Attribute-based Subsidies and Market Power: an Application to Electric Vehicles

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Abstract

Attribute-based subsidies (ABS) are commonly used to promote the diffusion of energy-efficient products, whose manufacturers often wield significant market power. We develop a theoretical framework for the optimal design of ABS to account for endogenous product attributes, environmental externalities, and market power. We then estimate an equilibrium model of China's vehicle market under ABS and conduct counterfactual simulations to evaluate the welfare impacts of various subsidy designs. Compared to the uniform subsidies, ABS lead to higher product quality and are more effective in mitigating quantity distortions, albeit with a modest environmental cost. Between 42% to 62% of welfare gains under ABS relative to uniform subsidies are attributed to more desirable product attributes, with the remainder explained by reductions in market power distortions. Allowing subsidy redistribution through product-level subsidies, as suggested by our theoretical model, further enhances welfare gains by an additional 34% to 62%. Among the ABS designs, China's notched subsidy design based on driving range leads to vehicle downsizing that undermines welfare benefits. Subsidies based on battery capacity, as implemented in the U.S., achieve the highest welfare gains by effectively balancing market power and environmental impacts.

Keywords: Attribute-based subsidies, electric vehicles, product attributes, market power, environmental impacts

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1 Introduction

Attribute-based regulations are common across industries and countries, where the intensity of regulations is contingent upon specific attributes of the entities being regulated. Prominent examples in the environmental and energy areas include Corporate Average Fuel Economy Standards for passenger vehicles, the New Source Review Program for power plants, and consumer subsidies for energy efficient products (Stavins, 2006). While existing research has investigated the advantages of attribute-based regulations (Ito and Sallee, 2018; Kellogg, 2018), the literature has largely abstracted away from firms' market power, a common feature in markets subject to attribute-based regulations. Our paper bridges this gap and analyzes both theoretically and empirically the optimal design of attribute-based subsidies (ABS), one type of attribute-based regulations, in oligopolistic industries. To the best of our knowledge, our framework represents the first attempt in the literature to incorporate three key features — namely market power, externalities, and endogenous attributes of products by multi-product firms — in the context of attribute-based policy design.

ABS in our setting take the form of a two-part subsidy (i.e., a two-part tariff): a base subsidy that is the same across products and a variable subsidy that is tied to product attributes. This is common in practice and standard in the theoretical literature. Our theoretical analyses begin by considering an ideal benchmark where a government can perfectly target the environmental externality and faces no budget constraints, and there is a single-product monopoly. It is straightforward to show that the government can achieve the first-best social outcome with a Pigouvian policy design, where the base subsidy fully addresses quantity distortion, and the variable subsidy corrects environmental externality. In practice, all three assumptions are likely violated. Environmental externality may be hard to quantify and target, governments face limited budgets, and many industries are characterized by differentiated product oligopolies.

When a government has a limited budget, it is sub-optimal to tie the variable subsidy to environmental externality as prescribed by the traditional Pigouvian subsidy. This would entail a limited base subsidy to address market power distortions when the budget constraint is binding. We show that the optimal policy design for a single-product monopoly is characterized by the contract curve between the social surplus indifference curves and the private surplus indifference curves in the product attribute space. Under multi-product oligopolies, optimality conditions require higher subsidies to products that exhibit potentially high welfare gains for the marginal unit and products whose demand is more responsive to subsidies in order to equalize the marginal social surplus generated by each subsidy dollar across all products.

The theoretical characterization of optimal policy design crucially hinges on the underlying consumer preferences and production technology. With the theoretical insights in hand, we turn to the empirical analysis of the market for electric vehicles (EVs). Together with a cleaner electricity grid, EVs offer considerable promise for reducing carbon emissions and local air pollution. Many governments have provided generous consumer purchase subsidies, with global public spending on consumer EV subsidies approaching $30 billion in 2021 (IEA, 2022). The design of these subsidies varies across countries. Some countries tie the subsidy amount to vehicle attributes, such as driving range in China and Japan, battery capacity in the U.S. and India, and vehicle size and weight in South Korea. Other countries offer uniform subsidies, as seen in Germany, the Netherlands, and Sweden. Our analysis focuses on China, by far the world's largest automobile and EV market, accounting for 40% of global new passenger vehicle sales and 60% of global EV sales in 2022.

We estimate an equilibrium model of the Chinese automobile market by extending the framework in Berry et al. (1995) to incorporate endogenous attributes. Our model allows firms to change product designs in response to subsidy schemes, which is a crucial factor in the welfare impacts and policy comparisons. The demand side captures rich consumer preference heterogeneity and controls for extensive fixed effects to capture local variations that affect demand for EVs and ICEs. On the supply side, firms choose prices and design vehicle attributes (battery capacity and vehicle weight net of battery) for EVs to maximize profits. Crucially, both the marginal and fixed cost of production depend on vehicle attributes.

To estimate consumer preferences, we utilize China's notched subsidy design, where the subsidy amount is a step-wise function of the driving range and varies across vehicle models and over time. This design creates a regression discontinuity type of variation that facilitates the identification of consumer preference. In addition, we employ cost-side shifters as instruments for endogenous product attributes, such as information on battery suppliers which affects costs but are unlikely to directly affect demand. On the supply side, we use variation in prices (after controlling for markups) and the attributes chosen by firms to recover the curvature of the variable and fixed cost of production with respect to attributes. Variations in various taxes and demand shifters serve as powerful instruments for product attributes that could be correlated with cost shocks.

With model primitives estimated, we next conduct counterfactual simulations to compare the uniform subsidy (which does not target attributes) with commonly used ABS, such as those based on driving range, battery capacity, and vehicle weight. Solving the industry equilibrium for a given policy design requires finding new prices for hundreds of EVs and ICEs as well as new attributes for all EVs. Searching for the optimal policy design that maximizes social surplus necessitates solving the industry equilibrium hundreds of times. To address computational challenges, we design an iterative Newton–Raphson algorithm that greatly speeds up the solution process.

Our counterfactual simulations provide several key findings. First, China's notched subsidy design leads to a large welfare loss relative to a linear subsidy, consistent with findings in the public finance literature. Compared to a linear subsidy, the current policy generates excess bunching at the range cutoffs and distorts automakers' choices of vehicle weight and battery capacity to reach the cutoffs. On the other hand, it provides no incentives for firms to improve the driving range between the cutoffs.

Second, ABS generates significant gains in consumer surplus relative to the uniform subsidy, ranging from ¥226 million in 2017 under the notched range-based design to ¥643 and ¥680 million under capacity- and weight-subsidies, respectively. ABS induces more desirable vehicle attributes and more effectively addresses quantity distortions than the uniform subsidy. The increase in consumer surplus is relatively modest for range-based policies because it leads to vehicle downsizing, which is undesirable to consumers. Firms producing BEVs also benefit from the ABS design that redistributes subsidies from the low-end spectrum of the vehicle attribute space to the high-end spectrum, though such profit gains are an order of magnitude smaller than increases in consumer surplus and are more than offset by profit losses of ICEs. The environmental performance of the EV fleet deteriorates moderately under ABS as sales shift to larger and less environmentally friendly EVs. In total, ABS designs result in significant welfare gains compared to the uniform subsidy, ranging from ¥97.2 million under the current notched range subsidy to ¥448 million under the capacity subsidy in 2017.

Third, a decomposition exercise indicates that changes in vehicle attributes account for 42-62% of total welfare gains under ABS relative to the uniform subsidy. The reduction in market power distortions explains the remaining 38% to 58% of the welfare gains. Allowing subsidy redistribution at the product level, as suggested by the theoretical discussions, further enhances welfare gains by another 34% to 62%. Fixing vehicle attributes, as is commonly done in the literature, significantly understates aggregate welfare gains and leads to the erroneous conclusion that firm profit increases for the auto sector. These findings underscore the role of endogenous product attributes in understanding the impacts of attribute-based subsidies.

Our study contributes to four strands of literature. First, our paper advances the emerging literature on attribute-based regulations and imperfect corrective policies.[1] Relative to non-attribute-based regulations, attribute-based regulations could exhibit efficiency advantages by reducing abatement costs across heterogeneous firms and mitigating demand uncertainty (Ito and Sallee, 2018; Kellogg, 2018, 2020). While the previous studies abstract away market power, our study contributes to this literature by examining the welfare implications of attribute-based regulations under

[1] Jacobsen et al. (2020) provides an intuitive and easy-to-implement method to quantify the efficiency loss from imperfect corrective policies under the perfectly competitive assumption: the R^2 from a regression of true externalities on the policy attribute/variable measures the welfare gain from the imperfect policies relative to policy ideals.

imperfectly competitive markets.[2] Both our theoretical model and empirical analysis highlight the important tradeoff between market power and environmental externalities in policy design.

Second, our study adds to the large literature on the effects of subsidies on energy-efficient products, such as alternative-fuel vehicles (Beresteanu and Li, 2011; Sallee, 2011; Li et al., 2017a; Kiso, 2021; Springel, 2019; Remmy, 2022; Kwon, 2023; Wang and Xing, 2023), home appliances (Boomhower and Davis, 2014; Houde and Aldy, 2017), and residential solar panels (Gillingham and Tsvetanov, 2019; Pless and van Benthem, 2019; Langer and Lemoine, 2018). These studies focus on understanding demand responses to subsidies and identifying policy elements that could increase consumer and firm adoption. Unlike these studies, our analysis also examines the impact of subsidies on product attributes. Echoing the literature on endogenous attributes (Fan, 2013; Fan and Yang, 2016; Wollmann, 2018; Crawford et al., 2019; Barahona et al., 2023), our findings illustrate the important welfare and policy implications of firms' ability to choose product designs in response to government policies.

Third, our study contributes to the literature that examines the impacts of government policies on the passenger vehicle market. Earlier studies have documented the changes in vehicle attributes and technology adoption in response to the U.S. fuel economy regulations (Knittel, 2011; Anderson et al., 2011; Klier and Linn, 2016). Our study is more closely related to studies that endogenize product attributes in response to the fuel economy and carbon emissions regulations or government bailout (Klier and Linn, 2012; Whitefoot et al., 2017; Wollmann, 2018; Reynaert, 2021; Leard et al., 2023). Our paper sheds light on the underlying forces of the optimal subsidy design in the presence of market power and multi-product oligopoly and compares equilibrium outcomes under different designs.

Lastly, our paper is related to the literature on pollution control in the presence of other distortions. The literature shows that the efficiency of environmental taxes could be compromised by pre-existing distortions such as market power (Buchanan, 1969; Barnett, 1980), distortionary taxes (Bovenberg and Goulder, 1996; Goulder et al., 1997), and imperfect information and consumer inattention (Allcott and Taubinsky, 2015; Allcott and Sunstein, 2015). Our study is also closely related to Fowlie et al. (2016), which documents that market-based emission regulations in the U.S. cement industry affect firm entry and exit, and exacerbate distortions from market power. Our paper contributes to this literature by emphasizing the importance of endogenous product attributes, which affect social welfare through both environmental externalities and quantity distortion.

The paper proceeds as follows. Section 2 presents the theoretical characterization of an optimal policy design. Section 3 explains the policy background and provides descriptive data evidence.

[2] A recent exception is Kiso (2021) which shows that a subsidy design where the amount of subsidy is inversely related to product prices could reduce firm market power and improve the cost-effectiveness of the subsidy program.

Section 4 and Section 5 discuss the empirical framework and estimation results. Section 6 conducts the counterfactual simulations and welfare decomposition. Section 7 concludes.

2 Theoretical Framework

In this section, we present a theoretical framework for optimal attribute-based subsidies to address environmental externalities in the presence of market power and endogenous attributes. As a key departure from the literature of pollution control under market power (Buchanan, 1969; Barnett, 1980; Fowlie et al., 2016), firms respond to government policies by changing *both* prices *and* product attributes in our model. A product (e.g., an EV) is characterized by a K-element attribute vector $\boldsymbol{x} = (x_1, x_2, \ldots, x_K)$. Both consumer willingness-to-pay (WTP) in monetary terms, $B(\boldsymbol{x})$, and the marginal cost of production, $C(\boldsymbol{x})$, depend on product attributes. The product generates environmental externalities represented as $\phi \cdot e(\boldsymbol{x})$ per unit of output, where ϕ is a scalar and reflects the marginal social benefit or damage of the environmental externality. For EVs, $e(\boldsymbol{x})$ represents emission reductions relative to the dirty alternatives and $\phi \cdot e(\boldsymbol{x})$ captures health benefits and other positive externalities. The aggregate demand for the product is denoted by $Q(P, \boldsymbol{x})$, where P is the product price.

Throughout the theoretical analysis, we assume that consumer WTP for the product attributes $B(\boldsymbol{x})$ is *additively* separable from the price disutility in demand:

$$Q(P, \boldsymbol{x}) = Q\big(P - B(\boldsymbol{x})\big).$$

This demand function is motivated by discrete choice models where utility depends on prices and attributes additively. Allowing for arbitrary interactions between $B(\boldsymbol{x})$ and product prices P with multi-product oligopolies presents significant challenges, with the equilibrium existence in this setting only recently established.[3] As we illustrate below, the additive separability makes the firms' choices of prices and attributes independent and greatly simplifies the model. Most importantly, it enables us to characterize the optimal policy design in the presence of market power, which has not been done in the literature. A limitation of the additivity assumption is that the marginal value of product attributes is the same across consumers, which rules out the Spence distortion in quality provision (Spence, 1975). While our theoretical model abstracts away from the Spence distortion,

[3]This is achieved in Chade and Swinkels (2021) under the assumptions of quasi-linear preferences and ranked production costs. That is, a low-quality firm has an advantage in producing low-quality goods, and a high-quality firm has an advantage in producing high-quality goods. In addition, consumers' WTP for quality increases with their private type. Analyzing optimal policy design with general preferences and production technology remains an open question.

the empirical analysis adopts a much richer demand system that allows heterogeneous marginal values of product attributes across consumers. We discuss the importance of the Spence distortion for the counterfactual analyses in Section 6.

The theoretical analysis compares the privately and socially optimal outcomes and discusses the choice of policy instruments to rectify market failures with and without a government budget constraint.[4] To build intuition, we first analyze the baseline case of a single-product monopoly before extending our results to an oligopoly with differentiated products.

2.1 Choices by Monopoly and Social Planner

Consider a monopoly that chooses price and attributes to maximize profit:

$$\max_{P,\ \boldsymbol{x}} \Big(P - C(\boldsymbol{x})\Big)\ Q\big(P - B(\boldsymbol{x})\big).$$

The privately optimal price P^m and attributes $\boldsymbol{x}^o$ satisfy the following first-order conditions:

$$[P]: \qquad \frac{P^m - C(\boldsymbol{x}^o)}{P^m} = \frac{1}{\varepsilon_P(P^m,\ \boldsymbol{x}^o)}, \tag{1}$$

$$[x_k]: \quad B_k(\boldsymbol{x}^o) - C_k(\boldsymbol{x}^o) = 0 \ \text{ for } \ k = 1, 2, ..., K, \tag{2}$$

where $\varepsilon_P(P,\ \boldsymbol{x})$ is the price elasticity of demand. The subscript k in Equation (2) stands for the partial derivative with respect to the k-th element of $\boldsymbol{x}$.[5] We use $\boldsymbol{x}^o$ to denote the monopolist's choices absent government intervention. The additive $B(\boldsymbol{x})$ and P in aggregate demand, together with a marginal cost that is constant in quantity, makes the firm's choices of attributes independent of price.[6] The monopolist's decision becomes a two-stage problem: it first selects attributes that maximize the per-unit private surplus, $B(\boldsymbol{x}) - C(\boldsymbol{x})$, and then sets the price to extract as much consumer surplus as possible.

The social planner maximizes the social welfare that consists of consumer surplus, producer

[4] Government subsidies are transfers and do not directly affect social welfare except through changing product attributes and quantity. We abstract from distortionary taxes.

[5] The setup can accommodate monopoly, monopolistic competition, and a perfectly competitive environment. With monopolistic competition, $Q(\cdot)$ denotes the firm's residual demand. With perfect competition, the firm's demand becomes flat, and $\varepsilon_P(P,\ \boldsymbol{x})$ approaches infinity, yielding a markup of zero, i.e., $P - C(\boldsymbol{x}) = 0$.

[6] To see the intuition, consider a simple change of variables. Define $\bar{P} = P - B(\boldsymbol{x})$, which can be interpreted as a base price with the minimum quality. The profit equation becomes $(\bar{P} + B(\boldsymbol{x}) - C(\boldsymbol{x}))Q(\bar{P})$, thus the optimal choice of attributes is independent of price.

surplus, and the externality:

$$SW(P,\ \boldsymbol{x}) = \underbrace{\int_0^{Q(P,\ \boldsymbol{x})} [B(\boldsymbol{x}) + Q^{-1}(s) - P] ds}_{\text{Consumer surplus}} + \underbrace{\big(P - C(\boldsymbol{x})\big) Q(P,\ \boldsymbol{x})}_{\text{Producer surplus}} + \underbrace{\phi \cdot e(\boldsymbol{x}) Q(P,\ \boldsymbol{x})}_{\text{Externality}},$$

where $Q^{-1}(.)$ is the inverse of $Q(P - B(\boldsymbol{x}))$. The socially optimal price P^* and attributes $\boldsymbol{x}^*$ satisfy the following first-order conditions:

$$[P]: \qquad P^* - C(\boldsymbol{x}^*) + \phi \cdot e(\boldsymbol{x}^*) = 0, \tag{3}$$

$$[x_k]: \quad B_k(\boldsymbol{x}^*) - C_k(\boldsymbol{x}^*) + \phi \cdot e_k(\boldsymbol{x}^*) = 0 \ \text{ for } \ k = 1, 2, ..., K. \tag{4}$$

The derivation of Equations (3) and (4) is in Appendix A.1. The first-order conditions differ from Equations (1) and (2) because attributes are chosen to maximize per-unit social surplus, $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$, and price reflects the social cost of production, $C(\boldsymbol{x}^*) - \phi \cdot e(\boldsymbol{x}^*)$. The socially optimal price P^* eliminates the quantity distortion at the socially optimal attributes $\boldsymbol{x}^*$ that internalize the environmental externality.

To facilitate graphical illustrations, we assume the attribute space is two-dimensional. Figure 1 displays the differences in price, attributes, quantity, and social welfare between the privately and socially optimal solutions. Panel (a) depicts the attribute space with two attributes: x_1 and x_2. The top dotted contour lines are iso-quant curves for the social surplus, $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$, while the bottom dashed contour lines represent the iso-quant curves for the private surplus, $B(\boldsymbol{x}) - C(\boldsymbol{x})$. The monopolist chooses $\boldsymbol{x}^o$, which is privately optimal, while the planner's choice, $\boldsymbol{x}^*$, has a larger environmental benefit and is socially optimal.

Panels (b) to (d) plot the demand and supply curves, deadweight losses, and social surplus in the product market. Panel (b) draws the demand and supply curves that are associated with the attributes chosen by the monopolist. The red triangle labeled as DWL_1 is the deadweight loss from the suboptimal quantity, $Q^m(\cdot)$, due to market power and the positive environmental externality. This is standard in the literature. Panel (c) adds demand and supply at the socially optimal attributes. We plot the non-trivial case where the demand curve associated with the socially optimal attributes $\boldsymbol{x}^*$ shifts to the left relative to that for $\boldsymbol{x}^o$ at any given price level. While $\boldsymbol{x}^*$ reflects the socially optimal and environmentally friendly design, $\boldsymbol{x}^o$ is more appealing to consumers.[7] The first-best outcome is given by $(\boldsymbol{x}^*,\ P^*(\boldsymbol{x}^*),\ Q^*(\boldsymbol{x}^*))$.

Panel (d) illustrates the welfare loss from the monopoly relative to the first-best outcome. The

[7]By construction, since $\boldsymbol{x}^o$ maximizes the private surplus and $\boldsymbol{x}^*$ maximizes the social surplus, the cost curve $C(\boldsymbol{x}^*)$ is above $C(\boldsymbol{x}^o)$ while the social cost curve $C(\boldsymbol{x}^*) - \phi \cdot e(\boldsymbol{x}^*)$ is below $C(\boldsymbol{x}^o) - \phi \cdot e(\boldsymbol{x}^o)$.

deadweight loss labeled as DWL_2 arises from distortions in both attributes ($\boldsymbol{x}^o$ vs. $\boldsymbol{x}^*$) and quantity ($Q^m(\cdot)$ vs. $Q^*(\cdot)$). The difference between DWL_1 in Panel (b) and DWL_2 in Panel (d) represents the additional deadweight losses as a result of product attribute distortions.

Attribute-based Subsidies The social planner can use attribute-based subsidies to address distortions.[8] Common subsidies consist of a two-part tariff, $T + t \cdot z(\boldsymbol{x})$, where T is the base subsidy invariant to attributes, t is the subsidy intensity, and $z(\boldsymbol{x})$ is the policy attribute that depends on product attributes. For example, the policy attribute is driving range in China (which is a function of vehicle weight and battery capacity) and battery capacity in the U.S..[9] With attribute-based subsidies, the firm's profit maximization problem is:

$$\max_{P,\, \boldsymbol{x}} \Big(P - C(\boldsymbol{x}) + T + t \cdot z(\boldsymbol{x})\Big)\, Q\big(P - B(\boldsymbol{x})\big) \tag{5}$$

$$[P]: \qquad \frac{P^z - C(\boldsymbol{x}^z) + T + t \cdot z(\boldsymbol{x}^z)}{P^z} = \frac{1}{\varepsilon_P(P^z,\, \boldsymbol{x}^z)},$$

$$[x_k]: \quad B_k(\boldsymbol{x}^z) - C_k(\boldsymbol{x}^z) + t \cdot z_k(\boldsymbol{x}^z) = 0 \ \text{ for } \ i = 1, 2, ..., K.$$

The solution to the profit maximization problem is denoted by $(P^z(T,\, t),\, \boldsymbol{x}^z(t))$ for a given policy triad (T, t, z). Note that the base subsidy T affects price but not product design. This is intuitive as T is invariant to attributes. In contrast, both the subsidy intensity t and the policy attribute $z(\boldsymbol{x})$ affect product design. Given the monopolist's response, the social planner chooses the optimal policy instrument to maximize social welfare.

Perfect Targeting We begin with a theoretical benchmark of perfect targeting, where the policy attribute is proportional to the externality (e.g., $z = e$). It is simple to show that the government can obtain the first-best with perfect targeting. The proof is provided in Appendix A.1.

Proposition 1. *Under perfect targeting (e.g., $z = e$), the per-unit subsidy following the two-part structure $T^* + t^* \cdot e(\boldsymbol{x})$, where $t^* = \phi$ and T^* are chosen such that $P^e(T^*,\, \phi) = C(\boldsymbol{x}^e(\phi)) - \phi \cdot e(\boldsymbol{x}^e(\phi))$, achieves the socially first-best outcome of $P^e(T^*,\, \phi) = P^*$ and $\boldsymbol{x}^e(\phi) = \boldsymbol{x}^*$.*

The optimal subsidy $T^* + t^* \cdot e(\boldsymbol{x})$ is Pigouvian and incentivizes the monopolist to internalize the environmental externality. The subsidy intensity t^* induces socially optimal attributes $\boldsymbol{x}^*$, while

[8]The discussion focuses on subsidies because EVs generate positive externalities. Our framework also applies to taxes that correct negative externalities.

[9]The formula for EV subsidies in the U.S. is \$2500+\$415*(kWh-4), with a minimum battery capacity of 4 kWh and a maximum subsidy of \$7500. China's range-based subsidies have a notched design but can be approximated by a two-part tariff (see Section 3). We evaluate the welfare distortions of the notched design in Section 6.

the base subsidy T^* offsets market power and leads to socially optimal quantity $Q^*(\boldsymbol{x}^*)$.[10]

The top two graphs of Figure 2 illustrate the optimal policy design. Panel (a) presents the attribute space. Under perfect targeting $z(\boldsymbol{x}) = e(\boldsymbol{x})$, the firm's response function is the straight line that connects $\boldsymbol{x}^*$ and $\boldsymbol{x}^o$.[11] A positive t pulls the firm to move closer to $\boldsymbol{x}^*$, while a negative t pushes the firm's product design further away from $\boldsymbol{x}^*$. The optimal subsidy intensity t^* induces the monopolist to choose the socially optimal $\boldsymbol{x}^*$. Panel (b) plots the product space. Under $\boldsymbol{x}^*$ and the optimal base subsidy T^*, the monopolist chooses the socially optimal price $P^*(\boldsymbol{x}^*)$ and quantity $Q^*(\boldsymbol{x}^*)$. The green-shaded triangle represents the social welfare under the first-best outcome. To address distortions in both the attribute and product spaces, neither T nor $t \cdot z(\boldsymbol{x})$ alone is sufficient.

Imperfect Targeting In practice, perfect targeting is rarely feasible. Under imperfect targeting with $z(\boldsymbol{x}) \neq e(\boldsymbol{x})$, the socially optimal attributes, $\boldsymbol{x}^*$, are usually unattainable. In response to subsidy $T + t \cdot z(\boldsymbol{x})$, the monopoly chooses attributes along the line that is determined by the policy target $z(\boldsymbol{x})$. The product attribute that achieves the highest per-unit social surplus under the policy attribute $z(\boldsymbol{x})$ is denoted by $\boldsymbol{x}^z$ in Panel (c) of Figure 2. This is the tangency point between the social surplus indifference curve and the firm's response line. The subsidy intensity that achieves $\boldsymbol{x}^z$ is denoted by t^z. Panel (d) depicts the equilibrium outcome in the product space. Given attributes $\boldsymbol{x}^z$, the quantity that equates price with social marginal cost of production is $Q^*(\boldsymbol{x}^z)$. The government uses base subsidy T^z to achieve $Q^*(\boldsymbol{x}^z)$. The social surplus is smaller than in Panel (b), reflecting the social planner's inability to perfectly target externalities.

2.2 Attribute-based Regulations with Budget Constraints

The discussion thus far has implicitly assumed that the social planner has infinite resources. In practice, governments often face a limited budget, which results in a trade-off between reducing the environmental externality and mitigating the quantity distortion. This section examines the implications of a budget constraint on the optimal policy design.

Panel (a) of Figure 3 illustrates the tension between addressing environmental distortions and quantity distortions for a given policy attribute z subject to a budget constraint. The equilibrium attribute that maximizes social surplus under policy z without a budget constraint, denoted as $\boldsymbol{x}^z_{\text{w/o BC}}$, is the tangency point between the firm's response curve and the social surplus indifference

[10]Subsidies are transfers and do not directly affect social welfare except through changing product attributes and price. We abstract away from the distortion of tax collection to fund subsidies.

[11]Following Ito and Sallee (2018), we use a quadratic loss function and assume the policy attribute z is linear in $\boldsymbol{x}$. These two assumptions imply that the iso-surplus curves are ellipses and that the monopoly chooses product attributes along a straight line that passes through $\boldsymbol{x}^o$. See Appendix A.1 for details.

curve. However, $\boldsymbol{x}^z_{\text{w/o BC}}$ requires a large subsidy intensity t and leaves limited funds for the base subsidy T to address quantity distortions. As shown in Appendix A.2, the equilibrium product attribute associated with the optimal policy T and t that maximizes social welfare under z with budget level R, $\boldsymbol{x}^z_{\text{with } BC=R}$, lies between the monopolist's choice without intervention, $\boldsymbol{x}^o$, and $\boldsymbol{x}^z_{\text{w/o BC}}$. The smaller the budget, the closer $\boldsymbol{x}^z_{\text{with } BC=R}$ is to $\boldsymbol{x}^o$.

Before presenting the optimal policy design, we first discuss a lemma showing that the per-unit private surplus, $B(\boldsymbol{x})-C(\boldsymbol{x})$, is closely related to the equilibrium quantity achievable under a given budget constraint. It serves as a sufficient statistic for a policy's ability to address the quantity distortion.

Lemma 1. *Consider two policy triads (T,t,z) and (T',t',z') that satisfy the budget constraint R: $\left[T+t\cdot z\big(\boldsymbol{x}^z(t)\big)\right]\cdot Q\big(P^z(T,t),\ \boldsymbol{x}^z(t)\big)=\left[T'+t'\cdot z'\big(\boldsymbol{x}^{z'}(t')\big)\right]\cdot Q\big(P^{z'}(T',t'),\ \boldsymbol{x}^{z'}(t')\big)=R$. Then,*

$$B\big(\boldsymbol{x}^z(t)\big)-C\big(\boldsymbol{x}^z(t)\big)\gtreqless B\big(\boldsymbol{x}^{z'}(t')\big)-C\big(\boldsymbol{x}^{z'}(t')\big) \text{ implies } Q\big(P^z(T,t),\boldsymbol{x}^z(t)\big)\gtreqless Q\big(P^{z'}(T',t'),\ \boldsymbol{x}^{z'}(t')\big).$$

The proof of Lemma 1 is in Appendix A.2. Lemma 1 facilitates comparisons between different policy triads. Suppose two policy triads (T,t,z) and $(T',t,'z')$ entail identical government expenses. If the policy triad (T,t,z) leads to product attributes with a higher per-unit private surplus $B\big(\boldsymbol{x}^z(t)\big)-C\big(\boldsymbol{x}^z(t)\big)$, then the equilibrium quantity under (T,t,z) is higher as well.

This can be seen by rewriting firm profit in Equation (5) using a change of variable $\bar{P}=P-B(\boldsymbol{x})$: $\pi(\cdot)=[\bar{P}+B(\boldsymbol{x})-C(\boldsymbol{x})+T+t\cdot z(\boldsymbol{x})]Q(\bar{P})$. The effect of $B(\boldsymbol{x})-C(\boldsymbol{x})$ on the profit is similar to that of the subsidy $T+t\cdot z(\boldsymbol{x})$. Intuitively, since higher per-unit subsidies lead to higher sales, so does higher $B(\boldsymbol{x})-C(\boldsymbol{x})$. As a higher quantity implies a lower deadweight loss, $B(\boldsymbol{x})-C(\boldsymbol{x})$ becomes a sufficient statistic for the effectiveness of the policy triads to address quantity distortions and deadweight loss under market power.

Lemma 1 is a stepping stone in establishing Proposition 2 below that characterizes the optimal policy design with a budget constraint. Since the per-unit private surplus, $B(\boldsymbol{x})-C(\boldsymbol{x})$, only depends on product attributes, its sufficient-statistics property allows us to depict quantity distortions in the attribute space without referencing the product market. Higher iso-quant private surplus curves represent equilibrium outcomes with lower quantity distortions. In the meantime, the per-unit social surplus, $B(\boldsymbol{x})-C(\boldsymbol{x})+\phi\cdot e(\boldsymbol{x})$, captures the externality. Higher iso-quant social surplus curves represent equilibrium outcomes that exhibit higher environmental benefits. These two sets of iso-quant curves capture the two types of distortions that the government tries to mitigate. This intuition is the foundation of the characterization of the optimal policy design below.

Optimal Policy Triads with budget constraints Panel (b) of Figure 3 compares two policy triads (T,t,z) and (T',t',z') that are associated with an identical budget R. The subsidy rates (T,t) and (T',t') are chosen optimally to maximize social welfare with budget R under z and z', respectively. Let $\boldsymbol{x}^z_{\text{with } BC=R}$ denote the equilibrium outcome under policy triads (T,t,z). Suppose it is not a tangent point between the social iso-quant curve of $B(\boldsymbol{x})-C(\boldsymbol{x})+\phi\cdot e(\boldsymbol{x})$ and the private iso-quant curve of $B(\boldsymbol{x})-C(\boldsymbol{x})$. The private iso-quant curve that passes $\boldsymbol{x}^z_{\text{with } BC=R}$ intersects the response curve under policy z' at $\tilde{\boldsymbol{x}}$. Let $(\tilde{T},\tilde{t},z')$ denote the policy triad that leads to equilibrium outcome $\tilde{\boldsymbol{x}}$ under budget R.[12] By construction, policy triad (T',t',z') delivers a higher social welfare than policy $(\tilde{T},\tilde{t},z')$ with budget level R. We now show that policy $(\tilde{T},\tilde{t},z')$ achieves higher social welfare than (T,t,z). Since their corresponding equilibrium product attributes $\tilde{\boldsymbol{x}}$ and $\boldsymbol{x}^z_{\text{with } BC=R}$ are on the same private iso-quant curve with budget R, they lead to the same equilibrium quantity in the product market (by Lemma 1). However, $\tilde{\boldsymbol{x}}$ is on a higher social iso-quant curve and hence delivers more environmental benefits than $\boldsymbol{x}^z_{\text{with } BC=R}$. Hency, policy triad $(\tilde{T},\tilde{t},z')$ achieves higher social welfare than (T,t,z). By induction, (T',t',z') dominates $(\tilde{T},\tilde{t},z')$, which in turn dominates (T,t,z) in terms of social welfare. In fact, the social planner can do better than (T',t',z'), as prescribed by Proposition 2 below.

Proposition 2. *Define the contract curve as the collection of tangent points of the iso-social- and iso-private-surplus curves with $\boldsymbol{x}^o$ and $\boldsymbol{x}^*$ as the two endpoints.*

i) If a policy triad $(T^R,\ t^R,\ z^R)$ maximizes the social welfare for a given budget R, its equilibrium product attribute $\boldsymbol{x}^{z^R}(t^R)$ lies on the contract curve.

ii) If a product attribute $\boldsymbol{x}$ is on the contract curve, there exists a budget level R and corresponding optimal policy triad $(T^R,\ t^R,\ z^R)$ such that the equilibrium product attribute $\boldsymbol{x}^{z^R}(t^R)$ is equal to $\boldsymbol{x}$.

iii) As R increases, $\boldsymbol{x}^{z^R}(t^R)$ moves away from $\boldsymbol{x}^o$ towards $\boldsymbol{x}^*$ along the contract curve.

The proof is in Appendix A.2. Proposition 2 argues that the optimal policy designs are associated with the product attributes that are the tangent points between the iso-social- and iso-private-surplus curves. In addition, every point on the contract curve is associated with an optimal policy design. Suppose an optimal policy design results in an equilibrium product attribute not on the contract curve. By the argument above, there exists at least one policy design that generates higher social welfare, and vice versa.

[12] The subsidy intensity $\tilde{t}$ induces the monopoly to choose $\tilde{\boldsymbol{x}}$ under policy target z'. The corresponding base subsidy $\tilde{T}$ is determined by $\tilde{t}$ and z' given R.

Panel (c) of Figure 3 draws four tangency points: $\boldsymbol{x^1}$, $\boldsymbol{x^2}$, $\boldsymbol{x^3}$, and $\boldsymbol{x^4}$, each of which represents an equilibrium attribute vector under a different budget. The four lines passing through them represent the associated policy attributes, $\{z^1, z^2, z^3, z^4\}$. The corresponding budget level is denoted by $\{R^1, R^2, R^3, R^4\}$. Proposition 2 implies that a higher level of budget is needed to move from x^1 to x^4: $R^1 < R^2 < R^3 < R^4$. The contract curve represents product attributes that are associated with the constrained optimal policy triads (T, t, z) with different budget levels. As the budget increases, the planner's choice moves towards $\boldsymbol{x}^*$ to focus more on the environmental externality, given the increased ability (via subsidies) to tackle market power with a higher budget.

2.3 Oligopoly with Differentiated Products

While the setting of a single-product monopoly helps illustrate the trade-offs between mitigating different sources of distortions with a budget constraint, most industries subject to ABS operate in an oligopolistic market structure with differentiated products. In these situations, the extent of quantity distortion and environmental externalities differ across products, making the optimal allocation of subsidies among products an important consideration.

Suppose there are J products ($j = 1, \ldots, J$) with characteristics $\boldsymbol{x}_j$, consumer benefit $B(\boldsymbol{x}_j)$, marginal cost C_j, and demand Q_j. Assume that the social planner can allocate the budget across products using product-specific subsidies $b_j = T_j + t \cdot z(\boldsymbol{x}_j)$, where $\sum_j b_j Q_j = R$. Appendix A.3 shows that the optimal subsidy allocation can be characterized as follows:

$$b_j = \mu \cdot m_j \cdot \frac{\varepsilon^b_{jj} + \sum_{k \neq j} \frac{m_k Q_k}{m_j Q_j} \varepsilon^b_{kj}}{1 + \varepsilon^b_{jj} + \sum_{k \neq j} \frac{b_k Q_k}{b_j Q_j} \varepsilon^b_{kj}} \quad \text{for } \ j = 1, \ \ldots, \ J, \tag{6}$$

where $\mu > 0$ is the inverse of the shadow value of the budget constraint and is the same across all products, and $m_j = P_j - C_j(\boldsymbol{x}_j) + \phi \cdot e(\boldsymbol{x}_j)$ is the social markup of product j. Lastly, $\varepsilon^b_{kj} = \frac{\partial Q_k}{\partial b_j} \frac{b_j}{Q_k}$ is the demand elasticity of product k with respect to the subsidy for product j. With independent demand, Equation (6) simplifies to $b_j = \mu \cdot m_j \cdot \frac{\varepsilon^b_{jj}}{1+\varepsilon^b_{jj}}$. This formula is intuitive. It indicates that we should allocate more subsidies to products that exhibit potentially high welfare gains for the marginal unit and whose demand is responsive to subsidies. Such an allocation will ensure that the marginal social surplus generated by the last dollar of subsidy is equalized across products.

Equation (6) requires a product-specific base subsidy T_j, which may be politically and administratively challenging. Appendix A.3 describes the first-order conditions that characterize the optimal policy triad (T, t, z), though there is no analytic formula given the complexity. Nonetheless, the theoretical results highlight three critical roles of an optimal policy design: encourage quantity expansion, incentivize the provision of environmentally friendly attributes, and allocate subsidies across differentiated products.

2.4 Discussions

Our theoretical framework illustrates the trade-off between addressing environmental externalities and mitigating market power under a limited budget. The optimal policy triad (T, t, z) needs to strike the right balance to address these two market failures with differentiated products and varying degrees of distortions. In any specific context, the optimal subsidy design is ultimately an empirical question and hinges on consumer preferences, production costs, environmental externalities, and the nature of competition. Our empirical analysis incorporates these key objects to compare different policy designs in terms of their impacts on market outcomes and social welfare.

It is worth noting that while our theoretical model abstracts away from the Spence distortion, the presence of such a distortion provides another rationale for implementing ABS in industries with oligopolies and heterogeneous consumers. This is because the privately chosen attributes $\boldsymbol{x}$ might not maximize the aggregate $B(\boldsymbol{x}) - C(\boldsymbol{x})$ in a society with heterogeneous consumers, leading to quality distortion. In these contexts, ABS has the potential to also address quality distortion, as demonstrated in Section 6.

3 Background and Data

In this section, we discuss the industry background, describe the data, and present stylized facts that motivate the structural analyses in Section 4.

3.1 Industry and Policy Background

Since the introduction of mass-market EV models in 2010, worldwide passenger EV sales reached 10.2 million units, or 14% of the passenger vehicle market in 2022. Many countries have outlined aggressive goals to electrify passenger transportation (Appendix Figure A2). Norway aims to achieve 100% electric among new vehicle sales by 2025, the Netherlands 100% by 2030, the U.S. 50% by 2030, and China 40% by 2030. The market share of EVs among new vehicle sales in these countries in 2022 was 90%, 35%, 7%, and 29%, respectively.

China became the largest EV market in 2015, and its global share increased to 60% by 2022 (Appendix Figure A3). More than half of all EVs on the road worldwide were in China. While there was a proliferation of EV producers with many brands in 2022, the market remains concentrated with the top five EV firms accounting for 55% of the market.[13] The largest EV firm, BYD, had a market share of nearly 30% in 2022. In comparison, the number of EV brands in the U.S. was 40 in 2022. The U.S. market was more concentrated, with Tesla accounting for over 45% and the top five firms accounting for about 80% of the market in 2022.

The rapid growth of the EV market in China was at least partly driven by the generous consumer subsidies from both central and local governments as well as non-financial incentives as documented in Li et al. (2022). The Chinese government considers the EV sector a strategic priority to increase the global competitiveness of its domestic automobile industry and to reduce energy consumption and emissions from the transportation sector. Accelerating EV adoption is an important strategy to achieve China's national average fuel economy targets of four liters/100km (or 47 mpg) and 3.2 liters/100km (or 74 mpg) by 2025 and 2030, respectively.

China's central government initially introduced consumer subsidies in select pilot cities before 2014. By 2014, these initiatives had expanded to 88 cities before a nationwide implementation in 2016. Consumers pay for the post-subsidy price at the time of purchase and subsidies are distributed to automakers either quarterly or annually by the government. Table 1 presents the schedules of central subsidies from 2013 to 2018. The subsidies are based on the driving range and set differently for battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs).[14] For BEVs, the subsidies are notched with several cutoffs. The minimum range requirement increased from 80km in 2013 to 100km in 2016 and further increased to 150km in 2018, while the amount of subsidies was reduced over time. For PHEVs, the subsidy was uniform across models with a minimum range requirement of 50km that remained constant, though the subsidy amount decreased over time.

It is important to note that the driving range of EVs is not self-reported by the automakers. Rather, all vehicles undergo rigorous testing by government-designated agencies, with the resulting data publicly disclosed by the Ministry of Industry and Information Technology (MIIT). Furthermore, the subsidy schedules were jointly formulated and disseminated by four governmental bodies: MITT, the Ministry of Finance (MoF),the Ministry of Science and Technology (MoST), and the National Development and Reform Commission (NRDC). The lead time of policy announcement varied but it was typically several quarters.[15] In these policy contexts, opportunities

[13] During our sample period, approximately half of the traditional ICE producers also manufactured EVs (including both BEVs and PHEVs), while 60% to 80% of EV firms also produced ICEs. For instance, there were 37 Chinese automobile producers in 2018. Of these, 26 were ICE firms and 28 specialized in EVs. 17 of these companies were involved in the production of both ICEs and EVs.

[14] To incentivize quality improvement, the government tightened the eligibility rules in 2018 by incorporating additional technical requirements that include the minimum battery density of 105Wh/kg and minimum energy efficiency in kWh/100km as a function of vehicle weight. Consumer subsidies for EVs were phased out by the end of 2022.

[15] For example, the four government agencies jointly published the draft of the 2016 subsidy policy on April 26,

for automakers to manipulate driving range data or influence the selection of range cutoffs are likely minimized. Nevertheless, as we document below, automakers can and do respond to the changes in subsidy schedules by modifying vehicle attributes.

As shown in Table A1, central subsidies amount to 11-28% of consumer prices for most range groups. In addition to the central subsidies, many cities provided additional consumer subsidies up to the amount of central subsidies. In total, central and local subsidies add up to 30-60% of product prices.[16] We collected comprehensive information on both central and local EV subsidies and control for them in our analysis. In addition to consumer subsidies, cities offer several non-financial incentives: exemption from driving restrictions, exemption from vehicle purchase restrictions, and green license plate policy. We control for these local policies via city by year by fuel type fixed effects in our analysis.

3.2 Data and Descriptive Evidence

Data Description Our analysis is based on three main data sets from 2015 to 2018: (1) annual vehicle registration data by city and vehicle model for both ICEs and EVs; (2) data on detailed vehicle attributes by model; and (3) comprehensive central and local financial and non-financial policies. We define a product by its model name, vehicle type (sedan, SUV, minivan/MPV, and crossover), fuel type, engine displacement, and driving range (in the case of EVs). Our analysis focuses on the 40 cities with the largest EV sales in China during the sample period, accounting for 69% of national EV sales. We have panel data with a total of 34,329 observations, covering 497 ICE, 38 PHEV, and 164 BEV products. Appendix B provides details on the sample construction.

In addition, our analysis benefits from multiple auxiliary data sets, including (1) nationally representative household surveys on new vehicle buyers from 2015 to 2017 that allow us to construct micro-moments to identify consumer preference heterogeneity; (2) battery supplier information by vehicle model, which proves to be powerful supply-side instruments; and (3) all new vehicle models that the government tested for safety and functionality from August 2014 to December 2018, including roughly half of the models that were not eventually launched commercially. The last data set enables us to estimate the engineering relationship between EV driving range and vehicle attributes; see Section 4.2 below.

We do not observe transaction prices and use MSRPs in our estimation. MSRPs are set by

2014 to solicit public comments. The finalized 2016 policy was announced on April 29, 2015.

[16] Only EVs produced by domestic companies or joint ventures are eligible for central subsidies, with imported EVs excluded. Local subsidies use the same range cutoffs as the central subsidies and are pegged to central subsidies in most cases.

manufacturers and are the same nationwide for each model-year. Evidence in Appendix B indicates that price discounts are limited in China due to the practice of "minimum retail price maintenance" (RPM), whereby automakers either explicitly or implicitly prohibit dealers from selling below a preset price to reduce price competition among dealers (Barwick et al., 2021).

New vehicle purchases are subjected to four types of taxes: consumption tax from 1% to 40% depending on engine size, value-added tax at 17%, import tariffs at 25% (if applicable), and sales tax normally set at 10% but varies with engine size over time during our data period.[17] MSRPs include the consumption tax, value-added tax, and import tariffs, while the sales tax is levied on MSRP exclusive of the value-added tax. Let $\tilde{P}$ denote the consumer price of a vehicle and P the producer price:

$$\tilde{P} = MSRP \times \frac{1+t^{\text{ValueAdded}}+t^{\text{Sales}}}{1+t^{\text{ValueAdded}}}, \quad P = MSRP \times \frac{1-t^{\text{Consumption}}}{1+t^{\text{ValueAdded}}}. \tag{7}$$

We use consumer price in demand estimation and producer price in calculating firm (post-tax) profits. These tax rates exhibit rich variation and are strong instruments for vehicle prices.

We follow the industry's convention and define nine vehicle segments (mini sedan, sub-compact sedan, compact sedan, mid-size sedan, large sedan, compact SUV, mid-size SUV, large SUV, and MPV/van). We control for brand fixed effects and segment fixed effects in our demand and supply analyses. China's charging station infrastructure has improved significantly over time. We use city-year by fuel type (ICE and EV) fixed effects in all demand specifications to control for the time-varying charging network.

Table 2 presents the summary statistics. EVs are, on average, 27% more expensive than gasoline vehicles, 15.6 times more fuel efficient (using the EPA's conversion rate between electricity and fuel), but are 7% lighter (in vehicle weight net of battery weight) and 13% less powerful in terms of horsepower.[18] The average driving range is 208km with a battery capacity of 29.9kWh.

Descriptive Evidence on Attribute Changes Figure 4 shows the histogram of driving range on an annual basis from 2015 to 2018. The dark blue bars represent vehicle models with a driving range that is just above the subsidy cutoffs. These graphs display two salient features. First, the distribution of the driving range exhibits pronounced bunching at the cutoffs, likely the result of the notched subsidy design. Notched schedules generate bunching and could lead to efficiency

[17] An unconventional feature of China's tax system is that consumption tax is included in the "pre-tax" price and therefore is in the tax base for other taxes. For example, if the pre-tax price is ¥100k and the consumption tax is 25%, the manufacturer gets ¥75k while the government collects ¥25k as the consumption tax.

[18] Throughout the entire analysis, we use 'net vehicle weight', which is vehicle weight net of battery weight, as the measure of vehicle weight.

losses relative to a continuous subsidy schedule, which we study in one of the counterfactual simulations.[19] Second, a noticeable annual shift to the right in the range distribution highlights EV firms' strong responses to policy incentives. For instance, during the period from 2013 to 2015 when the minimum range requirement was 80km, all vehicles in the market had ranges exceeding 80km. In 2016, when the minimum requirement was raised to 100km, accompanied by a substantial jump in subsidies between 100km and 150km, all vehicles in our sample surpassed the 150km range threshold. Subsequently, in 2018, as the government introduced new cutoffs at 300km and 400km, bunching emerged around these new range limits, a pattern absent in earlier years.

How did automakers manage to enhance their driving ranges in response to policy changes? The driving range is primarily affected by battery capacity and vehicle weight, both of which can be adjusted relatively quickly. Figure 5 illustrates the year-to-year changes in vehicle weight (excluding battery weight) on the x-axis and battery capacity on the y-axis. Blue circles represent models with increased driving ranges, while red diamonds are models with decreased driving ranges. The size of the symbol corresponds to the magnitude of the change. Almost all vehicles in our sample expanded their driving ranges, with some increases exceeding 100km. These enhancements in the driving range were accompanied by significant increases in battery capacity and, quite often, a reduction in net vehicle weight. Given the evidence presented in this figure, we focus on firms' choices of battery capacity and vehicle weight in the structural model below.

4 Empirical Framework

The empirical framework is an equilibrium model of the automobile sector with both the demand and supply sides in the spirit of Berry et al. (1995). A key departure of our model is that we endogenize multiple product attributes on the supply side. As shown in the theoretical model, firms' attribute choices in response to policies affect both environmental externality and quantity distortion (market power). Allowing endogenous product attributes turns out to be critical for the welfare analysis across different attribute-based subsidy designs. Throughout the estimation and counterfactual simulations, we assume ICE attributes are exogenous (prices are endogenous), both because of limited changes during our sample relative to those for EVs and computational traceability.

[19] A large literature has examined policy inefficiencies with notches. Notched design in regulations (e.g., standards or taxes) could lead to compliance test manipulation (Sallee and Slemrod, 2012), tax evasion (Almunia and Lopez-Rodriguez, 2018), and price discrimination (Houde, 2022, 2018).

4.1 Demand Side

Consumer i chooses from a set of available products $\mathscr{J} = \{0, 1, 2, ..., J\}$ that includes both ICEs and EVs, where $j = 0$ represents the outside option of not buying a new vehicle. Let m represent a market (i.e., city) and t denote time (i.e., year). Consumer i's utility from vehicle model j ($j \neq 0$) in market m and year t is specified as:

$$u_{ijmt} = -\alpha_i(\tilde{P}_{jmt} - b_{jmt}) + \boldsymbol{x}_{jmt}\boldsymbol{\beta_i} + \xi_{jmt} + \varepsilon_{ijmt}. \tag{8}$$

The utility of the outside option is normalized to zero: $u_{i0mt} = 0$ for all i, m, and t. Consumer price of model j in market m at time t, $\tilde{P}_{jmt}$, is defined in Equation (7) that accounts for various taxes. For eligible EVs, the effective price paid by consumers is net of time-varying central and local subsidies b_{jmt}.

We use an extensive list of demand controls $\boldsymbol{x}_{jmt}$ that consists of three categories. The first category includes product attributes that are commonly used in this literature, such as vehicle weight, horsepower, fuel economy and engine size for ICEs and PHEVs, and driving range for PHEVs and BEVs. The second category is a rich set of fixed effects, including city-by-year-by-fuel type (ICE or EV) fixed effects to control for time-varying city-level demand shocks for different fuel types, brand (e.g., BMW) by year-by-fuel type fixed effects to control for demand shocks or brand awareness over time that could be especially important for the nascent EV technology, segment (e.g., small sedan) fixed effects, and vintage (the year when a model was launched) fixed effects. In addition, we collect a comprehensive list of non-financial incentives that local governments use to encourage EV adoption, such as exemption from driving restrictions and vehicle purchase restrictions, green license plate policies, etc. The literature has shown that these non-financial policies can be effective drivers of EV market penetration (Li et al., 2022). The city-year-fuel type fixed effects included in our baseline model absorb these local incentives as well as changes in the charging infrastructure. Finally, ξ_{jmt} represents unobserved attributes of model j or demand shocks to j in market m at time t, and ε_{ijmt} is an idiosyncratic preference shock that is assumed to have an i.i.d. type I extreme value distribution.

Parameters $\boldsymbol{\beta_i} = \{\beta_{ik} \mid k = 1, ..., K\}$ represent heterogeneous preference for vehicle attributes. Preferences for attribute k are defined as $\beta_{ik} = \bar{\beta}_k + \sigma_k \nu_{ik}$, where $\bar{\beta}_k$ is the mean preference constant across all individuals and $\sigma_k \nu_{ik}$ stands for individual i's deviation from the population average. We assume ν_{ik} follows a normal distribution and σ_k captures preferences heterogeneity. The price coefficient is specified as $\alpha_i = exp(\alpha_1 + \alpha_2 log(y_{im}) + \sigma_p \nu_{ip})$ and depends on consumer i's income, y_{im}. We use log-income to moderate the skewness in the income distribution to facilitate the model fit. The random price coefficient ν_{ip} is log-normally distributed, and σ_p captures the dispersion of the price sensitivity.

As is standard in the literature, we decompose utility u_{ijmt} in Equation (8) into three elements: 1) the mean utility $\delta_{jmt}(\boldsymbol{\theta_1}) = \boldsymbol{x}_{jmt}\bar{\boldsymbol{\beta}} + \xi_{jmt}$ that is common across all individuals, 2) the consumer-specific utility $\mu_{ijmt}(\boldsymbol{\theta_2}) = -\alpha_i(\tilde{P}_{jmt} - b_{jmt}) + \sum_k \sigma_k \boldsymbol{x}_{jkt}\nu_{ikmt}$, and 3) the idiosyncratic preference shock ε_{ijmt}. Product j's sales share in market m at time t can be specified as:

$$S_{jmt}(\boldsymbol{\theta_1}, \boldsymbol{\theta_2}) = \int \frac{e^{\delta_{jmt}(\boldsymbol{\theta_1}) + \mu_{ijmt}(\boldsymbol{\theta_2})}}{1 + \sum_k e^{\delta_{kmt}(\boldsymbol{\theta_1}) + \mu_{ikmt}(\boldsymbol{\theta_2})}} dF(\mu).$$

Market shares are computed by aggregating individual choice probabilities. We match these model predictions to the observed market shares in the estimation in Section 5.

4.2 Supply Side

All automakers, whether producing EVs or ICEs, choose the prices of their products to maximize total profits. Firms also choose vehicle weight (net of battery weight) and battery capacity for their EV models to achieve a desired driving range in response to EV subsidies:[20]

$$\max_{\{P_j, k_j, w_j\}} \sum_{j \in J_f} \pi_j(\boldsymbol{P}, \boldsymbol{k}, \boldsymbol{w}, \boldsymbol{b}) - \sum_{j \in J_f} FC_j(k_j, w_j) \quad \text{s. t.} \quad D_j(k_j, w_j) \geq D_c.$$

Note that k_j and w_j are battery capacity and net vehicle weight, respectively. The operating profit from selling product j is the product of per-unit variable profit and total units sold: $\pi_j(\boldsymbol{P}, \boldsymbol{k}, \boldsymbol{w}, \boldsymbol{b}) = \big(P_j - mc_j(k_j, w_j)\big) \cdot Q_j(\tilde{\boldsymbol{P}}, \boldsymbol{D}, \boldsymbol{w}, \boldsymbol{b})$.[21] The per-unit variable profit depends on the MSRP and taxes and the marginal cost of production $mc_j(k_j, w_j)$. Aggregate consumer demand Q_j is the sum of demand in each market and depends on post-subsidy prices $\tilde{\boldsymbol{P}} - \boldsymbol{b}$, driving range $\boldsymbol{D}$, and vehicle weight $\boldsymbol{w}$ of all vehicles. The subsidy amount depends on a model's driving range and the subsidy schedule: $b_j = b_c \cdot \mathbb{1}\{D_j \geq D_c\}$, where D_c is the highest cutoff satisfied by model j and b_c denotes the subsidy amount for vehicles whose driving range exceeds D_c. Note that battery capacity k does not directly enter consumer demand because battery capacity alone does not generate consumer utility except for its effects on the driving range. Nevertheless, vehicle weight w does enter utility directly due to consumers' preference for vehicle safety. Finally, fixed costs $FC_j(k_j, w_j)$ reflect expenses firms incur when (re)designing product attributes.

[20]Our model is static so we suppress the time dimension t in the supply analysis for notational simplicity.

[21]The EV subsidy differs across cities due to differential local subsidies. The discussion here abstracts away from differences in local subsidy for notation simplicity, but the empirical analysis accounts for it. Consumer price and producer price are defined in equation (7) that accounts for taxes.

We now discuss the three sets of supply-side model primitives: the technology frontier for the driving range, the marginal cost function, and the fixed cost function. We assume the technology frontier that determines the relationship between driving range, battery capacity, and net vehicle weight is as follows:

$$D_j(k_j, w_j) = \eta_k k_j + \eta_w w_j + \kappa_j. \tag{9}$$

The error term κ_j captures motor efficiency, vehicle frame aerodynamics, and factors unrelated to battery capacity and vehicle weight. To estimate the technology frontier, we utilize data on all models that have undergone MIIT's inspection for market entry, including models that were not eventually launched in the market. This nearly doubles the number of observations as half of the designed models did not make it to commercial launch. We assume that the technology frontier is accessible to all firms.[22] The estimation of Equation (9) is performed separately from the estimation of the marginal and fixed cost parameters.

The marginal cost function is assumed to take the following form:

$$mc_j(k_j, w_j) = \mathbb{1}\{EV_j\} \cdot \rho^t \gamma_k \, k_j + \gamma_w \, w_j + G_j' \gamma_g + \omega_j, \tag{10}$$

where $\mathbb{1}\{EV_j\}$ is equal to one if model j is an EV and ρ^t represents the decline in battery cost (per kWh) over time. This decline is influenced by factors such as improvements in production efficiency and battery technology. For example, $\rho = 0.9$ implies a 10% reduction in the battery cost each year. The vector G_j includes other vehicle attributes (e.g., horsepower, engine size, and fuel efficiency), as well as fuel type, segment, year, and brand fixed effects. Lastly, ω_j captures unobserved shocks to the marginal cost. The parameters to be estimated are ρ, γ_k (these two for EVs only), γ_w, and γ_g.

As shown in Figure 5, EV firms make frequent adjustments to vehicle attributes, especially battery capacity and vehicle weight. As a result, k_j and w_j are likely to be correlated with the marginal cost shocks ω_j. For instance, a negative marginal cost shock may lead firms to reduce battery and net vehicle weight for cost savings. We explain how to address the endogeneity issue below in Section 4.3.

Following Fan (2013), we use the following fixed cost specification for EV models:

$$\frac{\partial FC_j}{\partial k_j} = \phi_k + FE + v_j^k \quad \text{and} \quad \frac{\partial FC_j}{\partial w_j} = \phi_w + FE + v_j^w,$$

where ϕ_k and ϕ_w capture the slope of the fixed costs for battery capacity and vehicle weight, re-

[22] We take the technology frontier as given. Barwick et al. (2024) analyzes how government subsidies accelerate the evolution of the technology frontier through learning by doing.

spectively. As in the marginal cost specification, we include segment, year, and brand fixed effects to capture the variation in the slope of the fixed costs across models (fuel type is irrelevant as we only estimate the fixed costs for EVs). We allow the fixed cost residuals ν_j^k and ν_j^w to be correlated with battery capacity k_j and vehicle weight w_j.

Firm f that produces EVs solves a constrained optimization problem by maximizing the following Lagrangian function:

$$\mathscr{L}_f = \sum_{j \in J_f} \pi_j(\boldsymbol{P}, \boldsymbol{k}, \boldsymbol{w}, \boldsymbol{b}) - \sum_{j \in J_f} FC(k_j, w_j) + \sum_{j \in J_f} \lambda_j [D_j(k_j, w_j) - D_c],$$

where λ_j is the shadow value of relaxing the driving range constraint. It varies across vehicle models and is positive when $D_j = D_c$ and zero otherwise.

With the supply side primitives, the first-order conditions of prices and attributes are:

$$\text{FOC for } P_j : Q_j + \sum_{l \in J_f} (P_l - mc_l) \frac{\partial Q_l}{\partial P_j} = 0, \ \forall j; \tag{11}$$

$$\text{FOC for } k_j : \sum_{l \in J_f} (P_l - mc_l) \frac{\partial Q_l}{\partial k_j} = \underbrace{\rho^t \gamma_k}_{\frac{\partial mc_j}{\partial k_j}} Q_j - \underbrace{\lambda_j}_{\text{shadow value}} \underbrace{\eta_k}_{\frac{\partial D_j}{\partial k_j}} + \underbrace{\phi_k + FE + \nu_j^k}_{\frac{\partial FC_j}{\partial k_j}}, \ \forall j; \tag{12}$$

$$\text{FOC for } w_j : \sum_{l \in J_f} (P_l - mc_l) \frac{\partial Q_l}{\partial w_j} = \underbrace{\gamma_w}_{\frac{\partial mc_j}{\partial w_j}} Q_j - \underbrace{\lambda_j}_{\text{shadow value}} \underbrace{\eta_w}_{\frac{\partial D_j}{\partial w_j}} + \underbrace{\phi_w + FE + \nu_j^w}_{\frac{\partial FC_j}{\partial w_j}}, \ \forall j. \tag{13}$$

The first-order condition for prices is standard in the literature and allows researchers to recover the marginal cost mc_j for every product given demand estimates. Once the marginal costs are recovered, we use the marginal cost function (Equation (10)) and the remaining two FOCs (Equations (12) and (13)) to estimate the supply side parameters jointly.

In addition to endogenous attributes in these equations — battery capacity k_j and vehicle weight w_j are correlated with marginal and fixed cost shocks, ω_j, ν_j^k, and ν_j^w — there is another challenge that arises from the binding constraints of range subsidies. The Lagrangian multiplier λ_j, the shadow value of relaxing the constraint on firm profit, is product-specific and unobserved. The only theoretical constraint on λ_j is that it is positive for products whose ranges are at the subsidy cutoff.[23] Assuming ν_j^k and ν_j^w are mean independent of exogenous shifters but without further assumptions, Equations (12) and (13) would lend to inequality conditions in the form of $E[\lambda_j | W_j] \geq$

[23] Among the 279 EV model-year observations, 41% has a driving range at a cutoff and is associated with $\lambda_j > 0$. We assume the cutoff is binding if the driving range is equal to or exceeds the cutoff by less than 5km.

0, where W_j are exogenous shifters. We discuss how we address these issues in Section 4.3 below.

4.3 Estimation and Identification

Demand Analysis Our estimation of demand parameters follows the literature (Berry et al., 1995; Petrin, 2002; Berry et al., 2004) with a key difference: in addition to prices, we also allow driving range and vehicle weight to be endogenous. These attributes are adjusted frequently and likely correlated with the demand shock ξ_{jm}. We use four sets of IVs (9 in total) for these endogenous variables: 1) the central subsidies, 2) sales tax rates, 3) wheelbase, and 4) battery weight interacted with battery supplier dummies.

The central subsidies are step functions of the driving range, as shown in Table 1, and create a regression-discontinuity type of variation in vehicle prices. In addition, both the subsidy amount and the driving range cutoffs change over time, generating rich variation in the sample. Analyzing demand responses to vehicles with driving ranges slightly below and above the subsidy thresholds helps identify the price sensitivity. The identification assumption is that the variation in prices induced by the discrete jumps in subsidies provides a plausible source of exogenous variation.[24] The central subsidies are also powerful instruments for driving range and vehicle weight, as shown in Figure 5.

Similarly, the discrete changes in sales tax rates with respect to engine size provide another source of useful exogenous variation. The sales tax rate is normally set at 10%, but it was lowered to 5% in 2015 and 2016, and reset to 7.5% in 2017 for vehicles with an engine size of 1.6 liters or lower. Engine size is included in the utility function. Our identification assumption is that the unobserved product attribute ξ does not change discretely with engine size. Both central subsidies and sales tax rates are strongly correlated with prices.

The third set of IVs follows the strategy in Whitefoot et al. (2017), which recognizes that vehicle design is a multi-stage process that could take several years. In particular, the vehicle frame (and hence wheelbase) is determined in the early stage of the vehicle design. Wheelbase affects vehicle attributes such as vehicle weight. It also affects battery capacity because battery packs are stored beneath the floorboard of vehicles, between the front and rear wheels. We assume that wheelbase does not enter consumer utility directly because consumers are unlikely to care about this attribute or know the wheelbase size.

The fourth set of IVs is based on battery weight and battery suppliers. It serves as a set of stan-

[24] As discussed in Section 3.1, the subsidy schedule was established by the central government and was unlikely to be influenced by firm lobbying. In addition, our rich set of controls and fixed effects alleviate concerns that the subsidy schedule is correlated with demand shocks ξ.

dard supply-side instruments for demand analysis. These cost-side shifters affect the battery price and, consequently, the vehicle price. Battery weight and supplier identity also affect the driving range and vehicle weight but are excluded from consumer utility because they are typically unknown to consumers. This makes them suitable instruments for driving range and vehicle weight. We categorize battery suppliers into three groups: BYD, CATL, and others. BYD is the largest EV maker in China and supplies batteries for its own EV models. CATL is the largest battery supplier and supply for many EV producers. We include three battery supplier dummies and their interactions with battery weight, yielding six IVs.

To facilitate the identification of heterogeneous consumer preferences, we construct micro-moments based on a household survey of new vehicle buyers (Petrin, 2002; Berry et al., 2004). We use the model to fit the observed shares of vehicle buyers by six income groups based on household annual income (below ¥48k, ¥48-72k, ¥72-96k, ¥96-120k, ¥120-144k, and above ¥144k) by year for 2015-2017, leading to a total of 15 micro-moments.

The demand estimation is carried out using simulated GMM and a nested contraction mapping to recover product-specific mean utility δ_{jmt}. The two sets of moment conditions are:

- Moment condition 1: $E[\xi_{jmt}(\theta)|\boldsymbol{Z}_{jmt}] = 0$, where $\boldsymbol{Z}$ is a vector of exogenous variables for the demand analysis
- Moment condition 2: Predicted shares = observed shares of vehicle buyers by income group

Supply Analysis As mentioned in Section 4.2, there are two challenges in taking Equations (10), (12), and (13) to data to estimate cost parameters. First, vehicle attributes are endogenous. We leverage three sets of IVs: central subsidies, consumption tax, and sales-weighted average gasoline price interacting with fuel type. Subsidies affect sales and vehicle attributes, as discussed above, but are unlikely to be correlated with production cost shocks. The consumption tax rate is zero for BEVs but has seven different levels in the range of 1-40% for ICEs and PHEVs, depending on engine size. The consumption tax directly enters producer price as shown in Equation (7) and likely affects attribute choices such as vehicle weight. The third instrument is the weighted average of gasoline prices across cities for each model, where the weight is a model's city-level sales shares. This variable takes a larger value if the corresponding vehicle model is popular in cities with higher gasoline prices. High gasoline prices result in high user costs for ICEs and boost demand for EVs. The identification assumption is that gasoline prices, which are heavily regulated in China, are not affected by cost shocks to EV production.[25]

[25] The NRDC sets the ceiling of retail gasoline prices by province based on the moving average price of crude oil on the international market. Retail prices usually stay close to the ceiling price set by the NRDC (Chen and Sun, 2021).

The second challenge in estimating the supply-side parameters arises because the product-specific Lagrangian multiplier λ_j is unobserved. We propose two solutions. Our first solution follows Moon and Schorfheide (2009) and adds a slackness parameter to Equations (12) and (13) that captures the population average shadow value conditioning on exogenous shifters $E[\lambda_j|W_j]$. This converts inequality constraints to equality conditions and allows us to recover cost parameters via a standard GMM procedure. Our second solution imposes parametric assumptions on λ_j to reflect the fact that it captures changes in firm profits when the range constraint tightens by one unit. If the subsidy threshold increases by 1km, then firm f could lose up to the incremental subsidy amount times its sales of product j. In light of this, we assume that the shadow value is proportional to Q_j: $\lambda_j \simeq \zeta \cdot Q_j$ if $\lambda_j > 0$, where ζ is a parameter to be estimated.

We estimate the cost parameters $(\rho, \gamma, \phi, \zeta)$ jointly with GMM using Equations (10), (12), and (13), where the cost shocks are assumed to be mean independent of instruments W_j:

$$E[\omega_j|W_j] = 0, \;\; E[\nu_j^k|W_j] = 0, \;\; \text{and} \;\; E[\nu_j^w|W_j] = 0. \tag{14}$$

We use data on both ICEs and EVs for the first set of moment conditions on marginal cost shocks ω_j, yielding a total of 1540 model-year observations. The other two sets of moment conditions on ν_j^k and ν_j^w only use data on EVs (as FOCs for attributes are irrelevant for ICEs), with 279 model-year observations

Covariation of prices and vehicle attributes, net of product markups, is informative of the curvature of the variable cost curve. Firms' choices of battery capacities and vehicle weights at the model level allow us to learn about the fixed costs of choosing different attributes. For example, if the driving ranges increase significantly when the government increases subsidies for long-range models, the fixed cost of adding battery capacity cannot be prohibitively high. The parametric assumptions on the cost structure also help with the supply-side identification.

5 Estimation Results

5.1 Demand Estimates

Table 3 presents estimates of the preference parameters in Equation (8). All columns control for city-by-year-by-fuel type (ICE of EV) fixed effects, brand-by-year-by-fuel type fixed effects, segment fixed effects, and vintage fixed effects. The first column shows results from a simple multinomial logit model using OLS. The second column instruments for price, vehicle weight, and driving range using the four sets of IVs discussed in Section 4.3. As common in the demand literature, the

OLS coefficient estimate on vehicle price is positive (implying an upward-sloping demand curve) due to the positive correlation between demand shocks (i.e., unobserved product attributes) and prices. The OLS coefficient estimates on vehicle weight and engine size are also counter-intuitive. Once we instrument for price and the endogenous attributes, these coefficients are all intuitively signed, highlighting the importance of controlling for price and attribute endogeneity.

Column (3) reports results from the random coefficient model with heterogeneous preferences. As in Column (2), all parameter estimates are intuitively signed: consumers prefer heavy vehicles, EVs with a longer driving range, vehicles with better fuel efficiency, and more powerful and larger engines. High-income households are less price sensitive. In addition, the sizeable and significant σ_p suggests significant heterogeneity in price sensitivity among households with different income levels. In addition to the price, we allow random coefficients on the constant term, the EV indicator, and the engine displacement. The random coefficient on the constant term captures differences in the outside option across individuals (used vehicles or public transit) and is large and statistically significant. The random coefficient estimate on the EV dummy is also large and statistically significant, implying a large preference heterogeneity for EV purchases among consumers. The random coefficients for other vehicle attributes, such as horsepower, fuel economy, and engine size are insignificant, partly due to the extensive list of fixed effects.

Figure 6 plots demand elasticities and markups. Given substantial differences between EV models' MSRPs and post-subsidy prices, both panels use post-subsidy consumer prices, which are more appropriate for documenting demand patterns. The left panel depicts the price semi-elasticities: the percentage change in sales for a ¥1,000 reduction in own prices. The increase in the percentage of sales is more pronounced for cheaper vehicles, implying more sensitive demand. Demand for EVs is less price-sensitive than that for ICEs at comparable prices. This is partly due to the higher income levels of EV buyers and the relatively smaller number of alternatives among EV models. The implied price elasticities range from -1.74 to -6.50, with an average of -4.15 and a sales-weighted average of -4.36. These estimates are in line with the literature on ICEs and EVs (Li et al., 2017a; Li, 2018; Xing et al., 2021; Muehlegger and Rapson, 2022; Springel, 2019). The right panel in Figure 6 shows markups (i.e., price minus the marginal cost) for all vehicles. High-end models are more profitable: markups increase with prices. This is an important feature that we examine in counterfactual simulations below. EVs tend to have higher markups than ICEs, driven by less intense competition in the EV segment and the pass-through of EV subsidies.

Based on our demand estimates, shutting down central subsidies and allowing firms to adjust attributes in response to subsidy removal would reduce EV sales by 70.9% in 2017. The estimated sales impact is slightly larger than, though broadly in line with that from Li et al. (2022), which shows that the subsidies attributed to 55% of EVs during the same data period based on a less flexible demand model and simulations with product attributes fixed. EV subsidies in the U.S. and Norway generated sales impact of similar magnitude (Li et al., 2017a; Springel, 2019).

5.2 Supply Side Estimates

Technology Frontier Table 4 presents estimation results for the driving-range technology frontier separately for BEVs and PHEVs because they use different technologies. The first two columns utilize all BEVs and PHEVs (at the trim level) that underwent the driving range test administered by China's MIIT. It has nearly twice as many observations as the subset of trims that were commercially launched, which forms the basis of the subsequent analysis on marginal costs and fixed costs. The last two columns report results using the subset of commercially launched trims. All regressions include fixed effects for report dates to control for the technology progress over time as well as potential changes in testing technology and methodology. These two sets of estimates are nearly identical for BEVs and slightly more precise for PHEVs using the full sample.

The adjusted R^2 is 0.9 for BEVs and over 0.7 for PHEVs, suggesting a good model fit. Our policy analysis below is based on the results from the full sample in Columns (1) and (2). For both EVs and PHEVs, an additional 1 kWh of battery capacity increases the driving range by about 6 km, aligning with industry consensus. A 10kg increase in net vehicle weight reduces the driving range by 1.1km for BEVs and about 0.5km for PHEVs (the average EV weighs 1,220kg, exclusive of batteries). EV batteries' energy density is a crucial factor that determines how much power a battery stores, given the weight. Raising the battery density by 1kWh/10kg increases the driving range by a whopping 27km for BEVs, perhaps not surprising given the average battery density of 1.1kWh/10kg.[26]

Vehicle weight has a smaller impact on the driving range for PHEVs than BEVs, which is intuitive because PHEVs are powered by both a battery motor and a gasoline engine. Battery density has a counter-intuitive sign but is imprecisely estimated for PHEVs, likely due to the small battery size in PHEVs and the fact that battery capacity rather than density determines the driving range. As expected, a larger engine size for PHEVs is associated with a longer driving range: raising the engine displacement by one liter increases its driving range by 5.7km.

[26] Battery density is at the core of the EV battery technology. Most EV makers, with the notable exception of BYD, outsourced battery production to battery suppliers during our data period. We assume EV firms take the battery density as given when choosing battery capacity and vehicle weight.

Cost Functions Table 5 reports supply-side parameter estimates from three specifications. Column (1) reports the OLS results for the marginal cost Equation (10). Columns (2) and (3) estimate the marginal and fixed cost parameters simultaneously using GMM as shown in Equation (14). The difference in Columns (2) and (3) lies in the treatment of the shadow value (i.e., Lagrangian multiplier) λ_j in Equations (12) and (13). Column (2) adds a slackness parameter that converts inequality conditions to equalities following Moon and Schorfheide (2009). Column (3) specifies the product-specific shadow values λ_j as a function of sales. We use Column (3) for counterfactual analyses that require knowing the shadow value for each vehicle. All estimations include year, fuel type, segment, and brand fixed effects separately for marginal costs and fixed costs.

We report the parameter estimates for the marginal cost in Panel A and the fixed cost in Panel B. The slackness parameter and the shadow value parameter are presented in Panel C. Compared with the results from GMM which addresses the endogeneity of vehicle attributes, OLS estimates on net vehicle weight and especially battery capacity are biased toward zero, suggesting a negative correlation between unobserved cost shocks and these attributes. Results in Columns (2) and (3) are very similar, indicating that cost estimates are robust to how we treat the shadow values. Based on the results in Column (3), adding 10kg of vehicle weight increases the marginal cost by ¥1,130 for both ICEs and EVs.

Increasing battery capacity by 1kWh in EVs costs ¥3,620 in 2015, the base year. The coefficient estimate of ρ, which captures the reduction in battery cost as the technology improves, is 0.803 and statistically different from 1. In other words, the marginal cost of battery capacity declined by 19.7% annually and fell to ¥1,874 per kWh by 2018. The nearly 20% annual cost reduction — likely driven by technological progress, economies of scale, and learning by doing in the rapidly evolving battery industry — aligns remarkably well with estimates from the literature (Ziegler and Trancik, 2021) and industry reports.[27] Figure 7 plots our estimates of the battery cost against the battery pack price per kWh from Bloomberg New Energy Finance's annual battery price surveys. The pattern of annual reduction in battery prices is very similar between our estimates and the industry surveys. Bloomberg's battery pack prices are 28-35% lower than our marginal cost estimates, which is intuitive because our estimates include not only the cost of purchasing battery packs but also installation costs.

The estimates of γ^{other} in Panel A are similar across columns and have intuitive signs: marginal costs increase with horsepower, engine size, and fuel efficiency. Marginal costs decreased significantly over time, reflecting both the technological progress and economies of scale as EV production ramped up.

[27] See Bloomberg New Energy Finance report on November 26, 2023 at `https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/`.

The estimated parameters in Panel B capture the slope of the fixed cost function with respect to battery capacity and vehicle weight. The coefficient estimates on battery capacity are large, positive, and statistically significant, implying that the fixed cost of production increases with battery size. The coefficient estimates for vehicle weight are noisy. Designing larger vehicles can be more expensive, but the use of lighter materials to reduce weight can also be costly.

The estimated slackness parameter (i.e., the average shadow value $E[\lambda_j|W_j]$ for observations with a driving range at the cutoffs) in Panel C is large, indicating that relaxing the range cutoffs could result in significant benefits. This is consistent with the shadow value estimate in Column (3), where an automaker is willing to pay ¥140 per EV to reduce the driving range cutoff by 1km. Given the average subsidy of ¥100 to ¥390 per km, these estimates indicate that the automakers are willing to forego a considerable fraction of the subsidies to relax these constraints.

6 Counterfactual Simulations

In this section, we conduct counterfactual simulations to examine the impact of ABS on firm choices, consumer demand, and environmental externalities, following the theoretical discussions in Section 2. We compare five subsidy designs for BEVs.[28] The first scenario is a uniform subsidy that is the same across all EV models. This serves as a benchmark for four attribute-based designs. The second scenario represents the current notched range-based subsidies. The third scenario implements linear range-based subsidies with a two-part tariff in the form of $T + t\cdot$ driving range, where T and t are chosen to maximize the social welfare subject to the government's budget constraint. The fourth and fifth scenarios follow the same two-part structure but are based on battery capacity and vehicle weight, respectively. Appendix C.3 provides details and a discussion of the simulation algorithm.[29]

Throughout the counterfactual analyses, we hold attributes for ICE models fixed. This simplification is driven by two considerations. First, the market share of EVs was less than 3% before 2017 and 5.5% in 2018. EV subsidies likely had a limited impact on the attributes of ICEs. Second, solving for the new market equilibrium is computationally intensive with a larger number of multiple-product firms. Endogenizing attribute choices for ICEs would make the optimization more demanding due to the presence of many ICE models. Our simulations are based on the 2017

[28] We maintain the existing subsidy rate for PHEVs (see Table 1), but allow their attributes to change in response to different subsidy designs for BEVs.

[29] The counterfactual analyses are computationally intensive. Searching for the optimal choices of T and t for each subsidy design requires evaluating many guesses of T and t. For each guess, we need to solve the entire industry equilibrium with hundreds of vehicle prices for both ICEs and EVs and endogenous attributes for both BEVs and PHEVs. We provide analytical gradients for the Newton–Raphson algorithm that greatly speeds up the solution process.

cohort, though results are qualitatively similar with other cohorts. To facilitate comparison, we fixed the total subsidy amount from the central government at ¥6.33 billion as under the observed policy in 2017 throughout all counterfactual simulations.[30]

Social welfare is the sum of consumer surplus and firm profits minus the cost of emissions. The environmental benefit for an EV model is calculated as the monetized savings from emission reductions (including CO_2 and local pollutants PM, SO_2, and NO_x) relative to alternative ICEs that the EV replaces, following the literature (Holland et al., 2016; Xing et al., 2021). The calculation crucially considers the following: 1) substitution patterns between EVs and ICEs, based on our demand estimates; 2) tailpipe emissions standards and average fuel economy of ICEs that an EV replaces, 3) the energy efficiency of an EV model in kWh/km, calculated as the ratio of battery capacity over driving range; 4) the emission intensity of thermal power generation and the share of thermal power generation in the province where an EV is sold; and 5) the monetized marginal health damages of different pollutants. See Appendix C.1 for more details.

We additionally evaluate accident externalities in robustness analyses. Accident externalities from traffic safety vary under different policy scenarios due to changes in vehicle weight. Heavier vehicles are shown to impose larger accident externalities (Li, 2012; Anderson and Auffhammer, 2014; Bento et al., 2017). Appendix C.2 presents details on the calculation of accident externalities. They are approximately half the magnitude of environmental externalities and do not change the welfare results qualitatively.

6.1 Optimal Subsidy Rates

We report the optimal ABS policy design in the form of $T + t \cdot z$ in Table A3. To illustrate how we solve for these optimal designs, Figure A4 depicts the equilibrium consumer surplus, firm profit, and emissions as we vary the subsidy intensity t for each of the three ABS designs. The base subsidy T is determined by the budget constraint. As the subsidy intensity t rises, firms respond by producing EVs with extended driving ranges, increased battery capacity, and greater vehicle weights. Initially, this boosts consumer surplus. However, as t continues to increase, consumer surplus begins to decline for two reasons. First, marginal and fixed costs of production increase in vehicle attributes, leading to higher consumer prices. Second, the marginal utility derived from these attributes diminishes. Consequently, consumer surplus is concave in t.

The environmental benefit from the emission reduction diminishes as the subsidy intensity t increases across all three ABS designs. This is driven by two mechanisms. First, ABS offers

[30] This is the total central subsidy that was distributed to the 40 cities in our sample. We fix local subsidy designs at the observed level.

greater incentives for vehicles with enhanced attributes and changes the composition of vehicle sales in favor of larger and heavier models. This sales channel results in a fleet that is less fuel efficient on average. Second, a higher subsidy intensity t encourages the provision of the targeted attribute for a given vehicle. Capacity- and weight-based subsidies lead to larger battery capacities and vehicle weights, which reduce fuel efficiency and diminish environmental benefits. While a higher subsidy intensity under the range-based subsidy prompts the downsizing of vehicles and improves environmental performance for a given vehicle, this effect is dominated by changes in the composition of EV sales (the sales channel).

Firms' profits from selling BEVs are moderately concave in subsidy intensity t for range- and capacity-based subsidies and close to flat for weight-based subsidies. This is partly because higher subsidies are offset by the increases in the costs of offering these attributes. Altogether, the social welfare is concave in t, with a well-defined optimal subsidy intensity t^* and the corresponding T^*.

6.2 Notched vs. Linear Subsidies

We first compare equilibrium outcomes under the observed *notched* subsidy to the *linear* subsidy. Under the notched design, the range cutoffs are 100km, 150km, and 250km, and the corresponding subsidy levels are ¥20k, ¥36k, and ¥44k, respectively, as shown in Table 1. Under the linear design, the per-unit subsidy is ¥24,704 + ¥70 $\times$ driving range, which gives ¥31.7k, ¥35.2k, and ¥42.2k for vehicles with a driving range of 100km, 150km, and 250km, respectively.

Figure 8 plots the distribution of the BEV driving range under the notched design in red and the linear design in blue. The contrast between the two distributions is stark: while there is strong bunching with the notched subsidy design, bunching disappears with the linear subsidy design. As documented by Sallee and Slemrod (2012) in the context of fuel economy standards, there are two inefficiencies associated with a notched policy. First, there might be excessive bunching whereby firms alter weight and battery capacity to reach the driving range cutoffs. Second, firms have no incentive to improve attributes incrementally between the cutoffs.

Table A4 tabulates changes in vehicle attributes, prices, marginal costs, and sales separately for BEVs with driving ranges at the subsidy cutoffs and for those with driving ranges away from the cutoffs. Transitioning from notched to linear subsidies prompts automakers to adjust the characteristics of individual vehicles, depending on whether the cutoffs are binding or not. Models at the cutoffs experience increases in net vehicle weight and decreases in battery capacity, resulting in reduced driving ranges. MSRPs, marginal costs, and subsidies all decline. Conversely, vehicles with driving range away from the cutoffs witness increases in battery capacity and reductions in vehicle weight as firms respond to the stronger incentive to provide range under the linear policy.

These disparate responses underscore the distortions inherent to the notched policy.

Sales for BEV models with the longest driving ranges increase while sales for the other groups drop, because the former group has more desirable attributes and receives much larger subsidies under the linear design. Lastly, social welfare improves by ¥135 million annually, as shown in Table 6 below.

6.3 Welfare Analysis

We first discuss differences in vehicle attributes under different ABS designs, then examine welfare implications, and finish with a welfare decomposition exercise that highlights underlying channels.

Changes in Vehicle Attributes Figure 9 illustrates the average vehicle price, battery capacity, net vehicle weight, and driving range under the uniform subsidy and the four ABS designs: the current notched range-based subsidy and linear subsidy designs based on driving range, battery capacity, and vehicle weight.

Vehicle prices are higher under all ABS designs than under the uniform subsidy. This is due to the increased provision of vehicle attributes that consumers desire. The capacity subsidy results in the largest price increase of 6.3%. The increase in prices reflects the fact that capacity-based subsidies prompt firms to increase the provision of battery capacity, vehicle weight, and driving range the most relative to all other designs.

Panels (b)-(d) exhibit an intuitive pattern: firms increase the vehicle attribute that is targeted by the policy. For example, battery capacity is the highest under capacity-based subsidy compared to all other designs. Vehicle weight is the largest and driving range is the lowest under weight-based subsidy, highlighting the trade-off between vehicle weight and driving range. Range-based subsidies incentivize firms to increase battery capacity while reducing vehicle weight, leading to the longest driving range but the lowest vehicle weight.

Changes in Markups A key theoretical insight of Section 2 is that ABS designs can also effectively mitigate market power and quantity distortions. To illustrate this, Figure 10 plots changes in markups $P_j(\boldsymbol{x}) - C_j(\boldsymbol{x})$ for products in each quartile of the price distribution when we move from the uniform subsidy to ABS designs. Each of the four panels depicts changes for one of the four ABS designs. A consistent pattern emerges across all panels: markups decrease for products above the median price and they increase for products below the median price. Notably, the reduction in markups for products above the median price is most pronounced under capacity-based subsidy. Given that high markups are typically associated with quantity distortions, and such distortions are more pronounced among higher-priced products, capacity-based subsidy appears most effective at addressing quantity distortions among all policies we examine.

Changes in Sales Table A5 reports changes in sales for BEVs with different qualities when we move from the uniform subsidy to ABS. We divide the BEVs into high-quality models (where the WTP is above the median of ¥130k) and low-quality models (WTP below ¥130k) using consumer WTP under the uniform policy.[31] The uniform subsidy favors low-quality models compared to ABS. High-quality models receive more subsidies under ABS, especially with weight- and especially capacity-based subsidies. The sales impact under different designs is an important underlying channel for the welfare comparison we discuss below.

Welfare Comparison Table 6 presents changes in welfare under different ABS designs *relative to* the uniform subsidy, where welfare is consumer surplus plus firm profit net of the monetized cost of emissions. We use the uniform subsidy as the baseline because it does not directly target product attributes. All cells report changes when we move from the uniform subsidy to ABS.

There are several key findings from this table. First, all ABS designs generate significant gains in consumer surplus relative to the uniform subsidy, ranging from ¥226 million in 2017 under the notched design to ¥643 and ¥680 million under capacity- and weight-based subsidies, respectively. These consumer gains arise from two channels. First, ABS subsidies induce more desirable vehicle attributes, as shown in Figure 9. Second, ABS designs more effectively address quantity distortions that arise from market power and high mark-ups, as demonstrated in Figure 10. The increase in consumer surplus is relatively modest for range-based designs because it leads to vehicle downsizing, which is undesirable to consumers.

Firms producing BEVs benefit from the ABS designs that redistribute subsidies from the low-end models to the high-end ones. Sales of high-end products increase significantly relative to the uniform subsidy (see Table A5). These vehicles are more profitable and boost the profits of BEVs.[32] Compared to gains in consumer surplus, however, profit increases from selling EVs are about an order of magnitude smaller and slightly negative for the notched design. The increase in BEV profits is mostly offset by losses in ICE profits. In general, automakers collectively suffer a net loss under ABS relative to the uniform subsidy.

[31] The average WTP for each model is simulated using 150 pseudo consumers in each market and 10,000 idiosyncratic preference shocks for each pseudo consumer, ε_{ijm}. It is defined as the payment level that makes consumers indifferent between buying and not buying the vehicle.

[32] The profit gains of BEVs is much lower at ¥5.4 million under the weight-based subsidy because increasing vehicle weight is costly. Both the marginal and fixed costs of production increase significantly with heavier vehicles.

The environmental performance of the EV fleet worsens as sales shift to larger and less environmentally friendly EVs under ABS. Compared to the uniform subsidy, the social cost of emissions increases by ¥70 million under the notched range subsidy to ¥182 million under the weight subsidy. The environmental performance under the weight-based design is the most compromised due to the EVs becoming heavier. As a robustness check, Table A6 reports changes in accident externalities, which are about half of the welfare cost of the increased emissions. Perhaps not surprisingly, weight-based subsidies lead to the largest increase in accident externality due to the larger vehicle weight.

In total, ABS designs result in significant welfare gains compared to the uniform subsidy, ranging from ¥97.2 million under the current notched range subsidy to ¥448 million under the capacity subsidy. These gains stem from consumer benefits outweighing the losses in automakers' profits and the social costs associated with increased emissions.

Second, the capacity-based subsidy design — the policy implemented in the U.S. — yields the largest welfare gain. This design strikes the best balance between moderating negative environmental externalities and mitigating quantity distortions as a result of market power. This is because the variation in market power across products has a higher correlation with battery capacity than it does with other attributes. As a result, capacity-based subsidies can more effectively correct quantity (i.e., market power) distortion than other designs as outlined in Section 2.2 and illustrated in Figure 10. In addition, capacity-based subsidies incentivize firms to produce high-quality vehicles, further boosting consumer surplus.

Third, the uniform subsidy design that is adopted in several European countries turns out to be less efficient than ABS as a result of two countervailing forces. On the one hand, the uniform subsidy increases the market share of smaller vehicles due to the relatively higher subsidies for these vehicles and achieves the best environmental outcome. On the other hand, the uniform subsidy does not provide incentives for quality provision, and firms produce vehicles with smaller batteries and lower weight (see Figure 9). Overall, the environmental benefit is outweighed by a much higher expense of consumer surplus due to the lower consumer WTP for smaller and low-quality vehicles.

Welfare Decomposition ABS designs could improve welfare through several channels: they mitigate market power and redistribute subsidies toward products with more severe distortions. If quality under-provision is relevant, ABS also incentivizes attribute provision. These channels are intertwined in the welfare analyses above. We perform a decomposition exercise to disentangle them and further understand the role of each of the channels.

Let $\boldsymbol{Y}^o = (\boldsymbol{X}^o, \boldsymbol{P}^o, \boldsymbol{Q}^o, \boldsymbol{R}^o)$ denote the equilibrium outcomes under the uniform subsidy: vectors of vehicle attributes, prices, quantities, and total subsidies for each product under the uniform policy. The total subsidy for a given product is the per-unit subsidy times quantity: $R_j = b_j \cdot Q_j$. Let $\boldsymbol{Y}' = (\boldsymbol{X}', \boldsymbol{P}', \boldsymbol{Q}', \boldsymbol{R}')$ denote equilibrium outcomes under an ABS alternative. We decompose the welfare changes, $\Delta SW = SW(\boldsymbol{Y}') - SW(\boldsymbol{Y}^o)$, into the following two components:

$$\begin{aligned}\Delta SW &= SW(\boldsymbol{X}', \boldsymbol{P}', \boldsymbol{Q}', \boldsymbol{R}') - SW(\boldsymbol{X}^o, \boldsymbol{P}^o, \boldsymbol{Q}^o, \boldsymbol{R}^o) \\ &= \underbrace{SW(\boldsymbol{X}', \boldsymbol{P}', \boldsymbol{Q}', \boldsymbol{R}') - SW(\boldsymbol{X}', \widetilde{\boldsymbol{P}}, \widetilde{\boldsymbol{Q}}, \boldsymbol{R}^o)}_{\text{Benefits from Mitigating Market Power}} + \underbrace{SW(\boldsymbol{X}', \widetilde{\boldsymbol{P}}, \widetilde{\boldsymbol{Q}}, \boldsymbol{R}^o) - SW(\boldsymbol{X}^o, \boldsymbol{P}^o, \boldsymbol{Q}^o, \boldsymbol{R}^o)}_{\text{Benefits from Improved Attributes}},\end{aligned}$$

where $(\boldsymbol{X}', \widetilde{\boldsymbol{P}}, \widetilde{\boldsymbol{Q}}, \boldsymbol{R}^o)$ refers to the scenario that fixes subsidy expenditures across products at $\boldsymbol{R}^o$, but adjusts attributes to $\boldsymbol{X}'$ and allows firms to choose prices $\widetilde{\boldsymbol{P}}$ (which pins down quantities $\widetilde{\boldsymbol{Q}}$) to maximize profit given $\boldsymbol{X}'$ and $\boldsymbol{R}^o$.

In the first channel, which is labeled 'Benefits from Mitigating Market Power,' products receive different subsidies according to the ABS design while attributes are fixed at $\boldsymbol{X}'$. Vehicles equipped with better attributes benefit from higher subsidies, which lowers the post-subsidy markups. The only difference between $SW(\boldsymbol{X}', \boldsymbol{P}', \boldsymbol{Q}', \boldsymbol{R}')$ and $SW(\boldsymbol{X}', \widetilde{\boldsymbol{P}}, \widetilde{\boldsymbol{Q}}, \boldsymbol{R}^o)$ arises from subsidy levels across products (and the associated price responses) which allows us to measure the effectiveness of ABS subsidies in mitigating market power distortions. In the second channel, which is labeled 'Benefits from Improved Attributes,' the subsidies across products are fixed at $\boldsymbol{R}^o$ while product attributes change. This isolates the welfare effect of attribute changes separate from changes in the level of subsidies across products as a result of ABS. As pointed out in Section 2.1, while our theoretical setup rules out the Spence distortion, the presence of such a distortion serves as another rationale for ABS designs.

In addition to the decomposition exercise, we conduct another counterfactual simulation that is motivated by Section 2.3, where we allocate subsidies across products in the form of $T_j + t * z(X_j)$ with a product-specific base subsidy T_j. This enables the government to redistribute subsidies more effectively across products with varying degrees of market failures.[33] We call this the 'Subsidy Redistribution Channel.' Denote these outcomes as $\hat{\boldsymbol{Y}} = (\boldsymbol{X}', \hat{\boldsymbol{P}}, \hat{\boldsymbol{Q}}, \hat{\boldsymbol{R}})$, where $\hat{\boldsymbol{R}} = \hat{\boldsymbol{b}} \cdot \hat{\boldsymbol{Q}}$ and $\hat{\boldsymbol{b}}$ is the vector of product-specific optimal subsidies and $\hat{\boldsymbol{P}}$ ($\hat{\boldsymbol{Q}}$) stands for the optimal prices (quantities) given $\hat{\boldsymbol{b}}$. The magnitude of welfare changes $\Delta SW = SW(\hat{\boldsymbol{Y}}) - SW(\boldsymbol{Y}')$ speaks to the importance of subsidy redistribution.

Table 7 reports the welfare results. Columns (1) to (3) in Panel A show that changes in at-

[33] ABS designs in the form of $T + t * z(X_j)$ also redistribute subsidies across products, though the extent of redistribution is somewhat limited.

tributes account for 42-62% of total welfare gains. These results echo the importance of endogenizing product attributes in evaluating ABS. Columns (4) to (6) in Panel A illustrate that ABS designs effectively address market power distortions, which explains the remaining 38% to 58% of the welfare gains. The capacity- and weight-based designs allocate larger subsidies to products with more severe market power (and quantity) distortions, resulting in a larger boost to consumer surplus. However, the gains are partially offset by increased emissions. Overall, all ABS designs lead to significant welfare gains relative to uniform subsidies.

Allowing subsidy redistribution in the form of $T_j + t * z(X_j)$ further improves welfare. The magnitude of the welfare gains is comparable to the gains associated with reducing market power, from ¥143 million for range policy to ¥190 million for weight policy, enhancing welfare gains by another 34% to 62% (Panel B of Table 7). A third of these additional welfare gains can be attributed to increases in firm profits, with the remainder explained by improvements in consumer surplus and a moderate decline in environmental benefits.

Endogenous Attributes Finally, to shed light on the importance of endogenizing product attributes, we conduct simulations holding product attributes fixed and only allowing prices and sales to adjust, as commonly done in the literature. The results are in Table A7. While the sign of the total welfare changes is the same as the baseline results in Table 6, the magnitude of the impact is only 28% of the baseline results for capacity and weight subsidies and 40% for range subsidies. In addition, fixing product attributes leads to the spurious conclusion that ABS designs increase firm profits, contrary to the results shown in Table 6 with endogenous attributes.

7 Conclusion

Attribute-based subsidies (ABS) are commonly used to promote the diffusion of energy efficient products. These products are often manufactured by firms with market power. To the best of our knowledge, this study offers the first theoretical and empirical analysis of how ABS affects product attributes, consumer demand, and environmental externalities in a differentiated product oligopoly.

Our theoretical model traces out the locus of optimal EV subsidy design with a two-part subsidy structure under varying government budget constraints, highlighting the importance of balancing environmental externalities and market power distortions in policy design. The empirical analysis uses China's passenger vehicle market to evaluate the impact of ABS. Counterfactual simulations indicate that, although the uniform EV subsidy generates the largest emission reductions, ABS generates significant gains in overall welfare relative to the uniform subsidy. It does so by incentivizing quality provision and alleviating quantity distortions. Battery capacity subsidies generate the largest increase in social welfare relative to uniform subsidies and other ABS designs because they most effectively balance quantity distortions and environmental impacts. The analysis also underscores the importance of including endogenous product attributes when evaluating the welfare impacts of ABS. Our framework takes product offerings as given and does not consider the effect of government subsidies on technological innovations, which we leave for future research.

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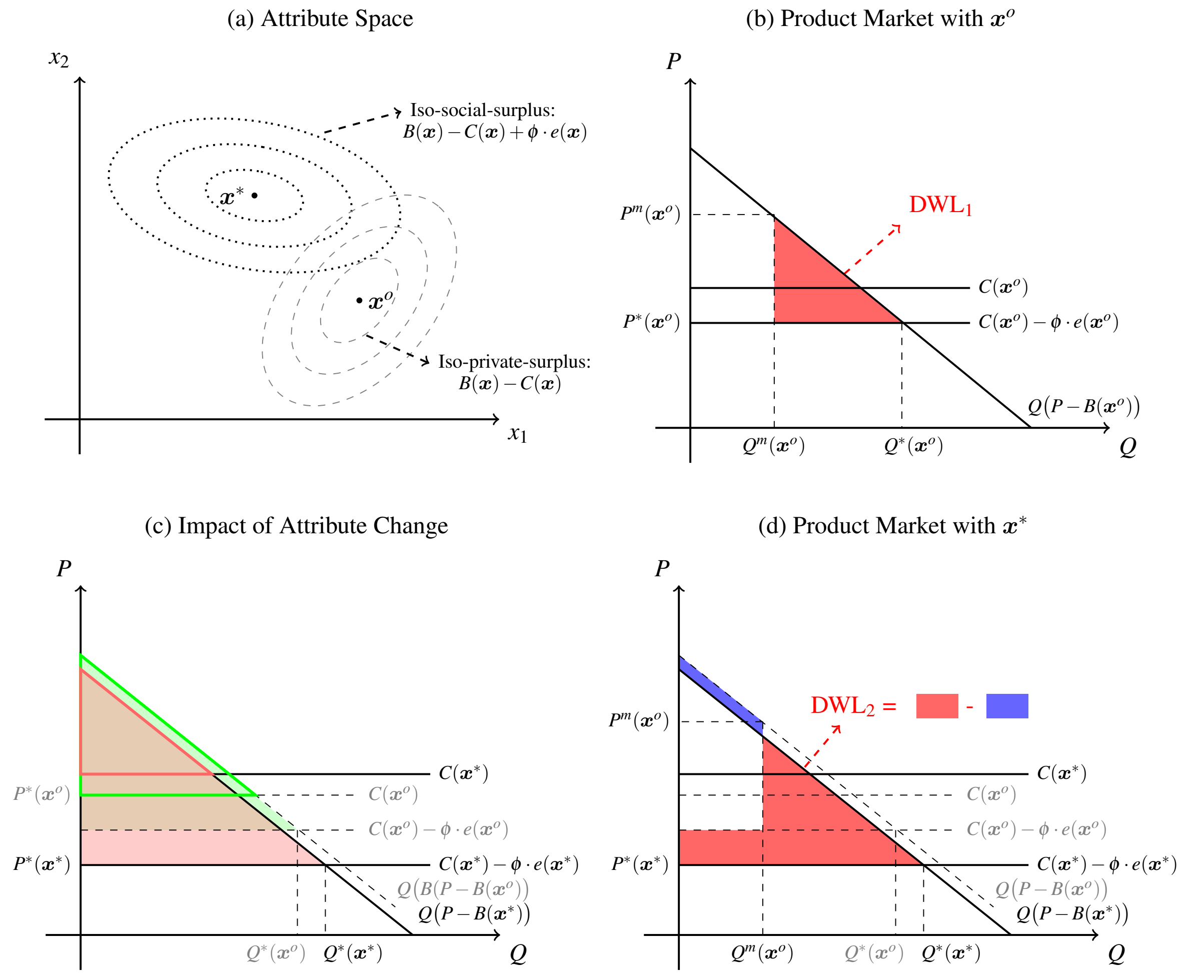
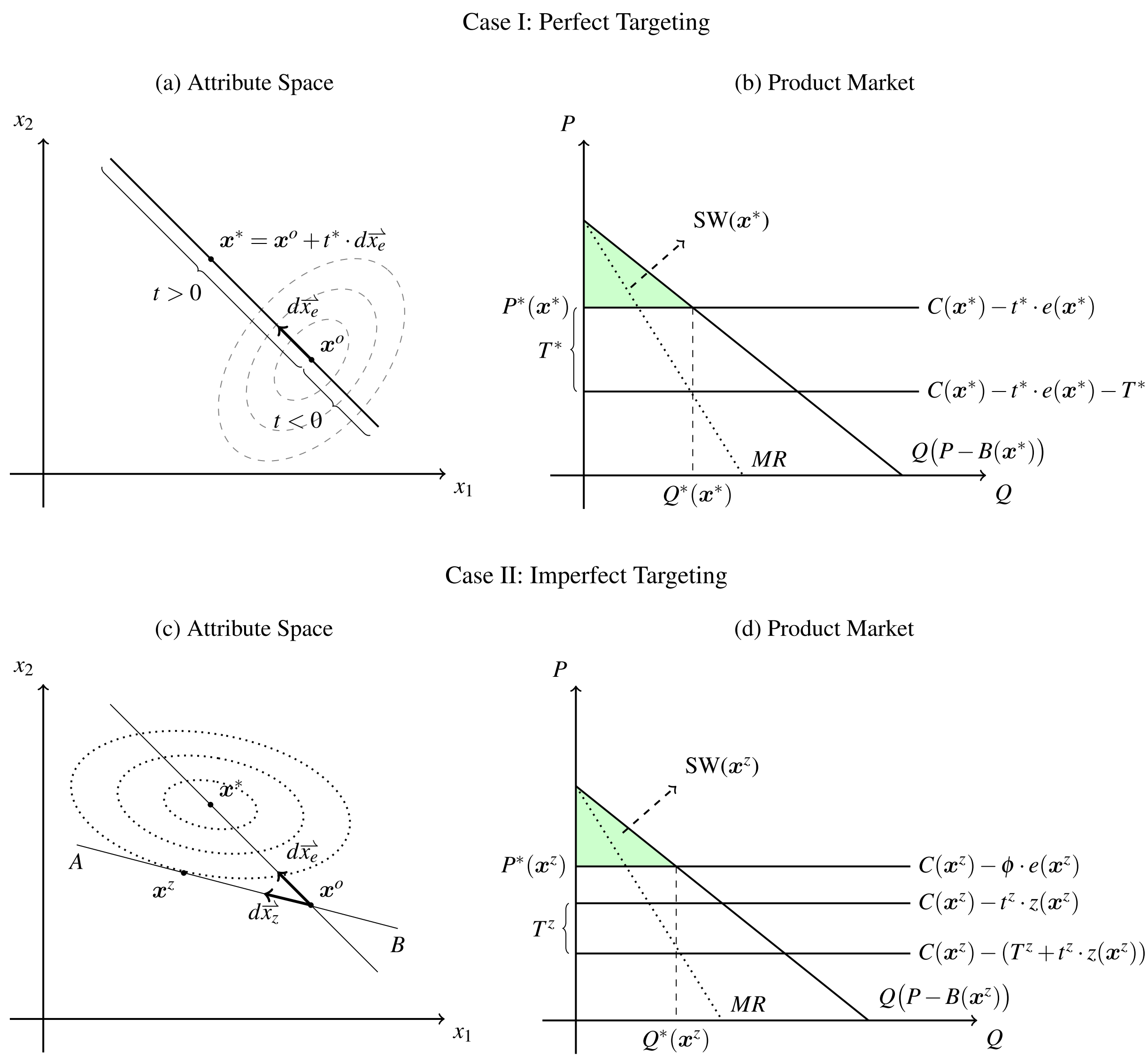
Figures & Tables

Figure 1: Attribute Choices and Social Welfare under Monopoly



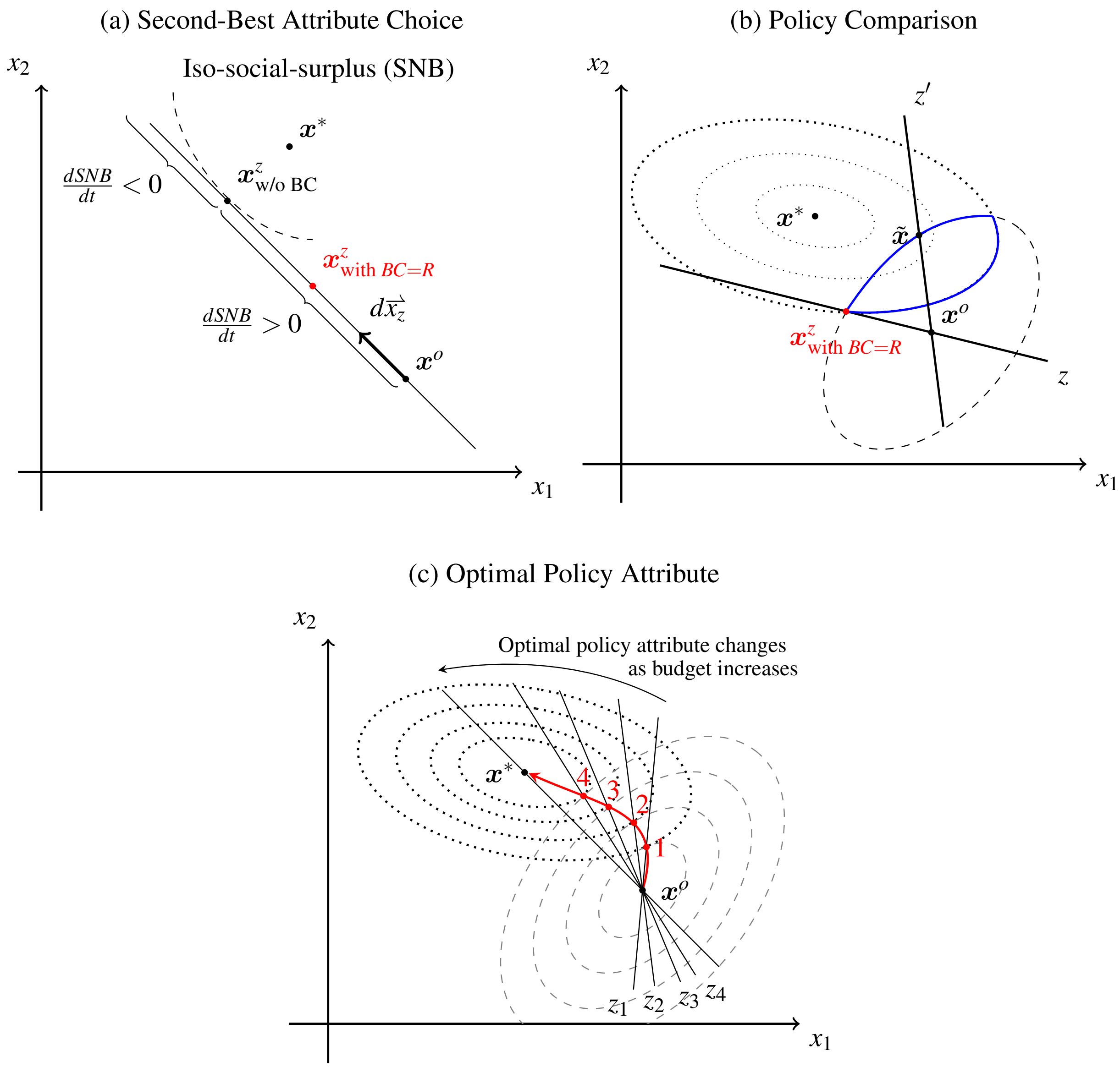
Notes: Panel (a) depicts the attribute space where the contour lines represent the iso-quant curves for the private surplus $B(\boldsymbol{x}) - C(\boldsymbol{x})$ and social surplus $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$. The monopolist chooses $\boldsymbol{x}^o$ and the social planner picks $\boldsymbol{x}^*$. Panel (b) illustrates the product market outcomes conditioning on product design $\boldsymbol{x}^o$. $P^m(\boldsymbol{x}^o)$ and $Q^m(\boldsymbol{x}^o)$ are the price and quantity chosen by the monopolist while the socially optimal price and quantity are $P^*(\boldsymbol{x}^o)$ and $Q^*(\boldsymbol{x}^o)$. The red triangle DWL$_1$ is the deadweight loss due to market power when the attributes are chosen at $\boldsymbol{x}^o$. Panel (c) depicts the impact of attribute change from $\boldsymbol{x}^o$ to $\boldsymbol{x}^*$. $\boldsymbol{x}^o$ maximizes the private surplus $B(\boldsymbol{x}) - C(\boldsymbol{x})$, so the green solid-line triangle (with the base defined by line $C(\boldsymbol{x}^o)$) is larger than the red solid-line triangle (with the base defined by line $C(\boldsymbol{x}^*)$). $\boldsymbol{x}^*$ generates the largest social surplus $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$, hence the pink shaded triangle (with the base defined by $C(\boldsymbol{x}^*) - \phi \cdot e(\boldsymbol{x}^*)$) is greater than the green shaded triangle (with the base defined by $C(\boldsymbol{x}^o) - \phi \cdot e(\boldsymbol{x}^o)$). The first best is defined as $\{\boldsymbol{x}^*, P^*(\boldsymbol{x}^*), Q^*(\boldsymbol{x}^*)\}$. Panel (d) illustrates the welfare loss from the monopoly relative to the first best. It shows the distortions from two market failures: i) product attributes is distorted due to environmental externality; and ii) quantity is distorted due to both market power and environmental externality. The difference between $Q^m(\boldsymbol{x}^o)$ and $Q^*(\boldsymbol{x}^o)$ is driven by market power while that between $Q^*(\boldsymbol{x}^o)$ and $Q^*(\boldsymbol{x}^*)$ is driven by the fact that attribute $\boldsymbol{x}^o$ is less environmental friendly than attribute $\boldsymbol{x}^*$.

Figure 2: Perfect Targeting vs. Imperfect Targeting



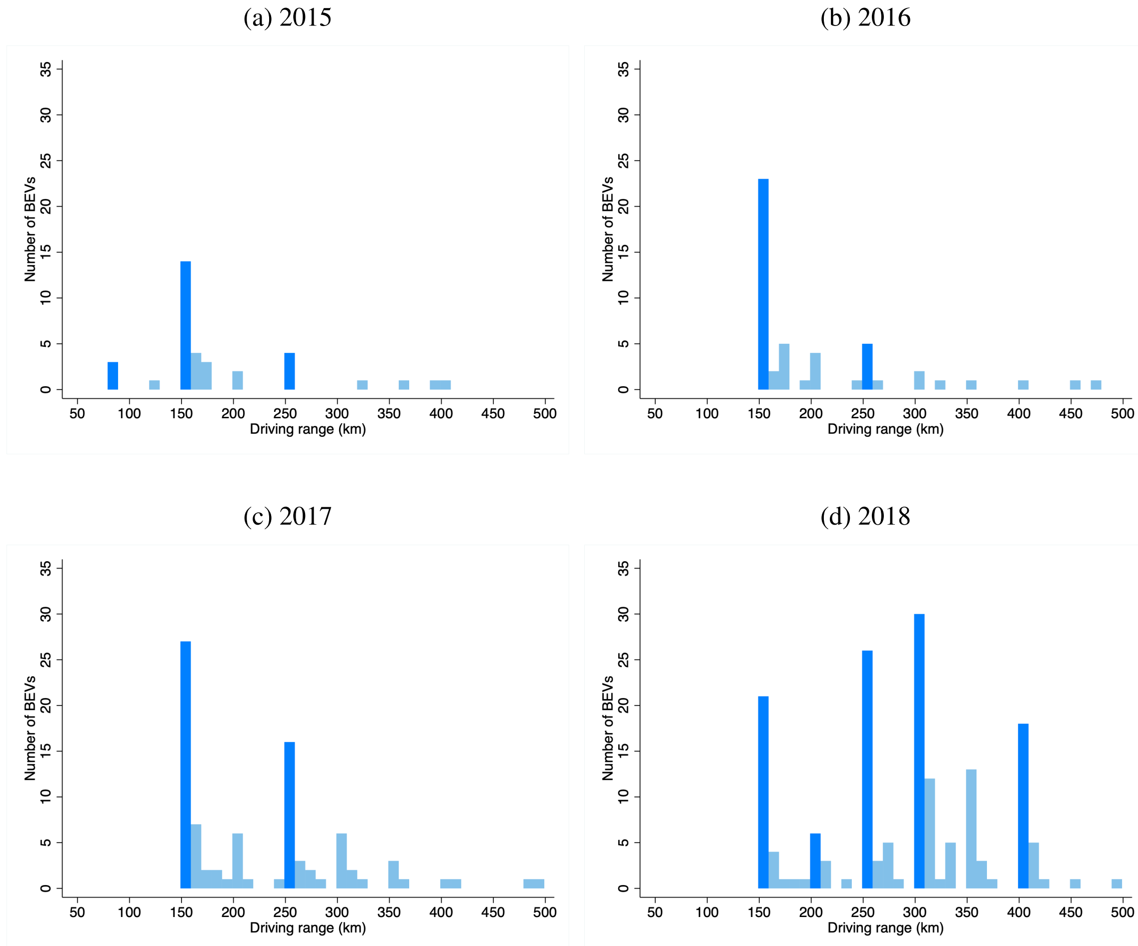
Notes: Panels (a) and (b) depict the case of perfect targeting, while Panels (c) and (d) illustrate the case of imperfect targeting. Panel (a) shows that the optimal subsidy intensity t^* induces the firm to choose the socially optimal attributes $\boldsymbol{x}^*$. The line connecting $\boldsymbol{x}^o$ and $\boldsymbol{x}^*$ denotes the firm's best responses to different subsidy intensities: any point on the line represents the firm's optimal attribute choice for a given subsidy intensity t (see Appendix A.1). Panel (b) shows that given $\boldsymbol{x}^*$, the optimal base subsidy T^* induces the monopoly to choose the socially optimal quantity $Q^*(\boldsymbol{x}^*)$. The green triangle represents the social welfare under the first-best outcome. Panel (c) shows that when the policy attribute differs from the externality (i.e., $z \neq e$), the first-best attributes $\boldsymbol{x}^*$ cannot be attained as the firm responds to the subsidy intensity t along the line connecting $\boldsymbol{x}^o$ and $\boldsymbol{x}^z$. The best attribute that is attained under imperfect targeting is $\boldsymbol{x}^z$. Panel (d) illustrates the optimal choice of T given $\boldsymbol{x}^z$. T^z induces monopoly to choose $Q^*(\boldsymbol{x}^z)$, the socially optimal quantity for product design $\boldsymbol{x}^z$. The green triangle represents the social welfare with $\{\boldsymbol{x}^z, P^*(\boldsymbol{x}^z)\ Q^*(\boldsymbol{x}^z)\}$, which is smaller than the green triangle in Panel (b).

Figure 3: Policy Choice with a Budget Constraint



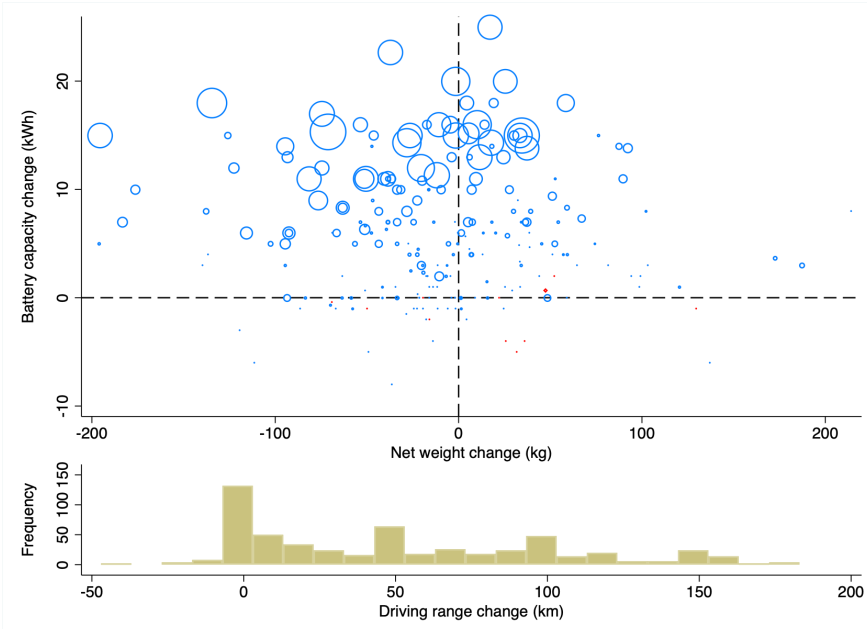
Notes: This figure demonstrates the optimal choices of policy attribute z and subsidy intensity t when the planner cannot eradicate market power due to a limited budget. In Panel (a), '$\boldsymbol{x}^z_{\text{w/o } BC}$' provides the highest per-unit social surplus given the policy attribute z without a budget constraint. With a limited budget, the planner chooses subsidy rates (T,t) to maximize social welfare under z with budget R, which induces the monopolist to choose '$\boldsymbol{x}^z_{\text{with BC=R}}$.' Panel (b) compares two policy attributes. Suppose policy attribute z does not go through a tangency point between iso-social-surplus and iso-private surplus curves. Any policy line that penetrates the blue lens leads to higher social welfare with the same budget constraint. For example, policy z' (and its corresponding optimally chosen subsidy rates (T',t')) dominates z (and T,t) in terms of social welfare. Panel (c) illustrates the choice of optimal policy attribute z. The red dots in Panel (c) are the tangency points between the iso-social- and iso-private-surplus curves. As the government budget increases, the optimal policy line shifts from z_1 to z_4, and the corresponding product attributes move away from $\boldsymbol{x}^o$ toward $\boldsymbol{x}^*$.

Figure 4: Distribution of Driving Ranges among BEV Models during 2015-2018



Notes: The horizontal lines represent the driving ranges of BEVs with a bin size of 10km. The dark blue bars represent the BEV models with a driving range just above the policy thresholds of the corresponding years. The light blue bars show the number of BEVs for which the driving range cutoffs are not binding. Bunching is pronounced. In addition, firms adjust driving ranges in response to the annual changes in subsidy cutoffs.

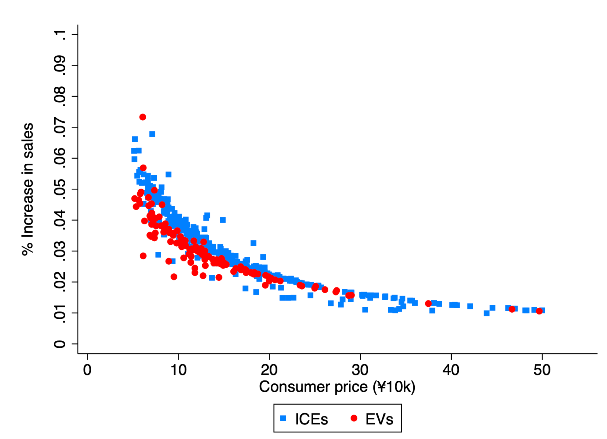
Figure 5: Changes in Vehicle Attributes



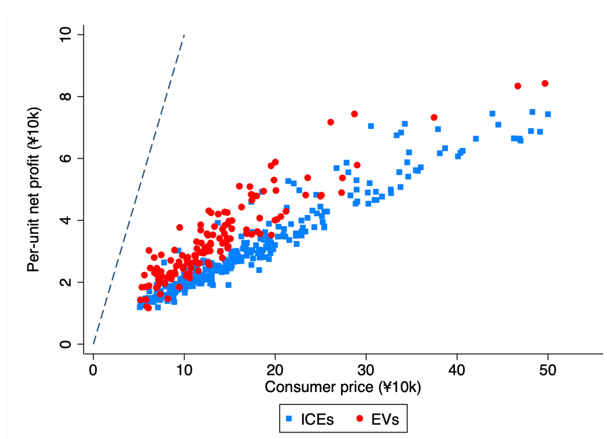
Notes: The top figure plots the year-to-year changes in net vehicle weight (exclusive of battery weight) on x-axis, and battery capacity on y-axis by vehicle model. The blue circles depict models with increasing driving ranges; the size of the circle represents the magnitude of the change. The red diamonds depict models with decreasing driving ranges; these changes are small, as shown by the sizes of the diamonds. The bottom figure depicts the histograms of the changes in driving range.

Figure 6: Semi-elasticities and Implied Markups

(a) Semi-elasticity

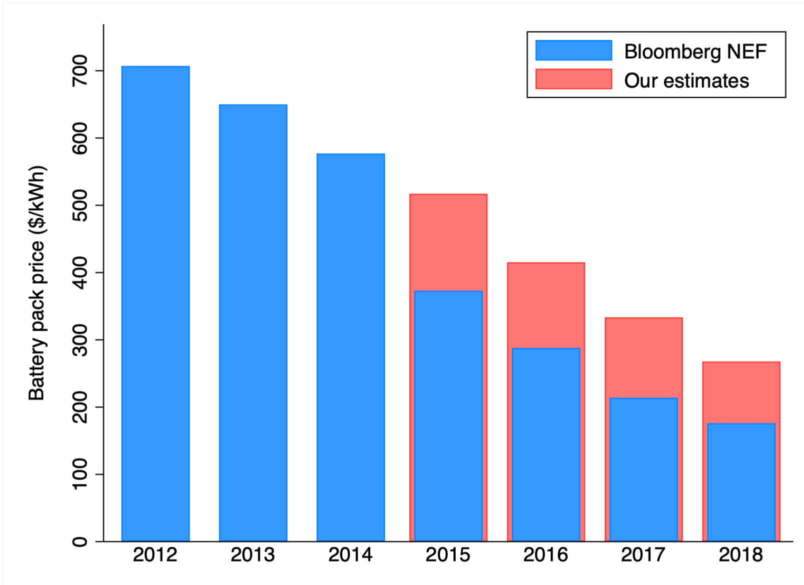


(b) Markup



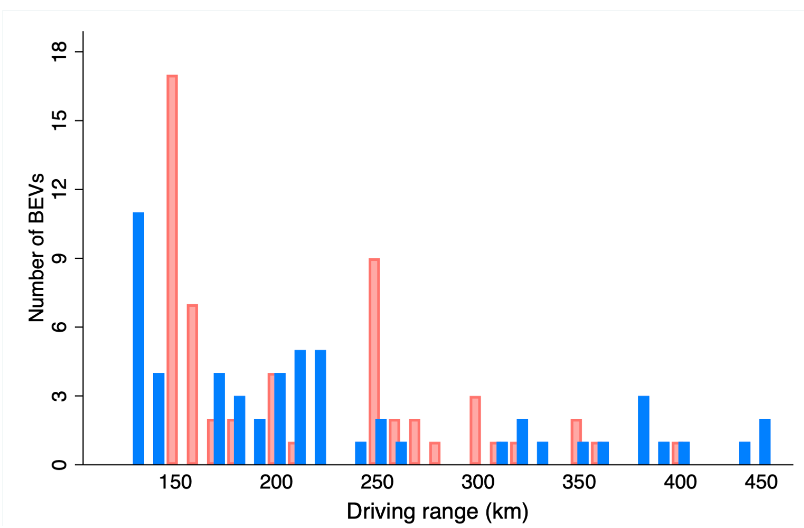
Notes: The left panel plots the price semi-elasticities, the % increase in sales when the price decreases by ¥1,000, against consumer prices (net of central and local subsidies). The right panel plots the markups (firm price as defined in Equation (7) minus marginal cost) against post-subsidy consumer prices. The red dots represent EVs while the blue dots represent ICEs.

Figure 7: Bloomberg Battery Pack Prices and Estimated Battery Costs



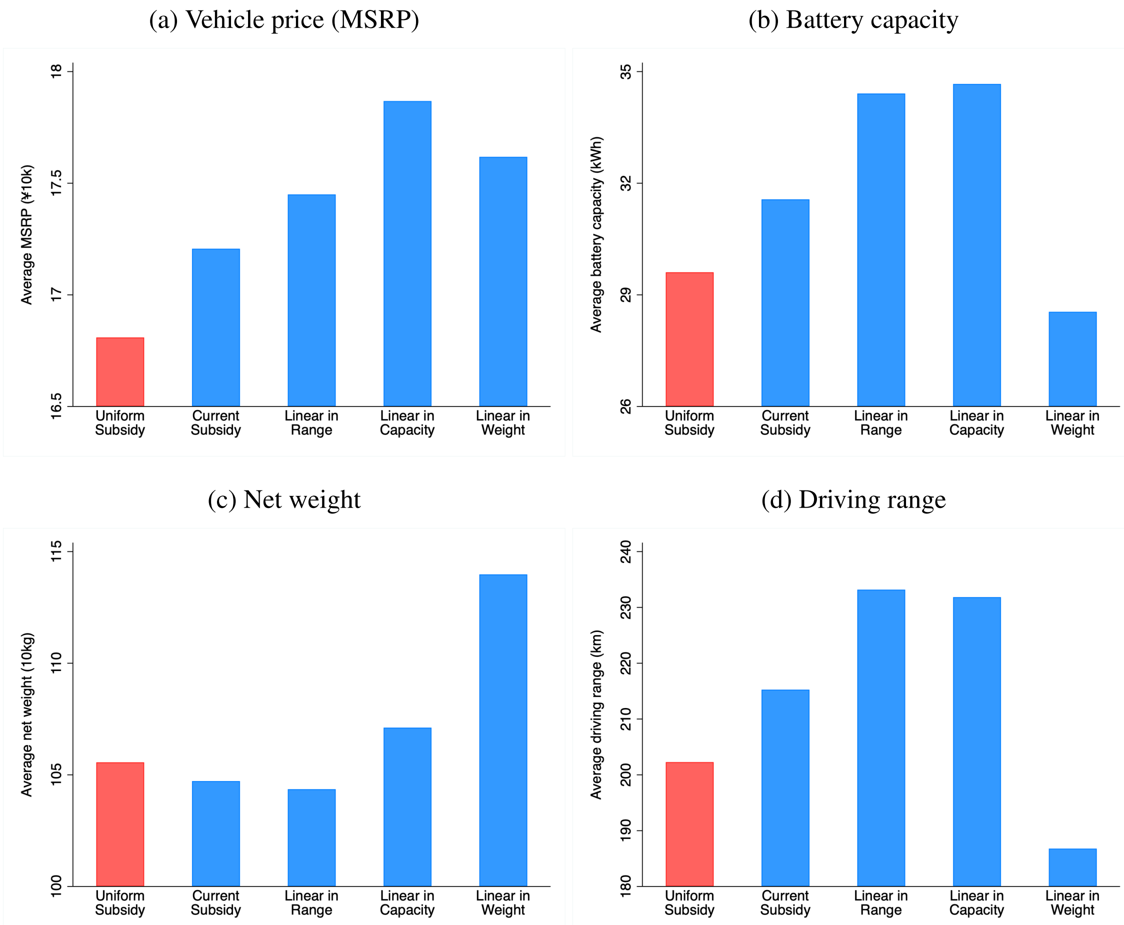
Notes: The blue bars represents Lithium-ion battery pack price (in 2018 $/kWh) from 2012 to 2018 from BloombergNEF's annual battery price survey. The pink bars show the battery cost estimates from our model. Our cost estimates are higher than Bloomberg prices because they include additional costs, such as installation costs. According to BloombergNEF's survey, battery costs declined by around 20% annually from 2012 to 2018, consistent with our estimates.

Figure 8: Notched versus Linear Subsidies



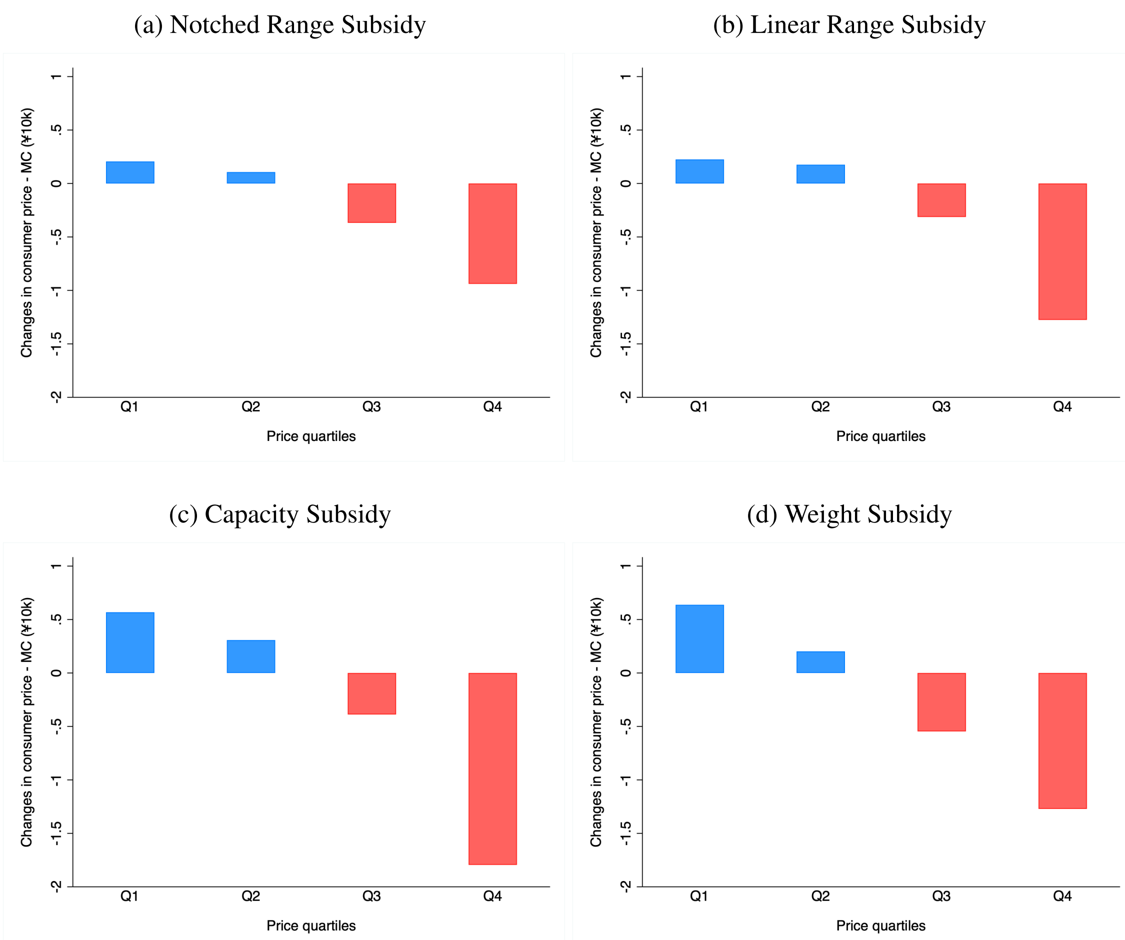
Notes: The figure depicts the observed distribution of BEVs' driving ranges under the notched subsidy policy in 2017 (in red) and the counterfactual distribution under the linear subsidy design ($T + t\cdot$ driving range) (in blue). Aggregate subsidy expenditures are the same under both designs. With a linear subsidy, bunching along the cutoffs disappears and the social welfare increases by ¥135 million.

Figure 9: Vehicle Attributes under Different Policy Designs



Notes: The plots depict average vehicle attributes (price, battery capacity, net vehicle weight exclusive of battery weight, and driving range) under the uniform subsidy and four attribute-based subsidies (ABS) for BEVs. All five scenarios have the same subsidy budget. The base subsidy rate T and the subsidy intensity t under linear ABS are chosen to maximize social welfare given the budget level.

Figure 10: Markup Changes under ABS Relative to Uniform Subsidies by Price Quartiles



Notes: The plots illustrate changes in markups (measured by post-subsidy consumer price minus marginal cost) when we move from a uniform subsidy to attribute-based subsidies (ABS) in each quartile of the price distribution (denoted by the x-axis). Relative to the uniform subsidy, ABS designs lead to a much bigger reduction in markups for products with above-median prices. These products tend to experience larger quantity distortions as a result of high markups. Capacity subsidy leads to the largest markup reduction among higher-priced products.

Table 1: Consumer Subsidies for EVs from the Central Government

Type	Range	2013	2014	2015	2016	2017	2018
BEV	$\geq$ 80km	35,000	33,250	31,500	-	-	-
	$\geq$ 100km				25,000	20,000	-
	$\geq$ 150km	50,000	47,500	45,000	45,000	36,000	15,000
	$\geq$ 200km						24,000
	$\geq$ 250km	60,000	57,000	54,000	55,000	44,000	34,000
	$\geq$ 300km						45,000
	$\geq$ 400km						50,000
PHEV	$\geq$ 50km	35,000	33,250	31,500	30,000	24,000	22,000

Notes: The table presents subsidies in ¥ for EV buyers offered by the central government from 2013 to 2018. The exchange rate between US dollar and Chinese RMB was between 6.2 and 7 (¥/$) during the period.

Table 2: Summary Statistics

	ICEs			EVs		
	# of Obs.	Mean	Std. Dev.	# of Obs.	Mean	Std. Dev.
Panel A: Model-city-year observations for demand-side analysis						
Sales	28,661	1056.58	1335.01	5,628	150.07	659.92
MSRP (¥10k)	28,661	15.46	8.79	5,628	19.62	6.93
Net weight (10kg)	28,661	141.32	21.87	5,628	121.90	41.10
Horsepower	28,661	146.29	37.17	5,628	127.47	92.67
Fuel economy (L/100km)	28,661	6.85	0.95	1,433	1.74	0.36
Engine size (L)	28,661	1.66	0.25	1,433	1.60	0.32
Central subsidy (¥10k)	-	-	-	5,628	3.76	1.32
Local subsidy (¥10k)	-	-	-	5,628	1.33	1.41
Driving range (km)	-	-	-	5,628	208.02	112.11
Battery capacity (kWh)	-	-	-	5,628	29.94	15.85
Battery density (kWh/10kg)	-	-	-	5,628	1.11	0.23
Panel B: Model-year observations for supply-side analysis						
Sales	1,261	24014.72	30916.53	279	3027.20	4493.07
MSRP (¥10k)	1,261	14.40	8.48	279	19.43	7.58
Net weight (10kg)	1,261	142.52	23.88	279	118.66	38.44
Horsepower	1,261	144.77	37.13	279	116.06	80.88
Fuel economy (L/100km)	1,261	6.99	1.06	61	1.79	0.40
Engine size (L)	1,261	1.66	0.26	61	1.59	0.32
Driving range (km)	-	-	-	279	205.68	105.19
Battery capacity (kWh)	-	-	-	279	29.72	15.73
Battery density (kWh/10kg)	-	-	-	279	1.10	0.23

Notes: Panel A shows the summary statistics for the demand analysis that uses city by year by model level observations during 2015-2018 for the top 40 cities with the largest EV sales in China. Panel B shows the summary statistics for the supply-side analysis that uses model-by-year level observations. The summary statistics for fuel economy and engine size under the EV columns are only computed for PHEVs. There are 84 firms, 497 ICE models, 164 BEV models, and 38 PHEV models during the sample period.

Table 3: Estimates of Preference Parameters

	(1) OLS Logit		(2) IV Logit		(3) Full Model	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Linear Parameters						
Price (¥10k)	0.01	0.00	-0.16	0.02	-	-
log(net vehicle weight)	-0.15	0.12	2.48	0.51	5.58	0.30
log(driving range)	0.46	0.07	0.87	0.09	1.09	0.16
Fuel economy (L/100km)	-0.05	0.01	-0.14	0.03	-0.23	0.03
Horsepower	0.00	0.00	0.01	0.00	0.02	0.00
Engine size (displacement, L)	-0.21	0.05	0.81	0.12	0.83	0.05
Price Sensitivity: $\alpha_i = -exp(\alpha_1 + \alpha_2 log(y_{im}) + \sigma_p v_{im}^p)$						
α_1 (constant)	-	-	-	-	2.31	0.35
α_2 (income)	-	-	-	-	-1.21	0.12
σ_p (random coefficient on price)	-	-	-	-	0.59	0.11
Other Random Coefficients: σ_x						
Constant	-	-	-	-	3.16	0.28
EV	-	-	-	-	1.72	0.57
Displacement (L)	-	-	-	-	0.25	0.62
No. of observations	34,329		34,329		34,329	

Notes: Column (1) reports results for the multinomial logit regression without any instruments. Columns (2) and (3) instrument price, vehicle weight, and driving range with four sets of IVs: (1) the central subsidies; (2) the sales tax rate; (3) wheelbase; and (4) supplier dummies and their interactions with battery weight. Column (3) is the random coefficient multinomial logit model and is estimated using simulated GMM with micro-moments. Net vehicle weight is the same as curb weight for ICEs and excludes battery weight for EVs. The price coefficient α_i is specified as $-exp(\alpha_1 + \alpha_2 log(y_{im}) + \sigma_p v_{im}^p$ where y_{im} is consumer income and v_{im}^p is unobserved preference shocks (i.i.d. log-normal draws). All regressions include city-by-year-by-fuel type (ICE or EV) fixed effects, brand-by-year-by-fuel type fixed effects, segment fixed effects, and vintage fixed effects (the year when the model was first introduced into the market).

Table 4: Technology Frontier: Determinants of Driving Range

	Full Sample				Commercially Launched			
	BEVs		PHEVs		BEVs		PHEVs	
	(1)		(2)		(3)		(4)	
Dep. var: driving range (km)	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Battery capacity (kWh)	6.17	0.15	6.07	0.29	6.05	0.19	4.24	0.37
Net vehicle weight (10kg)	-1.06	0.07	-0.47	0.05	-1.06	0.08	-0.37	0.07
Battery density (kWh/10kg)	27.24	7.47	-8.00	7.48	24.25	9.55	-3.00	10.32
Engine displacement (L)			5.68	3.53			14.60	4.75
# of observations	926		175		553		86	
Adj. R^2	0.90		0.79		0.90		0.74	

Notes: The dependent variable is driving range in km. The results are from OLS. Columns (1) and (2) use the full sample that includes all BEVs and PHEVs (at the trim level) that underwent the driving range test administered by China's Ministry of Industry and Information Technology (MIIT). MIIT conducted 22 batches of tests during our sample period, for a total of 926 BEV trims and 175 PHEV trims. Columns (3) and (4) use the subset of trims that were commercially launched in the Chinese market. Columns (1) and (3) report results for BEVs and Columns (2) and (4) report results for PHEVs. Net vehicle weight excludes the weight of batteries. All regressions include the fixed effects for the test result announcement dates to control for the technology progress as well as potential differences in testing technology and methodology over time.

Table 5: Marginal Cost, Fixed Cost, and Shadow Value Estimates

		(1) OLS		(2) GMM with common slackness		(3) GMM with model specific λ_j	
Panel A: Marginal cost (¥10k)		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
γ_w	Net vehicle weight (10kg)	0.08	0.01	0.11	0.01	0.11	0.01
γ_k	Battery capacity (kWh)	0.05	0.01	0.36	0.05	0.36	0.04
ρ	Battery cost depreciation			0.80	0.03	0.80	0.03
γ^{other}	Horsepower	0.02	0.00	0.02	0.00	0.02	0.00
	Displacement (L)	2.68	0.37	2.60	0.45	2.60	0.45
	Fuel consumption (L/100km)	-0.69	0.11	-0.65	0.11	-0.67	0.11
	Year FE (base year: 2015)						
	2016	-0.43	0.15	-0.28	0.15	-0.29	0.15
	2017	-0.98	0.15	-0.68	0.15	-0.69	0.15
	2018	-1.71	0.16	-1.15	0.16	-1.17	0.16
Panel B: Fixed cost (¥10k)							
ϕ_w	Net vehicle weight (10kg)			-24.53	85.34	-37.40	74.58
ϕ_k	Battery capacity (kWh)			842.96	414.53	907.4	299.6
Panel C: Shadow value (¥10k/1km)							
$E[\lambda \vert W]$	Slackness parameter			198.9	89.1		
ζ	Sales					0.014	0.007

Notes: Column (1) reports the OLS results for the marginal cost Equation (10). Columns (2) and (3) estimate all marginal and fixed cost parameters simultaneously using GMM. Column (2) estimates the slackness parameters in Equations (12) and (13) for observations with binding constraints following Moon and Schorfheide (2009). Column (3) estimates the product-specific shadow value λ_j as a function of sales. The number of observations is 1,540 for Panel A and 279 for Panels B and C. In Panel A, parameters γ_w and γ^{other} (coefficients for other exogenous variables in the marginal cost equation) are for both EVs and ICEs; the other parameters are only for EVs. Parameters γ_w and $\rho^t \cdot \gamma_k$ represent the marginal cost slope with respect to weight and battery capacity, and ρ captures battery costs' annual depreciation relative to the base year 2015. The estimated battery cost decreased from ¥3,620/kWh in 2015 to ¥1,874/kWh in 2018. In Panel B, ϕ_w and ϕ_k represent the slope of fixed costs with respect to net vehicle weight and battery capacity. In Panel C, the ζ estimate implies that EV makers are willing to pay ¥140 per vehicle to reduce the binding driving range constraint by 1km. All estimations include year, fuel type, segment, and brand fixed effects separately for marginal costs and fixed costs.

Table 6: Welfare Impacts of ABS Subsidies Relative to Uniform Subsidy

		Changes relative to the uniform subsidy			
		Notched Range (1)	Linear Range (2)	Capacity (3)	Weight (4)
Δ Total welfare (in ¥mil.)		97.2	232.1	448.0	376.7
Δ Consumer surplus		226.2	316.7	643.2	679.9
Δ Firm Profit	BEV	-16.0	57.0	92.1	5.4
	PHEV	-3.8	-4.7	-8.9	-7.3
	ICE	-38.8	-52.6	-123.3	-119.5
	Total	-58.6	-0.2	-40.1	-121.5
Δ Emissions	CO_2	60.6	71.9	131.2	151.7
	PM	1.2	1.6	3.0	3.6
	NOx	8.1	10.5	18.4	20.7
	SO_2	0.5	0.4	2.6	5.8
	Total	70.4	84.4	155.2	181.8

Notes: Aggregate central subsidies are fixed in all columns. The unit is ¥million (in 2017) for all cells. Each cell represents the change under an attribute-based subsidy (ABS) relative to the uniform subsidy. The four columns are the observed notched-range subsidy and the optimal linear design (i.e., the two-part tariff) based on driving range, battery capacity, and vehicle weight, respectively. The rows titled 'Δ Emissions' represent monetized health damages (in ¥mil.) from increased emissions: a positive value implies an increase in the health costs of emissions relative to the uniform subsidy.

Table 7: Channels Underlying Welfare Changes

Panel A: Welfare Decomposition

Welfare changes relative to uniform subsidy (in ¥mil.)		Benefits from Improved Attributes			Benefits from Mitigating Market Power		
		Range (1)	Capacity (2)	Weight (3)	Range (4)	Capacity (5)	Weight (6)
Δ Total welfare		97.8	277.7	209.5	134.3	170.3	167.2
Δ CS and Profit	CS	138.8	375.3	401.5	178.0	267.9	278.5
	Profit	-16.1	-49.1	-138.8	15.9	9.0	17.3
	Total	122.7	326.3	262.7	193.8	276.8	295.8
Δ Emissions		24.9	48.6	53.2	59.6	106.5	128.6

Panel B: Welfare Changes from Subsidy Redistribution

Welfare gains from subsidy redistribution (in ¥mil.)		ABS Design with Optimal T_j		
		Range (1)	Capacity (2)	Weight (3)
Δ Total welfare		143.2	152.6	190.2
Δ CS and Profit	CS	121.8	112.6	153.6
	Profit	36.8	50.7	55.5
	Total	158.6	163.3	209.1
Δ Emissions		15.4	10.7	18.9

Notes: Aggregate central subsidies are fixed in all columns. The unit is ¥million (in 2017) for all cells. Panel A decomposes welfare gains into two sources: improved attributes and reduced market power distortions. In the first three columns, we fix subsidy expenditures at the baseline (the uniform subsidy) but use the equilibrium attributes associated with each ABS and allow firms to adjust prices and quantities given the ABS attributes. This isolates the effect of improved attributes. In the last three columns, attributes are the same as the first three columns but subsidies adjust to the ABS level. ABS designs provide more subsidies to products with above-median prices and are more effective at mitigating market power distortions. In Panel B, we allocate subsidies optimally at the product level in the form of $T_j + t * z(X)$ with a product-specific base subsidy T_j. Welfare further improves due to the improved subsidy redistribution that better addresses varying degrees of distortions among products (i.e., higher subsidies to products with more severe distortions and with demand more responsive to subsidies).

Online Appendix

Attribute-based Subsidies and Market Power: an Application to Electric Vehicles

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A Theoretical Model

This appendix provides additional materials (e.g., discussions and proofs) for the theoretical model.

A.1 Details of Section 2.1: Choices by Monopoly and Social Planner

Socially Optimal Attributes and Price The social welfare consists of consumer surplus, producer surplus, and externality:

$$\begin{aligned} SW(P,\ \boldsymbol{x}) &= \underbrace{\int_0^{Q(P,\ \boldsymbol{x})} \big(B(\boldsymbol{x}) + Q^{-1}(s) - P\big) ds}_{\text{Consumer surplus}} + \underbrace{\big(P - C(\boldsymbol{x})\big) Q(P,\ \boldsymbol{x})}_{\text{Producer surplus}} + \underbrace{\phi \cdot e(\boldsymbol{x}) Q(P,\ \boldsymbol{x})}_{\text{Externality}} \\ &= (B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x}))Q(P,\ \boldsymbol{x}) + \int_0^{Q(P,\ \boldsymbol{x})} Q^{-1}(s) ds. \end{aligned}$$

The derivatives of the social welfare with respect to price and attributes are given as follows:

$$\begin{aligned} SW_P(P,\ \boldsymbol{x}) &= (P - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x}))Q_P(P,\ \boldsymbol{x}) \\ SW_k(P,\ \boldsymbol{x}) &= (B_k(\boldsymbol{x}) - C_k(\boldsymbol{x}) + \phi \cdot e_k(\boldsymbol{x}))Q(P,\ \boldsymbol{x}) + (P - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x}))Q_k(P,\ \boldsymbol{x}), \end{aligned}$$

where the subscript P or k implies a partial derivative with respect to the price or kth element of $\boldsymbol{x}$. If the regulator can choose any combinations of price and attributes, the optimal price P^* and attributes $\boldsymbol{x}^*$ should satisfy $SW_P(P,\ \boldsymbol{x}) = 0$ and $SW_k(P,\ \boldsymbol{x}) = 0$ for all k. $SW_P(P,\ \boldsymbol{x}) = 0$ requires $P^* - C(\boldsymbol{x}^*) + \phi \cdot e(\boldsymbol{x}^*) = 0$. In addition, $SW_k(P,\ \boldsymbol{x}) = 0$ implies $B_k(\boldsymbol{x}^*) - C_k(\boldsymbol{x}^*) + \phi \cdot e_k(\boldsymbol{x}^*) = 0$.

Proof of Proposition 1 With attribute-based subsidies, firm's profit maximization problem is:

$$\max_{P,\ \boldsymbol{x}} \Big(P - C(\boldsymbol{x}) + T + t \cdot z(\boldsymbol{x})\Big)\, Q\big(P - B(\boldsymbol{x})\big) \tag{A1}$$

$$[P]: \qquad \frac{P^z - C(\boldsymbol{x}^z) + T + t \cdot z(\boldsymbol{x}^z)}{P^z} = \frac{1}{\varepsilon_P(P^z,\ \boldsymbol{x}^z)}, \tag{A2}$$

$$[x_k]: \quad B_k(\boldsymbol{x}^z) - C_k(\boldsymbol{x}^z) + t \cdot z_k(\boldsymbol{x}^z) = 0 \ \text{ for } \ i = 1, 2, ..., K. \tag{A3}$$

Proof: Under the perfect targeting ($z = e$), the private first-order condition, Equation (A3), becomes identical with the social optimal condition, Equation (4), when $t = \phi$. Thus, the social planner can achieve the socially optimal attributes $\boldsymbol{x}^e(\phi) = \boldsymbol{x}^*$. Since $\boldsymbol{x}^e(\phi) = \boldsymbol{x}^*$, $P^e(T^*,\ \phi) - C(\boldsymbol{x}^e(\phi)) + \phi \cdot e(\boldsymbol{x}^e(\phi)) = 0$ satisfies the other social optimal condition, Equation (3). Therefore, the social planner attains socially optimal pricing as well: $P^e(T^*,\ \phi) = P^*$.

Graphical Illustration of ABS Suppose the regulator provides subsidies based on a policy attribute z. We specify the private welfare loss as a quadratic function and assume the policy attribute z is linear in $\boldsymbol{x}$. Suppose any deviation from $\boldsymbol{x}^o$ incurs private welfare losses as a quadratic function:

$$\begin{aligned} L(\Delta x_1, \Delta x_2) &= L(x_1 - x_1^o, x_2 - x_2^o) \\ &= \{B(\boldsymbol{x}^o) - C(\boldsymbol{x}^o)\} - \{B(\boldsymbol{x}) - C(\boldsymbol{x})\} \\ &= \alpha(x_1 - x_1^o)^2 + \beta(x_2 - x_2^o)^2 + \gamma(x_1 - x_1^o)(x_2 - x_2^o). \end{aligned}$$

The quadratic private loss function makes the iso-private-surplus curves ellipse. If e is linear in $\boldsymbol{x}$, the social benefit, $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$, also has ellipse convex contour lines.

From Equation (A3), we know

$$\begin{aligned} \boldsymbol{x}^z(t) &= \operatorname*{argmax}_{\boldsymbol{x}} B(\boldsymbol{x}) - C(\boldsymbol{x}) + t \cdot z(\boldsymbol{x}) \\ &= \operatorname*{argmax}_{\boldsymbol{x}} B(\boldsymbol{x}^o) - C(\boldsymbol{x}^o) + t \cdot z(\boldsymbol{x}) - L(\Delta x_1, \Delta x_2). \end{aligned}$$

Thus, $\boldsymbol{x}^z(t)$ should satisfy the following first-order conditions:

$$\begin{aligned} t \cdot z_1(\boldsymbol{x}^z(t)) &= 2\alpha(x_1^z(t) - x_1^o) + \gamma(x_2^z(t) - x_2^o) = 2\alpha\Delta x_1^z(t) + \gamma\Delta x_2^z(t) \\ t \cdot z_2(\boldsymbol{x}^z(t)) &= 2\beta(x_2^z(t) - x_2^o) + \gamma(x_1^z(t) - x_1^o) = 2\beta\Delta x_2^z(t) + \gamma\Delta x_1^z(t), \end{aligned}$$

where $z_1(\boldsymbol{x})$ and $z_2(\boldsymbol{x})$ are the partial derivatives with respect to the first and second element of $\boldsymbol{x}$. If the policy attribute z is linear in $\boldsymbol{x}$, the partial derivatives are constant, z_1 and z_2. Then, we can express the firm's best response to subsidies as follows:

$$(\Delta x_1^z(t), \Delta x_2^z(t)) = t \cdot (\frac{2\beta z_1 - \gamma z_2}{4\alpha\beta - \gamma^2}, \frac{2\alpha z_2 - \gamma z_1}{4\alpha\beta - \gamma^2}) = t \cdot d\overrightarrow{x_z}.$$

Thus, the firm's best response to subsidies becomes a straight line. If the subsidy intensity t is zero, the deviation $\Delta \boldsymbol{x}^z(t)$ become zero and the firm chooses $\boldsymbol{x}^z(t) = \boldsymbol{x}^o$. Also, a larger $|t|$ results in a greater deviation in the firm's attribute choices away from $\boldsymbol{x}^o$.

A.2 Details of Section 2.2: Attribute-based Regulations with Budget Constraints

Proof of Lemma 1 With attribute-based subsidies, firm's profit maximization problem is:

$$\max_{P,\ \boldsymbol{x}} \Big(P - C(\boldsymbol{x}) + T + t \cdot z(\boldsymbol{x})\Big)\ Q\big(P - B(\boldsymbol{x})\big) \tag{A4}$$

$$[P]: \qquad \frac{P^z - C(\boldsymbol{x}^z) + T + t \cdot z(\boldsymbol{x}^z)}{P^z} = \frac{1}{\varepsilon_P(P^z,\ \boldsymbol{x}^z)}, \tag{A5}$$

$$[x_k]: \quad B_k(\boldsymbol{x}^z) - C_k(\boldsymbol{x}^z) + t \cdot z_k(\boldsymbol{x}^z) = 0 \ \text{ for } \ i = 1, 2, \ldots, K. \tag{A6}$$

Proof: Given a policy triplet (T, t, z), the equilibrium quantity $Q\big(P^z(T,t),\ \boldsymbol{x}^z(t)\big)$ is determined by Equation (A5). Using the fact that $\boldsymbol{x}^z(t)$ does not depend on Equation (A5), we can rewrite the firm's pricing decision separately as follows:

$$\max_{P} \Big(P - C(\boldsymbol{x}^z(t)) + T + t \cdot z(\boldsymbol{x}^z(t))\Big)\ Q\big(P - B(\boldsymbol{x}^z(t))\big).$$

We can switch the decision variable from P to $\tilde{P} = P - B(\boldsymbol{x}^z(t))$. Then, the problem becomes

$$\max_{\tilde{P}} \Big(\tilde{P} + B(\boldsymbol{x}^z(t)) - C(\boldsymbol{x}^z(t)) + T + t \cdot z(\boldsymbol{x}^z(t))\Big)\ Q\big(\tilde{P}\big).$$

Further simplify it by denoting $b = T + t \cdot z(\boldsymbol{x}^z(t))$ and $k = B(\boldsymbol{x}^z(t)) - C(\boldsymbol{x}^z(t))$. Then, the equilibrium quantity comes from a solution of the following problem.

$$\max_{\tilde{P}} (\tilde{P} + k + b)\ Q(\tilde{P}). \tag{A7}$$

The solution $\tilde{P}^*(b,k)$ should satisfy

$$\text{FOC}: \quad Q\big(\tilde{P}^*(b,k)\big) + (\tilde{P}^*(b,k) + k + b)\ Q'\big(\tilde{P}^*(b,k)\big) = 0, \tag{A8}$$

$$\text{SOC}: \quad \underbrace{2Q'\big(\tilde{P}^*(b,k)\big) + (\tilde{P}^*(b,k) + k + b)\ Q''\big(\tilde{P}^*(b,k)\big)}_{\text{denoted by } S(b,k)} < 0. \tag{A9}$$

Taking the partial derivative of Equation (A8) with respect to b and k, we have

$$S(b,k)\frac{\partial \tilde{P}^*(b,k)}{\partial b} = S(b,k)\frac{\partial \tilde{P}^*(b,k)}{\partial k} = -Q'\big(\tilde{P}^*(b,k)\big) > 0.$$

Based on Equation (A9), we know

$$\frac{\partial \tilde{P}^*(b,k)}{\partial b} = \frac{\partial \tilde{P}^*(b,k)}{\partial k} < 0. \tag{A10}$$

Write the equilibrium quantity as $Q(b,k) = Q(\tilde{P}^*(b,k))$, Equation (A10) implies

$$\frac{\partial Q(b,k)}{\partial b} = \frac{\partial Q(b,k)}{\partial k} > 0.$$

By the assumption in Lemma 1, the budget constraint $b \cdot Q(b,k) = R$ holds. Take the total differentiation of the budget constraint with the fact that R is a constant, we get

$$\Big(Q(b,k) + b \cdot \frac{\partial Q(b,k)}{\partial b}\Big)db + b \cdot \frac{\partial Q(b,k)}{\partial k}dk = 0.$$

Therefore, b and k should move in the opposite direction to keep the budget constraint satisfied. Suppose there is another policy (T', t', z') that results in (b', k') while (b,k) is attained from the policy (T,t,z). If $k > k'$, then $b < b'$. Thus, $Q(b,k) > Q(b',k')$ because $b \cdot Q(b,k) = b' \cdot Q(b',k')$.

Second Best Design with a Budget Constraint The social planner's problem under the budget constraint is:

$$\max_t \; SW\big(P^z(T(t),\, t),\, \boldsymbol{x}^z(t)\big) \;\text{ where }\; \big(T(t) + t \cdot z(\boldsymbol{x}^z(t))\big) \cdot Q\big(P^z(T(t),\, t),\, \boldsymbol{x}^z(t)\big) = R.$$

Here, $T(t)$ is uniquely determined by t and R because the left-hand side of the budget constraint is strictly increasing in T. The first-order condition becomes

$$\begin{aligned}\frac{dSW}{dt} =& \Big[\underbrace{\sum_k \Big(B_k(\boldsymbol{x}^z(t)) - C_k(\boldsymbol{x}^z(t)) + \phi \cdot e_k(\boldsymbol{x}^z(t))\Big)\frac{dx_k^z(t)}{dt}}_{dSNB/dt}\Big] Q\big(P^z(T(t),\, t),\, \boldsymbol{x}^z(t)\big) \\ &+ \Big(\underbrace{P^z(T(t),\, t) - C(\boldsymbol{x}^z(t)) + \phi \cdot e(\boldsymbol{x}^z(t))}_{>\,0 \text{ due to the budget constraint}}\Big)\underbrace{\frac{dQ\big(P^z(T(t),\, t),\, \boldsymbol{x}^z(t)\big)}{dt}}_{<\,0 \text{ by Lemma 1}} = 0,\end{aligned} \tag{A11}$$

where $SNB = B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$. As t increases, $\boldsymbol{x}^z(t)$ deviates further from the private best choice, $\boldsymbol{x}^o$, reducing $B(\boldsymbol{x}) - C(\boldsymbol{x})$. Therefore, the greater the subsidy intensity t is, the smaller the quantity is achievable in the product market by Lemma 1. Thus, if the budget constraint is binding, which leaves a positive markup $P - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x}) > 0$, then $dSNB/dt$ should be positive. Figure 3 (a) shows where $dSNB/dt > 0$ holds on the best-response line. The second-best product design "$\boldsymbol{x}^z_{\text{with}BC=R}$" lies between "$\boldsymbol{x}^z_{\text{w/o BC}}$" and $\boldsymbol{x}^o$ to satisfy $dSNB/dt > 0$.

We further discuss how the position of "$\boldsymbol{x}^z_{\text{with}BC=R}$" changes as the budget level R increases. If the social planner has extra subsidy funds, there are two options to enhance social welfare. First, the planner can increase the per-unit benefit, SNB, without compromising sales by raising both T and t. Second, the planner can boost sales without affecting the product design (i.e., keeping SNB unchanged) by raising T only. If the demand function does not exhibit an extreme shape, the planner would improve both SNB and sales, utilizing the additional subsidy budget. The statement that the demand function is regular implies the following: Suppose that the entire increase in R is solely used for the increase in T, and t does not change (implying $x^z(t)$ also remains unchanged). Then, in Equation (A11), $dSNB/dt$ does not change, Q increases, and $P^z - C + \phi \cdot e$ decreases. Therefore, unless the increase in R leads to a substantial increase in $|dQ/dt|$,[34] dSW/dt becomes positive. So, it is optimal for the planner to increase t to enhance SNB. Consequently, "$\boldsymbol{x}^z_{\text{with}BC=R}$" shifts towards "$\boldsymbol{x}^z_{\text{w/o }BC}$" as R increases. If R becomes high enough so that the budget constraint is no longer binding, the planner opts for "$\boldsymbol{x}^z_{\text{w/o }BC}$" as the second-best product design.

Proof of Proposition 2 *Proof of i):* Suppose (T^R, t^R, z^R) maximizes the social welfare for a given budget limit R. Then, $\boldsymbol{x}^{z^R}(t^R)$ should be on the contract curve. Otherwise, we can create a lens from $\boldsymbol{x}^{z^R}(t^R)$ as in Figure 3 (b), which leads to the contradiction that there exists another policy attribute z' that dominates z^R.

Proof of ii): Consider a product design $\boldsymbol{x}$ on the contract curve and z that creates the firm response line passes through $\boldsymbol{x}$. First, there exists a budget level R that makes $\boldsymbol{x}$ as the second-best product design.[35] Since $\boldsymbol{x}$ is on the contract curve, we cannot create a lens from $\boldsymbol{x}$. Therefore, z is the best policy attribute with R. Given that $\boldsymbol{x}$ is the best product design on the firm response

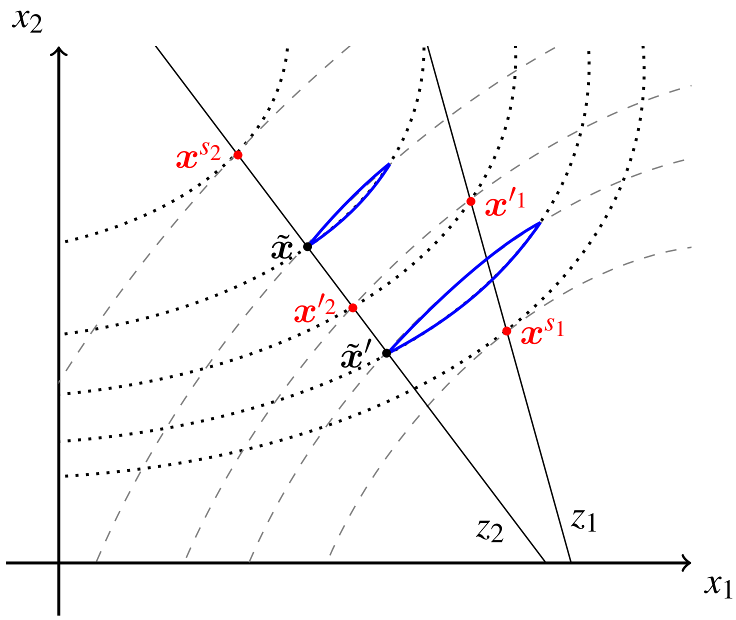
[34] Let's explore the meaning of dQ/dt. An increase in t leads to a decrease in k in Equation (A10), thereby reducing Q. Since $\tilde{P}$ is a function of $b + k$, we can express the planner's budget constraint as $b \cdot Q(\tilde{P}(b+k)) = R$. If we denote $\tilde{Q}(.) = Q(\tilde{P}(.))$ and the per-unit subsidy that satisfies the budget constraint given k as $b(k)$, then we have $b(k) \cdot \tilde{Q}(b(k)+k) = R$. Consider

$$\frac{dQ}{dt} = \frac{d\tilde{Q}(b(k)+k)}{dk} \cdot \frac{dk}{dt}.$$

Here, dk/dt is negative and does not depend on the budget level R. On the other hand, $d\tilde{Q}(b(k) + k)/dk$ is positive due to Lemma 1 and either increasing or decreasing in R. For example, if $\tilde{Q}(.)$ is linear, $|d\tilde{Q}(b(k)+k)/dk|$ decreases as R increases.

[35] As discussed in the previous subsection, the second-best design moves along the firm response line depending on the budget level R.

Figure A1: Second-Best Attribute Choice with a Budget Constraint



Notes: The figure demonstrates how to compare the budget levels to achieve two tangent points of iso-social and iso-private surplus curves as the second-best choice. Specifically, this figure is used to prove that the required budget level for $\boldsymbol{x}^{s_2}$ to be the second-best choice is greater than that for $\boldsymbol{x}^{s_1}$.

line with z and z is the best policy attribute with R, we can conclude that $\boldsymbol{x}$ is the optimal product design. Furthermore, there exists a unique t that incentivizes the firm to select $\boldsymbol{x}$ with the given policy attribute z. Finally, the combination of (t,z,R) determines T through the budget constraint. If we denote these values as (T^R, t^R, z^R, R), this policy triad achieves $\boldsymbol{x}' = \boldsymbol{x}^{z'}(t^R)$.

Proof of iii): We provide Figure A1 to prove the statement. Suppose (R^1, z^1) makes $\boldsymbol{x}^{s_1}$ the second-best design while $\boldsymbol{x}^{s_2}$ the second-best under (R^2, z^2). We want to show that R^2 is greater than R^1. Note that we can always find two points, $\boldsymbol{x}'^1$ and $\boldsymbol{x}'^2$, on the two policy lines where the iso-social-surplus curve and iso-private-surplus curve cross. From the discussion in the previous subsection, we know there are budget levels R'^1 and R'^2 such that $\boldsymbol{x}'^1$ and $\boldsymbol{x}'^2$ are the second-best product design given (R'^1, z^1) and (R'^2, z^2), respectively. In addition, $R'^1 > R^1$ and $R'^2 < R^2$ should hold. Therefore, if we prove $R'^1 = R'^2$, then we have $R^2 > R'^2 = R'^1 > R^1$.

If a budget level R is greater than R'^2, the planner should prefer z_2 to z_1 with R. For instance, suppose $\tilde{\boldsymbol{x}}$ is the second-best choice given (R, z_2). Since R is greater than R'^2, compared to $\boldsymbol{x}'^2$, $\tilde{\boldsymbol{x}}$ should be closer to $\boldsymbol{x}^*$ (i.e., more away from $\boldsymbol{x}^o$). Then, the z_1 line does not pass the blue lens from $\tilde{\boldsymbol{x}}$ in Figure A1. Therefore, z_2 is better than z_1 when the budget level is R. Let's denote this statement by $z_2 \succ_R z_1$. In contrast, if R is less than R'^2, the planner must prefer z_1 to z_2. For example, suppose $\tilde{\boldsymbol{x}}'$ is the second-best given (R, z_2), then $z_1 \succ_R z_2$ since the z_1 line passes through the blue lens generated from $\tilde{\boldsymbol{x}}'$.

Thus, we can establish that $R \geq R'^2$ if and only if $z_2 \succsim_R z_1$. This implies $R'^1 \geq R'^2$. To reach a contradiction, let's assume $R'^1 < R'^2$. This assumption leads to $z_1 \succ_{R'^1} z_2$, which is not true as the z_2 line does not intersect with the lens from $\boldsymbol{x}'^1$. By a similar reasoning, we can deduce $R'^2 \geq R'^1$. Consequently, we reach the conclusion that $R'^2 = R'^1$. The preceding discussion indicates the existence of a budget level $\tilde{R} \in (R^1, R^2)$ where the planner is indifferent between z_1 and z_2. The planner favors z_1 over z_2 if the budget is below $\tilde{R}$ and prefers z_2 over z_1 if the budget exceeds $\tilde{R}$.

Two Roles of ABS under Monopoly Section 2.2 discusses how to balance considerations of externalities and market power when designing attribute-based incentives for a monopoly. This subsection provides mathematical representations of the considerations that the regulator should make to choose the optimal policy.

Recall the definition of social welfare:

$$SW(P,\ \boldsymbol{x}) = \underbrace{\int_0^{Q(P,\ \boldsymbol{x})} [B(\boldsymbol{x}) + Q^{-1}(s) - P] ds}_{\text{Consumer surplus}} + \underbrace{\big(P - C(\boldsymbol{x})\big) Q(P,\ \boldsymbol{x})}_{\text{Producer surplus}} + \underbrace{\phi \cdot e(\boldsymbol{x}) Q(P,\ \boldsymbol{x})}_{\text{Externality}}. \tag{A12}$$

Suppose the regulator tries to maximize social welfare in Equation (A12) given a base attribute z with a budget constraint: $b \cdot Q(P,\ \boldsymbol{x}) = R$ where $b = T + t \cdot z(\boldsymbol{x})$. Then, the objective function becomes:

$$\mathscr{L}(T,\ t) = SW\left(P^z(T,\ t),\ \boldsymbol{x}^z(t)\right) + \lambda\Big(R - b \cdot Q\big(P^z(T,\ t),\ \boldsymbol{x}^z(t)\big)\Big),$$

where P^z and $\boldsymbol{x}^z$ are the firm's optimal responses to the policy. Also, $\lambda > 0$ is the shadow value from the budget constraint. Note that t determines down $\boldsymbol{x}^z$ in Equation (A3) and b pins down P^z given $\boldsymbol{x}$ in Equation (A5). Therefore, we can write the regulator's first-order conditions as follows:

$$[T] \quad \frac{\partial \mathscr{L}}{\partial T} = \left.\frac{\partial \mathscr{L}}{\partial b}\right|_{\boldsymbol{x}} \cdot \frac{\partial b}{\partial T} = 0 \tag{A13}$$

$$[\,t\,] \quad \frac{\partial \mathscr{L}}{\partial t} = \left.\frac{\partial \mathscr{L}}{\partial b}\right|_{\boldsymbol{x}} \cdot \frac{\partial b}{\partial t} + \sum_k \frac{\partial \mathscr{L}}{\partial x_k^z} \cdot \frac{x_k^z}{\partial t} = 0. \tag{A14}$$

In the above equations, $\frac{\partial \mathscr{L}}{\partial b}\big|_{\boldsymbol{x}}$ represents the impact of subsidy amount change on the objective function via affecting only P^z with fixed $\boldsymbol{x}$. If T is optimally chosen, then $\frac{\partial \mathscr{L}}{\partial b}\big|_{\boldsymbol{x}}$ should be equal to zero, and only the last term remains in in Equation (A18), which can be decomposed as follows:

$$\sum_k \frac{\partial \mathscr{L}}{\partial x_k^z} \cdot \frac{x_k^z}{\partial t} = Q \cdot \sum_k \frac{\partial \left(B(\boldsymbol{x}^z) - C(\boldsymbol{x}^z) + \phi \cdot e(\boldsymbol{x}^z)\right)}{\partial x_k^z} \cdot \frac{x_k^z}{\partial t} \quad \text{: intensive margin} \tag{A15}$$

$$+ \left(P^z - C(\boldsymbol{x}^z) + \phi \cdot e(\boldsymbol{x}^z)\right) \sum_k \frac{\partial Q}{\partial x_k^z} \cdot \frac{x_k^z}{\partial t} \quad \text{: extensive margin}$$

$$- \lambda \cdot b \cdot \sum_k \frac{\partial \mathscr{L}}{\partial x_k^z} \cdot \frac{x_k^z}{\partial t} = 0 \quad \text{: from the budget constraint}$$

The first term shows the impact of the subsidy intensity t through the intensive margin by changing the product design. The second term captures how t affects social welfare through the extensive margin by varying the output level. Therefore, the former is related to the externality consideration (about how to make the product more socially desirable), whereas the latter is relevant to the market power consideration (about how to enhance the output level). Therefore, the above equation clearly demonstrates that the regulator needs to address both market power and externalities when designing attribute-based incentives.

A.3 Details of Section 2.3: Oligopoly with Differentiated Products

Three Roles of ABS under Oligopoly Consider J heterogeneous goods $j = 1, \ldots, J$ with benefit B_j, marginal cost C_j, and demand $Q_j\left(P_1 - B_1(\boldsymbol{x}_1), \ldots, P_J - B_J(\boldsymbol{x}_J)\right)$. The planner chooses the per-unit subsidy $b_j = T + t \cdot z(\boldsymbol{x}_j)$ to maximize the social welfare subject to a budget constraint, $\sum_j b_j Q_j = R$. Given the policy (T, t, z), firms solve the following profit maximization problem:

$$\max_{P_j, \boldsymbol{x}_j} \left(P_j - C_j(\boldsymbol{x}_j) + T + t \cdot z(\boldsymbol{x}_j)\right) Q_j\left(P_1 - B_1(\boldsymbol{x}_1), \ldots, P_J - B_J(\boldsymbol{x}_J)\right)$$

$$[P_j] \quad \frac{P_j^z - C(\boldsymbol{x}_j^z) + T + t \cdot z(\boldsymbol{x}_j^z)}{P_j^z} = \frac{1}{\varepsilon_P\left(P_1^z - B_1(\boldsymbol{x}_1^z), \ldots, P_J^z - B_J(\boldsymbol{x}_J^z)\right)} \tag{A16}$$

$$[x_{jk}] \quad B_{jk}(\boldsymbol{x}^z) - C_{jk}(\boldsymbol{x}^z) + t \cdot z_k(\boldsymbol{x}^z) = 0 \quad \text{for} \quad i = 1, 2, \ldots, K. \tag{A17}$$

$\boldsymbol{P}^z$ and $\boldsymbol{x}^z$ denote firms' optimal responses to the policy as before. Equation (A17) shows that firms' attribute choices maximize $B_j(\boldsymbol{x}_j) - C_j(\boldsymbol{x}_j) + t \cdot z(\boldsymbol{x}_j)$ and do not depend on T. Therefore, as in the monopoly case, the base subsidy T cannot affect product design.

Social welfare is the sum of consumer surplus, producer surplus, and externality:

$$\begin{aligned}
SW(P,\,\boldsymbol{x}) &= \sum_{j=1}^{J}\Big[\int_0^{Q_j(\boldsymbol{P},\,\boldsymbol{x})} B_j(\boldsymbol{x}_j)+Q_j^{-1}(s,\,\boldsymbol{P}_{-j})-P_j\,ds+\big(P_j-C_j(\boldsymbol{x}_j)\big)Q_j(\boldsymbol{P},\,\boldsymbol{x})+\phi\cdot e(\boldsymbol{x}_j)Q_j(P,\,\boldsymbol{x})\Big]\\
&= \sum_{j=1}^{J}\Big[(B_j(\boldsymbol{x}_j)-C_j(\boldsymbol{x}_j)+\phi\cdot e(\boldsymbol{x}_j))Q_j(\boldsymbol{P},\,\boldsymbol{x})+\int_0^{Q_j(P,\,\boldsymbol{x})} Q_j^{-1}(s,\,\boldsymbol{P}_{-j})\,ds\Big].
\end{aligned}$$

For a policy attribute z, the regulator chooses $(T,\,t)$ to maximize social welfare given firms' optimal responses as constraints:

$$\max_{T,\,t} SW\big(\boldsymbol{P}^z(T,\,t),\,\boldsymbol{x}^z(t)\big)\ \ s.t.\ \sum_{j=1}^{J} b_j\cdot Q_j\big(\boldsymbol{P}^z(T,\,t),\,\boldsymbol{x}^z(t)\big)=R.$$

With the budget constraint, the regulator's objective function and first-order conditions become:

$$\mathscr{L}(T,\,t)\ =\ SW\big(\boldsymbol{P}^z(T,\,t),\,\boldsymbol{x}^z(t)\big)+\lambda\Big[R-\sum_{j=1}^{J} b_j\cdot Q_j\big(\boldsymbol{P}^z(T,\,t),\,\boldsymbol{x}^z(t)\big)\Big]$$

$$[T]\quad \frac{\partial\mathscr{L}}{\partial T}\ =\ \sum_j \frac{\partial\mathscr{L}}{\partial b_j}\bigg|_{\boldsymbol{x}}\cdot\frac{\partial b_j}{\partial T}\ =\ \sum_j \frac{\partial\mathscr{L}}{\partial b_j}\bigg|_{\boldsymbol{x}}\ =\ 0 \tag{A18}$$

$$[\,t\,]\quad \frac{\partial\mathscr{L}}{\partial t}\ =\ \sum_j \frac{\partial\mathscr{L}}{\partial b_j}\bigg|_{\boldsymbol{x}}\cdot\frac{\partial b_j}{\partial t}\ +\ \sum_j\sum_k \frac{\partial\mathscr{L}}{\partial x_{jk}^z}\cdot\frac{x_{jk}^z}{\partial t}\ =\ 0. \tag{A19}$$

As in the previous subsection, $\frac{\partial\mathscr{L}}{\partial b_j}\big|_{\boldsymbol{x}}$ represents the impact of b_j change on the objective function by affecting only P^z with fixed $\boldsymbol{x}$. Also, note that $\frac{\partial b_j}{\partial T_j}=1$ and $\frac{\partial b_j}{\partial t}=z(\boldsymbol{x}_j^z)$. We can rewrite Equation (A19) as follows:

$$\begin{aligned}
\frac{\partial\mathscr{L}}{\partial t}\ =\ & \sum_j \frac{\partial\mathscr{L}}{\partial b_j}\bigg|_{\boldsymbol{x}}\cdot z(\boldsymbol{x}_j^z) && :\text{ subsidy distribution} \qquad \text{(A20)}\\
&+\sum_j Q_j\sum_k \frac{\partial\big(B_j(\boldsymbol{x}_j^z)-C_j(\boldsymbol{x}_j^z)+\phi\cdot e(\boldsymbol{x}_j^z)\big)}{\partial x_{jk}^z}\cdot\frac{x_{jk}^z}{\partial t} && :\text{ intensive margin}\\
&+\sum_j\big(P_j^z-C_j(\boldsymbol{x}_j^z)+\phi\cdot e(\boldsymbol{x}_j^z)\big)\sum_k\frac{\partial Q}{\partial x_{jk}^z}\cdot\frac{x_{jk}^z}{\partial t} && :\text{ extensive margin}\\
&-\lambda\sum_j b_j\sum_k\frac{\partial\mathscr{L}}{\partial x_{jk}^z}\cdot\frac{x_{jk}^z}{\partial t}\ =\ 0. && :\text{ from the budget constraint}
\end{aligned}$$

The last three terms in the above equation are similar to those in Equation (A15) for the monopoly case. The first term, which is new for the oligopoly case, represents the welfare impact of changes in subsidy distributions across heterogeneous products. Because products exhibit different levels of the policy attribute, the regulator's choice of t affects how much subsidy expenditure is distributed across the products. Therefore, an ABS plays three distinct roles when there are multiple products in the market: i) distribution of subsidies, ii) product design change, and iii) sales promotion. In other words, the choice of t should take into account its impact on the subsidy allocations across products as well as balancing externalities and market power considerations.

Product-Specific Subsidies In this subsection, we discuss the optimal subsidy distribution that an ABS should aim for. Suppose the planner can choose product-specific base subsidy. The optimal choice of T_j's should satisfy the following condition:

$$\frac{\partial \mathscr{L}}{\partial T_j} = \frac{\partial \mathscr{L}}{\partial b_j}\bigg|_{\boldsymbol{x}} \cdot \frac{\partial b_j}{\partial T_j} = \frac{\partial \mathscr{L}}{\partial b_j}\bigg|_{\boldsymbol{x}} = 0. \tag{A21}$$

Thus, if the product-specific T_j's are optimally chosen, Equation (A21) cancels out the first term of Equation (A20). Therefore, how to design the attribute-based part $t \cdot z(\boldsymbol{x}_j^z)$ of the subsidy remains the same as in the monopoly case. On the other hand, T_j's take the role of optimally distributing subsidy expenditure across products.

Then, what is the desirable allocation of subsidies across heterogeneous products? We can rewrite Equation (A21) as follows:

$$\sum_{j=1}^{J} (P_j^z - C_j(\boldsymbol{x}_j^z) + \phi \cdot e(\boldsymbol{x}_j^z)) \tfrac{\partial Q_j}{\partial T_k} = \lambda \left(Q_k + \sum_{j=1}^{J} b_j \tfrac{\partial Q_j}{\partial T_k} \right) \text{ for } k = 1, \ldots, J, \tag{A22}$$

where $\lambda > 0$ is the shadow value from the budget constraint. By multiplying $\frac{b_k}{Q_k}$ to the both sides of Equation (A22), we attain:

$$b_k = \frac{1}{\lambda} \cdot m_k \cdot \frac{\varepsilon_{kk}^b + \sum_{j \neq k} \frac{m_j Q_j}{m_k Q_k} \varepsilon_{jk}^b}{1 + \varepsilon_{kk}^b + \sum_{j \neq k} \frac{b_j Q_j}{b_k Q_k} \varepsilon_{jk}^b} \quad \text{for } k = 1, \ldots, J, \tag{A23}$$

where $\varepsilon_{jk}^b = \frac{\partial Q_j}{\partial b_k} \frac{b_k}{Q_j}$ is the demand elasticity of product j with respect to the subsidy for product k. In the above equation, $m_j = P_j^z - C_j(\boldsymbol{x}_j^z) + \phi \cdot e(\boldsymbol{x}_j^z)$ is the social markup, which is equal to welfare gain from additional sale of product k. On the other hand, the last term consisting of the demand elasticities in the equation is increasing in ε_{kk}^b, which captures the percentage increase of product j's sales responding to the percentage increase of its subsidy. Thus, Equation (A23) indicates that more subsidies should be distributed to products with high social markups and demand sensitivities to efficiently mitigate heterogeneous market powers across products.

B Institutional Background and Sample Construction

B.1 Policy Background

During our sample period, only EVs produced by domestic companies or joint ventures with domestic partners are eligible for subsidies during this period, with imported EVs excluded. The joint-venture requirement for foreign automakers to manufacture automobiles in China is part of a long-term "technology-for-market" strategy by the Chinese government (Bai et al., 2020). Amid the recent trade war between China and the U.S., the Chinese government promised to end the joint-venture requirement for the auto industry in 2021. Tesla received special permission to build its fully-owned gigafactory in Shanghai. It began producing its Model 3 in December 2019, which was eligible to receive subsidies. In 2020, Tesla China received ¥2.1 billion ($325 million) EV subsidies, the highest amount granted to any automaker in the country.

Many cities in China and around the world have implemented some type of driving restrictions to address traffic congestion (Davis, 2008; Jerch et al., 2023). Typically, a vehicle is restricted from driving during certain hours in certain areas one day per week during the weekdays based on the last digit of the license plate. A number of Chinese cities have granted exemption to this policy for EVs, and the list of such cities grew from 7 in 2015 to 29 in 2018.

In addition, several major cities in China have adopted vehicle purchase restrictions by putting into place an annual/monthly cap on new vehicle registrations to curb the growth of vehicle ownership (Li, 2018). EVs are exempted from the cap or subjected to a laxer restriction in registration in these cities (e.g., Shanghai, Beijing, Tianjin, Guangzhou, Hangzhou and Shenzhen). The third non-financial incentive is the green license plate policy where EVs are eligible to use a distinctively looking green license plate. The policy started in five cities (Shanghai, Nanjing, Wuxi, Jinan, and Shenzhen) in December 2016, extended to 20 cities in 2017, and then throughout the country by the end of 2018.

B.2 Sample Construction

We focused our analysis on a subset of models from the main dataset, excluding those with limited sales or prices falling outside a designated range. Specifically, models with annual sales below 1000 for ICEs and 100 for EVs in the 40 cities were omitted. Additionally, a few GV models were excluded in local markets if their local market sales are less than 0.1%. These unpopular models account for 7.5% of total sales during the sample period. Lastly, models with consumer prices below 50,000 RMB or above 500,000 RMB were excluded, losing another 5.4% of total sales. This price range limitation was imposed due to the challenge of rationalizing consumers' behavior at the two extremes - purchasing excessively cheap or expensive models.

The subsidies in our datasets are compiled based on policy announcements made during our sample periods by both the central government and the 40 city governments. Both central and local governments have amended the subsidy policies over time, such as the subsidy amount, eligible models, other eligibility conditions, and the timing of applying new criteria through multiple disclosures. From September 2013 to December 2018, the central governments made 209 announcements, while each sample city also issued three to ten announcements during the same period. Using these hundreds of policy documents, we organized central and local subsidies on a monthly and model-specific level. Subsequently, when aggregating the data on a yearly basis, we calculated the subsidies each EV model receives from both central and local sources as the sales-average annual subsidy.

The individual incomes in the price disutility specification, represented as $\alpha_i = \exp(\alpha_1 + \alpha_2 \log(y_{im}) + \sigma_p v_{ip})$, are simulated from a lognormal distribution with parameters $(\hat{\mu}_m, \hat{\sigma}^2_m)$. These parameters vary across cities and years. The lognormal distribution parameters are estimated using city-year level income data from the CEIC database.[36]

We use MSRPs in demand analysis. Discounts at the dealer level are limited in China due to the practice of "minimum retail price maintenance" (RPM), whereby automakers either explicitly or implicitly prohibit dealers from selling below a preset price to reduce price competition among dealers (Barwick et al., 2021). To examine the correlation between MSRPs and transaction prices, we obtain monthly data on average dealer-level transaction prices in five cities (Beijing, Chengdu, Guangzhou, Hangzhou, and Shanghai) from 2011 to 2016. The data show that transaction prices and MSRPs are highly correlated with a correlation coefficient of 0.995. The average price discount is 6.9% with a standard deviation of 5.4%. Importantly, there is limited price variation across cities: the within-model variation in price discount across cities is 2%, compared to the between-model variation of 5%.

EVs' driving range is not self-reported by the automakers, but tested by government-designated agencies and publicly disclosed by the MIIT.[37] For the analysis of the technology frontier, we use all the EV models tested and then reported by the MIIT. MIIT announced batches of newly tested EVs three to seven times a year from 2014, and our analysis utilizes all 22 batches during our sample period. The first batch was announced on August 27th, 2014, and all EVs examined before the date were included in the first batch. The 22nd batch, which is the last one that this paper uses, was announced on December 14th, 2018. The lists include all models that were tested by

[36]See https://www.ceicdata.com).

[37]The testing was based on the New European Driving Cycle (NEDC) before 2021 and the China Light Duty Vehicle Test Cycle (CLTC) after 2021. The CLTC is considered to be more similar to the real driving conditions.

the government, including models not launched in the market. The data contain information on EV attributes such as range, battery density and capacity, net vehicle weight, and engine displacement for PHEVs. We use information on passenger vehicles (but not buses, trucks, and trailers) to estimate the technology frontier reported in Table 4.

C Counterfactual Analysis

C.1 Environmental Impacts

The baseline emission intensity (g/km) for ICEs and BEVs in different regions in China are provided in Table A2. We include CO_2 and three local pollutants: NO_x, PM, and SO_2. CO_2 emissions per kilometer For ICEs in Table A2 are calibrated from estimates in Huo et al. (2013), which measure fuel-cycle CO_2 emissions of ICEs. To account for local emissions from ICEs, we use Tailpipe Emission Standard Level 5 (for NO_x and PM) and Fuel Standard Level 5/6 (for SO_2) for ICEs.

The emission intensity of EVs is determined by the fuel source of electricity generation: their environmental advantage compared to ICEs is compromised in regions that rely more heavily on coal for electricity generation. For CO_2 emission intensity of the power sector, we refer to provincial-level estimates from Li et al. (2017b). They compiled data on existing power generation capacity (up to 2016) and that from plants under construction, which became operational by 2020 at the provincial level. The sources of power generation considered include coal, hydro, wind, solar, natural gas, nuclear, and others. Emission intensity for the year 2020 was computed under three scenarios regarding operating hours. In the first scenario, a 10% reduction in the operating hours of fossil fuel electricity generation by 2020 was assumed compared to the 2014 levels. In the second scenario, there was a 20% increase in renewable energy operating hours in 2020, in addition to the adjustments made in the first scenario. The third scenario introduced an additional assumption, building on the second scenario, by incorporating a further 20% increase in renewable energy capacity. For our analysis, we utilize the CO_2 emission intensity estimates derived under the second scenario.

For the assessment of local pollutants PM, SO_2, and NO_x that arise from electricity generation, we rely on estimates from Tang et al. (2020). The authors estimate local emission factors utilizing information from China's continuous emission monitoring systems (CEMS) network, which covers approximately 96–98% of the total thermal power capacity spanning from 2014 to 2017. Then, we compute the emission factors for the entire energy generation in the 40 cities by multiplying the share of thermal power generation within these cities in 2017. We assume zero emissions of local pollutants for renewable energy generation.

Lastly, the lifetime travel distance of vehicles that is used to compute the lifetime emissions of EVs and ICEs is assumed to be 200,000km. To monetize the damage from total emissions, the social cost of CO_2 is assumed to be $51 per ton based on 3% discount rate from the US Interagency Working Group.[38] The health cost of each local pollutant is from Parry et al. (2014).

C.2 Accident Externalities

Accident externalities measure the external cost of traffic accidents imposed by a vehicle. The external cost varies by vehicle weight: heavier vehicles pose a greater risk in multi-vehicle collisions as shown in the literature (Li, 2012; Anderson and Auffhammer, 2014; Bento et al., 2017). The calculation of accident externalities is based on the methodology outlined in Anderson and Auffhammer (2014). We focus on multi-vehicle collisions in our calculation and do not include accident costs arising from single-vehicle collisions (e.g., collisions involving only one vehicle, or involving a vehicle with pedestrians, bicyclists, and motorcycles). Accident externalities resulting from single-vehicle collisions are likely to be similar across our counterfactual simulations: Anderson and Auffhammer (2014) suggest that there is no evidence that heavy cars pose greater risks to pedestrians and motorcyclists than light cars.

Accident externalities per vehicle hinge crucially on the marginal impact of extra vehicle weight (per 1000 pounds) on fatality conditioning on being involved in a multi-vehicle accident. The marginal impact estimates are from Anderson and Auffhammer (2014). Accident externalities for vehicles heavier than 2400 pounds are:

$$\Big[\frac{0.109\%}{1000lb}(w_j - 2400lb) + \frac{0.058\%}{1000lb}(2400lb - w_{min})\Big] \times \text{ life time accident rate } \times \text{ VSL},$$

where w_j represents vehicle weight and w_{min} is the weight of the lightest vehicle, which is 1477 pounds in our sample. For vehicles lighter than 2,400 pounds, accident externalities are:

$$\Big[\frac{0.058\%}{1000lb}(w_j - w_{min})\Big] \times \text{ life time accident rate } \times \text{ VSL}.$$

The accident rate is 3.65% per 17,600 km from Anderson and Auffhammer (2014) and the life time accident rate is computed based on the lifetime travel distance of 200,000 km.[39] For the value of a statistical life (VSL) in China, we use a value of $0.7 million for 2017. Due to the lack

[38] https://www.whitehouse.gov/wp-content/uploads/2021/02/TechnicalSupportDocument_SocialCostofCarbonMethaneNitrousOxide.pdf.

[39] The traffic accident rate in China may differ from that in the US but the multi-vehicle collision rate is not readily available, and the reported traffic fatalities in China have faced criticism for potential under-reporting (Sills et al., 2018).

of national-level estimates on Chinese population's VSL, we obtain this value using a transfer approach based on: (1) the VSL of \$9.6 million by the U.S. Department of Transportation; and (2) an income elasticity of VSL at 1.2 (Narain and Sall, 2016). Per capita disposable income was \$3,886 and \$44,710 in 2017 in China and U.S. respectively, implying the VSL in the U.S. is 13.8 times that in China.

C.3 Simulation Algorithm for New Equilibrium

This appendix provides details on the simulation algorithm. In our model, an equilibrium outcome is the set of prices $\boldsymbol{P}$ and attributes $(\boldsymbol{P}, \boldsymbol{k}, \boldsymbol{w})$ that satisfy firms' first-order conditions. We introduce the following matrix notations to write the first-order conditions concisely:

$$M_x = \begin{pmatrix} \frac{\partial mc_1}{\partial x_1} & 0 & \cdots & 0 \\ 0 & \frac{\partial mc_2}{\partial x_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \\ 0 & 0 & & \frac{\partial mc_J}{\partial x_J} \end{pmatrix} \text{ and } dFC_x = \begin{pmatrix} \frac{\partial FC_1}{\partial x_1} \\ \frac{\partial FC_2}{\partial x_2} \\ \vdots \\ \frac{\partial FC_J}{\partial x_J} \end{pmatrix},$$

where $x = k$ and w, denoting battery capacity and vehicle weight. The first-order conditions are:

$$\begin{aligned} dOP_P &:= \quad \boldsymbol{Q} + \Omega \otimes \Delta_P(\boldsymbol{P} - \boldsymbol{mc}) \; = \; \boldsymbol{0} \\ dOP_k &:= -M_k \boldsymbol{Q} + \Omega \otimes \Delta_k(\boldsymbol{P} - \boldsymbol{mc}) \; = \; dFC_k \\ dOP_w &:= -M_w \boldsymbol{Q} + \Omega \otimes \Delta_w(\boldsymbol{P} - \boldsymbol{mc}) \; = \; dFC_w, \end{aligned}$$

where dOP implies the derivatives of the operating profit with respect to endogeneous attributes.

We updated one vehicle characteristic at a time in the order of weight, capacity, price, weight, capacity, price, and so forth until the attribute changes become trivial, following the Newton–Raphson method:

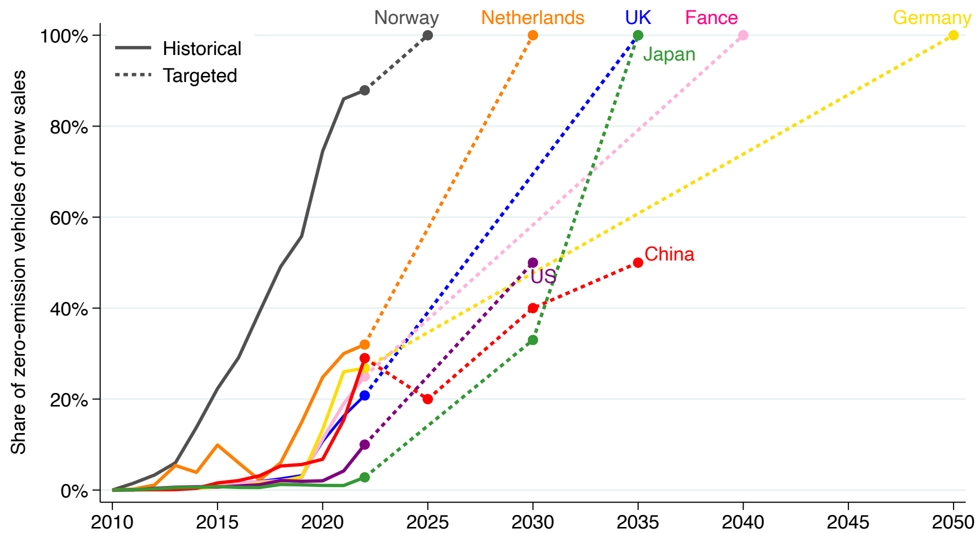
[Step 1] While fixing the demand derivatives Δ_P, Δ_k, and Δ_w, find the necessary changes in one attribute $\boldsymbol{dx}$ to make the corresponding first-order conditions satisfied, given the fixed demand derivatives, by solving the following equation:

$$\begin{aligned} dOP_x &+ [\, \Delta_x + (\Omega \otimes \Delta_x)^T \,]\, \boldsymbol{dx} \; = \; \boldsymbol{0} & \text{if } x = P; \\ dOP_x &- [\, M_x \Delta_x + (\Omega \otimes \Delta_x)^T M_x \,]\, \boldsymbol{dx} \; = \; dFC_x & \text{if } x = k \text{ or } w. \end{aligned}$$

[Step 2] Update $\boldsymbol{x}^{new} = \boldsymbol{x}^{old} + \boldsymbol{dx}$. Also, update sales $\boldsymbol{Q}$, marginal costs $\boldsymbol{mc}$, and demand derivatives Δ_x, using $\boldsymbol{x}^{new}$. Then, repeat **Steps 1** and **2** until $\boldsymbol{dx}$ becomes trivial.

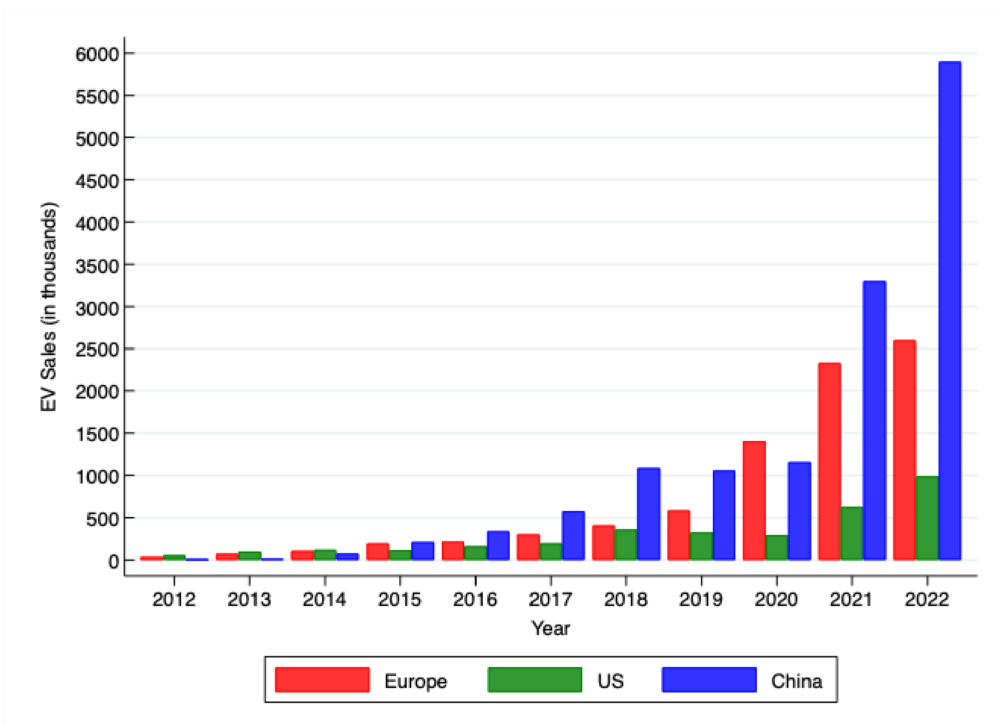
D Figures & Tables

Figure A2: ZEV Targets and Market Shares by Country



Notes: The figure depicts the Zero-emission vehicle (ZEV) targets and the market share over time by country. ZEVs include EVs and fuel cell vehicles but have been predominantly EVs. Source: International Energy Agency and the International Council on Clean Transportation.

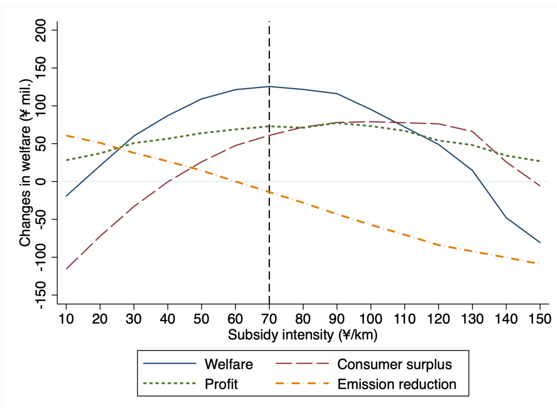
Figure A3: Global EV Sales by Region 2012-2022



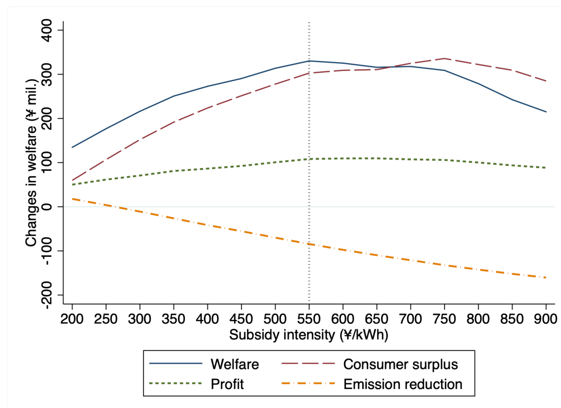
Notes: Annual sales of new EVs (including both BEVs and PHEVs) by country and region. China, Europe and the U.S. accounted for over 95% of global EV sales during the data period. Source: International Energy Agency.

Figure A4: Welfare Changes and Subsidy Intensity t

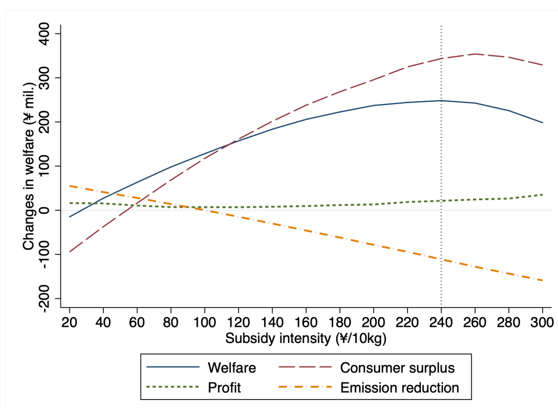
(a) Based on Driving Range



(b) Based on Battery Capacity



(c) Based on Net Vehicle Weight



Notes: this figure depicts welfare changes relative to the observed notched subsidy as subsidy intensity t varies. Panels (a), (b), (c) plot welfare changes for linear subsidies that are based on the driving range, battery capacity, and net vehicle weight, respectively. The aggregate subsidy amount is fixed. The horizontal axis represents the subsidy intensity t. The total welfare consists of consumer surplus, EV firm profit, and benefits from emission reduction. The vertical dotted lines indicate the optimal subsidy intensity that maximizes the welfare in the BEV market.

Table A1: Average Price of Domestic EVs by Range Groups

Type	Range	2013	2014	2015	2016	2017	2018
BEV	$\geq$ 80km	¥170,800 (20.5%)	¥139,300 (23.9%)	¥114,133 (27.6%)			
	$\geq$ 100km	¥267,450 (13.1%)	¥234,900 (14.2%)	¥238,350 (13.2%)	¥234,900 (10.6%)		
	$\geq$ 150km	¥207,583 (24.1%)	¥205,664 (23.1%)	¥191,026 (23.6%)	¥186,311 (24.2%)	¥144,729 (24.9%)	¥132,806 (11.3%)
	$\geq$ 200km		¥227,567 (20.9%)	¥241,233 (18.7%)	¥234,233 (19.2%)	¥168,521 (21.4%)	¥121,773 (20.5%)
	$\geq$ 250km			¥268,267 (20.1%)	¥249,495 (22.0%)	¥196,027 (22.4%)	¥159,662 (21.3%)
	$\geq$ 300km	¥369,800 (16.2%)	¥319,900 (17.8%)	¥319,900 (16.9%)	¥276,500 (19.9%)	¥233,944 (18.8%)	¥180,653 (24.9%)
	$\geq$ 400km			¥319,900 (16.9%)	¥319,900 (17.2%)	¥319,900 (13.8%)	¥215,588 (23.2%)
PHEV	$\geq$ 50km	¥159,800 (21.9%)	¥227,050 (14.6%)	¥325,050 (9.7%)	¥319,411 (10.3%)	¥273,123 (8.8%)	¥303,179 (7.3%)

Notes: The table presents the average consumer prices of EVs in different driving range groups across years. The values in parenthesis represent the ratio of central subsidies to the average prices.

Table A2: Emissions Intensity from ICEs and EVs

		BEV				ICE			
Region	Province	CO_2	NO_x	PM	SO_2	CO_2	NO_x	PM	SO_2
	Guangdong	748	0.165	0.016	0.101	3080	0.060	0.005	0.020
Centersouth	Guangxi	621	0.098	0.009	0.060	3045	0.060	0.005	0.020
	Henan	1130	0.210	0.020	0.128	3137	0.060	0.005	0.020
	Hubei	522	0.089	0.008	0.054	3038	0.060	0.005	0.020
	Hunan	738	0.122	0.012	0.075	3073	0.060	0.005	0.020
	Anhui	1162	0.207	0.017	0.088	3116	0.060	0.005	0.020
East	Fujian	754	0.112	0.009	0.047	3066	0.060	0.005	0.020
	Jiangsu	1019	0.202	0.017	0.086	3116	0.060	0.005	0.020
	Jiangxi	1019	0.182	0.015	0.077	3102	0.060	0.005	0.020
	Shandong	1063	0.208	0.017	0.089	3137	0.060	0.005	0.020
	Shanghai	1133	0.215	0.018	0.091	3116	0.060	0.005	0.020
	Zhejiang	808	0.169	0.014	0.072	3102	0.060	0.005	0.020
	Beijing	802	0.296	0.036	0.193	3130	0.060	0.005	0.020
North	Hebei	1025	0.273	0.034	0.177	3130	0.060	0.005	0.020
	Shanxi	1117	0.283	0.035	0.184	3116	0.060	0.005	0.020
	Tianjin	1159	0.305	0.038	0.199	3116	0.060	0.005	0.020
Northwest	Shaanxi	1098	0.252	0.036	0.154	3116	0.060	0.005	0.020
Southwest	Chongqing	844	0.285	0.033	0.350	3080	0.060	0.005	0.020
	Sichuan	201	0.049	0.006	0.060	3045	0.060	0.005	0.020
	Yunnan	124	0.036	0.004	0.044	3095	0.060	0.005	0.020
Unit		g/kWh	g/kWh	g/kWh	g/kWh	g/L	g/km	g/km	g/L
Source		Li et al [a]	CEAPP [b]	CEAPP [b]	CEAPP [b]	Huo et al. [c]	TPES [d]	TPES [d]	FS [e]

[a] Li et al. (2017b) [b] China Emission Accounts for Power Plants [c] Huo et al. (2013)
[d] Tailpipe Emission Standard Level 5 [e] Fuel Standard Level 5/6

Notes: The values represent emissions from BEVs and ICEs. Emission levels vary among vehicles depending on their fuel or energy efficiency. ICEs' NO_x, PM, and SO_2 emissions are regulated by China's tailpipe emission and fuel standards, which specify the allowed emission amount per unit of distance driven. Emission intensity varies across different provinces in China, although local pollutants emitted by ICEs are subject to emission and fuel standards and do not vary across provinces. In our sample, BEVs travel 7.48 km per kWh and ICEs cover 14.61 km per liter of fuel on average.

Table A3: Optimal Base Subsidy T and Subsidy Intensity t

Driving Range	Base subsidy T (¥)	30550	28655	26708	24704	22628	20487	18281
	Subsidy intensity t (¥/km)	40	50	60	70	80	90	100
Battery Capacity	Base subsidy T (¥)	27688	26289	24847	23373	21857	20325	18801
	Subsidy intensity t (¥/kWh)	400	450	500	550	600	650	700
Net Weight	Base subsidy T (¥)	20048	17956	15855	13693	11504	9289	7092
	Subsidy intensity t (¥/10kg)	180	200	220	240	260	280	300

Notes: This table shows combinations of base subsidy T and subsidy intensity t that would keep the aggregate government subsidy expenditure constant for linear subsidies based on the driving range, battery capacity, and weight. The fourth column, highlighted in red, displays the welfare-maximizing pairs of (T,t).

Table A4: Attribute Choices and Market Outcomes for BEV Models in 2017

Policy	Average attributes/outcomes	Driving range groups (1) $150 \leq D_j \leq 155$	(2) $155 < D_j < 250$	(3) $250 \leq D_j \leq 255$	(4) $155 < D_j < 250$
Notched Range	Net weight (10kg)	77.9	96.5	121.9	133.0
	Battery capacity (kWh)	18.9	24.1	41.4	48.4
	Driving range (km)	152.2	175.9	251.3	310.3
	MSRP	12.5	13.4	21.0	24.7
	Marginal cost	9.2	10.0	15.7	17.8
	Markup	2.2	2.2	3.3	4.5
	Central subsidy	3.67	3.67	4.49	4.49
	Sales	3673	3368	1448	1725
Linear Range	Net weight (10kg)	79.2	94.1	125.5	130.9
	Battery capacity (kWh)	17.1	28.7	36.3	59.1
	Driving range (km)	139.8	206.5	215.9	378.7
	MSRP	12.2	13.9	20.2	25.9
	Marginal cost	8.9	10.4	14.9	18.9
	Markup	2.2	2.2	3.3	4.5
	Central subsidy	3.45	3.92	3.98	5.12
	Sales	3468	3311	1426	1868

Notes: The marginal cost, markup, and subsidy are all in ¥10k. 'Notched Range' reports average attributes and outcomes under the notched range subsidy, while 'Linear Range' reports results under the linear range subsidy.

Table A5: BEV Sales and Subsidy Distribution

		(1) Uniform	(2) Notched Range Δ from (1)	(3) Linear Range Δ from (1)	(4) Capacity Δ from (1)	(5) Weight Δ from (1)
WTP < ¥130k	BEV sales	138881	-11302	-15606	-23024	-23210
	Ave. subsidy (¥10k)	3.73	.05	.01	0	-.01
WTP > ¥130k	BEV sales	20352	4962	6991	9672	10936
	Ave. subsidy (¥10k)	3.73	.71	1.06	1.46	1.12

Notes: This table divides BEVs into high-quality models (WTP > ¥130k) and low-quality models (WTP < ¥130k) based on consumer WTP under the uniform subsidy. WTP is defined as the price level that makes consumers indifferent between buying and not buying the vehicle. The average subsidy in ¥10k represents the average central subsidy per vehicle for each BEV group. Column (1) shows the BEV sales and average central subsidies in 2017 under the uniform subsidy as the baseline, while Columns (2) to (5) present the *changes* in BEV sales and subsidies under alternative ABS designs. Column (2) corresponds to the notched ranged-based subsidies as implemented by the government, and Columns (3) to (5) are linear subsides based on range, capacity, and vehicle weight, respectively. The total subsidy from the central government to BEVs is fixed at ¥6.33 billion.

Table A6: Welfare Impacts of ABS with Accident Externalities

		Changes relative to the uniform subsidy			
		Notched Range	Linear Range	Capacity	Weight
Δ Total welfare (in ¥mil.)		72.4	191.5	373.5	278.6
Δ Consumer surplus		226.2	316.7	643.2	679.9
Δ Firm profit	BEV	-16.0	57.0	92.1	5.4
	PHEV	-3.8	-4.7	-8.9	-7.3
	ICE	-38.8	-52.6	-123.3	-119.5
	Total	-58.6	-0.2	-40.1	-121.5
Δ Emissions	CO_2	60.6	71.9	131.2	151.7
	PM	1.2	1.6	3.0	3.6
	NOx	8.1	10.5	18.4	20.7
	SO_2	0.5	0.4	2.6	5.8
	Total	70.4	84.4	155.2	181.8
Δ Accident externality		24.8	40.6	74.4	98.0

Notes: The unit is ¥million in 2017 for all cells. The results represent changes under the four ABS designs relative to the uniform subsidy. The first column reports changes in welfare when we move from uniform subsidy to the notched range-subsidy. The next three columns report welfare changes for the linear design (i.e., the two-part subsidy structure) that is based on the driving range, battery capacity, and vehicle weight, respectively. The total subsidy is held the same under all counterfactual scenarios as under the observed policy. The row titled "Δ Accident externality" represents monetized changes in accident externality. Appendix C.2 describes the calculation of accident externalities.

Table A7: Welfare Impacts of ABS Holding Product Attribute Fixed

		Changes relative to the uniform subsidy			
		Notched Range	Linear Range	Capacity	Weight
Δ Total welfare (in ¥mil.)		73.9	92.1	125.7	107.7
Δ Consumer surplus		80.0	92.8	160.5	151.9
Δ Firm profit	BEV	20.3	33.1	40.5	29.8
	PHEV	-0.5	-1.2	-2.1	-1.0
	ICE	3.1	2.5	1.2	14.3
	Total	22.9	34.3	39.6	43.2
Δ Emissions	CO_2	23.0	28.0	60.6	71.9
	PM	0.8	0.9	1.8	2.0
	NOx	4.8	5.6	10.4	11.6
	SO_2	0.5	0.5	1.6	1.9
	Total	29.0	35.0	74.4	87.4

Notes: The unit is ¥million in 2017 for all cells. The results represent welfare changes under the four ABS designs relative to the uniform subsidy, holding vehicle attributes *fixed* at the equilibrium level under the uniform subsidy. The first column reports welfare changes when we move from uniform subsidy to the notched range subsidy. The next three columns report welfare changes for the linear design (i.e., the two-part subsidy structure) that is based on the driving range, battery capacity, and vehicle weight, respectively. The total subsidy is held the same under all counterfactual scenarios as under the observed policy.