the policy. Jenn et al. (2019), on the other hand, do not model consumers at all, thus neglecting consumer-automaker dynamics completely. Ou et al. (2018) provide one of the few examples of technology adoption models that endogenously represent an automaker perspective, examining the effects of a ZEV mandate (combined with a fuel economy standard) in China. The authors develop a model which explicitly represents an optimizing aggregate automaker and examine the effects of the two policies on ZEV market share. However, they examine only the short-term effects of the policies (2016-2019), thus ignoring longer-term learning effects, and they assume homogenous consumers. Moreover, they treat the ZEV requirement as a constraint, forcing 100% compliance from automakers, which may not happen in the real world (say, if the cost of compliance is higher than the penalty).

To the best of our knowledge, no published studies have explored the impacts of different designs of the ZEV mandate. One potentially important design feature is the magnitude of non-compliance penalties. In current North American versions (California, Quebec and British Columbia), a penalty of US$ 5000 per credit is imposed for non-complying automakers – though it is unclear if such a penalty is strong enough to induce automakers to comply with more ambitious ZEV sales targets (i.e., 2030 or later). Another design feature is the credit system. As noted above, under California-style ZEV mandates, different vehicle types earn different number of credits. For example, BEVs on average earn higher (between 1 and 4) credits than PHEVs (between 0.5 and 1.2), because BEVs have a longer electric range. British Columbia, plans to implement a “One credit per ZEV” system instead (post-2025). A third design feature is the potential for credit “banking”, which allows manufacturers to carry over excess credits from one year to the next. We intend to contribute to the relatively sparse ZEV modelling literature by examining the effects of these ZEV policy design features on new vehicle market share, GHG emissions, consumer surplus, automaker profits, and overall policy cost-effectiveness.

In short, we attempt to answer the following research questions: can a national ZEV mandate help achieve the 30% by 2030 target set by the national government? And what are the various impacts of different ZEV mandate designs? More specifically, the objectives of this work are to:

1) Simulate the impacts of ZEV mandate designs on ZEV adoption, GHG emissions, consumer surplus, and automaker profits.
2) Compare the impacts of design features, namely: different penalties for non-compliance, different allocations of credits per ZEV type, and the allowance of banking credits across years
3) For each combination of policy design features, calculate cost-effectiveness (CDN$/tonne mitigated) as one perspective to balance trade-offs in policy effectiveness and economic impact.

The organization of the paper is as follows: Section 2 provides the details of the model used to conduct this study as well as describes the scenarios used to analyse results. Section 3 presents the results. Section 4 concludes and discusses policy implications of the results.

2. Method

To explore these research objectives, we use a light-duty vehicle technology adoption model, AUM (Fig. 1) focussing on Canada as a case study. AUM simulates the dynamics within the light-duty vehicle sector in Canada, treating the rest of world as exogenous. AUM combines a behaviourally realistic consumer component with a profit-maximizing automaker component to endogenously model consumer-automaker interactions and simulate ZEV new market share up to 2030. The consumer component is a simplified representation of the Canadian consumers and the automaker component is a simplified representation of the Canadian auto industry. The automaker (or vehicle supply) model and the consumer choice (demand side) model interact by passing data at each one-year timestep. As examples, the automaker model selects prices, R&D, and the number of vehicle models available, while in each year, consumers purchase a certain quantity of vehicles. For a given year, the main outputs of the model are ZEV sales (as a proportion of light-duty vehicle sales), automaker profits and consumer utility, which feedback into the model to affect the output for the following years. The model can thus be used to analyse the long-term effects of a variety of policies (in particular supply-side regulations). A more detailed description of the model, including model validation steps and how the model fits in the literature can be found in Bhardwaj et al (2021). We presently provide a summary of this validation in Section S1 of the Supplementary Information (SI) document.

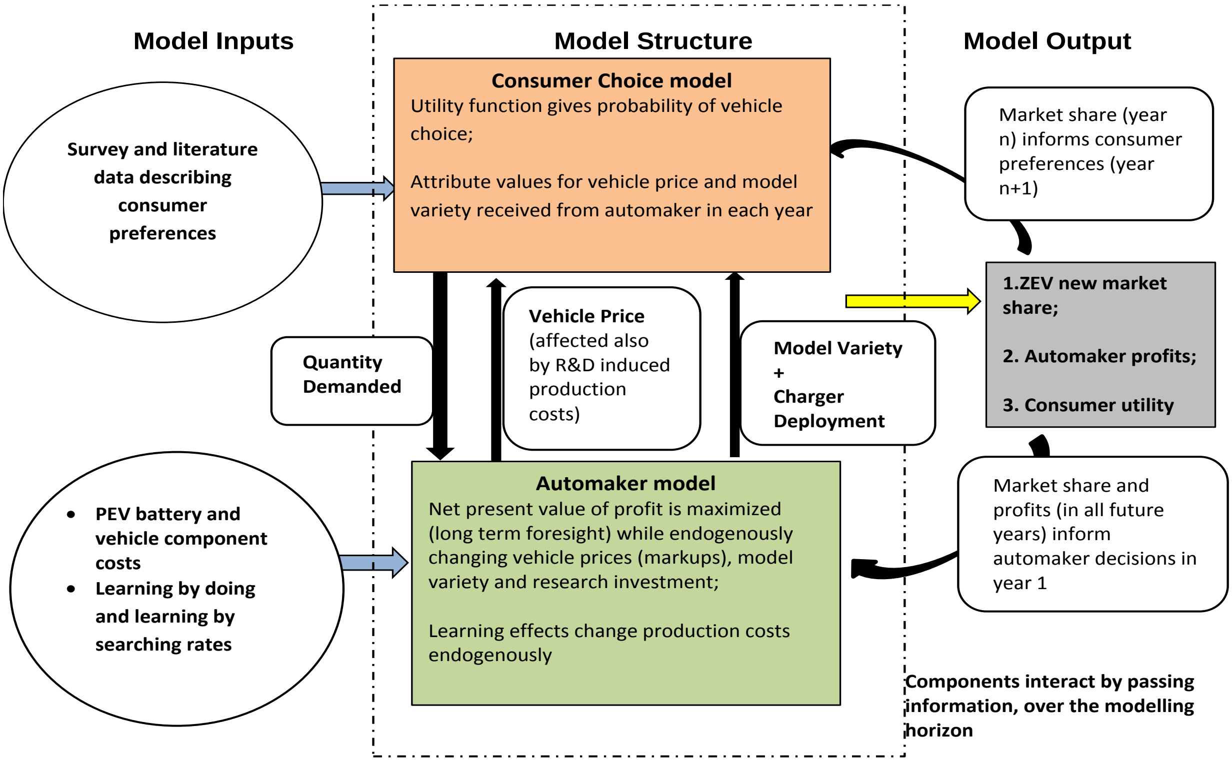

Fig. 1 Structure of the Automaker-consumer model (AUM)

2.1 Demand-side: The consumer choice model

The consumer choice model simulates annual new light-duty vehicle sales over the modelled time horizon. Total vehicle sales are in turn affected by prices generated by the automaker model using own price elasticities, where values (-0.3 to -1) are taken from Fouquet (2012) and Holmgren (2007) and are listed in Table 2. In each year, consumers choose from the available options to satisfy the demand for new vehicles, generating annual light-duty vehicle market share.

The consumer choice model is a nested discrete choice model, similar to that used by the LAVE-Trans model in National Research Council (2013). At the first level of the nest, a consumer chooses between different vehicle classes (compact, sedan, SUV, mini-truck) as shown in Fig. 2. These coefficients are informed by the LAVE –Trans model. Although it would have been more appropriate to use Canada-specific coefficients, we use US data from

National Research Council (2013) as a simplifying assumption. At the second level, the consumer chooses between different vehicle drivetrain technologies (conventional internal combustion engine vehicles or CVs, hybrid, plug-in hybrid electric vehicles or PHEVs, battery electric vehicles, or BEVs) within each class. As detailed next, the model availability of a given drivetrain in a given year is determined by the automaker model. For certain drivetrains (PHEV and BEV), the third level of the nested discrete choice hierarchy is a choice of vehicle electric-driving range. PHEVs can include electric ranges of 60, 100, and 120 km, and BEVs can include ranges of 100, 180, 240, 320, and 380 km.

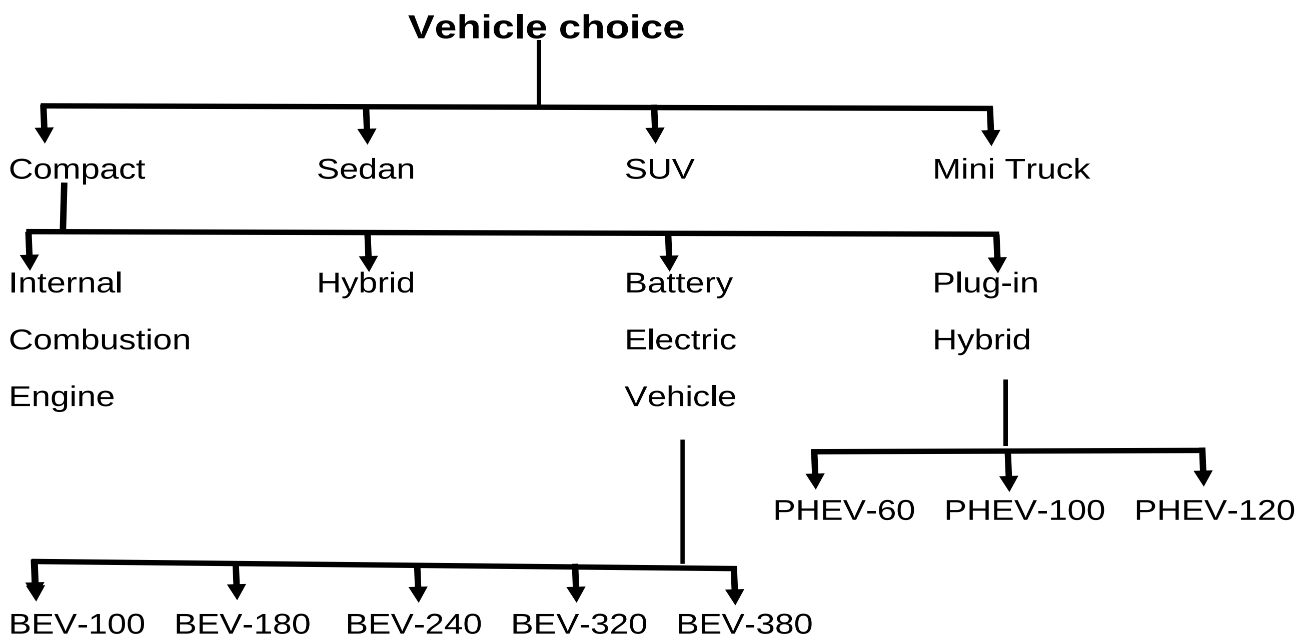

Fig. 2 Nested structure of the vehicle choice model. Level 1 is the top level with the vehicle class options (compact, sedan, SUV and mini-trucks). Level 2 represents the vehicle drivetrain technology options available in each vehicle class (CVs, hybrids, BEVs and PHEVs). Only one branch is shown here for the sake of compactness. Level 3 represents the range options available for BEVs and PHEVs.

Consumers choose the vehicle technology which provides the highest utility, based on a utility function. Our utility function, indicating the utility a consumer derives from the purchase of vehicle technology *i*, drawing largely from the LAVE-Trans model (National Research Council, 2013) is as follows:

$$U_i = ASC + \beta_{PP}X_{PP} + \beta_{FC}X_{FC} + \beta_{CA}X_{CA} + \beta_R X_R + \beta_{MV}X_{MV} \quad (1)$$

Where the utility of the consumer is influenced by the vehicle technology's purchase price (PP), fuel costs (FC), electric driving range (R), recharging access (CA), and vehicle model variety (MV). Purchase price indicates the vehicle price (vehicle cost + markup added by automaker) as observed by consumers. Fuel cost indicates the annual running costs of a vehicle. Electric driving range indicates the number of kilometres a vehicle can run without needing recharging. Recharging access is the percentage of filling/recharging stations with electric charging, relative to gasoline stations (Hackbarth, and Madlener, 2016). Model variety, expressed as natural logarithm of the percentage of models relative to conventional vehicles, captures the idea that availability of models for battery electric and plug-in hybrid electric vehicles (n_j) is limited, affecting consumers' purchase decisions. The value of model variety is given by the logarithm of the ratio (nj /N, N is the number of models of conventional vehicles) (Greene, 2001). For example, in 2020, only about 28 models for plug-in electric vehicles exist in Canada, in comparison to about 300 for conventional vehicles. Thus, in 2020, model variety for plug-in electric vehicles is about 10% relative to conventional vehicles. The ASC, or Alternative Specific Constant, contains the component of utility not captured by other attributes.

The probability $P_{i|j}$ (indicating the market share, MS) of a consumer choosing a technology 'i' is then given by:

$$P_{i|j}(MS) = \frac{e^{U_i}}{\sum_{k=1}^{n} e^{Uk}} \quad (2a)$$

The probability that technology *i* will be selected is the product of the probability of choosing a nest *j* (where *j* represents a nest at Level 1or 2 in Fig. 2) and the probability of choosing *i*, given that a choice will be made from the nest *j*: $Pij = Pi|j*Pj$.

We use empirical data sources to inform our consumer utility equation. ASC base-year values and the base year weights for the other attributes in equation (1) are empirically derived largely from the Canadian Plug-in Electric Vehicle Study (CPEVS) and Canadian Zero Emissions Vehicle Study (CZEVS) survey data (Axsen et al., 2015; Kormos et al., 2019), and in part from international literature (Brand et al., 2017; Dmitripoulos et al., 2013; Ferguson et al., 2018). Consumers' base year willingness to pay for the different attributes are listed in Table 1. The CPEVS included a three-part survey completed by a representative sample of 1754 new vehicle buying Canadian households in 2013 while the CZEVS 2017 survey is essentially an updated version of the previous study. Both studies contain responses to survey questions on PEV awareness, weekly driving distance, vehicle class for the next planned vehicle purchase, and preferences for vehicle attributes. The latent-class choice model was used to identify five heterogeneous consumer classes in the sample for both surveys. These are "CV-oriented", "HEV-oriented", "ZEV-neutral", "PHEV-oriented" and "PEV-enthusiasts" We combine these into three classes in our model, as described below in the paragraph on consumer heterogeneity.

To simulate dynamics in consumer preferences, the ASC parameter changes endogenously over time as a function of cumulative vehicle sales of drivetrain technology *k* (either conventional, battery electric or plug-in hybrid electric) as follows:

$$ASC_{tk} = ASC_{ok} \times e^{b(\,cumulative\ sales\ of\ drivetrain\ technology\ k\ in\ Canada)} \qquad (3)$$

Where the ASC_{ok} represents the value of the ASC parameter at time $t=0$ for technology k; b = constant (as used in National Research Council, 2013).

While the data for all attributes in equation (1) for the first modelling year is exogenously specified, the data for each attribute for the remaining years are determined either exogenously (for fuel prices and charger availability, Table 2) or endogenously as inputs from the automaker model (Fig. 1). As shown in Fig. 1, vehicle purchase price and model variety values are endogenously taken from the automaker model. However, model variety also has an exogenous component, to represent the global increase in the number of models. The exogenous assumptions regarding model variety are also listed in Table 2.

Table 1: List of attributes and the corresponding estimated Willingness to pay values of their coefficients

Attribute	**WTP (in CAD$)**			**Range in literature (in CAD$)**	**Sources with comparable values of WTP**
	ZEV -Enthusiasts (15%)	Mainstream (50%)	Resistors (35%)		
Purchase price	-	-	-		Axsen et al (2015), Kormos et al. (2019)
Fuel cost (per $1k a year in fuel savings)	6000	4000	2000	(1000,7000)	Brand et al. (2017)
Driving range (per km increase in electric range)	30	15	15	(20,200)	Ferguson et al. (2018); Dmitripoulos et al. (2013)
Model variety (natural log of per 1% increase in number of PEV models, relative to CVs)	3500	3500	3500	(0,10000)	Brand et al. (2017); Greene (2001)
Recharging access (per 1% increase in recharging stations)	550	550	550	(100,1000)	Ferguson et al. (2018); Hackbarth and Madlener (2016)
ASC in 2020					
PHEV	5000	-10000	-30000	(-50000, 8000)	Axsen et al. (2015), Kormos et al. (2019)
BEV	8000	-15000	-40000		
HEV	3000	-3000	- 5000		
ASC in 2030 (optimistic, pessimistic)					
PHEV	(2625,4375)	(-5250, - 8750)	(-15750, -26250)		
BEV	(3750,6250)	(-7875, -13125)	(-21000, -35000)		
HEV	(1575,2625)	(-1575, -2625)	(-2625, - 4375)		

Table 2: Optimistic, Median and Pessimistic values for key model parameters

Parameters	Optimistic (in 2030)	Median (in 2030)	Pessimistic (in 2030)	Source
Model variety (relative to CVs) (10% in 2020)	90%	70%	40%	Authors' judgement,
Recharging access (10% in 2020)	90%	70%	50%	Authors' judgement
Gasoline price (70 CDN$/bbl in 2020)	177.9	125.3	92.1	National Energy Board (2019), US EIA (2020)
Battery costs (230 CDN$/kWh in 2020)	70	120	175	Nykvist et al. (2019)
Consumer own-price elasticity for vehicle purchase (2020-2030)	-0.3	-0.6	-1	Fouquet (2012); Holmgren, (2007)
Consumer elasticity for travel demand (2020-2030)	-0.15	-0.2	-0.25	Small and van Dender (2007)
Automaker rate of learning (%) (2020-2030)	10	8	6	Weiss et al. (2012), Barreto and Kypreos (2004)
Automaker discount rate (%) (2020-2030)	8	10	15	Jagannathan et al. (2016)
Vehicle stock turnover rate (%) (2020-2030)	10	7	5	National Energy Board (2019), Author's judgement

Notes: Model variety represents the number of models of PEVs, as a percentage of the number of models of CVs. Recharging access represents the percentage of filling/recharging stations with electric charging, relative to gasoline stations Rate of learning indicates the percentage drop in vehicle costs for every doubling of cumulative capacity or knowledge stock (equation 8).

To represent heterogeneity in consumer preferences, we include three consumer segments: "ZEV Enthusiasts" (15% of consumers), "Mainstream" (50%) and "Resistors" (35%). These proportional splits are exogenous and constant across the modelling horizon. Dynamics in preferences are instead represented via changes in the ASC for a given segment. As noted, these three classes are drawn from the five consumer classes identified in past Canada-based consumer research (Axsen et al, 2015; Kormos et al, 2019). First, “ZEV Enthusiasts”, correspond to “PEV-enthusiasts (13%)” in Kormos et al. (2019) and Axsen et al. (2015) and have a high positive valuation (negative risk aversion) for electric vehicles. The “Resistors” segment, corresponding approximately to the combination of “CV-oriented (23%)” and “HEV-oriented (21%)” classes in Kormos et al. (2019) and Axsen et al (2015), favour the conventional vehicles and have a high negative valuation for electric vehicles. For the third segment "Mainstream", we approximately combine the "ZEV-neutral (21%)" and "PHEV-oriented (22%)" classes in Kormos et al. (2019) and Axsen et al (2015) into one segment. In the base year, the "mainstream" segment represents a moderate bias against ZEVs. For coefficients that we draw from other literature, which did not have identical number of consumer classes, we use our judgement to average them over these consumer segments.

2.2 Supply-side: The automaker model

The vehicle supply model is an optimization model that is designed to be a representation of the Canadian automaker industry at the aggregate level. That is, as a simplifying assumption, we model the Canadian auto industry as if it were one automaker. While it would be interesting to simulate and observe the behaviour of a heterogeneous set of automakers, the present research paper is more concerned with the overall impacts of a ZEV mandate -- not impacts on specific automakers. This portion of our model builds on the optimization framework suggested by Michalek et al. (2004) (and later adapted by Zhang et al., 2011) and Kang et al. (2018).

The objective for the aggregate Canadian automaker is to maximize the net present value of profits over the foresight horizon, which we can set as any number of years within the modelling time horizon (in this case, from 2020 to 2030). The consideration of a long-term planning horizon (foresight) for the automakers is a novelty in this model with very few other studies conducting similar analyses (notably Kang et al., 2018). Most other previous studies modelling automakers consider a short term (1 year) foresight for the automaker (e.g. Michalek et al. 2004; Goldberg, 1998; Bento et al., 2009; Jacobsen, 2013; Ou et al., 2018).

In AUM, the automaker can endogenously choose between four compliance mechanisms. In a given year, the automaker looks forward withing their planning time horizon (currently set to 2030), and makes several decisions relating to all drivetrain technologies, namely: i) R&D investment (which can in part contribute to lower ZEV costs nationally over time, apart from the global exogenous decline in battery and other component costs), ii) the number of ZEV models available for sale, iii) charger deployment, where the automaker can endogenously contribute to the exogenous increase in charging infrastructure, and iv) the price of all vehicles sold where the automaker adjusts relative prices of vehicles (e.g. by subsidizing ZEVs and adding a premium to conventional vehicles) while trying to maximize profits subject to policy.

The automaker seeks to maximize profits over the planning horizon *T* for all technologies 1 to *K*, specified as:

$$Profits = \sum_{t=1}^{T} \frac{1}{(1+i)^t} \sum_{k=1}^{K} [Q_{tk}(P_{tk}, n_{ctk}, CA_{ctk}). P_{tk} - C_{Ptk} - C_{Rtk} - C_{Itk}] \qquad (4)$$

Where, $Q_{tk}(P_{tk}, n_{ctk}, CA_{ctk})$ is the quantity of each vehicle type *k* produced in t^{th} time period and quantity is a function of price P_{tk}, and number of models $n_{ctk}$of the vehicle type *k*. n_{ctk} is endogenously added by the Canadian automaker, in addition to the exogenous increase in the number of models globally. Similarly, CA_{ctk} is the Canadian automaker's endogenous contribution to charging access (in %), in addition to the exogenous increase in charging access. The discount rate is 8%, which reflect the opportunity cost of capital for private firms (Jacobsen, 2013). The automaker thus adjusts P_{tk}, $n_{ctk,}$ $CA_{ctk}$and C_{Itk} in equation (4) to maximize profits. The quantity of vehicles of each type produced is assumed to equal the quantity demanded in the consumer choice model. The inclusion of model variety feedback and endogenous charging deployment are additional novelties of AUM. The profit equation (4) also includes three cost terms ($C_{Ptk}, C_{Rtk}, C_{Itk}$), each of which is described briefly next.

First, C_{Ptk} is the total cost of production of a vehicle technology type *k* in time *t*. given by the following equation. The quadratic cost curve equation indicates the effect of diseconomies of scale

$$C_{Ptk} = C_{0tk} * Q_{tk}(P_{tk}, n) + a * Q_{tk}(P_{tk}, n)^2 \qquad (5)$$

Where C_{0tk} is the cost of production of a single vehicle of type *k* in time *t*, *a* is a scaling constant (Table 3) and $Q_{tk}(P_{tk}, n)$ represents the total quantity of vehicles of type *k* produced in time *t*.

Table 3: Exogenous parameters used in the automaker model

Parameters	Value	Source
Scaling parameter, *a* (equation 5) CVs	0.01	Authors' judgement, based on model calibration to 2018 actual PEV market share
Scaling parameter, *a* (equation 5) PEVs	0.02, decreasing linearly to 0.015 in 2030	Authors' judgement, based on model calibration to 2018 actual PEV market share;
Cumulative capacity (*CC*) CVs in 2020	25 million	Statistics Canada (2020)
Cumulative capacity (*CC*), PEVs in 2020	100000	Statistics Canada (2020)
Knowledge Stock (*KS*), CVs in 2020	500 billion $CAD	Authors' calculation; based on Barreto and Kypreos (2004)
Knowledge Stock (*KS*), PEVs in 2020	3 billion $CAD	Authors' calculation; based on Barreto and Kypreos (2004)

The second cost term in equation (4), C_{Rtk}, indicates the total regulation costs related to policy. In this study, we consider regulation costs for a fuel economy standard (CAFE), low-carbon fuel standard, and ZEV mandate (policy scenarios detailed further in Section 3.3). We endogenously model the ZEV mandate and fuel economy standard as part of the profit function. For the ZEV mandate, the regulation costs are characterized by certain design features:

- ZEV credits requirement – this dictates the minimum credits that the automakers must earn to avoid penalties.
- ZEV penalty – this indicates the fine per credit for non- compliance.
- ZEV credits per vehicle – Based on their electric range, vehicles can be assigned either a single credit or multiple credits.
- Allowance of banking- Automakers may earn extra credits in one year for selling more vehicles than required by the policy for that year. If banking is allowed, these extra credits can be used to meet the policy requirement in a later year. The banking feature gives automaker greater flexibility, allowing them to optimize vehicle sales, also providing some incentive to over-comply in any year. If banking is not allowed, these extra credits become zero at the end of the year.

The regulation cost associated with the ZEV mandate is then modelled as $\rho_{ZEV} * (\emptyset_{ZEV} * Q_{Total} - Q_{ZEV})$, where ρ_{ZEV} is the penalty per ZEV credit below the stipulated quota, $\emptyset_{ZEV}$ is the minimum ZEV credits required by the quota (e.g. 4%), Q_{Total} is the total number of vehicles sold by the automaker, and Q_{ZEV} is the total number of zero emission vehicles sold by the automaker. Previous studies such as Ou et al. (2018) and Jenn et al. (2018) have treated the ZEV mandate as a hard constraint, thus forcing automakers to comply fully. Consideration of ZEV regulation costs as a part of automaker profit function is a novelty of this work – representing endogenous automaker response between compliance and non-compliance. For fuel economy standards, similarly, the regulation cost is $\rho_{FE} * Q_k * (Z_{FE} - Z_k)$, where ρ_{FE} is the penalty, Q_k is the number of vehicles of drivetrain technology *k* that are sold, Z_{FE} is the fuel economy limit, and Z_k is the fuel economy of vehicle *k*. The total regulation cost is given by

$$C_{Rtk} = \rho_{ZEV} * (\emptyset_{ZEV} * Q_{Total} - Q_{ZEV}) + \rho_{FE} * Q_k * (Z_{FE} - Z_k) \qquad (6)$$

The third cost component in equation (4) above, C_{Itk} represents the Canadian automakers' R&D investment. We assume that the cost of production (C_{0tk}in equation 5 above) of vehicles produced in Canada can be in part influenced by the investment in research, C_{Itk} made by automakers nationally over time (apart from the exogenous decline in vehicle costs due to global efforts). As noted previously, the automaker model represents the Canadian auto industry as a whole, as if it was one aggregate automaker. While it is true that Canadian auto industry is essentially a portion of international automakers, we intend to represent the Canadian contribution of R&D activity. While the international contribution is exogenous, the Canadian contribution is endogenous. For this novel formulation of R&D effects, we draw from Barreto and Kypreos (2004), Azevedo et al. (2013) and Chadwick (2016; personal communication) to represent the effect of R&D in the technological progress of innovative technologies. The automaker investment in research in time *t*, C_{Itk} endogenously adds to the knowledge stock KS_{tk} of the automaker as follows:

$$CC_{t-1k} = \sum_{t=1}^{t-1}[Q_{tk}(P,n)] \quad ; \quad KS_{t-1k} = \sum_{t=1}^{t-1}[C_{Itk}] \qquad (7)$$

Where knowledge stock, KS_{t-1k}, accumulates endogenously up to time *t-1* for technology *k* and along with the cumulative capacity (*CCtk*) of vehicles produced affects the cost of vehicle production in time *t* as shown in equation (8).

$$C_{0tk} = \{\gamma_k * C_{0t-1,k} * [CC_{t-1k}{}^{-LBD} + KS_{t-1,k}{}^{-LBS}]\} \qquad (8)$$

The cost of production for each drivetrain technology, C_{0tk} has two separate components affecting the evolution of costs over time. First, capital costs can decline as a result of production occurring elsewhere in the world, where γ_k represents the annual rate of exogenous (global) decline in the cost of production. Therefore, a vehicle's costs can still decline over time despite little to no production or investment occurring in Canada. Second, production costs decline endogenously as a result of an increase in the cumulative production and research investment in that technology in Canada. The cost of production of each drivetrain technology C_{0tk} in time *t* is affected (endogenously) by the cost of production in the previous year $C_{0t-1,k}$, cumulative capacity CC_{t-1k} (total number of vehicles of technology *k* produced up to time *t-1*in Canada) as well as knowledge stock $KS_{t-1,k}$ (synonymous with cumulative R&D investment in Canada) achieved up to period *t-1*. Thus, while on the one hand, investing in research increases automaker's costs in the present, on the other hand, such investment potentially reduces future production costs. When optimizing over the planning horizon, the automaker can trade-off between increased research costs in the present versus benefits from lower costs of production at a later date. The initial capital costs, initial knowledge stock, initial cumulative capacity, learning by doing (LBD), and learning by searching (LBS) values are exogenously specified in the model (Table 3). The cumulative capacity and knowledge stock for other modelling years are endogenously determined, where the functional form where the cost of production (capital costs) are a function of both cumulative capacity and knowledge stock is known as the Two Factor Learning curve (2FLC) (Barreto and Kypreos, 2004). Of course, we note that accurate automotive industry data on R&D investment is difficult to find and has been largely gathered from grey literature (e.g. Automotive News, 2019; Reuters, 2019; CleanTechnica, 2019; Deloitte, 2019; UCS, 2019; ACEA, 2020).

Battery pack costs are assumed to decline exogenously in line with literature (e.g. Islam et al.,2018; Nykvist et al.,2019; Lutsey et al, 2021). Thus, the rate of decline of battery costs informs the γ_k parameter (exogenous component) in equation 8. Battery costs and the other parameters used in the model are listed in Table 2 and Table 3. There is uncertainty over production costs of PHEVs and BEVs over the 2020–2030-time frame. Nykvist et al

(2019) and Lutsey et al (2021) suggest a range of battery costs for 2030, where the low (optimistic) case gives a battery back cost of USD$ 50/KWh (CDN $60/kWh), and the pessimistic case can be as high as USD$ 100/KWh (CDN $130/kWh). We consider this range in our analysis. Based on these battery cost assumptions, and depending on vehicle class, battery size and driving range, our model endogenously estimates vehicle production cost for PHEVs and BEVs. The production costs for the two technologies largely overlap over 2020-2030. For example, in our median assumption of battery costs, the production cost of a BEV-380 (380 km electric range) for a sedan car reaches parity with a PHEV-60 (with 60km of range) in 2026-27. We further discuss these cost ranges in Section S1 of the SI document.

2.3 Calculating GHG emissions and policy costs (CDN$/tonne)

AUM simulates the impacts of policy on both consumer utility (consumer surplus) and automaker profits. We define cumulative policy cost is the sum of changes in consumer surplus and profits under a policy scenario relative to the reference scenario. We translate this into a calculations of policy cost-effectiveness ($/tonne CO_2 abated) by also simulating the amount of GHG emissions reduced by the policy.

The net change in consumer surplus (CS) in policy scenarios ('1') relative to the Baseline ('0') is given by (β_{PP} is the coefficient of purchase price):

$$\Delta CS = -\frac{1}{\beta_{PP}}\left[\ln\left(\sum_{i=1}^{n} e^{Ui^{1}}\right) - ln\left(\sum_{i=1}^{n} e^{Ui^{0}}\right)\right] \quad (9)$$

Where U_i= utility of technology 'i' as in equation (1), and β_{PP} is the coefficient of purchase price.

Similarly, the change in profits (equation 4, in Section 2.2) can be summed to give the total costs (private) to automakers. The consumer surplus can be impacted through the following changes that may be induced by policy:

- Reduced total vehicle sales: under the effect of policy (largely due to higher costs of ownership);
- Higher vehicle prices;
- Amenity loss represents the loss in utility or welfare arising from consumers having to shift to a less preferable vehicle, such as shifting from trucks to cars, or from conventional vehicles to PEVs with associated range anxiety; and
- Fuel cost savings (negative costs) that accrue to the consumer due to shifting to a more fuel-efficient vehicle under the effect of the policy.

There is still considerable uncertainty about how consumers value the lifetime financial savings they might experience from purchasing a vehicle that is cheaper to operate (Long et al., 2021)—say a ZEV versus a conventional vehicle. Consumer valuation of fuel savings will influence their utility function (and purchase decision), as well as how a modeler will calculate consumer surplus from the lifetime of vehicle ownership. While some studies suggest that consumers are far-sighted (and not myopic) and that they fully value future fuel or maintenance costs in their vehicle purchase decisions (Busse et al, 2013), others find that car buyers tend to be short-sighted, and to “undervalue” fuel savings (Axsen et al., 2009; Mau et al., 2008; Greene et al, 2014; Newell and Siikamaki, 2015).

In this analysis, we account for both perspectives by categorising consumer surplus calculations into ”Utility function” valuation and “Full” valuation. Utility function valuation refers to consumer surplus estimate given by equation (9), which includes the fuel savings taken into account by the consumer when making a purchase decision, as captured directly from the utility function.

In contrast, the Full-valuation perspective incorporates the effect of fuel savings over the entire life-time of a vehicle into our consumer surplus calculations. The Full-valuation perspective thus represents the uncounted value of fuel savings that consumers did not consider at the time of vehicle purchase, potentially missed in a utility function-based calculation. To estimate fuel savings, we use results from Logtenberg et al (2018), a Canada-based study that finds the 10 years average savings of driving ZEVs are about $ 4k per ZEV per year. The change in the number of ZEVs under the policy (relative to the Baseline) is multiplied to the average saving and added to the total consumer surplus change for each yea (equation 9), where the annual total consumer surplus is discounted (at both 8% and 3%) to give the cumulative consumer surplus (full valuation). To avoid double counting, we deduct the fuel savings already accounted for in the consumer surplus in the full valuation calculations Though, unlike Small (2012), we do not include wider social benefits or co-benefits, such as the health benefits from reduced vehicle travel or local air pollution in this analysis.

The choice of discount rate can also significantly affect environmental and policy cost estimates in any modelling study (Stern, 2006). There are wide differences across the literature on the choice of discount rates. Discount rates used for private financial decisions (e.g., automakers) tend to be higher, often around 8% (Jacobsen, 2013). On the other hand, to represent social decisions, some modelling studies use a lower discount rate, for example a 2.3% rate by Greene et al (2014). To accommodate both perspectives, we calculate and depict overall policy costs using both an 8% rate, and a 3% rate.

To calculate policy cost-effectiveness, we also need to estimate the GHG reductions resulting due to each policy. We calculate cost-effectiveness (CDN$/ tonne) as the ratio between the net present value of total policy costs (sum of change in consumer surplus + change in profits) and reduced tonnes of well-to-wheel (WTW) GHG reductions over the forecast period. For estimating GHG emissions, we simulate the total stock of vehicles, their usage per year (vehicle km travelled), and the carbon intensity of travel, each of which we discuss next.

First, the total stock (S_{tk}) of vehicles of each technology type k surviving from year t to year $t+1$ is given by

$$\sum_{k=1}^{N} S_{t+1,k} = \sum_{k=1}^{N} S_{t,k} (1-d_{t,k}) + \sum_{k=1}^{N} Q_{t,k} \quad (10)$$

where $d_{t,k}$= stock turnover rate in time t for technology k; Q_{tk} is the quantity of new vehicles of technology k at time t.

Second, vehicle use (or travel demand) depends upon fuel costs. An increase in fuel costs (e.g. due to a tax) can decrease travel demand, while a reduction in fuel costs (e.g. due to fuel economy improvement) can increase travel demand. We use elasticity (e) to represent how consumers adjust vehicle usage rates as a result of changes to the cost of driving. The elasticity of travel demand is depicted in Table 2. The vehicle use under policy (V_p) is a function of the projected travel demand in the reference no policy case (V_0), the elasticity parameter (e), and the changes to the fuel cost in the policy scenario relative to the reference case, given by

$$V_p = V_0 \left(\frac{fuel\ cost_P}{fuel\ cost_0}\right)^e \quad (11)$$

where $fuel\ cost_P$ is the fuel cost under policy, while $fuel\ cost_0$ is the fuel cost in the reference no policy case. The reference case vehicle use (V_0) in Canada is assumed to be 16000 km a year (Statistics Canada, 2020).

Once the vehicle stock and vehicle use values are known, the total GHG emissions can be obtained by multiplying the product of vehicle stock and vehicle use values with the energy consumption per vehicle and fuel carbon intensity. The vehicle energy intensity for each drivetrain is set exogenously for each drivetrain based on U.S. EIA (2020) and National Energy Board (2019) estimates, and are shown in Table 4. For PHEVs, we assume that consumers use electricity to run the PHEVs 70% of the time and use gasoline for the remaining 30% -- which translates to a 70% “utility factor”. Plotz et al. (2021) calculate this utility factor from real world driving data across several countries, and find that utility factor varies with the electric range, and across countries (e.g., for a 100km electric range PHEV, utility was about 70% in Canada and Norway, but only 40% in China and Netherlands). To account for uncertainty in our sensitivity analysis, we assume the utility factor is 50% in the pessimistic case, and 90% in the optimistic case – however, in each scenarios the split is exogenous and does not respond to changes in fuel or electricity prices.

Table 4 also summarizes our exogenous assumptions about the WTW carbon intensity of each fuel, which include the GHGs emitted in the process of producing a fuel and transporting it to the point at which it enters a vehicle for consumption in Canada, based on GHGenius (version 5.05b) model and other literature (National Energy Board, 2019; EIA, 2020). Carbon intensity remains constant for gasoline in the no policy case, but decreases over time under the effect of the low carbon fuel standard, about to be imposed by the national government (Government of Canada, 2021). For electricity, it is assumed that the contribution of low-carbon, renewable sources in electricity production will increase in the future in Canada, stimulated by national policies to replace coal and natural gas fired power plants in the electricity sector (National Energy Board, 2019).

Table 4 Vehicle energy intensity and fuel carbon intensity (Canadian) assumptions

Vehicle energy intensity	**2020**	**2030**	**Source**
Conventional (L/100km)	7.55	5.73	National Energy Board (2019), EIA (2020)
PHEV (L/100 km: 30% Gasoline)	2.2	1.63	National Energy Board (2019); EIA (2020)
PHEV (kWh/100 km: 70% electric)	0.13	0.10	National Energy Board (2019); EIA (2020)
BEV-320 (kWh/100 km)	0.19	0.16	National Energy Board (2019)
Carbon intensity (gCO2/MJ)			
Gasoline (Default)	88.1	88.1	National Energy Board (2019); GHGenius
Gasoline (with Low Carbon Fuel Standard)	88.1	76	Government of Canada (2021)
Electricity	19.5	14	National Energy Board (2019); GHGenius

2.4 Policy scenarios

To analyze the effect of the various design features of a nationwide ZEV sales mandate, we compare ZEV mandate policy scenarios relative to the baseline scenario.

a. **Baseline scenario:** no ZEV mandate is in place across Canada. The Baseline scenario, however, includes four policies currently in place in Canada:

   (i) Purchase subsidies: We model purchase subsidies as being offered to consumers by the Government across Canada, however these subsidies last from 2018 until 2020, when the subsidies are assumed to be removed.

   (ii) Carbon tax: We include a nationwide carbon price on GHG emissions, increasing \$10 a year from \$30/tonne in 2020 until it reaches \$50 a tonne in 2022, where it stays constant till 2030.

   (iii) Low Carbon Fuel Standard (LCFS): A national-level LCFS, is assumed to be in place. The LCFS requires a 15% reduction in fuel carbon intensity by 2030 (relative to 2005 levels).

   (iv) Fuel Economy standard: A national-level fuel economy standard is in place requiring automakers to improve the fuel economy (and thus reduce the energy requirement per kilometre driven) of the vehicles produced, such that the average fuel economy improves linearly from 2.75 MJ/km in 2020 to 1.3MJ/km (~ 55 miles per U.S. gallon or alternatively 4.2L/100km) in 2025 and stays constant at that level until 2030.

We do not model other policies in place, such as High Occupancy Vehicle (HOV) lane access for ZEVs, which may be expected to have a small effect on market share (Melton et al., 2017).

b. **ZEV mandate** requirements: To examine the effect of the ZEV mandate policy, we consider scenarios where the ZEV credit requirement is 5% of new vehicle sales in 2020, 15% in 2025 and reaches 30% by 2030.

i. **ZEV penalty scenarios:** we consider four ZEV policy scenarios to analyse the effect of increasing ZEV penalty on new light duty vehicle market share and auto-industry profits. These penalty levels include $2,500/credit ($CDN), $5,000/credit, $7,500/ credit and $10,000/ creditFor all these scenarios we assume an Equal credit scheme (or "One credit per ZEV") where all ZEVs produced earn one credit each. Also, no banking of credits is assumed in all these scenarios.

ii. **ZEV credit scheme scenarios** - we consider two illustrative examples of ZEV credit systems. First, the California-style scheme assigns 2 credits per BEV and 0.75 credits per PHEV). Second, under an "One credit per ZEV" scheme (which is currently planned in the British Columbia ZEV mandate), one credit each is assigned equally to all ZEVs. (To aid comparison, a ZEV penalty of $10,000/ credit is assumed for these scenarios, with no banking of credits.

iii. **Credit banking:** we also consider the case where automaker is allowed to bank credits over time. As noted in the methods section, this means that extra credits earned in a year can be used to meet the credit requirement in a later year. As a simplifying assumption, we assume that an extra credit earned in the first year can be used in any of the later years up to 2030. The One credit per ZEV-- Bank scenario represents the One credit per ZEV credit scheme with banking and the California style Bank scenario represents the California - style scheme with banking in the results section.

2.5 Validation exercise

We consider broad approaches to validation of our model. First, as discussed in detail in Bhardwaj et al (2021), we apply a six-point exercise to test the structural and behavioural validity of our model. Our approach is summarized in Section S1 of the supplementary document.

Second, in Section S2 of the supplementary document, we further consider the case of California. One anonymous reviewer suggested that we compare the insights from our modelling results with actual findings in California, where the ZEV mandate has been in place for three decades. While it would be ideal to quantitatively calibrate our model and validate it using historical Californian data, it is beyond the scope of the present study. In Section S2 we provide a qualitative comparison, which provides four main insights:

1. Our model shows that a ZEV mandate is likely to increase ZEV market share, similar to empirical findings in California (as informed by Slowik and Lutsey, 2017; CNCDA, 2018), (Fig.3).
2. Regarding the share of PHEV versus BEV sales, we find that PHEV sales are projected to increase to over 60 percent of ZEV sales by 2025 (see Fig. 6), similar to analyses of California's ZEV mandate (CARB, 2017; Resources for the Future, 2019).
3. Regarding the use of credit banking, historical evidence informs that automakers over complied with ZEV regulation in California in recent years (2012-2016), similar to the automaker behaviour estimated by AUM (Fig. 5).
4. Regarding cross-price subsidies, our model finds that the auto industry will likely charge lower profit margins on ZEVs (Fig. S2), thus in effect offering them at a

discount to conventional vehicles, as also reported by some market research studies (e.g., UBS. 2017)

2.6 Uncertainty analysis

As outlined in Bhardwaj et al (2021), we follow multiple steps to explore and depict uncertainty in results, namely we: (i) identify key parameters (listed below) causing most uncertainty in model outputs; (ii) depict results as uncertainty bans with pessimistic and optimistic value assumptions of the input parameters determining the boundaries of these uncertainty bands; and (iii) perform sensitivity analysis to explore how variation in key parameters affects key results. In this paper, for the sake of clearly distinguishing the policy scenarios, we present our results as point estimates (corresponding the median input parameter assumptions) rather than as uncertainty bands. After these initial sections, we do however present a sensitivity analysis in section 3.5,

For the first four parameters listed below, we test the effect of pessimistic and optimistic estimates drawn from literature (optimistic/pessimistic values are listed in Tables 2 and 3). For the remaining parameters (5 through 9), we test the effect of varying the assumed base values by plus or minus 25%.

The key parameters affecting model results are:

(1) **Battery pack costs**: as seen by car manufacturers (including markups from battery manufacturers) are 230 CDN $/kWh in 2020, and assume values of 70 CDN$/kWh (optimistic) and 175 CDN$/kWh (pessimistic) in 2030, similar to the low (50 USD$/kWh) and high (125USD$/kWh) battery cost estimates made by Nykvist et al. (2019). In effect, PEV incremental costs vary by −42% to +45% relative to the base value of 120 CDN $/kWh in 2030.

(2) **Price elasticity** of demand, determining how vehicle ownership is affected in response to vehicle prices, assume values of -0.3 (optimistic) and -1 (pessimistic), corresponding to the low (Holmgren, 2007) and high (Fouquet, 2012) values suggested in literature. In effect, price elasticity varies by −50% to +66% relative to the base value of -0.6. The pessimistic and optimistic price elasticity values are constant from 2020 to 2030.

(3) **Discount rate** used by the automaker assumes values of 8% (optimistic) and 15% (pessimistic), corresponding to the low and high values suggested in Jagannathan et al. (2016). In effect, discount rates vary by −20% to +50% relative to the base value of 10%. The pessimistic and optimistic discount rate values are constant from 2020 to 2030.

(4) **Fuel prices** (gasoline) are taken to be 70 $CDN/bbl in 2020, and assume values of 92 $CDN/bbl (pessimistic) and 177 $CDN/bbl (optimistic) in 2030, corresponding to 2 US $/gallon (60 US $/bbl) and 4.23 US $/gallon (~ 128US $/bbl) gasoline price scenarios (NEB, 2019; U.S. EIA, 2020), or −27% to +40% of the base price assumption of 125 $ CDN/bbl. In 2030.

(5) **Foresight** parameter assumes two values: 5 year (pessimistic, representing a medium-term foresight) and 10-year (optimistic, indicating a long-term foresight), in line with previous studies (Klier and Linn, 2012).

(6) The **Consumer preferences** parameter, representing the endogenous change of ASC over time, varies across consumer segments (Table 1). As an example, the consumer preference for BEVs among the “Resistors” consumer segment is -40k CDN$ in 2020, and assume a base value of -28k CDN$, with -35k CDN$ as pessimistic and -21k CDN$ as optimistic values in 2030.

(7) The exogenous global increase in **Model variety** for PEVs is assumed to grow from 10% (relative to model availability for conventional vehicles) in 2020, to assume values of 40% (pessimistic) and 90% (optimistic) in 2030, with a median value of 70%, similar to Wolinetz and Axsen (2017).

(8) The **Recharging access** parameter, indicating the locational availability of public charging infrastructure, relative to existing gasoline infrastructure, is 10% in 2020, and assumes values of 50% (pessimistic), 70% (median) and 90% (optimistic) in 2030.

(9) The **Domestic Rate of learning** Parameter, which in AUM determines the rate at which technology improves in Canada, partly (in addition to global efforts) affecting how quickly domestic vehicle manufacturing costs drop over time, in response to increased domestic production (learning by doing) or domestic investment in R&D (learning by searching) (see equation 8 for reference). Since part of the decline in vehicle cots is assumed to be exogenous (due to global factors), this rate of learning can be understood to be the domestic learning rate. The Rate of Learning parameter assumes values of 6% (pessimistic) and 10% (optimistic), +/-25% relative to the median value of 8% (Weiss et al., 2012), These values are constant from 2020 to 2030.

3. Results

In this section we first examine the effects of the different ZEV mandate penalty scenarios on ZEV new market share out to 2030 and GHG emissions, as well as automaker profits and consumer surplus (Section 3.1). Then we examine the same impact for each ZEV credit scheme (Section 3.2) and the credit banking scheme (Section 3.3). Section 3.4 compares the cost-effectiveness ($CDN/tonne) of the different ZEV mandate designs. Note that in these initial sections we present our results as point estimates; this is for the sake of clarity, hence these results are largely illustrative of the processes in the model. Section 3.5 presents a sensitivity analysis to examine the magnitude of these different uncertainties.

3.1. The impacts of ZEV mandate penalty

Fig. 3i compares ZEV new market share under the Baseline and the four ZEV penalty scenarios (all with One credit per ZEV scheme). In the Baseline scenario with no ZEV mandate in place, we see that ZEV new market share initially peaks at around 4% in 2019. Once the financial incentives are removed in 2020, new market share drops to 2%, and then grows slowly to 8% by 2030. The new ZEV market share is the highest under the $10k penalty scenario and reaches the Government target of 30% ZEVs by 2030. The new ZEV market share is slightly lower at 27% for the $7.5k penalty scenario and much lower at about 20% for the $5k penalty scenario. The $2.5k penalty scenario is somewhat higher than Baseline with 13% new PEV market share by 2030. These ZEV scenarios demonstrate that ZEV sales could be highly dependent on the value of penalty imposed on non-compliance.

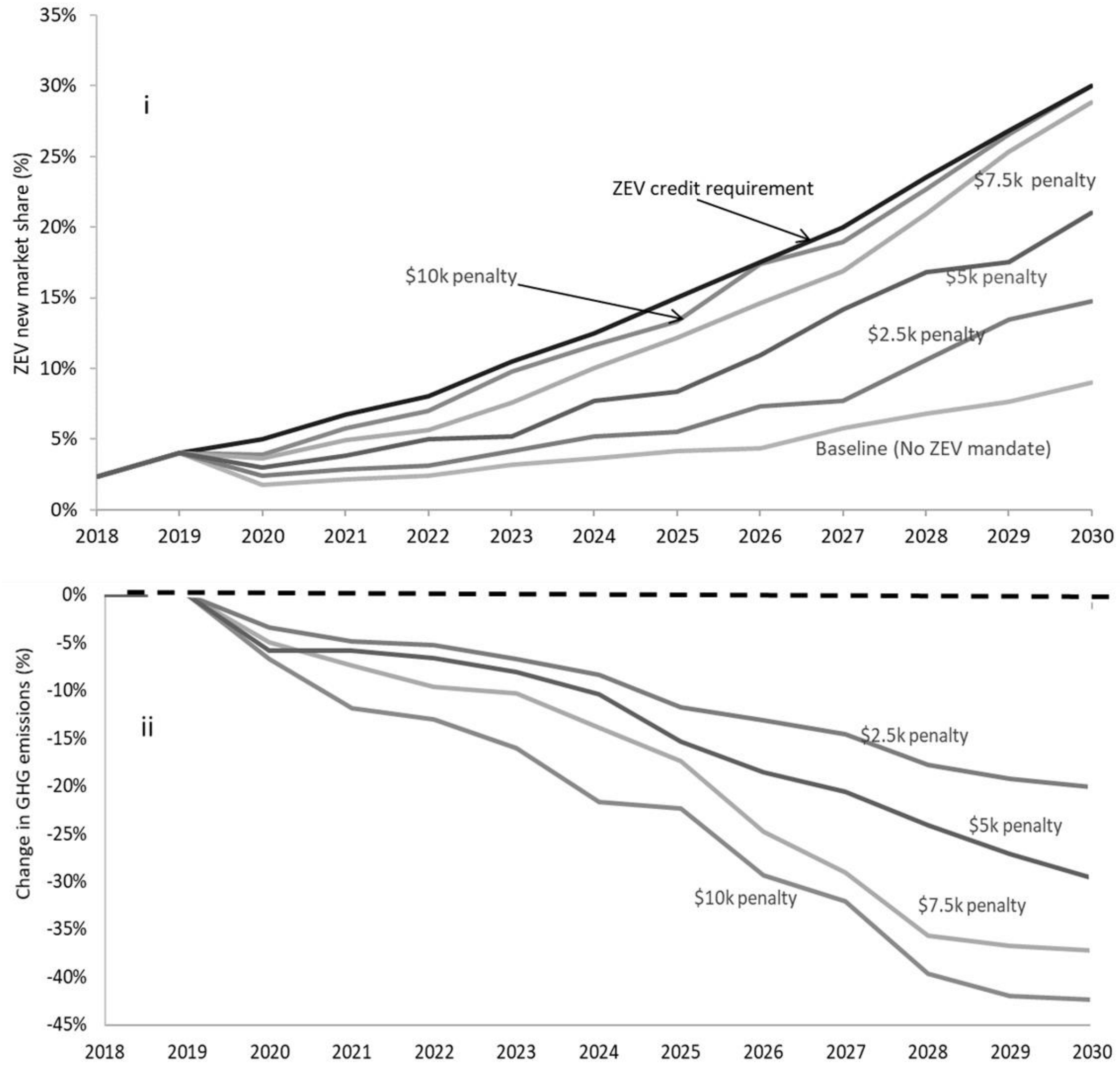

Fig.3. i. ZEVs new vehicle market share in Canada under the Baseline and ZEV penalty scenarios (all with One credit per ZEV credit scheme). ii Reduction in GHG emissions relative to the Baseline.

Because higher penalties induce the automaker to push more ZEVs to consumers, more GHG emissions reductions occur also (Fig.3ii). Reduction in GHG emissions in 2030 (compared to 2030 in the baseline) varies between a low of 21.8% under the $2.5k ZEV penalty to a high of 43.7% under the $10k ZEV penalty in 2030.

Fig.4i depicts the percentage change in consumer surplus under the four ZEV penalty scenarios relative to the Baseline (all with One credit per ZEV scheme). The surplus calculations represent the ”Full” fuel savings valuation which includes the effect of fuel savings over vehicle lifetime, as explained section 2.3. Consumer surplus drops further with an increasing ZEV penalty, ranging from a low of 9.5% under the $2.5k ZEV penalty to a high of 20.3% under the $10k ZEV penalty in 2030. Despite increased fuel savings, consumers on average are simulated to perceive a drop in surplus because of higher conventional vehicle prices, fewer vehicle purchases (i.e., drop in sales), and (for some consumers) being shifted away from their preferred vehicles (i.e., conventional vehicles).

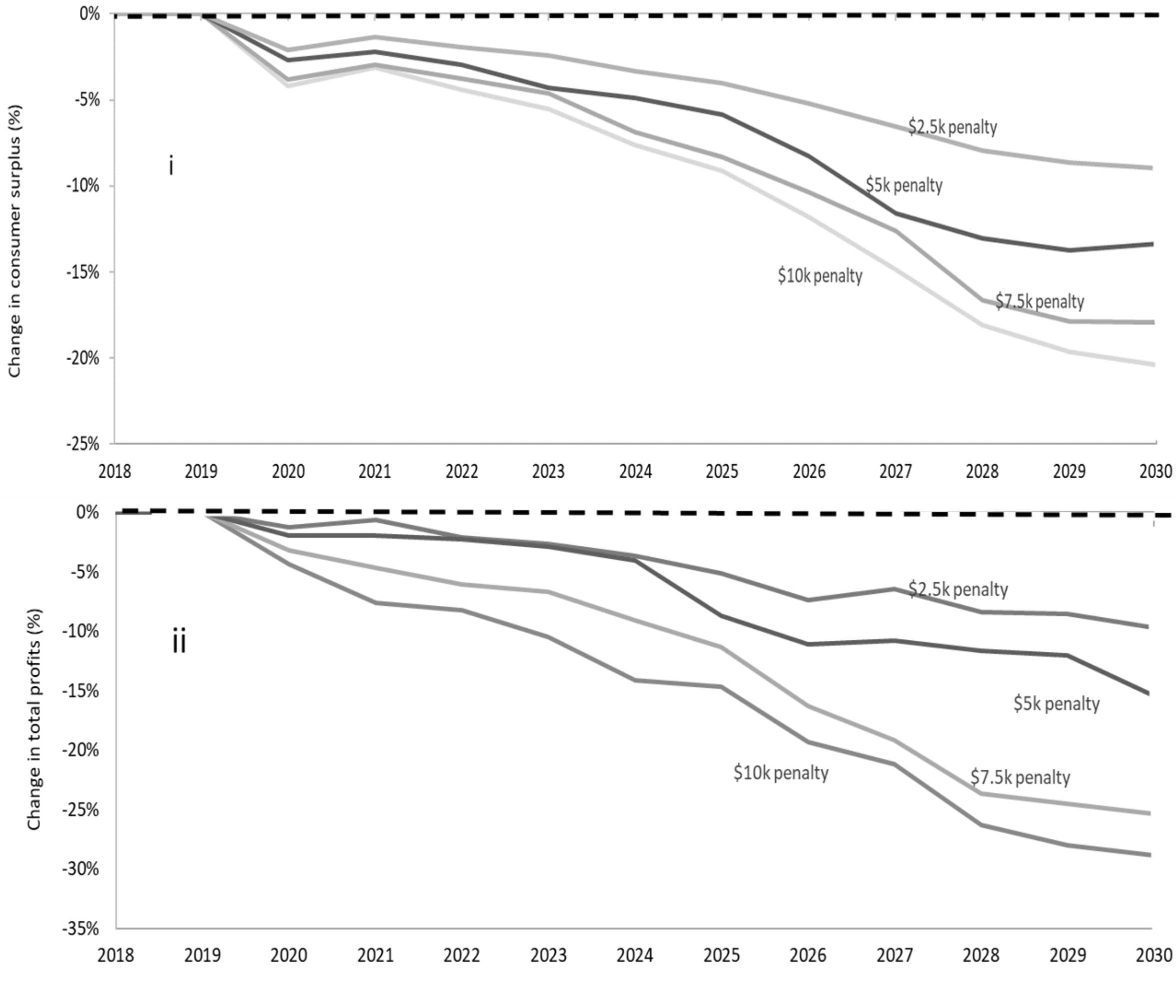

Fig. 4 i Percentage change in consumer surplus ('full' valuation) under the ZEV penalty scenarios relative to the Baseline. ii Percentage change in automaker industry profits under the ZEV penalty scenarios relative to the Baseline (All scenarios with One credit per ZEV credit scheme).

We also analyse the impacts of the ZEV mandate penalty on automaker profitability (Fig. 4ii). The drop in profits is larger with increasing penalty. The 2030 drop in profit is about 9.8% for the $2.5k penalty scenario, 16 % for the $5k penalty, 25% for the

$7.5k penalty and 28% for the $10k penalty. As ZEV penalty increases, automaker take more action to induce ZEVs in order to comply with the policy and to avoid paying the penalty for non-compliance.

Over the long term, automakers may be better off by incurring some impact on profitability initially, rather than suffer far more by not investing in advanced technology, or not producing more ZEV models. For example, when adjusting automaker foresight (say, from 5 years to 10 years), we find that automakers can increase their profits by having a longer-term (10 year) foresight, mainly by charging relatively lower average markups in the initial years. These lower markups facilitate higher ZEV market share sooner, which in turn contributes towards increasing consumer preferences towards ZEVs sooner, and thus earn higher profits in the later years and overall (Bhardwaj et al, 2021). However, given that our model is presently focused on domestic automaker activity, we do not presently have the capacity to examine dynamics among global automakers, or the interaction between domestic and global perspectives of automakers – say in how R&D activities much contribute to global competitiveness over the long-term.

3.2. The impacts of ZEV credit scheme

Fig. 5i depicts the difference in new ZEV market share between the One credit per ZEV (or "One-credit") and California style credit schemes (both with $10k ZEV penalty/ credit). The total ZEV new market share is higher under the One-credit scenario with substantial differential (~10%-points in 2030), and almost reaches the ZEV credit requirement in 2030 (indicated by the dark black line in Fig.5). Under the California style scheme (which assigns 2 credits per BEV), the ZEV market share is consistently lower than the ZEV credit requirement. The assignment of multiple credits allows automakers to meet (or even exceed) the ZEV credit requirement with the sale of fewer ZEVs. Fig. 5ii also compares the GHG remissions reductions for these schemes, which are more reductions are achieve with the One-credit scheme.

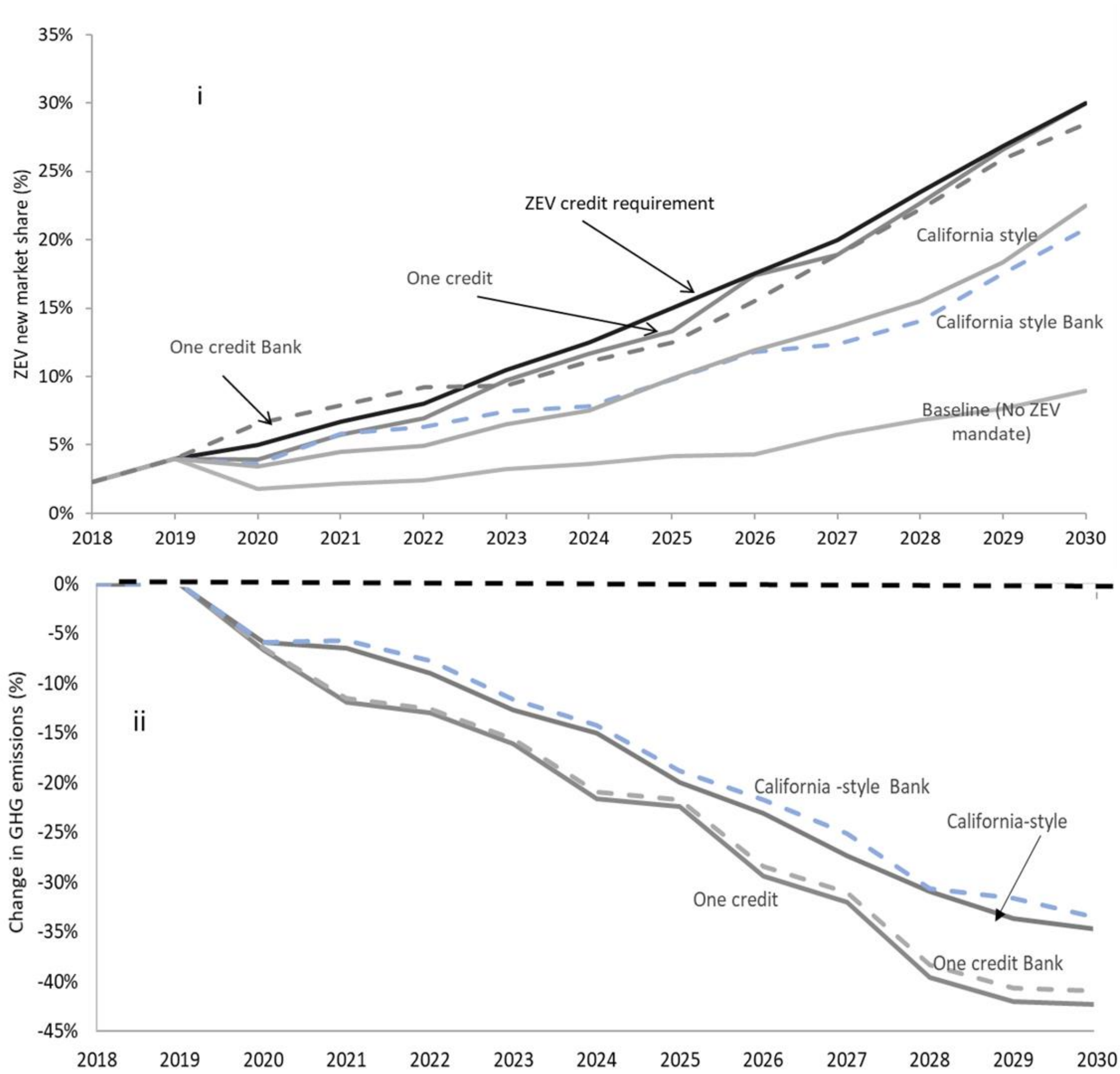

Fig. 5 i ZEVs new vehicle market share in Canada under the Baseline, One credit per ZEV scenario (with and without Banking) and California style scenario (with and without Banking); ii Reduction in GHG emissions relative to the Baseline. (all credit scenarios with same ZEV penalty of $10k/credit)

Fig.6 compares the effect of the two credit schemes on the distribution of different ZEV technologies, namely PHEVs versus BEVs. The One-credit scheme leads to PHEVs making up almost 90% of ZEV sales by 2030), while the California-style scheme leads to just over 70% PHEVs by 2030. PHEVs typically have lower cost of production (before reaching cost parity with BEVs around 2027) and higher acceptance among consumers compared to

BEVs. Thus, if PHEVs earn as many credits as BEVs (as is the case in One-credit scenario), there we simulate that automaker push for more PHEV sales to comply with the policy.

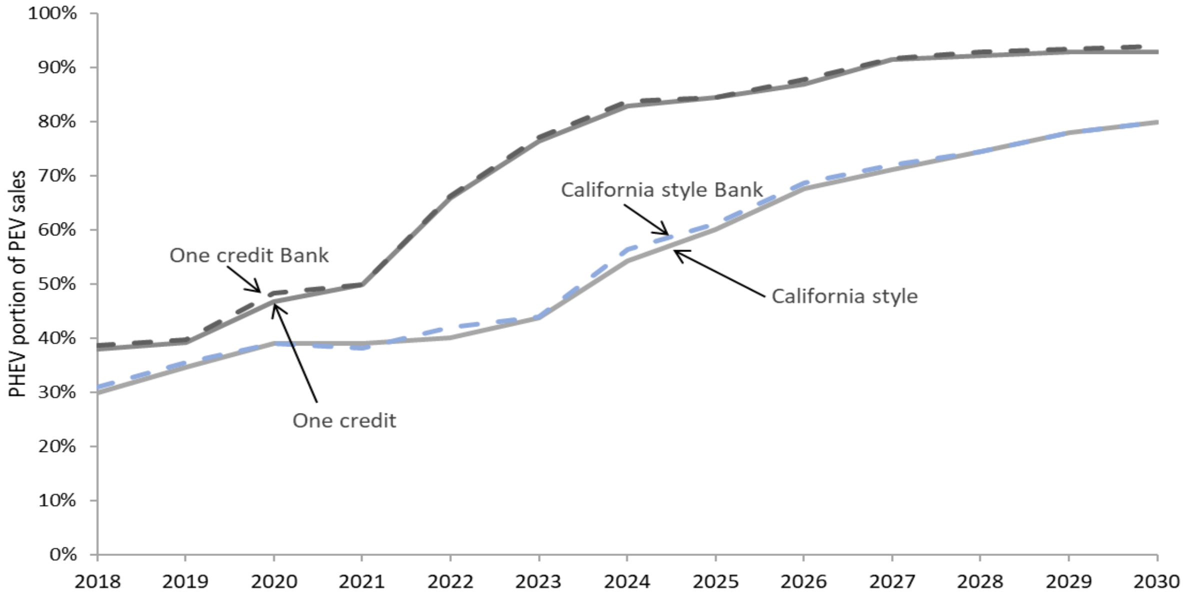

Fig. 6 PHEV sales as a percentage of the total ZEV new market share under the One credit per ZEV scenario (with and without Banking) and California style scenario (with and without Banking) (all scenarios are with same ZEV penalty of $10k/credit)

Fig. 7i depicts the change in consumer surplus (compared to Baseline) over time, where reductions are larger under the One-credit system than the California-style system. Similarly, the One-credit system leads to larger decreases in automaker profits out to 2030 (Fig. 7ii).

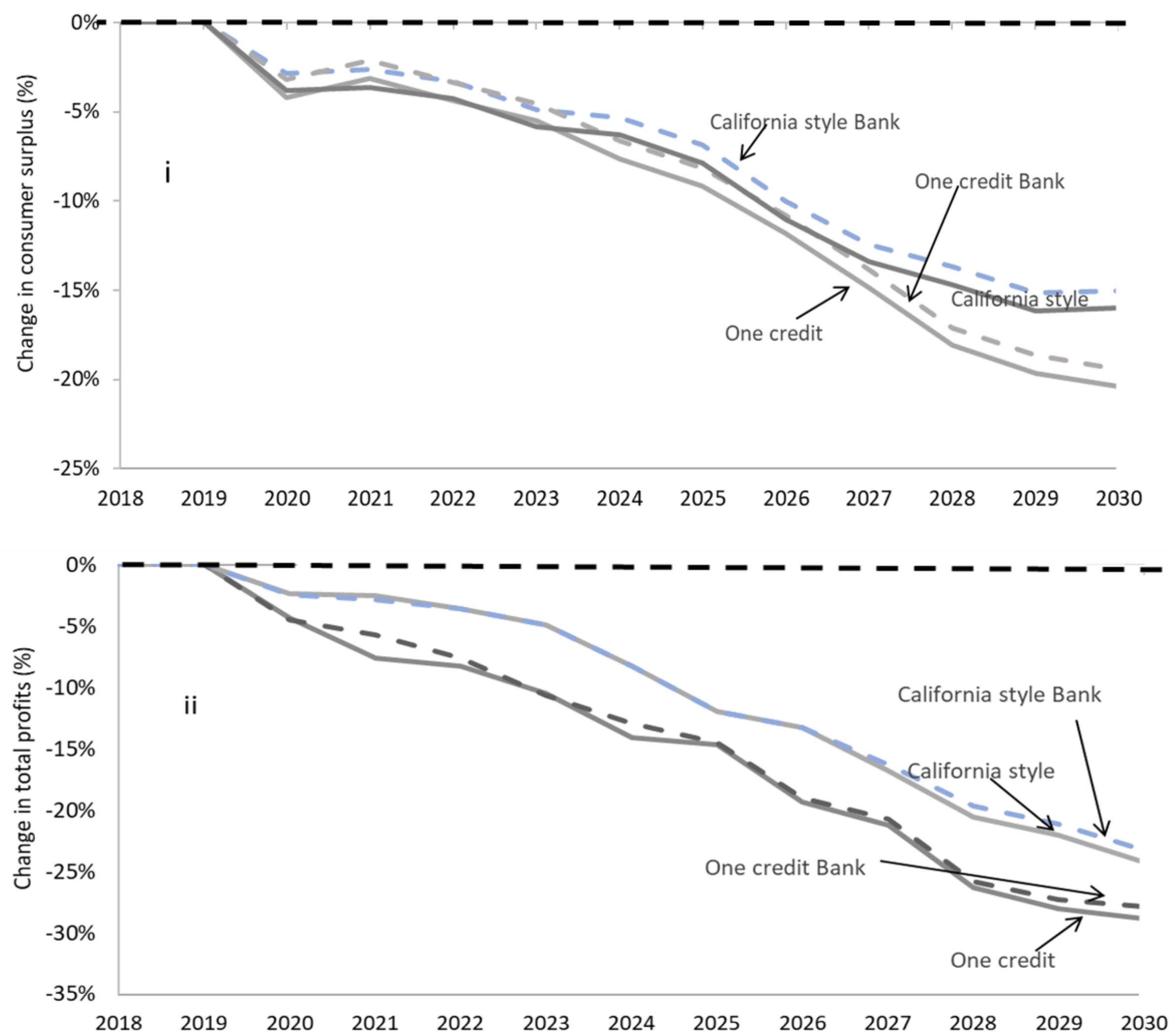

Fig. 7 i Percentage change in consumer surplus ('full' valuation) relative to the Baseline under the One credit per ZEV scenario (with and without Banking) and California style scenario (with and without Banking); ii Percentage change in automaker industry profits relative to the Baseline (all scenarios are with same ZEV penalty of $10k/credit).

3.3. The impacts of ZEV credit banking

The final ZEV mandate design feature we examine is the potential to allow automakers a to bank credits. With this feature, automakers can over-comply with the ZEV credits requirement in the initial years, and under-comply in future years (without necessarily paying a penalty). As shown in Figures 6 and 7, the presence or absence of this feature has relatively little impact on ZEV market share, GHG emissions, consumer surplus or automaker profits. When banking is allowed, the automaker takes advantage of it to some extent—with higher ZEV new market share (and potentially even over-compliance) in initial years, and lower ZEV new market share in future years. Additionally, the allowance of banking has a mildly positive impact (~1% in 2030) on automaker profits (Fig. 7i) and consumer surplus (Fig. 7ii).

This trend is driven by the fact that the ZEV credit requirement becomes increasingly difficult over time (5% in 2020, 15% in 2025 and 30% in 2030), even if some factors such as decline in battery costs or increase in public charging stations can support complianceAs a result, in these simulations we find that it is more profitable for the automakers to over-comply in the initial years and use the banked credits to meet part of the requirement in later years.

3.4. Summary of policy impacts and cost-effectiveness

Table 5 summarizes our key results for each combination of ZEV mandate design features. The left half depicts the policy impacts on four indicators for 2030: ZEV new vehicle market share; the GHG emissions reduction relative to Baseline emissions in 2030; the change (drop) in consumer surplus relative to the Baseline in 2030; and the change (drop) in profits relative to Baseline profits in 2030. The consumer surplus calculations are indicated for both "Utility function" valuation and "Full" valuation of fuel savings (explained in Section 2.3) Results demonstrate trade-offs among the policy designs. Generally, ZEV mandate designs that are more effective at increasing ZEV adoption and decreasing GHG emissions also induce stronger reductions in consumer surplus and automaker profits. For example, ZEV adoption and GHG reductions are higher for the "One credit per ZEV" scheme, rather than a "California-style" scheme that gives multiple credits per battery-electric vehicle. Though, this comes at a cost since the negative impact on consumer surplus and automaker profitability is also higher under the One-credit scheme.

As a final exercise that considers these trade-offs in impacts across ZEV mandate policy designs, we calculate policy cost-effectiveness for each combination of features (right-hand side of Table 5). As explained in the methods section, policy costs are the cumulative consumer surplus and profit changes due to the policy (relative to Baseline) up to 2030, per tonne of CO_2 abated. In these calculations, we consider multiple perspectives: i) both the Utility Function and Full valuation of fuel savings, and ii) both a 3% discount rate and 8% discount rate.

Comparing these cost-effectiveness values, we see the relative ranking of policy costs tend to hold for both valuation and discount rate scenarios. We find that the higher penalty scenarios (especially $10k per credit) generally lead to more cost-effective GHG reductions. Further, the One-credit scheme is generally more cost-effective than the California -style scheme, across different penalty levels. Finally, banking has a small positive effect on cost-effectiveness. Taking this together, we see that the most cost-effective ZEV mandate design (among our particular scenarios) is a ZEV mandate with $10k penalty, a One credit per ZEV scheme, and allowance of credit banking. Again, this finding holds across the different assumptions of discount rate and fuel savings perspective.

Table 5: Variation of cost-effectiveness (in S/tonne) with ZEV policy scenarios

	Policy impacts (2030)					Policy cost-effectiveness (2020-2030)			
	ZEV New market share	GHG reductions	Consumer Utility (%)		Profit Impacts	Total private cost-effectiveness ($CDN/ tonne, 8%)		Total private cost-effectiveness ($CDN/ tonne, 3%)	
	(%)	(%)	Utility-Function	Full-valuation	(%)	Utility-function	Full-valuation	Utility-function	Full-valuation
All with $ 10 k penalty									
One credit	30.0	43.2	-25.1	-20.3	-28.3	820	735	635	571
One credit -Bank	28.3	42.1	-25.0	-20.3	-27.7	815	722	627	564
California style	21.5	37.9	-20.4	-16.5	-24.4	853	766	672	604
California style- Bank	19.4	37.5	-19.6	-15.8	-24.0	851	752	661	593
All with $ 7.5 k penalty									
One credit	27.1	35.3	-22.4	-18.1	-25.1	845	760	662	595
One credit -Bank	25.6	31.9	-21.8	-17.9	-23.6	837	753	643	578
California style	18.1	28.2	-17.8	-14.4	-20.7	860	774	692	622
California style- Bank	16.7	26.7	-17.2	-14.0	-19.1	855	769	681	612
All with $ 5 k penalty									
One credit	20.2	29.9	-16.9	-13.7	-16.4	870	783	678	610
One credit -Bank	18.4	28.5	-16.2	-13.2	-15.8	862	775	669	602
California style	14.2	25.4	-13.5	-10.0	-13.6	893	803	718	646
California style- Bank	12.4	24.3	-13.3	-9.9	-13.0	882	793	711	639
All with $ 2.5 k penalty									
One credit	13.4	21.8	-11.8	-9.5	-9.8	910	819	694	624
One credit -Bank	12.2	20.1	-11.8	-9.4	-8.7	897	807	682	613
California style	10.7	18.8	-9.1	-6.8	-5.4	934	840	732	658
California style- Bank	10.4	17.6	-8.7	-6.7	-4.5	930	832	726	649

3.5 Sensitivity analysis

To better understand the sensitivity of these results, we use single value deterministic sensitivity analysis to explore how variations in seven key input parameters affect: ZEV new market share in 2030 (Fig. 8), automaker profits reductions in 2030 (Fig. 9), consumer surplus reductions in 2030 ('Full' valuation) (Fig. 10), as well as cost-effectiveness ('Full' valuation, with 3% discount rate) (Fig. 11). As an illustrative case, this sensitivity analysis considers ZEV mandate policy with $10k penalty per credit, under the One-credit scheme and without any banking of credits. The sensitivity of each model result to the input parameters is ordered from largest to smallest impact.

First, all results are quite sensitive to assumptions about consumer preferences for ZEVs—it is the biggest influencer for ZEV new market share, and second biggest influence for automaker profits and overall policy cost-effectiveness. Second, results are also quite sensitive to assumptions about battery cost ($/kWh), which is the biggest influence for consumer surplus, automaker profits and cost-effectiveness. In addition, model outputs are also fairly sensitive to assumptions about recharging access, model variety, and consumer (own-price) elasticity in demand for new vehicles. Across the different model outputs, we also notice that there is particularly large uncertainty in profit estimates, depending on critical parameters such as battery costs, consumer preferences, price elasticity (Fig. 9). Our results should be considered in light of these uncertainties, with future research efforts aimed at reducing the uncertainty bands for key input parameters. Despite these uncertainties, we generally find that the ranking of our ZEV mandate policy design scenarios by various impacts is largely consistent.

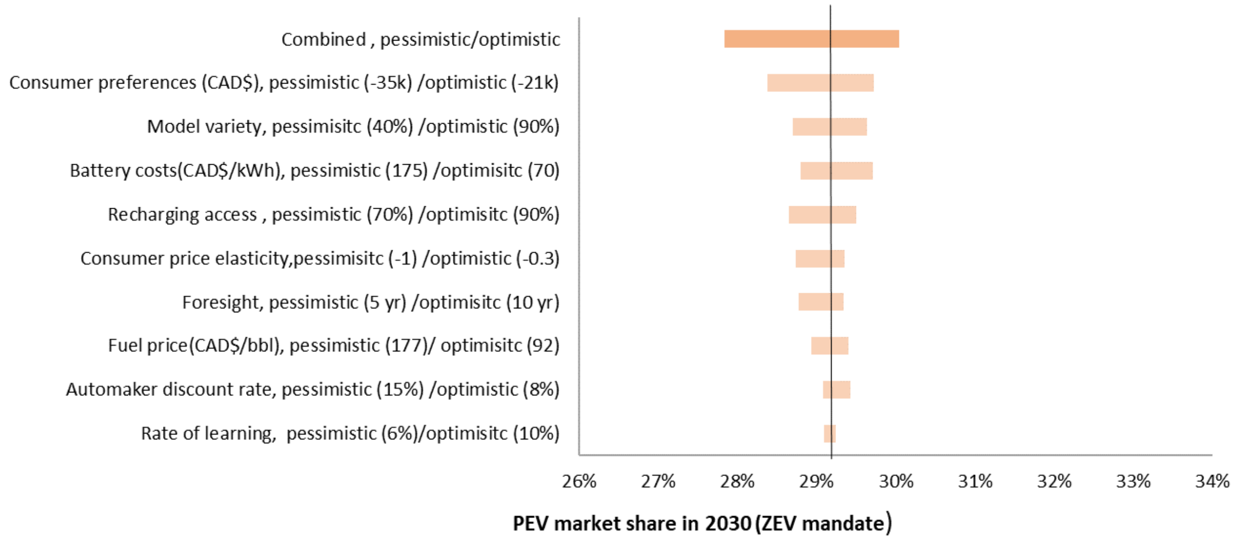

Fig. 8 Sensitivity analysis of PEV new market share in the ZEV mandate scenario in 2030 ($10k penalty; One credit per ZEV; No banking).

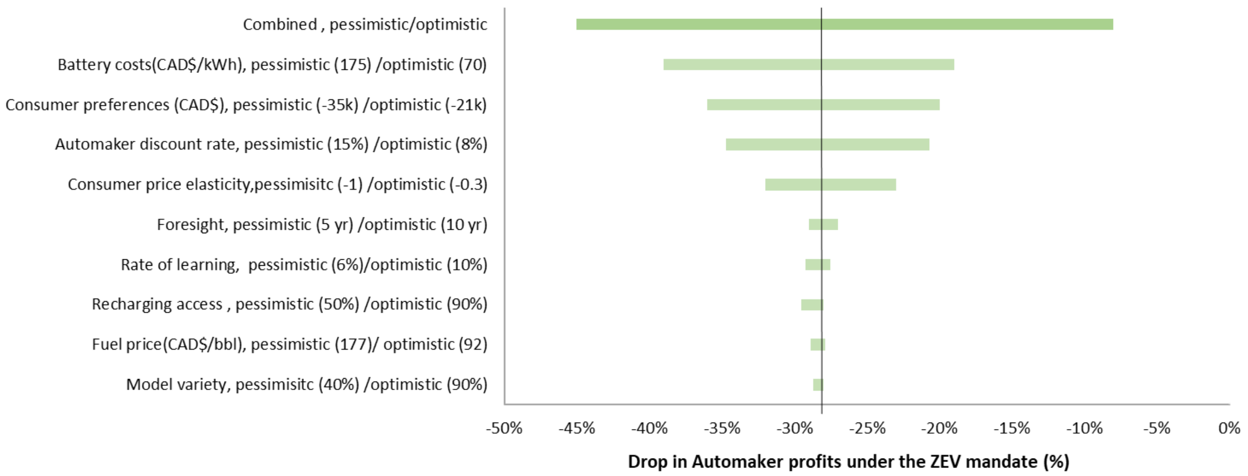

Fig. 9 Sensitivity analysis of the change in automaker profits under the ZEV mandate in 2030 ($10k penalty; One credit per ZEV; No banking).

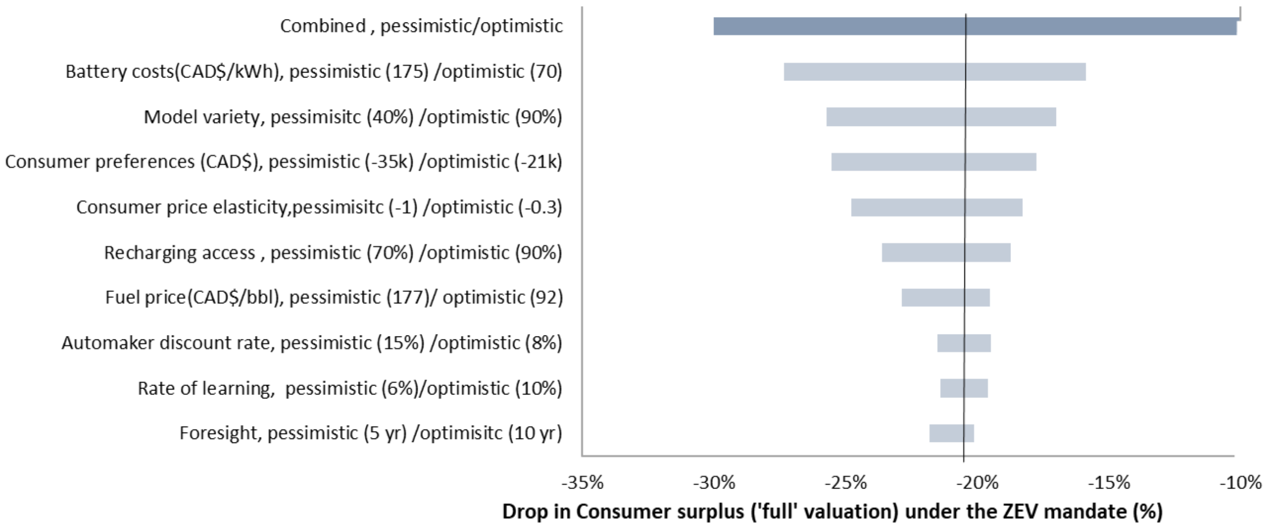

Fig. 10 Sensitivity analysis of the change in consumer surplus under the ZEV mandate in 2030 ($10k penalty; One credit per ZEV; No banking)

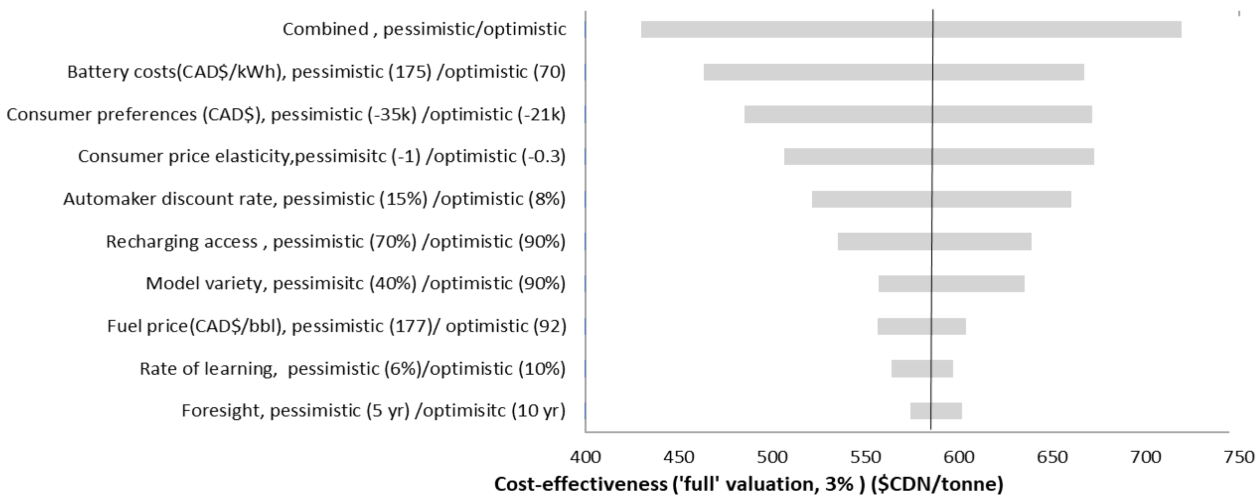

Fig. 11 Sensitivity analysis of the cost-effectiveness (‘full’ valuation, 3% discount rate) of the ZEV mandate ($10k penalty; One credit per ZEV; No banking).

4. Discussion and Conclusion

4.1 Summary and policy implications

In this paper, we simulate the impact of different ZEV mandate designs on ZEV market share, GHG emissions, consumer surplus, automaker profits, and overall policy cost-effectiveness ($/tonne CO_2 abated) in Canada’s light-duty vehicle sector from up to 2030. We consider the impacts of the selected penalty for non-compliance ($/credit), the selected scheme for how credits are allocated per BEV and PHEV sold (California-style or One credit per ZEV), and the effect of banking credits. We are aware of no other published studies that have modelled ZEV mandate designs in this detail.

In this effort we use a technology adoption model (AUM), with an explicit representation of both consumers and an automaker agent (the latter being at the aggregate level). The incorporation of the automaker perspective (with endogenous decision-making) in technology adoption models for climate policy analysis (specifically for the ZEV mandate) has rarely been attempted in literature (Wolinetz and Axsen, 2018). Specifically, AUM represents automaker decisions about ZEV model variety, R&D investment, and vehicle pricing, as well as compliance or non-compliance with the ZEV mandate (comparing penalty costs with compliance costs). The AUM model also contains other novel and useful methodological features, such as multi-year foresight for automakers (5 or 10 years), as well as representation of behaviourally realistic consumers, drawing from empirical survey data, representing heterogeneity among consumers, and simulating endogenous changes in preferences as a function of increasing ZEV stock.

From our analysis, we find that the design of the ZEV mandate could have a substantial effect on several model impacts, including ZEV new market share (achieving the 30% by 2030 goal set by the government), as well as GHG emissions reductions, and various economic impacts (consumer surplus, automaker profits and overall cost-effectiveness) . First, we find that a change in ZEV penalty has a significant effect on all model outputs. Specifically, a high penalty ZEV mandate (~$ 10k/credit) may be required to achieve the government target of 30% plug-in electric market share by 2030, while also leading to greater GHG reductions. On the other hand, increasing the ZEV penalty negatively affects the automaker profits and consumer surplus – with a greater impact on profits. With that in mind, our cost-effectiveness analysis finds that the most cost-effective ZEV mandate designs include a $10k per credit penalty.

Second, the choice of ZEV credit schemes also impacts most output parameters, and can especially influence the ratio of PHEVs to BEVs in the overall ZEV market. While the total ZEV market share is higher under a One-credit per ZEV scheme, it also has a much higher percentage of PHEVs (reaching almost 90% of ZEVs by 2030). In contrast, the California-style leads to a higher proportion of BEVs in the ZEV mix. Note that this emphasis on PHEVs comes with some risk--PHEVs present greater uncertainty regarding their GHG emissions over the long term as people buying these vehicles could continue to use the vehicles in gasoline mode (Plotz et al, 2017). That said, with our assumption of 70% utility rate for PHEVs, we find that GHG emissions reductions are higher for the One Credit system. On the other hand, we find that the California-style credit scheme leads to lower ZEV shares in total (5 percentage points lower in 2030), but higher BEV sales. The implication is that One-credit per ZEV scheme may be preferable for increasing the total new ZEV market share, while a California-style scheme may help to induce more BEV sales. From our cost-effectiveness analysis, the One-credit per ZEV system is the more efficient way to reduce GHG emissions (subject to our assumptions).

On this point, we note that we only explored two illustrative examples of real-world credit systems. The "California-style" is used in California and Quebec, and seems to be more influential among regions considering their own ZEV mandate. The One-credit system is what is planned in the British Columbia ZEV mandate. Our analysis does not prove that either of these credit systems is "best", and it doesn't disentangle the differences in magnitude of credits versus relative credits for PHEVs and BEVs. While it does seem clear that offering fewer credits per ZEV will result in higher ZEV market share, it is not clear how many credits should be provided for PHEVs relative to BEVs. Further analysis is needed to better understand the role of PHEVs in a transition to ZEVs and low-carbon transportation more generally.

The third and final design feature we examined is the impact of allowing automakers to bank ZEV credits over time. We find that automakers are likely to over-comply with the ZEV credits requirement in the initial years if banking of credits is allowed. The allowance of banking has a relatively small but positive impact on consumer surplus and automaker profits, and slightly improves the cost-effectiveness of ZEV mandate design.

Despite these limitations discussed next, we believe our results generate policy relevant insights. First, a ZEV mandate can provide a strong push to automakers to increase the supply of ZEVs and significantly increase ZEV market share compared to a baseline policy scenario. Second, the success of a ZEV mandate in pushing ZEV sales and GHG emissions highly depends on the design of the policy, especially the level of penalty for non-compliance. The choice of credit scheme can also influence policy outcomes, including overall compliance and the relative sales of different PHEVs versus BEVs. On this last point, policymakers may closely examine the trade-off between a higher total ZEV market share (One-credit scheme) versus a higher BEV proportion of sales (but lower overall ZEV market share) under the California-style scheme. Finally, the presence of credit banking does not have a large influence on policy impacts, though allowance of banking may improve the acceptability of the policy to automakers (given the potential to reduce profit impacts).

4.2 Limitations and future research directions

Our work is forward-looking and involves many present and future uncertainties, so our analysis and results come with several important limitations. The magnitude of our model results is strongly dependent on battery cost and other input assumptions. As literature on battery costs acknowledge (e.g., Lutsey et al, 2021; Nykvist et al, 2019), there is great uncertainty over future battery technology development. As depicted in our sensitivity analyses, the numerical value of consumer surplus, profit and cost-effectiveness results may change significantly if the underlying cost assumptions change. However, we found that the relative ranking of the policy scenarios did not change for the different cost assumptions, thus lending confidence to our comparative insights.

Relatedly, our results are strongly dependent on our representation of consumer preferences. In particular, the evolution of consumer preferences is highly uncertain. Some recent consumer surveys are more optimistic about consumers' preferences for ZEVs (e.g., Consumer Report, 2020). Further, different assumptions about how consumer preference might change or develop between 2020-2030 can substantially impact results. For example, the assumption that more mainstream consumer more quickly develop positive ZEV preferences would considerably lessen the impacts of a ZEV mandate on consumer surplus and automaker profits. Also, we presently do not specifically disaggregate consumer classes based on income or age groups (though these demographics are somewhat captured by the empirically-estimated consumer classes we use). As one specific example, younger people may have a higher likelihood of purchasing ZEVs, though past research have found contrary results as well (Peters and Dütschke, 2014; US Department of Energy, 2013; Axsen et al, 2016).

There also exist methodological limitations with our model. Our model is a representation of the Canadian auto industry at the aggregate level. Presently, we do not consider multiple automakers, and thus we do not consider the potential for buying and selling of credits among automakers. The credit trading feature allows the ZEV mandate to mimic other market-based instruments such as tradable permits, and can potentially help to reduce the costs (and improve the cost-effectiveness) of the policy. In other words, inclusion of a credit trading system in our model could lead to further improvements in ZEV mandate cost-effectiveness. Inclusion of multiple automakers at the global level could also improve the treatment of R&D investment in our model. While AUM includes R&D investment as a possible compliance mechanism for the automaker, a more sophisticated treatment of R&D effects would involve consideration of how delays in ZEV R&D and other innovation activities at the domestic level relate to the global competitiveness of a given firm compared to other automakers

The current focus on a 2020-to-2030-time horizon in AUM is another important limitation. Many countries are considering a 100% ZEV mandate (or a complete ban of internal combustion engines) by 2035 or 2040 (Plotz et al, 2019) – or even earlier in some cases. The feasibility and economic and GHG impacts of such an "ICE ban" remain under-studied. We intend to extend the model horizon of AUM to examine the impacts of ICE bans and more stringent ZEV mandate targets in a future study.

Finally, currently in AUM the vehicle-specific technological details (e.g., vehicle volume, number of seats) are capture by a blanket parameter (i.e., ASC in equation 1). A potential future research direction is to isolate the impact of each of these attributes on vehicle sales, for example as attempted in the ADOPT model (Brooker et al, 2015). We also acknowledge that AUM does not capture many of the more subtle complexities of the vehicle market. For example, AUM does not distinguish between purchase and lease of new vehicles.

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Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: Chandan Bhardwaj; Jonn Axsen; data collection, model development and analysis: Chandan Bhardwaj; draft manuscript preparation: Chandan Bhardwaj, Jonn Axsen, David McCollum; All authors reviewed the results and approved the final version of the manuscript.