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

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Abstract

Attribute-based subsidies are commonly used to promote the diffusion of energy-efficient products which are often manufactured in industries with significant market power. To understand the impacts of these subsidies, we first develop a theoretical framework of attribute-based subsidies in the presence of market power. The model illustrates that the welfare impact of subsidies critically hinges on firms' product attribute choices and their implications on environmental externalities and market power. We then develop and estimate an equilibrium model with endogenous product attributes using comprehensive data on China's vehicle market. Based on model estimates, we conduct counterfactual simulations to examine the impacts of different subsidy designs. Relative to attribute-based subsidies, uniform subsidies favor small and environmental-friendly vehicles but exacerbate the quantity distortion from market power for high-quality products. In contrast, subsidies based on driving range and battery capacity or vehicle weight generate a large consumer surplus by improving product quality and mitigating market power. Capacity-based subsides induce attributes valued by consumers, mitigate market power, and lead to the largest welfare gain at a moderate loss of environmental benefit. The findings highlight the importance of incorporating attribute choice and market power considerations in designing attributes-based policies.

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

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1 Introduction

Governments across countries routinely provide consumer subsidies to promote energy efficient or environmental-friendly products such as hybrid or electric vehicles, efficient home appliances, and solar panels. Both the eligibility and the level of subsidies are often tied to certain product attributes (e.g., battery capacity or energy efficiency). The subsidy policies are commonly motivated by several market failures inherent in the markets for these products: positive environmental externalities relative to alternative traditional product choices, technology spillovers during product development that cannot be fully appropriated, and potential consumer misperception on energy savings offered by these products.[1] In addition, the markets for these products can often be characterized as a differentiated products oligopoly. While a large literature has studied the impacts of these policies on product diffusion and the environment, little is known about the effects of these policies on product attribute choices and the resulting welfare consequences in the presence of market power.

Our paper fills this gap in the literature by: (1) developing a theoretical framework to characterize the subsidy structure and the optimal attribute to base the subsidy on; and (2) empirically examining how attribute-based subsidies affect consumer demand and firms' attribute choices, as well as comparing market outcomes and welfare impacts across different policy designs. The context of our study is the electric vehicle (EV) market in China. By relying on more-efficient and/or cleaner energy generation from power plants instead of internal combustion engines, the EV technology has a great potential in reducing carbon emissions and local air pollution. Many countries and local governments have set up ambitious goals to promote the EV technology (Holland et al., 2021). Since the introduction of mass-market EV models in 2010, worldwide passenger EV sales have grown to 4.2% (or 3.24 million units) of passenger vehicle market in 2020, thanks in part to generous government incentives of about $10 billion per year during the past several years.[2] China has been the largest EV market since 2015 and accounted for over 41% world's EV sales (or 1.34 million EVs) in 2020. In addition, China is by far the largest automobile market in the world with an annual passenger vehicle sales of over 20.2 million.[3]

Under the ambitious national goal of reaching seven million of EVs (or 20% of new passenger vehicle sale) by 2025, and 15 million (or 40%) by 2030, China's central and local governments have provided various incentives including both financial and non-financial incentives to promote the EV

[1]See Parry and Small (2005); Holland et al. (2016) on automobile usage externalities, Stoneman and Diederen (1994) on positive technology spillovers among firms in the early stage of new technology diffusion, and Jaffe and Stavins (1999); Allcott (2013) on consumer undervaluation of future energy savings in durable-goods adoption decisions.

[2]Sources: https://www.ev-volumes.com, and https://www.iea.org/reports/global-ev-outlook-2020

[3]The passenger vehicle sales in China dropped by 6% from 21.4 million in 2019. In comparison, total light vehicle sales in the US were 14.5 million units in 2020, down 14.7% from 17 million in 2019.

technology. The key incentive is in the form of generous consumer subsidies, and the amount of subsidies for battery electric vehicles (BEVs) follows a step function increasing in the driving range (i.e., a notched design). Subsidies in other countries often take different forms: flat subsidies in many European countries, a linear rather than notched design in Japan that is also based on driving range, or subsidies tied to other (base) attributes such as battery capacity in the U.S. and India, and vehicle size in Korea. This study focuses on these attribute-based consumer subsidies and aims to understand the impacts of different policy designs on consumer demand, product attribute choices, and social welfare in an equilibrium model of automobiles allowing for endogenous product attributes.

We first develop a theoretical model of attribute-based policies to understand the optimal policy choices aimed to address environmental externalities in a differentiated product oligopoly and to illustrate the channels through which attribute-based subsidies affect the market outcomes. In this model, the amount of environmental externalities (e.g., emissions reduction relative to a gasoline vehicle) from a product varies with attributes, and policy makers provide subsidies to promote the technology. Imperfect targeting arises when the policy attribute (e.g., driving range or battery capacity) is an imperfect proxy of the environmental externalities. Our model shows that under a monopoly, the optimal subsidy design follows a two-part tariff structure where the base subsidy (per unit of product) can be set to address the sub-optimal quantity due to market power and the subsidy rate (per unit of policy attribute) can be chosen to address environmental externalities. However under a differentiated-product oligopoly, the (constant) base subsidy cannot fully address varying market power across products, and the policy attribute should be chosen to balance both market failures through the impact on attribute choices. The model illustrates that the optimal policy attribute varies with the government budget on subsidies, and that the welfare impact of attribute-based subsidies critically hinges on how the policy attribute relates to environmental externalities and market power.

Our empirical analysis is based on an equilibrium model of vehicle market by extending the framework in Berry et al. (1995) (henceforth BLP) to allow for endogenous attribute choices. The demand side is a random coefficient discrete choice model to incorporate important consumer heterogeneity while allowing for endogeneity in multiple product attributes (i.e., price, vehicle weight, and driving range), which are assumed to be determined at the same time as unobserved product attributes. On the supply side, profit maximizing firms choose vehicle price and other endogenous attributes (vehicle weight and battery capacity) simultaneously following the first-order conditions of firms' decisions as in (Klier and Linn, 2012; Crawford et al., 2019; Reynaert, 2019). Different from these studies, we allow the fixed costs of changing product attributes to vary with attributes and follow Fan (2013) to specify and estimate the slope of fixed costs with respect to attribute changes.

With the parameter estimated, we conduct counterfactual simulations to examine market and welfare outcomes for several policy designs: a linear rather than notched subsidy schedule, subsidies based on battery capacity and vehicle weight rather the driving range, as well as a constant/uniform subsidy while holding the total subsidy amount to be the same.

Our empirical analysis provides several key findings. First, automakers respond to the subsidy design by altering product attributes. Attribute-based subsidies incentivize the provision of the attribute on which the subsidy is based, and could also lead to distortions in other attributes. For example, driving range-based subsidies incentivize automakers to reduce vehicle size in order to increase driving range. This result partly explains the prevalence of small EVs in China with range-based subsidies. Firms' attribute choices in response to the subsidy design have important welfare implications through their impacts on both emission reductions and consumer demand for EVs.

Second, consistent with the literature, our simulations show that the notched design with range-based subsidies as implemented in China leads to a large welfare loss relative to a linear subsidy design from two channels: (1) excess bunching whereby automakers alter vehicle weight and battery capacity to reach range cutoffs, and (2) reduced incentives for firms to incrementally improve range for models between the cutoffs relative to the incentives provided by a continuous subsidy design.

Third, the choice of the policy attribute should balance both environmental externality and market power considerations. Under a fixed budget, uniform subsidies which favor small EVs the most would lead to the largest emission reductions by increasing the sales of small EVs, compared with attribute-based (including range-, weight-, and capacity-based) subsidies. However, attribute-based subsidies can better mitigate market power through two channels: (1) providing larger subsidies for products with a larger market power, and (2) incentivizing automakers to increase product quality and hence pushing EV sales closer to the socially optimal level. In our context, capacity-based subsidies turn out to generate the largest welfare gain by better balancing the two market failures while uniform subsidies generate the least welfare gain.

Our study contributes to the following four strands of literature. First, our paper contributes to the emerging literature on attribute-based regulations and imperfect corrective policies.[4] Relative to uniform regulations (e.g., standards), attribute-based regulations could exhibit efficiency advantage by reducing abatement costs across heterogeneous firms, mitigating the negative impacts from demand uncertainty, and addressing market power (Ito and Sallee, 2018; Kellogg, 2018, 2020; Kiso, 2021). The attribute-based subsidies are imperfect policies that aim to correct externalities: due

[4] An attribute-based regulation consists of a target attribute and a policy attribute. Firms are required to meet a certain level of the target attribute to internalize externalities, and the policy attribute determines the required level. Attribute-based subsidies in this paper are a special case of attribute-based regulation in that it has the same target attribute with the policy attribute. The former decides the subsidy eligibility while the latter pins down the subsidy level.

to administrative, technical or political constraints, these policies deviate from theoretical ideals.[5] Our study contributes to this literature by examining the welfare impacts of attribute-based regulations under imperfectly competitive markets while allowing for the interaction of these policies with market power and comparing market outcomes under various policy designs.

Second, this study is related to the large literature to understand the effects of the subsidies on energy efficient products such as alternative-fuel vehicles (Beresteanu and Li, 2011; Sallee, 2011; Li et al., 2017; Kiso, 2019; Springel, 2019), home appliances (Boomhower and Davis, 2014; Houde and Aldy, 2017a,b), and residential solar panels (Gillingham and Tsvetanov, 2019; Pless and van Benthem, 2019; Langer and Lemoine, 2018). These studies focus on understanding consumer responses to the subsidies and identify the design elements that could affect the effectiveness of the subsidies in increasing consumer adoption. Different from these studies, our analysis examines the impacts of EV subsidies on both consumer demand and product choices, as well as the welfare consequences of alternative policy designs.

Third, our study adds to the literature that examines the impacts of government policies on firms' product choices especially in the vehicle market. Studies in this literature have documented the changes in vehicle attributes and technology adoption in response to U.S. fuel economy regulations (Knittel, 2011; Anderson et al., 2011; Klier and Linn, 2016). Our study is more closely related to several studies that endogenize firm choices in product attributes in response to fuel economy and carbon emissions regulations or government bailout by employing a structural model (Klier and Linn, 2012; Whitefoot et al., 2017; Wollmann, 2018; Reynaert, 2019). Different from these studies, our study focuses on EV subsidies and our counterfactual simulations solve for optimal attribute choices under different policy scenarios.

Lastly, this paper is broadly related to the literature on pollution control in the presence of market power. Classical studies in this literature have shown that Pigouvian tax aiming to correct for environmental externality may be welfare reducing in the presence of market power since the tax could further constraints sub-optimal firm output Buchanan (1969); Barnett (1980). Fowlie et al. (2016) empirically illustrates that market-based emission regulations could exacerbates distortions from market power by affecting firm entry and exit decisions in the U.S. cement industry. Our paper contributes to this literature by examining the welfare impact through the changes in product attributes in a differentiated-product oligopoly.

The paper is organized as follows: Section 2 presents a theoretical framework of attribute-based regulations with market power. Section 3 provides industry background and describes the data. Sec-

[5] 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.

tion 4 presents the empirical framework and estimation strategy. Section 5 presents the estimation results. Section 6 conducts counterfactual simulations and Section 7 concludes.

2 Theoretical Framework

In this section, we develop a model of attribute-based regulations (e.g., subsidies) to address environmental externalities under different types of market structure. We contrast the private outcomes with socially optimal solutions, and discuss the choice of policy instruments to address market failures. As a key departure from the literature on pollution control under market power (Buchanan, 1969; Barnett, 1980; Fowlie et al., 2016), the model allows firms to respond to policies by changing both prices and product attributes.

Consider a representative firm that produces a product (e.g., an EV) with attributes $\boldsymbol{x}$. The attributes consist of basis product attributes as $\boldsymbol{x} = (x_1, x_2, ..., x_K)$.[6] The marginal cost of production, $C(\boldsymbol{x})$, and the consumer benefit in monetary terms, $B(\boldsymbol{x})$, depend on product attributes. In addition to the private cost and benefit, the product generates environmental externalities denoted by $\phi \cdot e(\boldsymbol{x})$ per unit of output (or $\phi \cdot e(\boldsymbol{x})Q(P,\ \boldsymbol{x})$ in the aggregate), where ϕ denotes the marginal social damage of emissions. For EVs, $e(\boldsymbol{x})$ represents emission reductions relative to the dirty alternatives, therefore $\phi \cdot e(\boldsymbol{x})$ captures positive externalities. The aggregate demand for the product can be specified as:

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

where P is the product price. Note that the benefit from the product attributes is additively separable from the price dis-utility in the demand function. This type of demand function is consistent with the discrete choice models commonly used in the industrial organization literature.

2.1 Choices by Monopoly and Social Planner

The firm chooses price and product attributes to maximize profit:

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

[6]For example, battery capacity, vehicle frame weight, or exterior color can be considered as basis attributes. On the other hand, driving range or fuel efficiency are attributes determined by a combination of basis attributes. The manufacturer can change a basis attribute x_i itself without affecting another basis attribute x_j.

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

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

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

$\varepsilon_P(P,\, \boldsymbol{x})$ is the price elasticity of demand. The subscript k in Equation (2) implies the partial derivative with respect to k-th element of $\boldsymbol{x}$.[7]

The constant marginal cost and the additively separable benefit function (between $B(\boldsymbol{x})$ and P) make the firm's choices of attributes and price independent. Thus, firm's decision becomes a two-stage problem: the firm selects attributes that maximize the net per-unit benefit ($B(\boldsymbol{x}) - C(\boldsymbol{x})$) from the product and then, sets the price to extract the consumer surplus as much as possible.

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

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

The socially optimal price P^* and attributes $\boldsymbol{x}^*$ should satisfy the following first-order conditions:

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

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

The derivation of Equations (3) and (4) is in Appendix A.1. Different from Equations (1) and (2), the first-order conditions of the social planner's problem implies that attributes are chosen to maximize per-unit social benefit, $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$. In the meantime, prices are chosen to reflect the social cost of production $C(\boldsymbol{x}^*) - \phi \cdot e(\boldsymbol{x}^*)$ at the optimal attribute. The socially optimal price eliminates market power while incorporating environmental externality.

Figure 1 illustrates the divergence in attribute choice, quantity, and social welfare between the private and social solutions. Panel (a) depicts the two-dimensional attribute space with vehicle weight and battery capacity as the basis attributes. 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 monopoly would choose $\boldsymbol{x}^o$ as the

[7] The setup can accommodate both monopoly or a perfectly competitive environment. If the market is monopolistic, then the firm perceives the aggregate demand as the individual demand. If the market is competitive, the individual demand becomes flat and $\varepsilon_P(P,\, \boldsymbol{x})$ approaches to infinity, leading to zero markup $P - C(\boldsymbol{x}) = 0$.

privately optimal attribute choice while $\boldsymbol{x}^*$ is the socially optimal choice: the socially optimal design, being lighter and with a larger battery, has a larger environmental benefit.

Panel (b) illustrates the product market outcomes conditioning on the attribute choice by the monopoly: $\boldsymbol{x}^o$. The market price and quantity would be $P^m(\boldsymbol{x}^o)$ and $Q^m(\boldsymbol{x}^o)$ while the socially optimal price and quantity are $P^*(\boldsymbol{x}^o)$ and $Q^*(\boldsymbol{x}^o)$ conditioning on the product design $\boldsymbol{x}^o$. The red triangle (DWL_1) is the deadweight loss from the suboptimal quantity due to market power and (positive) externality. Note that the deadweight loss (DWL_1) in Panel (b) does not include the welfare loss from attribute distortion.

Panel (c) illustrates the impact of attribute changes from $\boldsymbol{x}^o$ to $\boldsymbol{x}^*$. The demand curve for $\boldsymbol{x}^*$ shifts to the left relative to that for $\boldsymbol{x}^o$ at any given price level: while $\boldsymbol{x}^*$ is the socially optimal design, $\boldsymbol{x}^o$ is more appealing to consumers. The green solid-line triangle (with the base defined by line $C(\boldsymbol{x}^o)$) represents the largest possible private surplus from product design $\boldsymbol{x}^o$. It is greater than the red solid-line triangle (with the base defined by line $C(\boldsymbol{x}^*)$) which represents the largest possible private surplus from product design $\boldsymbol{x}^*$. However, from the perspective of social surplus, the pink shaded triangle (with the base defined by $C(\boldsymbol{x}^*) - \phi \cdot e(\boldsymbol{x}^*)$), representing the largest social surplus from product design $\boldsymbol{x}^*$, is greater than the green shaded triangle (with the base defined by $C(\boldsymbol{x}^o) - \phi \cdot e(\boldsymbol{x}^o)$), the largest social surplus from product design $\boldsymbol{x}^o$.[8] The first-best outcome in both attribute space and product market is given by ($\boldsymbol{x}^*$, $P^*(\boldsymbol{x}^*)$, $Q^*(\boldsymbol{x}^*)$). This is in contrast to the socially optimal solution ($P^*(\boldsymbol{x}^o)$, $Q^*(\boldsymbol{x}^o)$) that *conditions* on product design $\boldsymbol{x}^o$.

Panel (d) illustrates the welfare loss from the monopoly relative to the first-best outcome. The deadweight loss (DWL_2) arises from the distortions in both attribute space and the product market. First, product attributes are distorted due to externality. Second, the output level is distorted due to both market power and 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 product design $\boldsymbol{x}^o$ is less environmental friendly than product design $\boldsymbol{x}^*$. The difference between DWL_1 in panel (b) and DWL_2 in panel (d) is driven by the distortion in product attributes.

2.2 Attribute-based Regulations without Budget Constraint

Perfect Targeting The social planner cannot dictate the monopoly to choose P^* and $\boldsymbol{x}^*$. To address the inefficiencies on the market, the social planner offers attribute-based subsidies. As implemented by governments across the world, the per-unit subsidy can be represented by a two-part

[8] This is because $\boldsymbol{x}^*$ maximizes $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$ by construction. In particular, $B(\boldsymbol{x}^*) - C(\boldsymbol{x}^*) + \phi \cdot e(\boldsymbol{x}^*) > B(\boldsymbol{x}^o) - C(\boldsymbol{x}^o) + \phi \cdot e(\boldsymbol{x}^o)$. Note that the socially optimal quantity increases in $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$. Since $Q(.)$ is decreasing in its argument, $Q\big(C(\boldsymbol{x}^*) - \phi \cdot e(\boldsymbol{x}^*) - B(\boldsymbol{x}^*)\big) > Q\big(C(\boldsymbol{x}^o) - \phi \cdot e(\boldsymbol{x}^o) - B(\boldsymbol{x}^o)\big)$ with social marginal cost pricing (i.e. $P = C(\boldsymbol{x}) - \phi \cdot e(\boldsymbol{x})$).

structure: $T + t \cdot z(\boldsymbol{x})$. T is the base subsidy while t is the subsidy rate (or slope). $z(\boldsymbol{x})$ is the policy attribute (e.g., driving range or fuel efficiency) that depends on the basis attributes.[9] When the policy attribute is proportional to the externality (e.g., when $z = e$), we call it perfect targeting (of the externality).

With the attribute-based subsidies, firm's profit maximization problem and the first-order conditions can be written as follows:

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

$$[P]: \qquad \frac{P^z - C(\boldsymbol{x}^z) + T + t \cdot z(\boldsymbol{x}^z)}{P} = \frac{1}{\varepsilon_P(P^z,\ \boldsymbol{x}^z)}, \tag{5}$$

$$[x_k]: \quad B_k(\boldsymbol{x}^z) - C_k(\boldsymbol{x}^z) + t \cdot z_k(\boldsymbol{x}^z) = 0 \ \text{ for } \ i = 1, 2, ..., K. \tag{6}$$

Denote the solution to the profit maximization problem by $(P^z(T,\ t), \boldsymbol{x}^z(t))$ for given policy triad (T, t, z). Note that the level of T only affects price but does not affect the product design. Knowing the response of the monopoly to the policy, the social planner can choose the optimal T and t to maximize the social welfare:

$$\max_{T,\ t}\ SW(P^z(T,\ t),\ \boldsymbol{x}^z(t)).$$

Proposition 1. *Under perfect targeting (e.g., $z = e$) and no budget constraint on total subsidies, the per-unit subsidy following the two-part structure $T^* + t^* \cdot e(\boldsymbol{x})$ where $t^* = \phi$ and T^* is set such that $P^e(T^*,\ \phi) = C(\boldsymbol{x}^e(\phi)) - \phi \cdot e(\boldsymbol{x}^e(\phi))$ achieves the first-best outcome.*

The proof is provided in Appendix A.2. Proposition 1 suggests that T and $t \cdot z(\boldsymbol{x})$ can serve as two policy instruments to address the two market failures: market power and externality. The optimal subsidy rate t^* together with the policy attribute $z(\boldsymbol{x}) = e(\boldsymbol{x})$ works as a Pigouvian policy to incentivize the firm to choose socially optimal product attributes $\boldsymbol{x}^*$. The optimal base subsidy T^* is set to induce socially optimal quantity $Q^*(\boldsymbol{x}^*)$ conditioning on attribute $\boldsymbol{x}^*$.[10]

The top panel of Figure 2 illustrates this. To ease exposition, assume that the private loss function (as a result of attributes $\boldsymbol{x}$ deviating from the privately optimal one $\boldsymbol{x}^o$) is quadratic following Ito and Sallee (2013) and that the policy attribute z is linear in $\boldsymbol{x}$. These two assumptions imply that firm

[9] The EV subsidies in the U.S. based on the battery capacity have the following structure: \$2500+\$415*(kWh-4) with the minimum battery capacity being 4 and the maximum subsidy to be \$7500. The range-based subsidies in China though in a notched design also approximate a two-part structure. Our analysis can also be applied to a setting of taxes where T and t represent taxes to correct for negative externalities.

[10] Subsidies are transfers and do not directly affect social welfare except by changing product attributes and quantity. We abstract away from the distortion of the taxes to fund subsidies in our analysis.

chooses product attributes along a straight line that passes through $\boldsymbol{x}^o$, with the slope determined by the shape of the loss function and the policy attribute z. See Appendix A.4 for detailed derivations. In Panel (a), $d\vec{x_z}$ denotes the direction of firm's response in the product design space when the policy attribute is $z(\boldsymbol{x})$. Under perfect targeting $z(\boldsymbol{x}) = e(\boldsymbol{x})$, firm's response function is the straight line that connects $\boldsymbol{x}^*$ and $\boldsymbol{x}^o$. Each point on the line, $\boldsymbol{x} = \boldsymbol{x}^o + t \cdot d\vec{x_e}$, represents firm's privately optimal attribute choice in response to certain subsidy rate t. A positive subsidy rate t will induce firms to move closer to $\boldsymbol{x}^*$, while a negative subsidy rate t will push firms' product design further away from $\boldsymbol{x}^*$. With the optimal subsidy rate t^*, the social planner can induce the firm to choose socially optimal product design $\boldsymbol{x}^*$.

Panel (b) of Figure 2 shows that given product $\boldsymbol{x}^*$, the optimal base subsidy T^* can be set to induce the monopoly to choose the socially optimal quantity $Q^*(\boldsymbol{x}^*)$. The green triangle represents the social welfare under the first-best outcome $(\boldsymbol{x}^*, Q^*(\boldsymbol{x}^*))$. It is worth emphasizing that neither T nor $t \cdot z(\boldsymbol{x})$ alone is sufficient to achieve the first-best outcome, as shown in Appendix A.3.

Imperfect Targeting In practice, it is difficult to quantify the exact emission reductions from EVs as they are affected by many factors such as the alternative vehicles replaced, the fuel source of electricity generation, and the driving behavior (Xing et al., 2021). Governments instead base the subsidy on a certain product attribute z to approximate the environmental performance of an EV.

Under imperfect targeting, the firm would choose attributes along the line defined by $\boldsymbol{x}^o$ and $\boldsymbol{x}^s$ in response to subsidy $t \cdot z(\boldsymbol{x})$ as illustrated in the bottom panel of Figure 2.[11] The socially optimal attributes $\boldsymbol{x}^*$ is not attainable under imperfect targeting. The product design that achieves the highest social surplus (per unit) under the policy attribute $z(\boldsymbol{x})$ is denoted by $\boldsymbol{x}^s$ in Panel (c). The subsidy rate t is set to induce the monopoly to choose $\boldsymbol{x}^s$ as the product design. As illustrated in Panel (d), an appropriate base subsidy T can induce the $Q^*(\boldsymbol{x}^s)$, the socially optimal quantity conditional on the product design $\boldsymbol{x}^s$. The green triangle, $\mathrm{SW}(\boldsymbol{x}^s)$, in Panel (d) represents the social welfare under the imperfect targeting. With imperfect targeting, $\mathrm{SW}(\boldsymbol{x}^s)$ in Panel (d) is smaller than $\mathrm{SW}(\boldsymbol{x}^*)$ in Panel (b) as $\boldsymbol{x}^*$ maximizes $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$ by construction. The welfare reduction is driven by social planner's inability to perfectly target emissions, leading to distortion in attribute choices.

Choice of Policy Attribute Under imperfect targeting, the social planner may have the freedom to choose the policy attribute in addition to the subsidy structure, leading to a policy triad: (T, t, z). If there is no budget constraint, the optimal policy attribute $z(\boldsymbol{x})$ should approximate the environmental externality $e(\boldsymbol{x})$ as close as possible so that the subsidy rate t can be chosen to achieve the per-unit

[11] See Appendix A.4 for the derivations.

social surplus that is closest to the level provided by the first-best outcome $\boldsymbol{x}^*$. Then T can be chosen to reach the socially optimal quantity conditioning on product design.

Panel (a) in Figure 3 compares two subsidies based on vehicle weight and driving range. The government can encourage firms to choose $\boldsymbol{x}^r$ ($\boldsymbol{x}^w$) using the range-based (weight-based) subsidies. It shows that ranged-based subsidies incentivize the firm to produce vehicles with a smaller weight but a larger battery capacity relative to $\boldsymbol{x}^o$, while weight-based subsidies increases the weight. In this example, $\boldsymbol{x}^r$, being a more environmentally friendly design, generates a larger social surplus per unit and a higher aggregate welfare in the product market. Therefore, driving range is the better choice as a policy attribute than vehicle weight.

2.3 Attribute-based Regulations with Budget Constraint

In practice, the social planner faces a budget constraint which may limit the level of t and T. Under a budget constraint, the choice of policy attribute $z(\boldsymbol{x})$ needs to balance its interaction with both the environmental externality captured by $e(\boldsymbol{x})$ and market power. Panels (b) and (c) in Figure 3 illustrate the product market outcomes for the two designs $\boldsymbol{x}^r$ and $\boldsymbol{x}^w$. Without any budget constraint, the government can achieve (P w/o BC, $Q^*(\boldsymbol{x}^r)$) in Panel (b) and (P w/o BC, $Q^*(\boldsymbol{x}^w)$) in Panel (c). In these cases, $\boldsymbol{x}^r$ generates greater total surplus than $\boldsymbol{x}^w$ does since $\boldsymbol{x}^*$ is closer to $\boldsymbol{x}^r$ than to $\boldsymbol{x}^w$ in Panel (a). However, such total surpluses are not feasible with a fixed government budget. The total subsidy, which is the same under the two designs, is represented by the yellow area. The government achieves greater sales with $\boldsymbol{x}^w$ than with $\boldsymbol{x}^r$ with the same subsidy expenditure because $\boldsymbol{x}^w$ is more attractive to the private sector (i.e. $B(\boldsymbol{x}) - C(\boldsymbol{x})$ is greater). As a result, the total surplus is greater under the weight-based policy, which is opposite to the result without the budget constraint.

The trapezoids with solid green lines represent the aggregate social surplus. The height of the trapezoids depends on the per-unit social surplus ($B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$). As shown in Panel (a), $\boldsymbol{x}^r$ commands a higher per-unit social surplus, therefore, the height of the trapezoid in Panel (b) is larger than that in Panel (c). However, the aggregate social surplus in Panel (b) is smaller due to a lower quantity of EVs and a larger deadweight loss denoted by the red triangle. This is driven by the larger unmitigated market power in Panel (b): because the product design $\boldsymbol{x}^r$ is less attractive to consumer (e.g., lower quality), a higher per-unit subsidy is needed to induce additional demand. With the fixed budget, the EV sales in the equilibrium in Panel (b), "Q with BC", is farther away from the socially optimal quantity, than that in Panel (c). The following lemma shows that the per-unit private surplus is closely related to the maximum sales that the planner can achieve with a given budget constraint.

Lemma 1. *Consider two policy triads (T, t, z) and (T', t', z') that satisfy the budget constraint:*

$$[T + t \cdot z(\boldsymbol{x}^z(t))] \cdot Q\big(P^z(T,t), \boldsymbol{x}^z(t)\big) = [T' + t' \cdot z'(\boldsymbol{x}^{z'}(t'))] \cdot Q\big(P^{z'}(T',t'), \boldsymbol{x}^{z'}(t')\big) = R,$$

where R is a fixed subsidy expenditure. Then,

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

The proof of Lemma 1 is in Appendix A.5. Lemma 1 facilitates comparisons between different policy triads. When two policy triads (T, t, z) and (T', t', z') are associated with identical government expenses, their ability to address market power considerations is captured by the sufficient statistics $B(\boldsymbol{x}) - C(\boldsymbol{x})$.

In the previous section, the planner could address two inefficiencies from externality and quantity distortion separately, by affecting firm's product design with t and the pricing decision with T. However, if the planner cannot eliminate the market power ($P - C(\boldsymbol{x}) + \phi e(\boldsymbol{x}) > 0$) due to the budget constraint, it is not anymore possible to address two inefficiencies separately.

Proposition 2. *For a given attribute z and budget limit R, consider the planer's problem*

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

Suppose (T, t) is the solution without the budget constraint while (T', t') is with the constraint. If the constraint is binding, the optimal attribute choice under the budget constraint can be characterized as:

$$\boldsymbol{x}^z(t') = \alpha \boldsymbol{x}^z(t) + (1 - \alpha)\boldsymbol{x}^o \;\; for \;\; \alpha \in (0,1),$$

where $\boldsymbol{x}^o$ is the firm's initial choice without policy intervention. In addition, α is increasing in R.

The proof of Proposition 2 is in Appendix A.6. Figure 4 (a) demonstrates the above proposition. If the planner can guarantee the efficient level of output in the product market for any product design $\boldsymbol{x}^z(t)$ by eliminating the markup using T, the second best product design should be "$\boldsymbol{x}^s$ w/o BC" in the figure since the isoquant of per-unit social surplus is tangent with the policy line at that point. But, if there exists a binding budget constraint, the planner cannot achieve the efficient level of output with the product design. Lemma 1 shows that if the planner chooses another design closer to $\boldsymbol{x}^o$, the planner can achieve the greater output level under the budget constraint. As the planner's choice on the policy line is closer to "$\boldsymbol{x}^s$ w/o BC", the per-unit product design becomes more desirable by internalizing the externality. In constrast, as the choice is closer to $\boldsymbol{x}^o$, it becomes easier for the planner to address the quantity distortion using the same level of subsidy expenditure. Therefore, the social planner should balance the externality and market power considerations when the private choice $\boldsymbol{x}^o$ is distorted. The last part of Proposition 2 suggests that the second-best choice moves towards $\boldsymbol{x}^o$ as the budget constraint becomes more stringent. With a lower budget, the planner has less ability to address the quantity distortion, and therefore should put more weight on the market power concern, resulting in lower α as demonstrated in Figure 4 (a).

Choice of Policy Attribute Figure 4 illustrates the choice of policy attribute when the government has the flexibility to determine which attribute to base the subsidies on. $\boldsymbol{x}^s$ in Figure 4 (b) represents the second-best product design under the range-based subsidies with a given budget constraint. However, a different policy attribute could lead to a better product design as illustrated by Figure 4 (b). Specifically, any point in the highlighted blue lens on the iso-social-surplus and iso-private-surplus curves would achieve both a higher social surplus and a higher private surplus within the given budget. Therefore, any policy attribute that leads to a best response curve passing through the lens would be a better attribute to based the subsidy on. Consider the capacity-based subsidies that generate a best response curve passing through $\boldsymbol{x}'$. $\boldsymbol{x}'$ may or may not be the best choice under the capacity-based policy. However, $\boldsymbol{x}'$ dominates the second-best choice, $\boldsymbol{x}^s$ with the range-based policy. By Lemma 1, $\boldsymbol{x}'$ and $\boldsymbol{x}^s$ would achieve the same level of output in the product market while $\boldsymbol{x}'$ generates a larger per-unit contribution to the social welfare. When the battery capacity is chosen as the policy attribute, the subsidies can address the externality better while maintaining the same level of quantity distortions from the market power as that under range-based subsidies. Since the second-best choice under the capacity-based subsidies should be weakly better than $\boldsymbol{x}'$, we can conclude that battery capacity is a better policy attribute than driving range in this example.

Proposition 3. *Consider the contract curve that collects tangent points of iso-social and iso-private surplus curves with $\boldsymbol{x}^o$ and $\boldsymbol{x}^*$ as the two ending points of it. Then, the followings are true.*

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

ii) If a product design $\boldsymbol{x}'$ is on the contract curve, then there exists an optimal triad (T^R, t^R, z^R) that satisfies $\boldsymbol{x}' = \boldsymbol{x}^{z^R}(t^R)$.

iii) $\boldsymbol{x}^{z^R}(t^R)$ moves towards $\boldsymbol{x}^*$ along the contract curve as R increases.

The proof of Proposition 3 is in Appendix A.7. Figure 4 (c) shows how the optimal policy attribute varies with the level of the total budget. The four red dots on the graph are the tangent points between the iso-social and iso-private surplus curves. The four lines passing through them represent different policy attributes, $\{z^1, z^2, z^3, z^4\}$. Proposition 2 shows that there exist a unique budget level R so that each red dot becomes the second-best product design given the corresponding policy attribute. Denote the budget level by R^i that makes the i^{th} red dot as the second-best choice under the subsidies based on z^i. Note that the red points do not create the lens as in Figure 4 (b). In other words, z^i is the optimal policy attribute that the planner can base the subsidies on given the budget level R^i. Moreover, Proposition 3 implies a higher level of budget is needed to move from z^1 to z^4, that is, $R^1 < R^2 < R^3 < R^4$.

The tangent points in Figure 4 (c) represent the best policy triads (T^*, t^*, z^*) for the social planner across different budget levels. By tracing those tangent points, we can construct the contract curve that is the collection of the Pareto-efficient policy designs. We can interpret the contract curve by introducing two agents. Agent 1 prefers a higher $B - C + \phi \cdot e$ while Agent 2 prefers a higher $B - C$. From Agent 1's perspective, $\boldsymbol{x}^*$ is the best, which is the one end of the contract curve. However, agent 2 most prefers the other end of the curve, $\boldsymbol{x}^o$. The budget level R plays the role of the Pareto weights in consumer theory that pins down a specific point on the contract curve. Here, the budget level affects the capability of the planner in remedying the quantity distortion. As the budget level R increases, the planner's choice moves towards $\boldsymbol{x}^*$ to focus more on the externality concern given the increased ability (via subsidies) to tackle market power with a higher budget.

The best policy direction starts with the *C*-*D* line under the most stringent (or zero) budget for total subsidies, but converges to the perfect targeting direction *A*-*B* as the budget constraint is relaxed. The *C*-*D* line represents the least harmful direction for the private sector since the per-unit private net benefit decreases most slowly in that direction. Therefore, the maximum quantity achievable with a given budget also decreases slowly as the policy line moves closer to *C*-*D* line. When the quantity distortion is severe due to a large markup, the planner should put more weight on the market power consideration than the exernality concern. On the other hand, if the planner can drastically reduce the markup with a large enough budget, the planner can focus more on the externality by selecting a policy attribute that approximates the externality better.

Differentiated Products Oligopoly Our empirical analysis compares the welfare consequences of different policy designs in the setting of a differentiated product oligopoly. In oligopoly markets, different products (e.g., car models) exhibit different levels of market power due to the nature of differentiated products. Suppose there are two products $j = 1, 2$ exhibiting heterogeneous structure of benefit B_j, marginal cost C_j, and demand $Q_j(B_1 - P_1,\ B_2 - P_2)$, which results in different level of markups and quantity distortions. The planner distributes a given subsidy expenditure $R = \sum_j b_j Q_j$

by offering product-specific subsidy intensity b_j. Appendix A.8 shows that the optimal incentive rate ratio b_1^*/b_2^* is increasing in $B_1 - C_1$ and decreasing in $B_2 - C_2$. Therefore, it is better to assign higher subsidies to the products that generates more net benefit to the society.

In practice, however, it may be politically and technically challenging to provide a product-specific subsidy rate b_j. Given the inability of a uniform subsidy in adequately mitigating market power that varies across products, attribute-based subsidies can take on the additional role of addressing market power. The two-part subsidies $b_j = T + t \cdot z(\boldsymbol{x}^j)$ vary across products based on the policy attribute. Thus, the attribute-based subsidy may mitigate heterogeneous market powers better depending on the correlation between the policy attribute $z(\boldsymbol{x}^j)$ and its per-unit contribution $B_j - C_j$. For example, if the policy attribute such as vehicle weight is more correlated with the per-unit contribution than driving range in the differentiated product oligopoly, weight-based subsidies would be better able to mitigate market power across products. But, the advantage of weight-based subsidies in mitigating market power needs to be balanced against the advantage of range-based subsidies in addressing environmental externality through inducing firms to choose more environmental friendly product design.

3 Background and Data

We first discuss the industry background, and then describe the data and present stylized facts.

3.1 Industry and Policy Background

As the governments in many other countries, the Chinese government considers developing the EV industry as a strategic priority in order to reduce energy consumption and emissions from the transportation sector, and to increase the global competitiveness of domestic automobile industry. The central government set the goal of reaching 20% of EVs and 40% in the new vehicle market by 2025 and 2030, respectively. In addition, accelerating EV adoption is an important strategy to achieve the 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. [12]

While the mass market EVs were first introduced in the US in 2011, China became the largest EV market from 2015 as shown in Appendix Figure A2. For the last few years, China has accounted

[12]These targets were announced in “The Medium and Long-term Development Plan of the Automobile Industry” jointly issued by the Ministry of Industry and Information Technology (MIIT), the Ministry of Science and Technology (MoST), and the National Development and Reform Commission (NDRC), and “The Technology Roadmap of Energy Conservation and New Energy Vehicles” by MIIT in 2017.

for 40-50% of global EV sales, with sales reaching nearly 1.4 million units in 2020. The rapid increase in EV sales in China was largely driven by the generous consumer subsidies from both central and local governments as well as non-financial incentives as shown in Li et al. (2021). With the strong support from the government, many Chinese automakers entered into the EV market. There were over 60 EV automakers and 150 models in 2018 in China. Nevertheless, the market is still concentrated with the top five EV firms accounting for over 55% of the market. The largest EV firm, BYD, had a market share of about 20%, followed closely by the Beijing Automotive Group.[13]

Table 1 presents the schedule of consumer subsidies provided by the central government from 2013 to 2018. The subsidies are ranged-based and set differently for BEVs and PHEVs.[14] For BEVs, the subsidies are notched with several cutoffs. Overtime, the minimum range requirement increased from 80km in 2013 to 100km in 2016 and further increased to 150km in 2018. At the same time, the amount of subsidies has been reduced. The amount of subsidies amounts to about 10-28% of consumer prices for most of range groups as shown in Table A1. The central subsidies rolled out first in a few pilot cities before 2014 and then expanded to 88 cities in 2014 and then roll out to the national level in 2016. Notably, during this period, only EVs produced by domestic companies or joint venture companies (with at least one Chinese company) could be subsidized and imported EVs were not eligible for subsidies.[15] 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 amounts to 30-60% of product prices.

There are three major non-financial incentives at the local level: exemption from driving restrictions, exemption from vehicle purchase restriction, and green license plate policy. Many cities in China and around the world have implemented some type of driving restrictions to address traffic congestion (Davis, 2008; Jerch et al., 2021).[16] A number of 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

[13]As a comparison, the numbers of EV firms and models, and EV sales in the United states were about one third of those in China in 2018. The market in the United States was more concentrated with Tesla alone accounting for over 50% and the top five accounting for over 80% of the market in 2018.

[14]In order to incentivize automakers to improve quality, the government tightened the eligibility rules by incorporating additional technical requirements including the minimum battery density of 105Wh/kg and minimum energy efficiency in kWh/100km (as a function of vehicle weight) from 2018.

[15]The joint-venture requirement for foreign automakers to manufacture automobiles in China is part of the long-term "technology-for-market" strategy by the Chinese government (Bai et al., 2020). Amid the recent trade war between China and the United States, 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 and these EVs are eligible to receive subsidies. In 2020, Tesla China received ¥2.1 billion ($325 million) in subsidies for EVs, the highest amount granted to any automaker in the country.

[16]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.

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. We control for these local policies in our analysis.

3.2 Data and Descriptive Evidence

Our analysis is based on three main data sets: (1) annual vehicle registration data by city and vehicle model from 2015 to 2018 for all vehicle models including both gasoline and EV models; (2) data on detailed vehicle attributes including Manufacturer Suggested Retail Prices (MSRPs) by model from 2012 to 2018; and (3) comprehensive central and local financial and non-financial policies from 2015 to 2018 as used in Li et al. (2021). We define a vehicle model by its name, vehicle type, 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. These cities accounted for 69 percent of national EV sales.

We do not observe (average) transactions prices but use MSRPs in our estimation. MSRPs are set by manufacturers and are the same nationwide for each model-year.[17] Using MSRPs instead of transaction prices could lead to bias in consumer preference estimates if discounts are correlated with demand shocks (Langer and Miller, 2013). However, different from the U.S. vehicle market, discounts especially 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 data on average dealer-level transaction prices in five cities (Beijing, Chengdu, Guangzhou, Hangzhou, and Shanghai) from 2011 to 2018. The data show that transaction prices and MSRPs are highly correlated with a correlation coefficient of 0.993.

We also utilize some auxiliary data for our analysis including: (1) nationally representative household surveys on new vehicle buyers from 2011 to 2017 that allow us to construct micro-moments to help with identification of consumer preference heterogeneity (Barwick et al., 2021);

[17]MSRPs in China includes value-added tax (17%), consumption tax, as well as import tariffs when applicable. Consumption tax is often levied to promote sales of small and fuel-efficient vehicles and varies from 1% to 40%, depending on vehicle size. MSRPs does not include the sales tax which is below 10% but varies with engine size. We add sales tax to MSRPs in our estimation following (Barwick et al., 2021).

(2) the number of public charging stations by city by quarter from 2012 to 2018 as a control variable; and (3) battery suppliers data by vehicle model which allow us to construct supply-side instruments for vehicle prices. The summary statistics are presented in Table 2.

Figure 5 shows the number of BEV models by driving range on an annual basis from 2015 to 2018. The dark blue bars represent the driving ranges that are just above the range cutoffs shown in Table 1. There are two important salient features from these graphs. First, the distribution of EV driving range exhibits strong bunching at the range cutoffs, likely the result of the notched design. Bunching associated with the notched design could lead to inefficiency relative to the smooth policy (e.g., a continuous subsidy schedule as a function of driving range) by creating uneven marginal incentives, which we study in one of counterfactual simulations.[18] Second, the range distribution shifts with the subsidy policy, suggesting that firms respond to the policy on an annual basis. For example, when the minimum range requirement was raised from 80 to 100 in 2016, the minimum range observed in the data increased. When the set of cutoffs increased in 2018 to include 200km, 300km and 400km, bunching appeared in these new cutoffs.

The driving range is primarily affected by battery capacity and vehicle size. Firms can change these attributes in response to policy changes. To examine whether the range-based subsidies have induced downsizing, Figure A3 compares the top 10 most popular EV (including both BEV and PHEV) models in China and the United States. The footprint (i.e., length by width) of the top three BEV models in the Chinese market ranges between 5m^2 to 6m^2, while that in the US market is larger than 8m^2 where the subsidies are based on battery capacity. One might argue that this is driven by that consumers in the United States may have a stronger preference for vehicle size than those in China. However, the size differences between the top PHEV models in these two countries are much smaller. The minimum range requirement for PHEVs in China is not binding for any of the PHEV models on the market. Therefore, automakers in China have no incentives to downsize their PHEVs.

4 Empirical Framework

The empirical framework is a market equilibrium model of automobiles 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 in the supply side in order to examine the welfare consequences of attribute-based subsidies. As discussed in the theoretical model, the changes in product attributes

[18] A large literature have examined the inefficiencies from a policy with notches. Notched design in regulations (e.g., standards or taxes) could lead to unintended responses such as compliance test manipulation (Sallee and Slemrod, 2012), tax evasion (Almunia and Lopez-Rodriguez, 2018), and price discrimination (Houde, 2018a,b).

in response to the policy design could in turn affect both externality and market power. Capturing these two welfare channels is critical for comparing different policy designs.

4.1 Demand Side

The individual utility of consumer i from product j in market m is specified as:

$$u_{ijm} = -\alpha_i \tilde{P}_{jm} + X_{jm}\boldsymbol{\beta_i} + \xi_{jm} + \varepsilon_{ijm}, \tag{7}$$

where $\tilde{P}_{jm}$ is the effective price of model j in market m that consumers pay: if j is an EV eligible for subsidies, $\tilde{P}_{jm} = P_j - \text{subsidy}_{jm}$, where P_j is the firm price of model j (MSRP). X_{jm} is a vector of observed product attributes such as vehicle weight w_j, driving range D_j for EVs, and fuel efficiency for gasoline vehicles. ξ_{jm} represents unobserved attributes of model j in market m (unobserved by the econometrician but observed by consumers and firms). ε_{ijm} is an idiosyncratic preference shock assumed to have a i.i.d. type I extreme value distribution. We define a market as a city by quarter and there are 640 markets in our analysis: 40 cities by 4 quarters from 2015 to 2018.

The preference parameters $(\boldsymbol{\beta_i}, \alpha_i)$ represent heterogeneous preference. $\beta_{ki} = \bar{\beta}_l + \sigma_l \nu_{ki}$ captures individual-specific preference for vehicle attribute k, where $\bar{\beta}_k$ is the mean preference constant across all markets and $\sigma_k \nu_{ki}$ stands for individual i's preference for attribute k. In estimation, we assume ν_{ki} follows a normal distribution and σ_k is its standard deviation. $\alpha_i = exp(\alpha_1 + \alpha_2 log(Y_{im}) + \sigma_p \nu_{pi})$ represents consumer i's marginal utility of income. α_1 captures the price sensitivity of consumers while α_2 captures the consumer heterogeneity in price sensitivity affected by the income level Y_{im}. ν_{pi} is assumed to follow a normal distribution and σ_p captures the dispersion of the price sensitivity.

The individual utility specified in Equation (7) can be divided into the mean (or household-invariant) utility $\delta_{jm}(\boldsymbol{\theta_1}) = X_{jm}\bar{\boldsymbol{\beta}} + \xi_{jm}$, the heterogeneous (or household-specific) term $\mu_{ijm}(\boldsymbol{\theta_2}) = -\alpha_i \tilde{P}_{jm} + \sum_l \sigma_l X_{jl} \nu_{ijm}$, and the idiosyncratic preference shock ε_{ijm}. Assuming ε_{ijm} to admit the type I extreme value distribution, the choice probability can be specified as:

$$Pr_{ij}(\boldsymbol{\theta_1}, \boldsymbol{\theta_2}) = \Pr(i \text{ chooses } j \text{ in market } m) = \int \frac{e^{\delta_{jm} + \mu_{ijm}}}{1 + \sum_k e^{\delta_{km} + \mu_{ijm}}} dF(\mu), \tag{8}$$

The individual choice probabilities can be aggregated to generate the market share for each model j, which can then be match to the observed market shares in estimation.

4.2 Supply Side

On the supply side, a firm chooses prices each model maximize the joint profit from all products including both gasoline models and EVs that the firm makes. To examine the attribute choices for EVs in response to subsidy policies, we allow firms to endogenize vehicle weight and battery capacity for EVs, and let driving range be determined by these two attributes through a technology frontier function.

Abstract away from gasoline models to ease exposition, a firm chooses price, battery capacity and weight to maximize the current-period total profit given the subsidies structure where a model j receives a per-unit subsidy $t_j \cdot \mathbb{1}\{D_j > \underline{D}\}$:

$$\max_{P_j,k_j,w_j} \sum_{j\in J_f} \pi_{jm}(\boldsymbol{P},\boldsymbol{k},\boldsymbol{w},\boldsymbol{s}) - \sum_{j\in J_f} FC_j(k_j,w_j),$$
$$\text{s. t. } \; D_j(k_j,w_j) \geq \underline{D}, \tag{9}$$

where $\pi_{jm}(\boldsymbol{P},\boldsymbol{k},\boldsymbol{w},\boldsymbol{t}) = \big(P_j - mc_j(k_j,w_j) + t_j\big)\cdot Q_j(\tilde{\boldsymbol{P}},\boldsymbol{D},\boldsymbol{w},\boldsymbol{t})$ is the operating profit. $mc_j(k_j,w_j)$ is the marginal cost function, assumed to be constant with respect to quantity as an approximation. $FC_j(k_j,w_j)$ is the fixed cost function for attribute changes. Both functions depend on battery capacity k_j and weight w_j. $Q_j(.)$ is the residual demand for product j and it is determined by the attributes of competing products and the subsidies. $\tilde{\boldsymbol{P}}$ is a vector of consumer prices for each model: $\tilde{P}_j = P_j - t_j\mathbb{1}\{D_j \geq \underline{D}\}$, and $\boldsymbol{t}$ is a vector of subsidies. Note that we suppress market index/city m but the subsidies include both central and local subsidies which vary across cities.

$D_j(k_j,w_j)$ represents the technology frontier: the relationship between driving range D and two key vehicle attributes, battery capacity k and vehicle weight w. We specify $D_j(k_j,w_j) = h(k_j,w_j) + \kappa_j$. κ_j captures the technology level that is affected by motor efficiency and aerodynamics of vehicle frame, as well as factors other than capacity and weight.[19] The technology frontier function links the two endogenous attributes, battery capacity and vehicle weight, to driving range which enters consumer utility function.

The firm solves the constrained optimization by maximizing the following Lagrangian function:

$$\mathscr{L}_f = \sum_{j\in J_f} \pi_j(\boldsymbol{P},\boldsymbol{k},\boldsymbol{w},\boldsymbol{s}) - \sum_{j\in J_f} FC(k_j,w_j) + \sum_{j\in J_f} \lambda_j[D_j(k_j,w_j) - \underline{D}],$$
$$\text{with } \; \lambda_j > 0 \text{ if } D_j = \underline{D}, \tag{10}$$

[19] The realized or real-world driving range is affected not only by vehicle hardware but also external factors such as temperature, road condition, and driving speed. In making vehicle purchase decisions, consumers are likely focusing on the official driving range rating.

where λ_j is the shadow price for relaxing the constraint $\underline{D}$. It varies across vehicle models and is positive only when $D_j = \underline{D}$ and zero otherwise. The first order conditions are as follows:

$$\begin{aligned} \sum_{l \in J_f^m} \sum_m \frac{\partial \pi_{lm}}{\partial P_j} &= 0, \\ \sum_{l \in J_f^m} \sum_m \frac{\partial \pi_{lm}}{\partial k_j} + \lambda_j \frac{\partial h(k_j, w_j)}{\partial k_j} &= \frac{\partial FC(k_j, w_j)}{\partial k_j}, \\ \sum_{l \in J_f^m} \sum_m \frac{\partial \pi_{lm}}{\partial w_j} + \lambda_j \frac{\partial h(k_j, w_j)}{\partial w_j} &= \frac{\partial FC(k_j, w_j)}{\partial w_j}. \end{aligned} \tag{11}$$

The first order conditions with respect to battery capacity and vehicle weight have as additional term capturing the effect of the constraint on firm profit.

4.3 Identification and Estimation

4.3.1 Demand Side

To estimate the preference parameters in Equation (7), our strategy follows Berry et al. (1995) and especially Petrin (2002) and Berry et al. (2004) but with a key difference: in addition to the endogeneity in the price variable, driving range and vehicle weight, D_j and w_j, are likely to be endogenous in that they are chosen at the same time as unobserved attributes ξ_{jm}. Recognizing endogeneity in vehicle prices, driving range, and weight, we use four sets of IVs for the three endogenous variables: (1) the central subsidies; (2) sales tax rates; (3) the number of compartments (EVs), the number of doors (gas models), and wheelbase; and (4) battery weight interacted with battery supplier dummies.[20] The first two and the fourth sets of IVs are for price, while the third and fourth sets are for driving range and vehicle weight.

The central subsidies directly affect consumer prices, and they vary by driving range in a discrete way. In addition, both the subsidy amount and the driving range cutoff change over time as shown in Table 1. Since driving range is included in the utility function, the identification assumption is that unobserved attributes ξ does not change discretely with driving range. That is, the variation in prices induced by the discrete jumps in subsidies provides plausibly exogenous variation for the identification of consumer price sensitivity. Similarly, sales tax rates changes discretely with engine size: vehicles with an engine size above 1.6 liters are required to pay the sales tax, which affects the consumer prices. The tax rate had varied between 5 to 10 percent during the sample period, and

[20] We categorized the battery suppliers into three groups: BYD, CATL, and others. BYD is the largest EV maker in China and supplies the batteries only for its own EV models. CATL is the largest supplier in the battery industry and supply for many EV producers.

these variations are the top-down decisions of the central governments. We assume that engine size is determined in the early stage of vehicle design, and thus, plausibly orthogonal to the unobserved attributes ξ.

The third set of IVs follows the strategy in Whitefoot et al. (2017) which recognizes that vehicle design is a multi-stage process taking several years. Vehicle attributes that determine Vehicle framework such as wheelbase as well as the number of compartments and doors are chosen in the earlier stage of vehicle design. While these attributes affect vehicle weight, we assume that they are not correlated with unobserved vehicle attributes that are chosen at a later stage. In addition, we assume that these attributes do not enter consumer utility directly conditional on a rich set of controls such as vehicle type, segment and fuel type.[21] The fourth set of IVs based on battery weight and battery suppliers should be correlated with vehicle price: the cost of battery production and the markups could be different across battery producers, which would affect vehicle prices. In addition, battery weight is correlated with battery capacity and vehicle weight (hence range) but consumers are unlikely aware of or care about battery weight itself.

To facilitate the identification of heterogeneous preference parameters, we construct micro-moments based on the household survey of new vehicle buyers (Petrin, 2002; Berry et al., 2004). Together, the demand estimation is carried out using simulated GMM (with a nested contraction mapping to recover product-specific mean utility δ_{jm}) based on the following two sets of moment conditions:

- **Moment condition 1**: $E[\xi_{jm}(\theta)|\boldsymbol{Z}_{jm}] = 0$, where $\boldsymbol{Z}$ is a vector of exogenous variables;
- **Moment condition 2**: Predicted shares = observed shares of buyers by income group.

4.3.2 Supply Side

There are three set of model primitives in the supply side: the technology frontier, the marginal cost function, and the fixed cost function. To estimate the technology frontier function, we use a linear function to approximate $h(.)$ and specify:

$$D_j(k_j, w_j) = \eta_k k_j + \eta_w w_j + \kappa_j. \tag{12}$$

To estimate the parameters, we collect vehicle attribute data on all EV models tested by the government for the purpose of approval for EV sales tax exemption by the MIIT. Some of the models have not been launched in the market. Since 2014, MIIT has been announcing a list of newly approved

[21] There are four vehicle types: van, SUV, MPV, and sedan, and five size segments: mini, sub-compact, compact, mid, large, luxury.

models three to seven times a year.[22] Our data contains all the models up to the list announced on April 18th, 2019. Among the models, we focus on passenger BEVs and exclude buses and trucks. The marginal cost is assumed to take the following form:

$$mc_j(k_j, w_j) = (\gamma_t)^t \gamma_k \, k_j + \gamma_w \, w_j + G'_j \gamma_g + \omega_j, \tag{13}$$

where $(\gamma_t)^t \gamma_k$ and γ_w represent the effect of battery capacity and vehicle weight on the marginal cost of production, respectively. γ_t captures the change in battery cost over year t as the technology improves. For example, γ_t being 0.8 implies a 20% reduction in the battery cost each year. $G'_j \gamma_g$ is the part of marginal costs determined by vehicle attributes other than battery capacity and vehicle weight: G_j is the vector of exogenous attribute: horsepower, engine size, and fuel efficiency. Lastly, ω_j captures the shock to the marginal cost.

Estimating the full fixed cost parameters would require leveraging product entry and exit decisions. Our analysis focuses on the part of the fixed costs that vary with attributes and hence could be identified via product attribute choices. Following Fan (2013), we specify the slope of the fixed cost as follows:

$$\frac{\partial FC_j}{\partial k_j} = \phi_k k_j + FEs + \nu_j^k \quad \text{and} \quad \frac{\partial FC_j}{\partial w_j} = \phi_w w_j + FEs + \nu_j^w, \tag{14}$$

where ϕ_k and ϕ_w captures curvature of the fixed costs with respect to battery capacity and vehicle weight, respectively. A positive coefficient implies convexity of the fixed cost function. We include year, vehicle type, fuel type, segment, and firm fixed effects to allow the slope of the fixed costs to have more variation.

With the specifications of the cost and technology frontier functions, the first order conditions of firm price and attribute choice in Equation (11) can be rewritten as:

$$\text{Price FOC: } Q_j + \sum_{i \in J_f^m} (P_i - mc_i) \frac{\partial Q_i}{\partial P_j} = 0; \tag{15}$$

$$\text{Battery Capacity FOC: } \sum_{i \in J_f^m} (P_i - mc_i) \frac{\partial Q_i}{\partial k_j} = (\gamma_t)^t \gamma_k Q_j - \lambda_j \eta_k + \phi_k + FE + \nu_j^k; \tag{16}$$

$$\text{Vehicle Weight FOC: } \sum_{i \in J_f^m} (P_i - mc_i) \frac{\partial Q_i}{\partial w_j} = \gamma_w Q_j - \lambda_j \eta_w + \phi_w + FE + \nu_j^w. \tag{17}$$

Q_j is the aggregate sales. The first order condition for price in Equation (15) is standard in the

[22] The first list was announced on August 27th, 2014, and all EVs tested before the date were included in this list.

literature (Berry et al., 1995). Together with the demand estimation, it can be used to back out the marginal cost mc for each product. With the estimated marginal costs, the marginal cost Equation (13) and the first-order conditions for battery capacity and vehicle weight in Equation (16) and (17) are then used for the estimation of the parameters in the model premises in the supply side. The left-hand side of these three equations (13), (16) and (17), are known and the right-hand side contains the unknown parameters.

There exist two challenges in taking Equations (13), (16) and (17) to data. First, the cost shocks ω and ν could be correlated with the attribute choices and vehicle sales. For instance, a negative marginal cost shock (a large ω) may lead firms to reduce the battery and vehicle size for cost saving. Similarly, a negative fixed cost shock (large μ) would dis-incentivize firms from making attribute changes. In addition, a large ν could have negative impacts on vehicle sales. Second, the shadow price λ_j is product-specific because the driving range constraints apply to each product. Shadow price λ_j should have a positive value if one of the policy cutoffs constrains product j's driving range.[23] Among the 279 EV models in the sample, 115 of them have a binding driving range constraint, implying that almost half of the models has positive and unknown shadow prices. We assume that the model-specific shadow prices as a function of the annual sales of the corresponding EV models:

$$\lambda_j \simeq \zeta \cdot Q_j \cdot 1\{\underline{D} \leq D_j \leq \underline{D} + 5\}$$

where ζ is the parameter to be estimated. The underlying intuition for this specification is as follows. Suppose the driving range of product j is constrained by a policy cutoff, that means that the automaker would need to deviate from the optimal product design for model j by increasing the driving range to receive the subsidy corresponding to the cutoff. λ_j represents the firm's WTP to increase the driving range by 1km and hence reduce the deviation from the optimal design. If product j is a popular model (i.e., with large sales), the automaker would have a larger WTP for achieving the optimal vehicle design.

We leverage three IVs in order to estimate parameters in Equations (13), (16) and (17): central and local subsidies, the consumption tax, and the average gasoline price weighted by city-level sales for each model. The subsidies should affect sales, battery capacity, and vehicle weight, but unlikely to be correlated with the production cost shock ν. The consumption tax rate is zero for BEVs but varies from 0% to 40% depending on the engine size for gasoline and PHEVs. The variation in the consumption tax rate could affect attribute choices especially vehicle weight. Our third IV is based on gasoline prices. For each model, we compute the sales-weighted average gasoline price across

[23] We assume the constraint is binding if D_j is equal to or greater than the cutoff, but does not exceed it by more than 5km.

cities where the model was sold. Gasoline prices could affect vehicle attributes and the impact could be larger if the model is more popular in areas with high gasoline prices, hence facing an higher effective gasoline price. The identification assumption is that gasoline prices, heavily regulated in China, are unlikely to be affected by the cost shocks to vehicle production.[24]

Denote the cost instruments by W_j and we have three sets of moment conditions for the supply side:

$$E[\omega_j|W_j] = 0, \;\; E[\nu_j^k|W_j] = 0, \;\; \text{and} \;\; E[\nu_j^w|W_j] = 0. \tag{18}$$

(γ, ϕ, ζ) are jointly estimated following Equations (13), (16) and (17). To estimate the marginal cost equation (13), we use both gasoline vehicles and EVs, leading to 1540 observations. We maintain the exogeneity assumption of product attributes for gasoline models as in the literature but endogenize battery capacity and vehicle weight for EVs (in response to the subsidy policy for EVs). Therefore, for the first order conditions in Equations (16) and (17), there are 279 observations composed of only EVs.

5 Estimation Results

We present parameter estimates from both the demand and supply sides, and then discuss the implications of the estimates.

5.1 Demand Side Results

Table 3 presents the estimates of the preference parameters in Equation (7). The first column shows the results from the Berry-logit (Berry, 1994) using OLS while the second column from the Berry-logit with the four sets of IVs to instrument for price, vehicle weight and driving range. The coefficient estimate on vehicle price in column (1) implies an upward sloping demand curve due to the fact unobserved product attributes tend to bias the price coefficient estimate upward to zero. The coefficient estimates on vehicle weight and engine size are also counter-intuitive in column (1). The coefficient estimates with IVs in column (2) are all intuitively signed. The comparison between the results in the first two columns illustrates the importance of controlling for endogeneity in price and vehicle attributes.

[24]The National Development and Reform Commission (NRDC) sets the ceiling of retail gasoline prices by province based on the moving-average price of crude oil on the international market and adjustments occur mostly from anywhere between two weeks to two months depending the crude oil price volatility Chen and Sun (2021). Retailers can determine the actual prices to charge below the ceiling set by the NRDC and the retail prices usually stay close to the ceiling.

Column (3) reports the results from the full model with heterogeneous preference. As in column (2), all the parameter estimates are intuitively signed: consumers prefer vehicles with a larger weight, a longer driving range, a better fuel efficiency, and a more powerful and larger engine. Both the green license plate policy and the exemption of EVs from the purchase registration have a positive effect on EV demand. In terms of the price sensitivity, consumers with a higher household income are less price sensitive. In addition, the estimate of σ_p suggests a large heterogeniety in price sensitivity due to unobserved demographics (taste shocks). The random coefficient on the constant terms captures preference heterogeneity in purchasing a new vehicle (relative to the outside good) and its estimates is large and statistically significant, suggesting a large heterogeneity. The random coefficient estimate on gasoline vehicle dummy is also large and statistically significant.

Figure 6 presents two plots to gauge the magnitude of the parameter estimates in the demand-side. The left panel depicts the price semi-elasticities, the percentage change in sales for a ¥1,000 reduction in own prices. It shows that sales increase more in percentage for vehicles of lower prices. Demand for EVs tends to be less price sensitive than that for gasoline models of comparable consumer prices. This is likely driven by the fact that there is less competition among EV models. The implied price elasticities ranges from 1.74 to 6.50, with the average being 4.15. The right panel in Figure 6 shows the markups or profit margin (i.e., firm price minus the marginal cost) per unit. The markups increase with consumer prices. EVs tend to have a higher markup compared with gasoline models of similar consumer price. This is due to the pass-through of subsidies to firms on the one hand, and less competition in the EV segment on the other.

5.2 Supply Side Results

Technology Frontier Estimation The estimation results for the technology frontier function are presented in Table 4. We estimate the function separately for BEVs and PHEVs. The first two columns of Table 4 are the results for BEVs, and the last two are for PHEVs. The regressions include the fixed effects for the announcement dates of (different batches of) test result from August 27, 2014 to December 14, 2018, which control for the technological progress over time (i.e., the shift of the technology frontier) as well as other time-varying unobservables.

The first column shows that the driving range is positively correlated with battery capacity and battery density, and negatively correlated with vehicle weight (net of battery weight). The model fit is high with an adjusted R^2 being close 0.9. The second column report the results for PHEVs which are fewer than BEVs. Both battery capacity and vehicle weight have smaller impacts on the driving range for PHEVs than BEVs. This is intuitive because PHEVs are powered by both a battery motor and a gasoline engine. Battery density has a counter-intuitive sign but is not precisely estimated.

This is likely due to the fact that batteries tend to be small in PHEVs, and hence battery capacity rather than density determines the driving range. Our data also contain the engine size information for PHEVs and the coefficient estimate is positive. The adjusted R^2 is not as high as that for BEVs but is still nearly 0.8.

Cost Function Table 5 reports the parameter estimates for the marginal cost and fixed cost functions. Panel A shows that the estimated marginal cost for adding 10kg of vehicle weight is ¥1,130. Increasing battery capacity by 1kWh would cost ¥3,620 in 2015, the base year. The coefficient estimate of γ_t implies that the battery cost declines by 19.7% each year during our sample period, hence the marginal cost of battery capacity becomes ¥1,874 per kWh in 2018. The substantial battery cost reduction of 20% per year is consistent with the estimate from the literature (Ziegler and Trancik, 2021) and industry reports.[25] Figure 7 shows our estimates of the battery cost per kWh against the battery pack price from Bloomberg NEF's annual battery price survey. The battery pack costs are smaller because our estimates include the cost of both the battery pack and the installation.

Panel B in Table 5 shows the parameters that capture the slope of the fixed cost with respect to attribute changes. The estimate of the fixed cost slope with respect to vehicle weight is not statistically significant, suggesting that making heavier vehicles can be either less or more costly in terms of the fixed cost of production. In general, designing larger vehicles can be more expensive. On the other hand, utilizing lighter materials to reduce weight can also be costly. The fixed cost slope for battery capacity is positive and statistically significant, implying that the fixed cost of production increases with battery size.

Panel C shows the shadow price estimate of the driving range cutoffs. We specify the model-specific shadow price of the driving range requirement as a linear function of EV sales. The coefficient estimate suggests that an automaker is willing to pay ¥140 per EV on average to reduce the driving range constraint by 1km if the constraint is binding for the EV model.

5.3 Willingness to Pay (WTP) and Environmental Impact of EVs

To better understand the magnitude of the parameter estimates from both the demand and supply sides, we simulate consumers' willingness to pay (WTP) for each model, and compare them with the implied marginal costs recovered from Equation (15) as well as the environmental benefit of EVs.[26]

[25] See for example https://www.bloomberg.com/news/articles/2020-12-16/electric-cars-are-about-to-be-as-cheap-as-gas-powered-models.

[26] 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 will make consumers indifferent

Appendix Figure A4 depicts consumer WTPs and the marginal costs for BEVs and PHEV models separately. Panel (a) shows that for many BEV models, consumer WTP is lower than the marginal cost, suggesting that these models are unlikely to have been produced without government subsidies. From the social welfare perspective, these models would be welfare improving only if the environmental benefit could make up the difference between the WTP and the marginal cost. Panel (b) shows that the WTP is higher than the marginal cost for nearly all PHEV models. Since the subsidy for PHEVs is much lower than that for BEVs, firms have less incentive to produce models with the marginal cost larger than the WTP.

Table 6 shows the number of BEV models whose production is not justified from the social welfare perspective, i.e., consumer WTP being less than the net social cost (the marginal cost of production minus the environmental benefit). The environmental benefit is the monetized emissions reduction of an BEV model relative to alternative choices (in the absence of the model) based on emission intensity of CO_2 and local pollutants (PM, SO_2, and NO_x) for each vehicle model taking into account: (1) the tailpipe emissions standards and average fuel economy of gasoline models, and (2) the fuel source of electricity generation at the power-plant level.[27] The environmental benefit of an EV model is calculated by comparing the fuel efficiencies of gasoline models that are replaced by the EV model and the energy efficiency of the EV model. The substitution pattern is from the demand estimation. The emissions from electricity generation come from emissions inventory (PM, SO_2, and NO_x) from power plants developed in Tang et al. (2020) based on China's continuous emission monitoring systems (CEMS) network over 96–98% of the total thermal power capacity. The details of the calculation are presented in Appendix B.

In 2015 and 2016 when the subsidies were more generous, very few BEV models are shown to be welfare improving. This is consistent with the observation that earlier EV models tend to be small and of low quality as shown in Figure A3 and documented in Li et al. (2021). The entry of these models could have been largely motivated by the large subsidies. As the subsidies become less generous in 2017 and 2018, the number of welfare-improving model increased. These results illustrate the potential impact of the subsidies on product offerings and shed light on product proliferation in the Chinese EV market.

between buying and not buying the vehicle.

[27] The emission intensity of an EV model is determined by the energy efficiency of the model, i.e., kWh/km, calculated as the battery capacity divided by the driving range.

6 Counterfactual Simulations

This section conducts counterfactual simulations to compare different designs of EV subsidies and to understand the impacts of attribute-based subsidies. For tractability, we endogenize prices but take other vehicle attributes as exogenous for gasoline models in response to EV subsidies. For EVs, we endogenize price, vehicle weight and battery capacity in simulations. There are two reasons for abstracting away from attribute choices for gasoline models. First, solving for the new market equilibrium is computationally intensive with a larger number of products and multiple-product firms. Endogenizing attribute choices for gasoline models would make the optimization more demanding. Appendix C provides details on the simulation algorithm for counterfactual simulations. Second, given that the market share of EV being less than 3% before 2017 and 5.5% in 2018, the EV subsidies likely have limited impact on the attributes of gasoline models. Hence, holding product attributes for gasoline models fixed in our simulations of EV subsidies is a reasonable approximation.

6.1 Counterfactual Scenarios

Holding the total subsidy amount the same as the policy implemented in practice, we examine four counterfactual scenarios with different subsidy designs for BEVs based on data in 2017.[28] The first scenario uses a two-part structure for the subsidies following our theory model rather than the notched structure as implemented. The per-unit subsidy is defined as $T + t\cdot$ driving range, while T and t are chosen to maximize the social welfare subject to the budget constraint. In the second and third scenarios, the subsidies follow the same two-part structure but are based on battery capacity and vehicle weight, respectively. The fourth scenario is a uniform subsidy across EV models while holding the total subsidy fixed.

Under each of the first three scenarios, the base subsidy T and the subsidy rate t are chosen to maximize the social welfare while taking into account the fact that firm re-optimize the product attributes in response to changes in subsidies. Table 7 shows the optimal base subsidy and subsidy rate under each of the three policy designs. Appendix Figure A5 shows the changes in the three welfare components, consumer surplus, firm profit, and emissions reduction as the subsidy rate t changes under each of the three scenarios.

[28] We base our simulations on 2017 sample because there were much fewer EV models before 2017. In addition, the driving range cutoffs and the subsidy level had changed drastically in 2018.

6.2 Attribute Choices

Notched vs. Linear Subsidies We first compare the attribute choices between the observed (notched) subsidy design and the two-part (linear) subsidy design (i.e., the first counterfactual scenario), both based on driving range using 2017 sample. 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 chosen to be ¥24,704 + ¥70 · driving range to maximize the social welfare with the same budget.

Figure 8 shows the observed distribution of driving range (in red) under notched design and the counterfactual distribution (in blue) under the linear design. The contrast between the two distributions is stark: while there is strong bunching under the notched design, bunching disappears under the linear design. This illustrates firm responses in attribute choices to subsidies, consistent with the data pattern shown in Figure 5. Consistent with Sallee and Slemrod (2012) in the context of fuel economy standards, there are two inefficiencies associated with the 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 for models between cutoffs. Our results show that the social welfare improves by ¥136 million under the linear subsidy design.

Product attributes Figure 9 shows average vehicle prices, battery capacity, vehicle weight, and driving range under baseline (observed) policy and the four counterfactual scenarios for BEVs. Panel (a) shows three interesting results. First, comparing the two range-based policy designs, the average price is higher under the linear subsidy than that under notched design. This is driven by the fact that the notched policy does not provide incentives for firms to incrementally change attribute (e.g., increasing battery capacity or reducing weight to increase range) for models that are in between range cutoffs. As a result, average battery capacity and driving range are both lower while vehicle weight is larger under the notched design than the linear design. Second, average vehicle prices are the highest under the capacity-based subsidies. This is driven by the fact that this policy design induces firms to increase the provision of battery capacity, vehicle weight as well as driving range relative to the baseline policy as shown in Panels (b), (c) and (d). Third, in contrast, average price is the lowest under the uniform subsidy as shown in Panel (a) because the policy design does not encourage quality provision compared with attribute-based designs.

Panels (b)-(d) show an intuitive pattern: when the policy is based on a certain attribute, that attribute is the largest on average. For example, average battery capacity is the largest under capacity-based subsidies. Under weight-based subsidies, vehicle weight is the largest while driving range is the lowest, highlighting the trade-off between vehicle weight and driving range. Under range-based subsidies, firms increase battery capacity and reduce vehicle weight, leading to the smallest vehicle weight and the highest driving range. These plots underscore the fact that firms change product attributes in response to different policy designs.

Appendix Table A3 presents the changes in vehicle attributes, prices, marginal costs, and sales for different BEVs based on their driving range under each of the five policy designs while appendix A4 presents the results for PHEVs and gasoline models. In Appendix Table A3, the first and third BEV groups have the driving range at the thresholds, 150km and 250km. The automakers of these models would likely have reduced the driving range without range requirements, leading to positive shadow prices. The second and fourth groups consist of BEVs with the driving range away from the cutoffs, and hence the shadow price is equal to zero by the slackness condition.

The first column in Table A3 presents the outcomes under the observed policy while columns (2)-(5) present the outcomes under the counterfactual policies. The difference between the first two columns reflects the impact of the notched versus linear subsidies, both based on driving range. The linear design allows BEV models at the cutoffs to better balance the gain from receiving the higher subsidy and the loss from the change of product attributes in the direction required by the policy. Under the linear subsidies, automakers increase vehicle weight and reduce battery capacity for the models at the cutoffs (the first and third groups), thus reducing the driving range. The MSRPs, marginal cost, and subsidies all decrease for these vehicles. Interestingly, the opposite is true for models not at the cutoffs (the second and fourth groups). The differential impacts for these two types of vehicles highlight the distortion by the notched policy as discussed above. In terms of vehicle sales, BEV models in the group with the largest driving range (the fourth group) would see an increase in sales while those in other groups would see an decrease in sales. This is partly driven by the fact that the models in the fourth group would receive much larger subsidies under the linear design. Columns (5) and (6) show that the attribute on which the subsidies are based on increases under the capacity- and weight-based designs. Vehicles sales drop for the first two groups (e.g., smaller models) but increase for the last two groups. In contrast, the uniform subsidy design favors models in the first two groups, leading to a larger share of smaller vehicles relative to attribute-based policy designs.

Appendix Table A4 summarizes the vehicle attributes of PHEV and gasoline models. In all scenarios, the subsidies for PHEVs are held the same as the observed policy, and gasoline models are not subsidized. Thus, the changes in attribute choices and market outcome in Table A4 are due to the changes in BEV models in response to different subsidy designs for BEVs. The policy changes for BEVs have very limited impact on PHEVs and especially gasoline models. The market shares of

BEV and PHEV models in 2017 were 3.4% and 0.8%, respectively. We expect the impact of BEV policies on gasoline vehicles' product design to be minimal and hence we only endogenize prices for gasoline models but not for other attributes. The average prices and sales of gasoline models remain roughly the same under all counterfactual scenarios.

Appendix Table A5 shows how the central subsidies are distributed across BEVs with different quality. We divided the BEVs into high-quality models (WTP > ¥150k) and low-quality models (WTP < ¥150k) using the willingness to pay under the current policy. More subsidies are distributed to high-quality BEVs when the subsidies are based on capacity and weight compared to the current policy. As discussed above, the uniform subsidy design favors low-quality models compared to attribute-based designs.

6.3 Welfare Changes

Table 8 presents the welfare changes including consumer surplus, emissions, and firm profit under counterfactual policy designs relative to the observed policy. Total subsidies are fixed at ¥8.86 billion across policy scenarios. There are three key findings from this table. First, switching from the current notched design based on the driving range to a continuous subsidy using a two-part structure would result in a welfare gain of ¥135.7 million by removing two types of distortions as discussed in Section 6.2. Consumer surplus and firm profit both rise as firms respond to the linear subsidy by producing heavier vehicles as shown in Figure 9. In addition, the market share of higher-quality and heavier vehicles, which generate high consumer surplus and firm profit, increase as shown in Appendix Table A5. However, the environmental performance of the EV segment worsens as the fleet shifts to larger and hence less environmental beneficial EVs.

Second, capacity-based subsidies as implemented in the U.S. would achieve the largest welfare gain due to the fact that the policy design best balances environmental externalities and market power. Comparing to the range-based design, capacity-based subsidies generate a higher consumer surplus but lower firm profit. This is because the capacity-based subsidies would better address market power by reducing the markups of more expensive and hence high-markup vehicles as shown in Figure 10. It turns out that the variation in market power across products has a higher correlation with battery capacity than other attributes, and hence capacity-based subsidies are better able to correct for quantity distortion than other designs as discussed in the theoretical model. In addition, while range-based subsidies lead to vehicle downsizing as shown in Figure 9, capacity-based subsidies would incentivize firms to produce high quality vehicles (i.e., heavier and with large batteries), leading to increase in consumer surplus. From the environmental perspective, the range-based design would result in smaller and more environmental friendly EVs. But the increase in consumer surplus dominates. The weight-based design would lead to a larger consumer surplus than range-based design, implying that consumer's willingness to pay for additional weights relative to the cost is higher than that for additional battery capacity. However, the environmental performance under the weight-based design is significantly comprised due to the EVs becoming heavier.

Third, the uniform subsidy design as used in many European countries turns out to be the least efficient design. Relative to the attribute-based designs, the uniform subsidy favors smaller and lower-quality EV models, leading to two changes. First, the design would lead to firms to produce vehicles with smaller battery and lower weight as shown in Figure 9. Second, the policy would increase the market share of smaller vehicles due to the relatively higher subsidies for these vehicles. As a result, the uniform subsidy achieves the best environmental outcome. However, this benefit is at the much larger expense of consumer surplus due to the lower consumer WTP for smaller and low-quality vehicles. Nevertheless, firm profit would increase due to the fact that the design exacerbates market power by increasing the markups of the more expensive (and high markup) products as illustrated in Figure 10, again at the expenses of consumer surplus.

A caveat is in order in terms of the welfare calculation of EVs. The environmental benefit from new EVs sold in 2017 was estimated to be ¥609 million based on the vehicles they replace, and the fuel source of electricity generation. The environmental benefit of EVs was comprised by the fact that the electricity generation largely relies on fossil fuels especially coal in China.[29] As the electricity grid becomes cleaner in China, EVs should generate larger environmental benefits. In addition, our welfare analysis does not take into account changes in externalities from traffic safety due to changes in vehicle weight and vehicle usage. Heavier vehicles are shown to impose a larger accident externality (Li, 2012; Anderson and Auffhammer, 2014; Bento et al., 2017) and drivers may change driving distance as the travel cost (e.g., due to improved fuel efficiency) changes (Small and Van Dender, 2007; Chan and Gillingham, 2015; Liao and Jacobsen, 2021).

7 Conclusion

Addressing climate change requires dramatic reductions in fossil fuel usage by adopting energy-saving technologies. Attribute-based subsidies are commonly used to promote the diffusion of energy efficient products. There is limited understanding on the impacts and welfare consequences of the subsidy design including both the choice of policy attribute and the subsidy structure in markets with market power. This study provides to our knowledge the first analysis on how attribute-based subsidies affect consumer demand, firm choices of product attributes, and social welfare in differen-

[29]The share of electricity generation from fossil fuels was 69.7%, with coal accounting for the vast majority.

tiated product oligopolies.

We first present a theoretical model of attribute-based policies with endogenous product attributes in the presence of market power. In a single-product monopoly, the optimal subsidy follows a two-part structure where the lump-sum portion and the attribute-based subsidy rate can be properly chosen to address quantity distortion due to market power and environmental externalities imperfectly tied to product attributes, respectively. However, in a differentiated-product oligopoly, the attribute-based subsidy rate should be chosen to balance both environmental externalities and market power due to the inability of the (uniform) lump-sum portion to adequately address varying market power across products. Our model also characterizes the choice of the policy attribute on which the subsidy level is based under various levels of budget constraint.

Our empirical analysis is based on an equilibrium model of vehicle market while endogenizing multiple product attributes. Based on comprehensive data on the electric vehicle market in China, the analysis shows that range-based subsidies in a notched design have led to vehicle downsizing and excess bunching at the subsidy cutoffs, both of which have negative welfare consequences. In comparison, subsidies based on battery capacity would result in larger increases in social welfare by incentivizing automakers to produce better-quality EVs that consumers value and thereby mitigating quantity distortion due to market power. Our findings show that properly designed attribute-based subsidies affect social welfare through two channels: inducing firms to choose attributes with smaller environmental externalities, and correcting for quantity under-provision due to market power. It is therefore important to take both channels into account in designing attribute-based subsidies in the presence of market power.

While allowing for endogenous product attributes, our empirical framework takes the product offering as given. Through changing consumer demand, consumer subsidies also intend to affect firm product development and investment behavior. Future research could further examine the product line decisions and firm entry and exit decisions, which would allow for a more comprehensive understanding on the policy impacts. In addition, firm R&D decisions under difference policy designs could be another important research direction.

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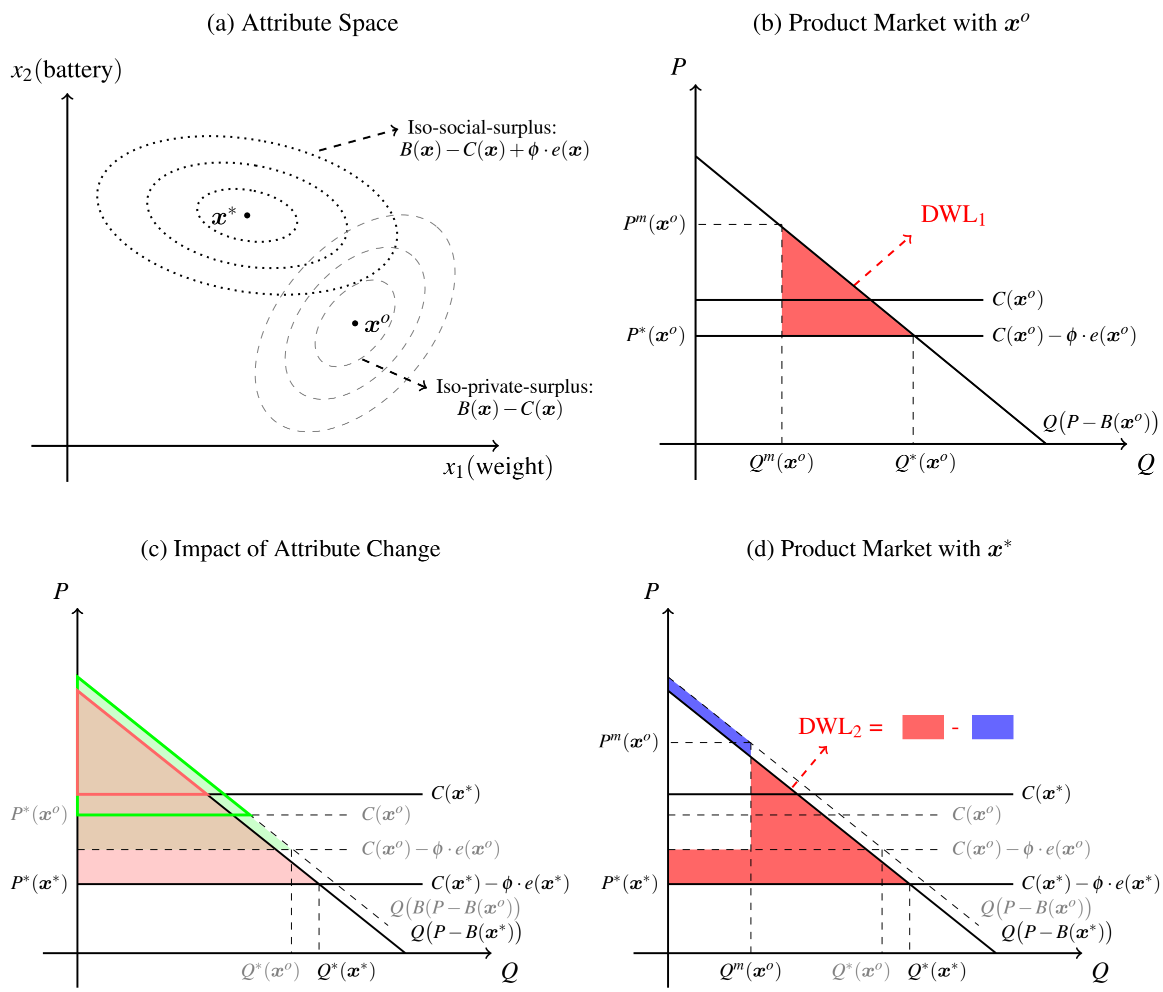
Figures & Tables

Figure 1: Attribute Choices and Social Welfare under Monopoly

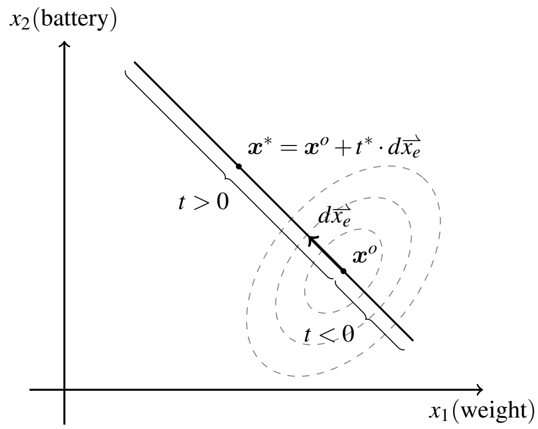


Notes: Panel (a) depicts the attribute space where the contour lines represent the Iso-surplus curves from the private and social perspectives. The monopoly would choose $\boldsymbol{x}^o$ as the privately optimal attribute choice while $\boldsymbol{x}^*$ is the socially optimal choice. Panel (b) illustrates the product market outcomes conditioning on product design $\boldsymbol{x}^o$. ($P^m(\boldsymbol{x}^o)$, $Q^m(\boldsymbol{x}^o)$) are the price and quantity chosen by the monopoly while the socially optimal price and quantity are ($P^*(\boldsymbol{x}^o)$, $Q^*(\boldsymbol{x}^o)$). The red triangle (DWL$_1$) is the deadweight loss due to market power and (positive) externality 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 greater than the red solid-line triangle (with the base defined by line $C(\boldsymbol{x}^*)$). $\boldsymbol{x}^*$ generates the largest social surplus $B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$. Therefore, 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 being distorted due to externality; and ii) quantity being distorted due to both market power and 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 product $\boldsymbol{x}^o$ is less environmental friendly than product $\boldsymbol{x}^*$.

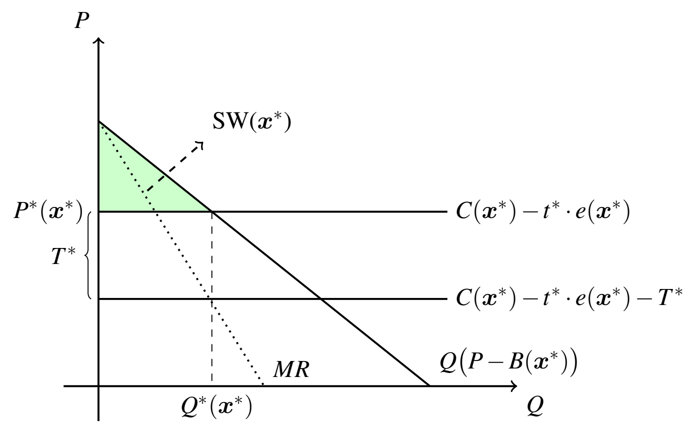
Figure 2: Perfect Targeting vs. Imperfect Targeting

Case I: Perfect Targeting

(a) Attribute Space

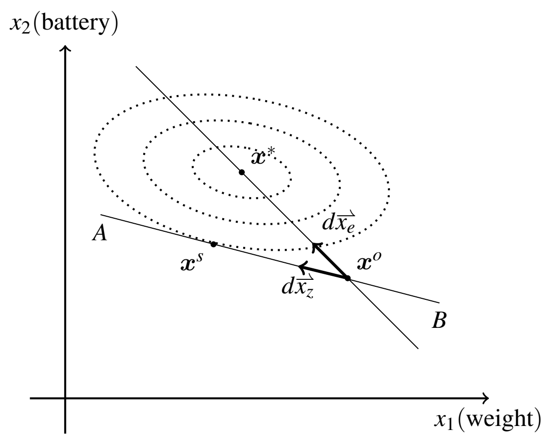


(b) Product Market

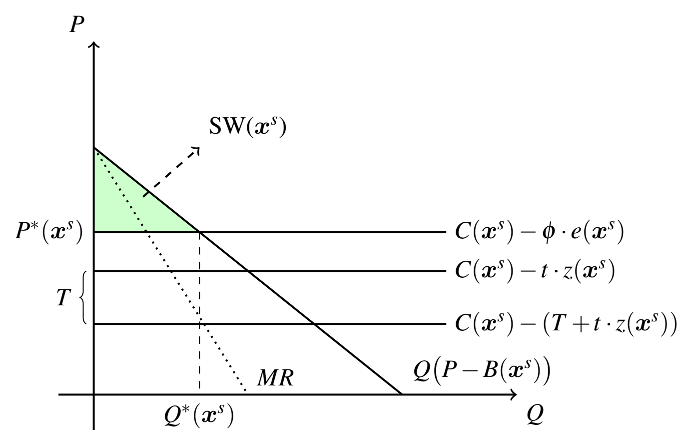


Case II: Imperfect Targeting

(c) Attribute Space



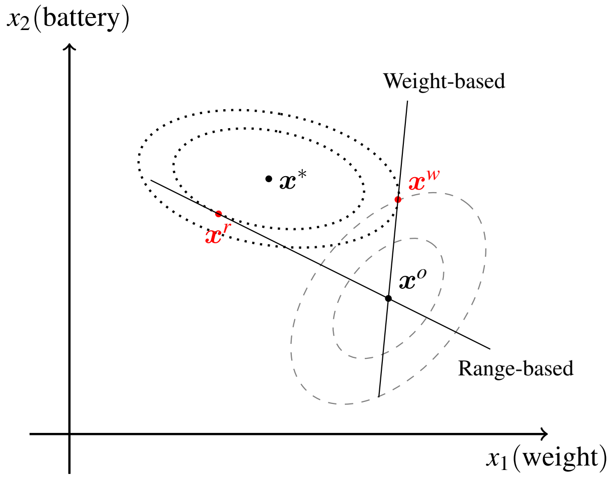
(d) Product Market



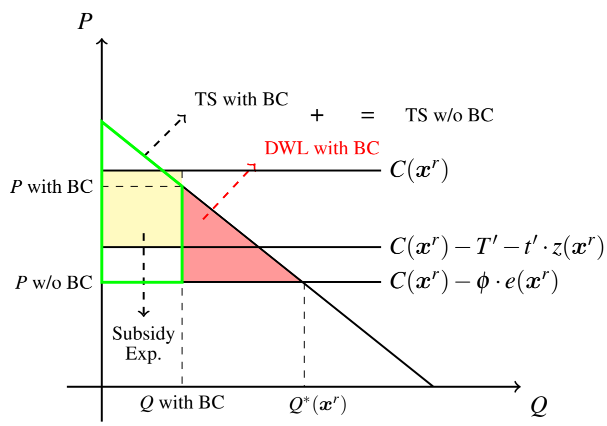
Notes: Panels (a) and (b) depict the case of perfect targeting while Panels (c) and (d) depict the case of imperfect targeting. Panel (a) shows that the optimal t^* induces the firm to choose the socially optimal attributes $\boldsymbol{x}^*$. The line connecting $\boldsymbol{x}^o$ and $\boldsymbol{x}^*$ denotes the firm's best response function to different subsidy rate t: any point on the line represents the optimal attribute choice of the firm for a certain subsidy rate. For the ease of exposition, the response function is linear under the assumption that the loss function (due to deviation from the optimal attributes) is quadratic and that z is linear in $\boldsymbol{x}$. Panel (b) shows that given product $\boldsymbol{x}^*$, the optimal base subsidy T^* can be set to induce the monopoly to choose the socially optimal quantity $Q^*(\boldsymbol{x}^*)$. The green triangle represents the social welfare under the first-best outcome ($\boldsymbol{x}^*$, $Q^*(\boldsymbol{x}^*)$). Panel (c) shows that when the policy attribute $z \neq e$, the first-best attributes $\boldsymbol{x}^*$ cannot be attained as the firm would response to the subsidy rate t along the line connecting $\boldsymbol{x}^o$ and $\boldsymbol{x}^s$. The best attribute that can be attained under the imperfect targeting is $\boldsymbol{x}^s$, defined as the second-best attribute. Panel (d) illustrates the choice of T under the second-best attribute $\boldsymbol{x}^s$. T can be set to induce monopoly to choose $Q^*(\boldsymbol{x}^s)$, the socially optimal quantity for product design $\boldsymbol{x}^s$. The green triangle represents the social welfare under the second-best outcome ($\boldsymbol{x}^s$, $Q^*(\boldsymbol{x}^s)$), which is smaller than the green triangle in Panel (b).

Figure 3: Choice of the Policy Attribute

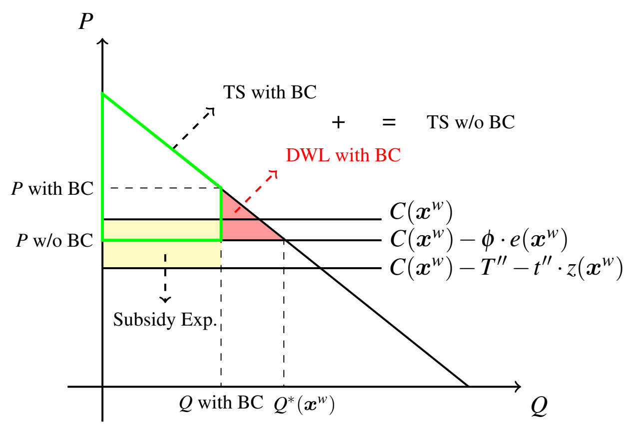
(a) Attribute Space



(b) Product Market with $\boldsymbol{x}^r$

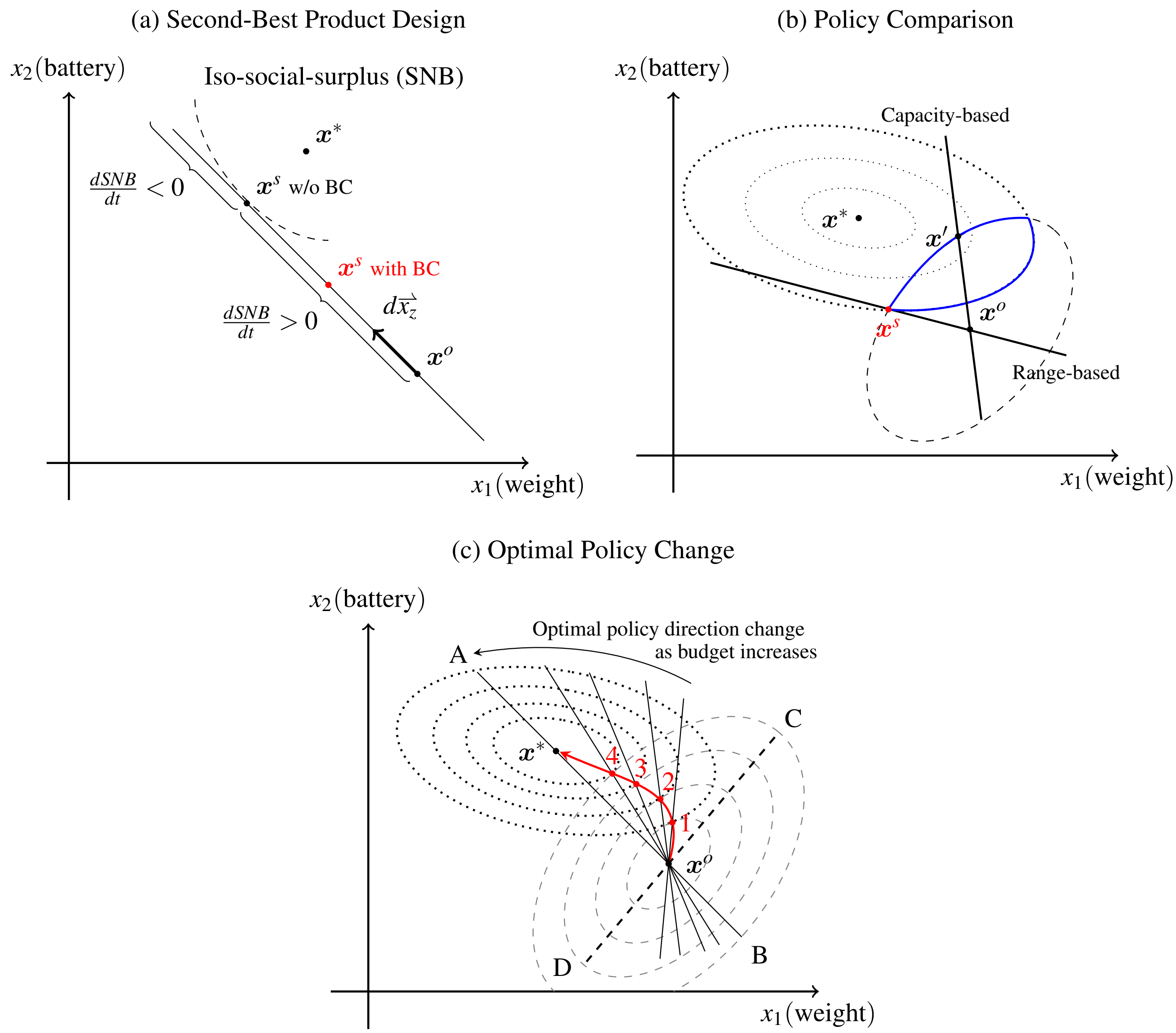


(c) Product Market with $\boldsymbol{x}^w$



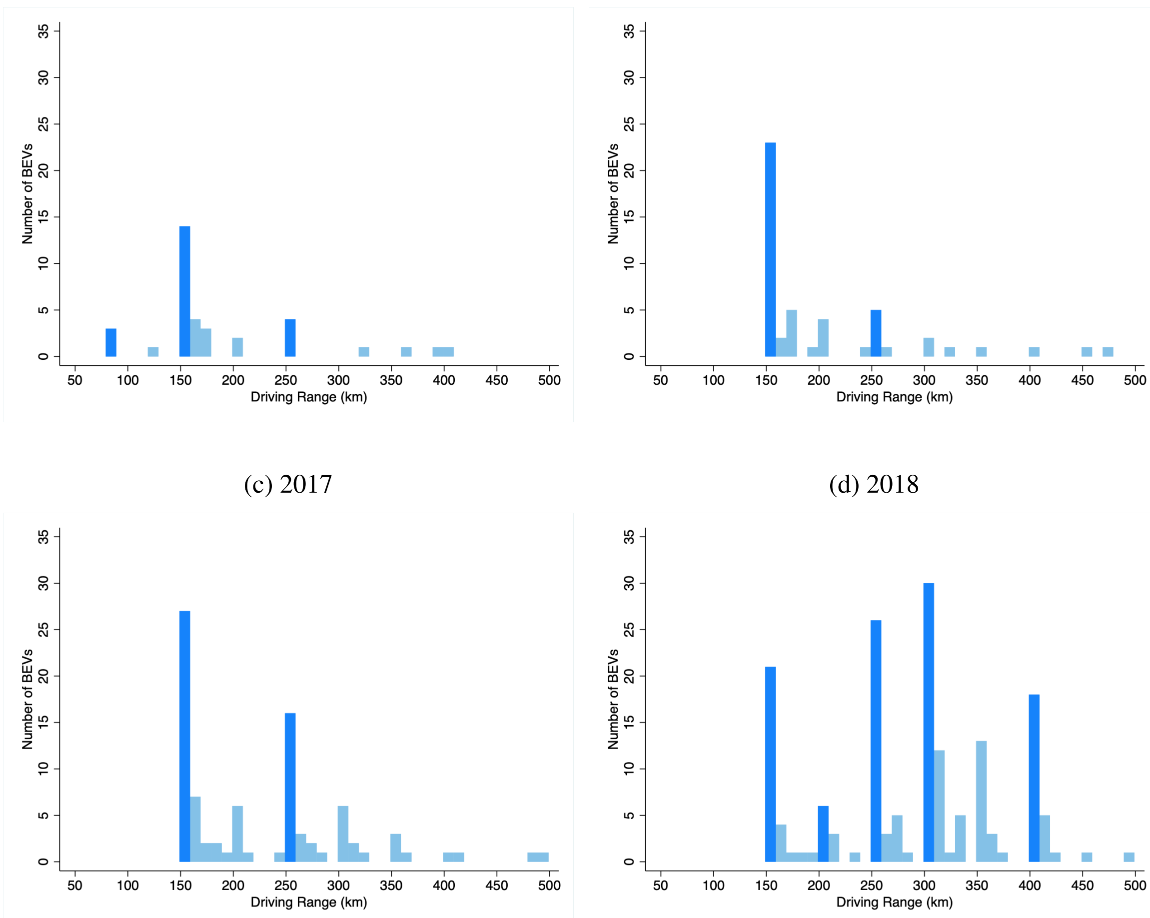
Notes: The figures illustrate the trade-off between externalities and market power in the choice of policy attribute $z(\boldsymbol{x})$ with a limited government budget for subsidies. Panel (a) shows the impact of imperfect targeting based on vehicle weight and driving range. The dotted ellipses represent the iso-quant curves in terms of per-unit social surplus where $\boldsymbol{x}^*$ denotes the socially optimal attributes. The dashed ellipses represent the iso-quant curves in terms of per-unit firm profit where $\boldsymbol{x}^o$ denotes the privately optimal attributes. The socially optimal attributes $\boldsymbol{x}^*$ is not attainable under imperfect targeting. Instead, the government can encourage firms to choose $\boldsymbol{x}^r$ ($\boldsymbol{x}^w$) using the range-based (weight-based) subsidy. Panels (b) and (c) show the product market outcomes for the two designs $\boldsymbol{x}^r$ and $\boldsymbol{x}^w$. Without any budget constrain, the government can achieve (P w/o BC, $Q^*(\boldsymbol{x}^r)$) in Panel (b) and (P w/o BC, $Q^*(\boldsymbol{x}^w)$) in Panel (c). In these cases, $\boldsymbol{x}^r$ generates greater total surplus than $\boldsymbol{x}^w$ does since $\boldsymbol{x}^*$ is closer to $\boldsymbol{x}^r$ than to $\boldsymbol{x}^w$ in Panel (a). However, such total surpluses are not feasible with a fixed government budget. The government achieves greater "Q with BC" with $\boldsymbol{x}^w$ than with $\boldsymbol{x}^r$ although the total subsidies, represented by the yellow area, are the same under the two designs. As a result, the total surplus with the budget constraint is greater under the weight-based policy, which is the opposite result without the budget constraint. The red triangles are the deadweight loss due to market power conditional on each product design. The green trapezoids represents social surplus obtained under each design with the same government budget on subsidies. While the range-based subsidies induce a more environmentally friendly vehicle design and a higher social surplus per unit of sales, the un-mediated market power and the resulting deadweight loss is larger in the product market, compared to the weight-based subsidies.

Figure 4: Second-Best Attribute Choice with a Budget Constraint



Notes: The figures demonstrate the optimal choices of subsidy intensity t and policy attribute z when the planner cannot eradicate the market power issue due to a limited budget. In Panel (a), "$\boldsymbol{x}^s$ w/o BC" is the second best choice providing the highest per-unit social surplus given the policy attribute z without any budget constraint. If the planner cannot achieve the efficient level of output with a binding budget constraint, the planner chooses "$\boldsymbol{x}^s$ with BC" as the second best, which is closer to $\boldsymbol{x}^o$. While Panel (a) tells how to choose the subsidy intensity t, Panel (b) and (c) show how to select the policy attribute z. $\boldsymbol{x}^s$ in Panel (b) represents the second-best choice under the range-based incentive for a given budget constraint. Any policy line penetrates the blue lens can lead to a better product design with the same subsidy expenditure. For example, consider $\boldsymbol{x}'$ that is on the capacity-based incentive line. By Lemma 1, $\boldsymbol{x}'$ and $\boldsymbol{x}^s$ guarantee the same level of output in the product market while $\boldsymbol{x}'$ generates the greater per-unit contribution to the social welfare. Thus, $\boldsymbol{x}'$ dominates $\boldsymbol{x}^s$ under the range-based policy, and so does the second best choice under the capacity-based policy. Therefore, battery capacity is a better choice than driving range in this example. The red dots in Panel (c) are the points where the iso-social and iso-private surplus curves are tangent. If one of them is chosen as the second best with a budget constraint, then the direction from $\boldsymbol{x}^o$ to it represents the best policy attribute choice with the budget limit. The best policy direction is close to *C*-*D* line with a stringent constraint, but converges to the perfect targeting direction *A*-*B* as relaxing the constraint.

Figure 5: Distribution of Driving Range among BEV Models during 2015-2018

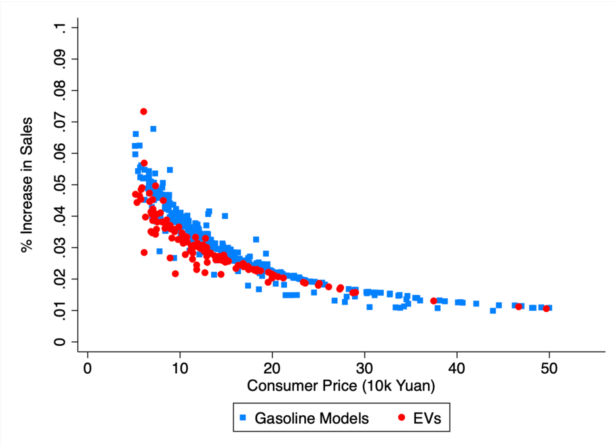


(a) 2015 (b) 2016 (c) 2017 (d) 2018

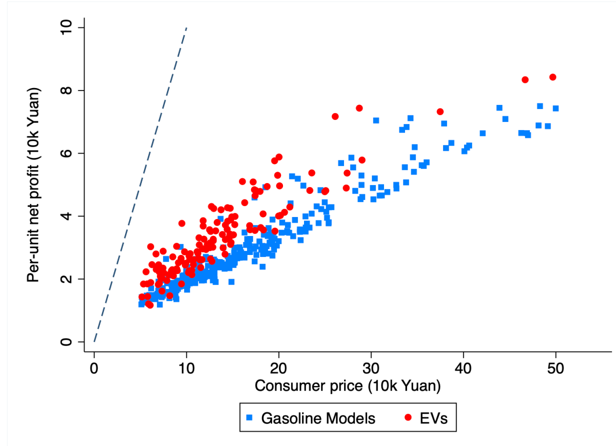
Notes: The horizontal line represents driving ranges of BEVs with a bin size of 10km. The dark blue bars represent the BEV models with a driving range just above the policy thresholds of the corresponding years. The other bars show the number of BEVs for which the driving range requirements are not binding. There is a strong pattern of bunching. In addition, firms adjust the driving range on an annual basis when the driving range cutoffs change from year to year.

Figure 6: Semi-elasticities and Implied Markups

(a) Semi-elasticity

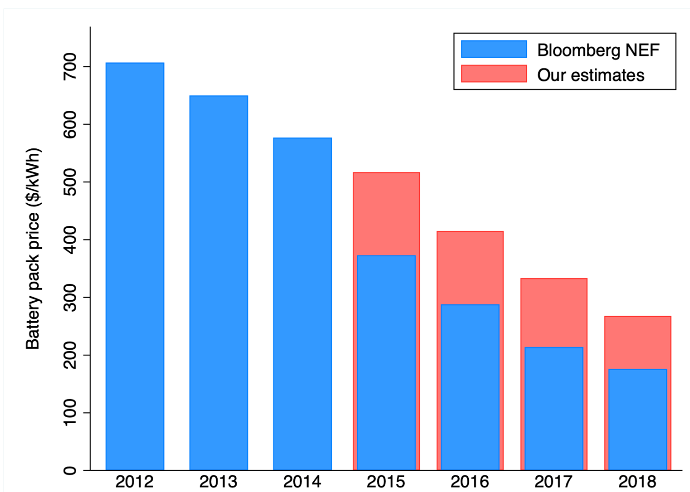


(b) Markup



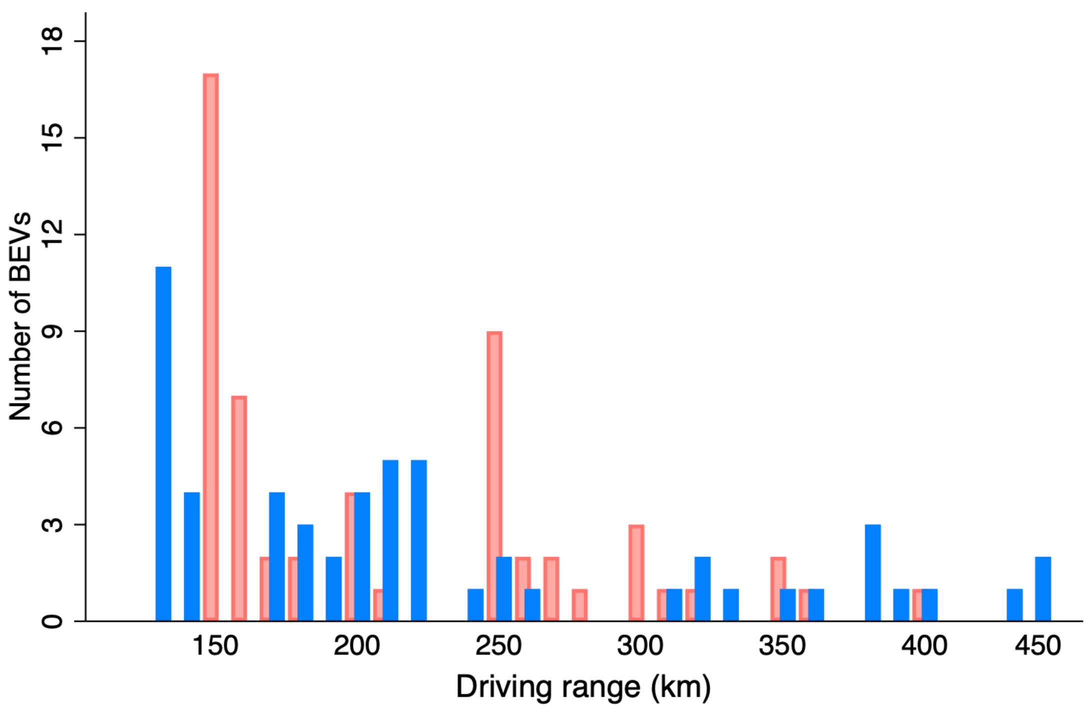
Notes: The left panel plots the price semi-elasticities, the % increase in sales when the price decreases by 1,000 yuan, against consumer prices. The right panel plots the markups (firm price minus the marginal cost) against consumer price. The red dots represent EVs while the blue dots represent gasoline models.

Figure 7: Battery Pack Prices and Estimated Battery Costs



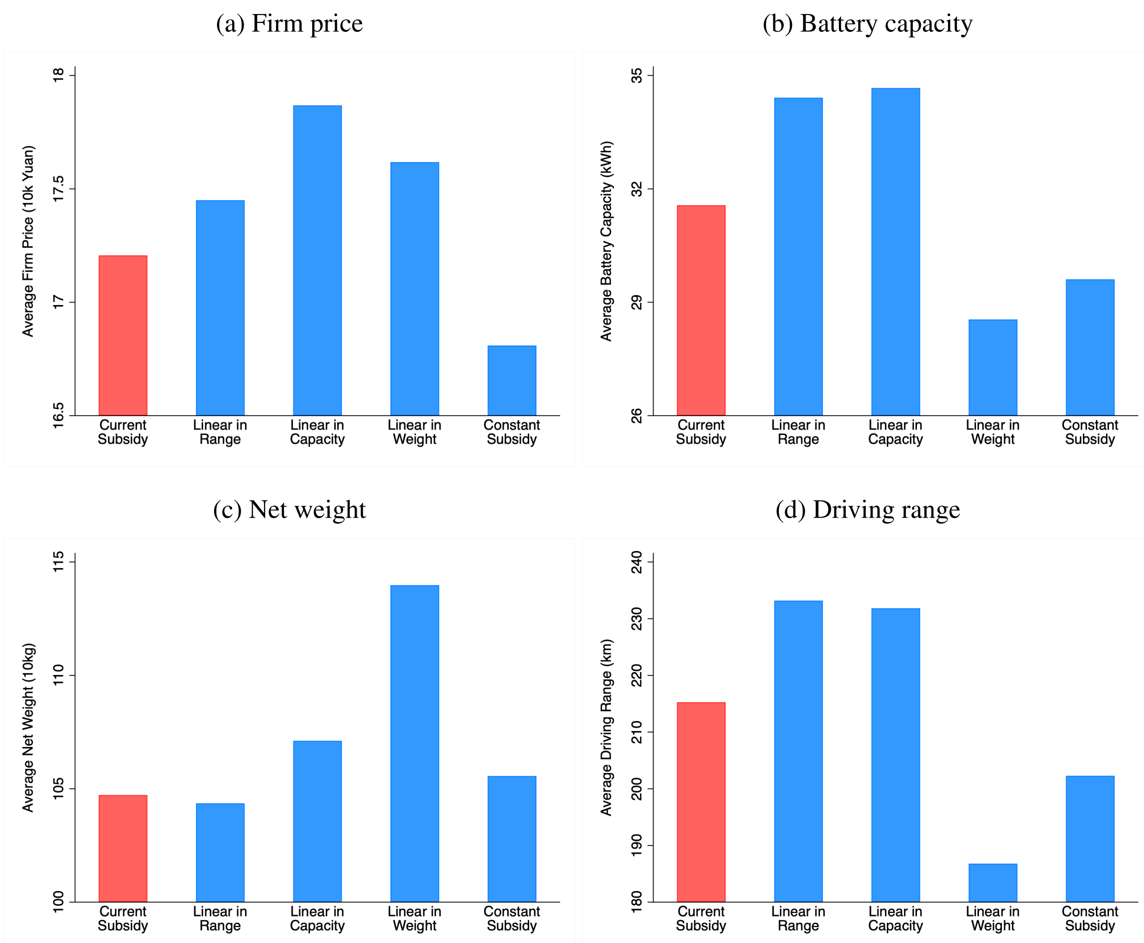
Notes: This bar chart shows the battery costs over year. The blue bars represents Lithium-ion battery pack price (in 2018 $/kWh) from 2012 to 2018 from BloombergNEF's annual battery price survey. The pink bars behind of the blue bars show the battery cost estimates assuming the exchange rate for dollars to yuan equal to seven in 2018. Blue bars indicates the battery pack prices only while our estimates include extra costs such as installation costs as well as the battery pack price. According to BloombergNEF's annual survey, the battery costs had declined by around 20% each year from 2012 to 2018, which is consistent with our estimates. Source: https://about.bnef.com/blog/battery-pack-prices-cited-below-100-kwh-for-the-first-time-in-2020-while-market-average-sits-at-137-kwh/.

Figure 8: Notched versus Linear Subsidies



Notes: The figure depicts the observed distribution of driving range (in red) under the notched subsidy policy in 2017 and the counterfactual distribution (in blue) under the linear subsidy design $T + t \cdot$ driving range. The total subsidies are the same under the two designs. In the linear design, bunching disappears and the social welfare increases by ￥120 million.

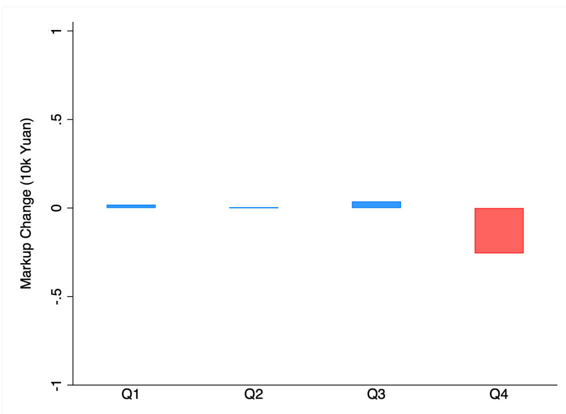
Figure 9: Attribute Choices under Counterfactual Simulations



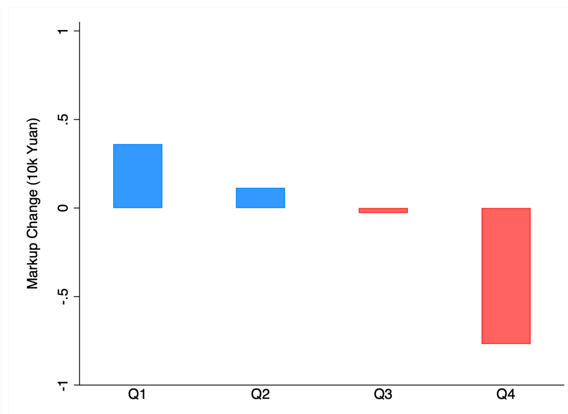
Notes: The plots depict average attributes under the observed policy and the four counterfactual scenarios for BEVs. All five scenarios have the same budget. The base subsidy T and the subsidy rate t under the linear subsidies on driving range, battery capacity, vehicle weight are chosen to maximize the social welfare. The last scenario imposes a uniform subsidy across all BEV models.

Figure 10: Markup Changes by Price Quartiles under Counterfactual Scenarios

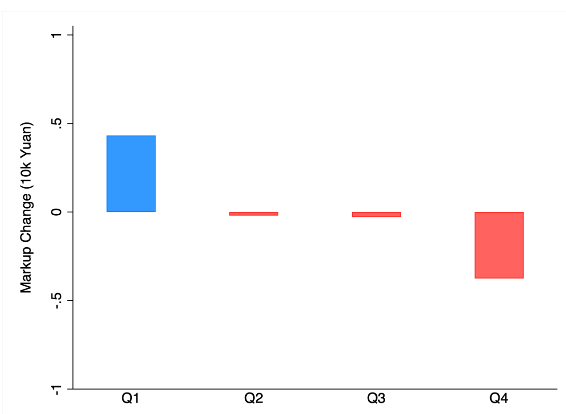
(a) Range-based



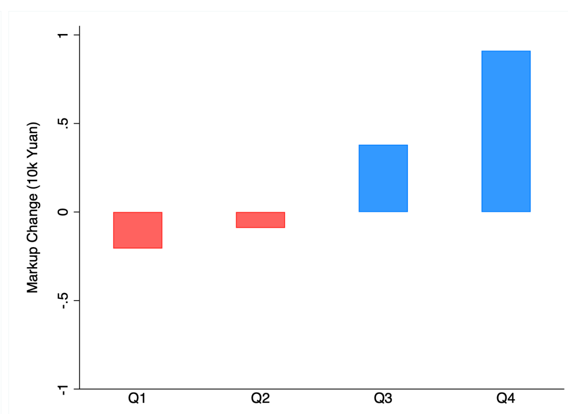
(b) Capacity-based



(c) Weight-based



(d) Constant subsidy



Notes: The plots depict the changes in firm markups for BEV models in each of the four quartiles of the price distribution under the counterfactual subsidy designs relative to the markups under the current policy.

Table 1: Consumer Subsidies for EVs from the Central Government

Type	Range	2013	2014	2015	2016	2017	2018
	$\geq$ 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
BEV	$\geq$ 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 the amount of subsidies for EV consumers from the central government during 2013 and 2018. The exchange rate between US dollar and Chinese RMB was between 6.2 and 7 (¥/$) during the period.

Table 2: Summary Statistics

	Gasoline models			EVs		
	# of Obs.	Mean	Std. Dev.	# of Obs.	Mean	Std. Dev.
Panel A: Model-year-city 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
Fuel economy (L/100km)	28,661	6.85	0.95	5,628	0.44	0.78
Horsepower	28,661	146.29	37.17	5,628	127.47	92.67
Engine size (L)	28,661	1.66	0.25	5,628	0.41	0.72
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
Fuel economy (L/100km)	1,261	6.99	1.06	279	0.39	0.76
Horsepower	1,261	144.77	37.13	279	116.06	80.88
Engine size (L)	1,261	1.66	0.26	279	0.35	0.68
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 data used in the demand side with the unit of observation being city by year by model in 40 cities with the largest EV sales in China during the sample period (2015-2018). Panel B shows the summary statistics for the data used in the supply side with the unit of observation being model by year. There are 84 firms, 497 gasoline 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)	0.007	0.003	-0.155	0.019	-	-
log(net vehicle weight)	-0.151	0.117	2.480	0.510	5.582	0.298
log(driving range)	0.458	0.071	0.865	0.085	1.091	0.157
Fuel consumption (L/100km)	-0.045	0.014	-0.144	0.030	-0.231	0.025
Horsepower	0.001	0.000	0.014	0.001	0.020	0.001
Engine size (displacement, L)	-0.210	0.047	0.805	0.122	0.833	0.052
Price Sensitivity: $\alpha_i = -exp(\alpha_1 + \alpha_2 log(y_{im}) + \sigma_p \nu_{im}^p)$						
α_1 (constant)	-	-	-	-	2.312	0.350
α_2 (income)	-	-	-	-	-1.207	0.124
σ_p (random coefficient on price)	-	-	-	-	0.593	0.105
Other Random Coefficients						
Constant	-	-	-	-	3.161	0.279
σ_x Gas Veh. or not	-	-	-	-	1.715	0.566
Displacement (L)	-	-	-	-	0.248	0.619
No. of observations	34,329		34,329		34,329	

Notes: Column (1) reports the logit regression results without instruments for price, weight, and driving range. Columns (2) and (3) instrument the three endogenous variables with four sets of IVs: (1) the central subsidies; (2) the number of own and rivals' products of the same fuel type in the same segment; (3) the number of compartments (EVs), the number of doors (gas models), and wheelbase; and (4) battery weight interacted with supplier dummies. Column (3) is the random coefficient multinomial logit model and is estimated using simulated GMM. Net vehicle weight is the same as curb weight for gasoline models but it is curb weight minus battery weight for EVs. The price coefficient α_i is specified as $-exp(\alpha_1 + \alpha_2 log(y_{im}) + \sigma_p \nu_{im}^p)$ where y_{im} is consumer income and ν_{im}^p is unobserved preference shocks (i.i.d. standard normal draws). α_2 captures the heterogeneous price sensitivity across households with different income. Brand, fuel type, city-EV-year, segment, vintage fixed effects are included. The vintage indicates the year when the model was first introduced into the market. The green plate policy for EVs and the exemption from purchase restrictions for EVs are included in the analysis. Both policies have positive and statistically significant coefficient estimates but there is limited residual variation in the data after controlling for the rich set of fixed effects.

Table 4: Relationship between Driving Range and Endogenous Attributes

	BEV models		PHEV models	
Driving range (km)	Coef.	S.E.	Coef.	S.E.
Battery capacity (kWh)	6.166	0.150	5.828	0.28
Net vehicle weight (10kg)	-1.063	0.066	-0.409	0.048
Battery density (kWh/10kg)	27.236	7.474	-9.529	7.257
Engine displacement (L)			7.078	3.394
Constant	75.871	10.605	47.539	6.966
# of observations	994		190	
Adjusted R^2	0.896		0.772	

Notes: The first two columns are the regression results for BEVs and the other two are for PHEVs. The observations include all EV models that went through the driving range test by MIIT while only a subset of the tested models could be introduced in the market. The results include the fixed effect for the test result announcement dates from August 27, 2014 to December 14, 2018.

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

		Coef.	S.E.
Panel A: Marginal cost (¥10k)			
γ_w	Net vehicle weight (10kg)	0.113	0.011
γ_k	Battery capacity (kWh)	0.362	0.044
γ_t	Battery cost time trend	0.803	0.032
	Note: Jointly estimated from the MC equation and FOCs		
γ^{other}	Horsepower	0.018	0.004
	Displacement (L)	2.595	0.454
	Fuel consumption (L/100km)	-0.667	0.113
	Year FE (base year: 2015)		
	2016	-0.286	0.149
	2017	-0.688	0.148
	2018	-1.166	0.156
	Note: Estimated from the MC equation		
Panel B:Fixed cost (¥10k)			
ϕ_w	Net weight (10kg)	-5.592	66.140
ϕ_k	Battery capacity (kWh)	593.49	263.79
	Note: Estimated from weight and capacity FOCs		
Panel C:Shadow price (¥10k/1km)			
ζ	Sales	0.0140	0.0067
	Note: Estimated from weight and capacity FOCs		

Notes: The number of observations are 1540 for the marginal cost equation and 279 for the attribute choice FOCs. γ_w and $(\gamma_t)^t \cdot \gamma_k$ represent the marginal cost slope with respect to weight and battery capacity. Also, γ_t captures the decreasing trend of battery costs over year compared to the base year 2015. For instance, the battery pack costs 3,620 yuan per kWh in 2015, which decreases to 1,874 yuan per kWh in 2018. γ_w, γ_t, and γ_k appear in both of the marginal cost equation and FOCs, and thus, they are jointly estimated. γ^{other} is the coefficients for the other exogenous variables in the marginal cost equation. ζ approximates the shadow prices using EV sales. The ζ estimates implies that EV makers are willing to pay 140 yuan per unit to reduce the driving range constraints by 1km if they have EV models affected by the constraints. ϕ_w and ϕ_k represent the slope of the annual fixed cost with respect to weight and battery capacity. Lastly, the estimation of the marginal cost equation and FOCs includes year, fuel type, car type, segment, and firm fixed effects.

Table 6: Willingness-to-pay and Marginal Costs for BEV Models

Year	Case	BEV models	WTP	MC	Emi. Red.	Firm price	Subsidy
2015	WTP < MC - Emi. Red.	14	11.15	14.71	0.27	18.94	8.19
	WTP > MC - Emi. Red.	3	21.28	20.95	0.08	28.77	8.71
2016	WTP < MC - Emi. Red.	28	10.30	14.40	0.21	18.44	8.70
	WTP > MC - Emi. Red.	1	29.29	26.27	-0.20	37.02	9.45
2017	WTP < MC - Emi. Red.	37	9.94	11.47	0.22	15.41	5.86
	WTP > MC - Emi. Red.	13	15.76	14.41	0.22	20.48	5.90
2018	WTP < MC - Emi. Red.	50	10.64	12.57	0.24	16.66	6.48
	WTP > MC - Emi. Red.	45	12.88	11.3	0.24	16.30	4.37

Notes: The table presents the number of BEV models whose WTP is above or below the social marginal cost (marginal cost minus the environmental benefit). It also shows the average WTP, marginal cost, the environmental benefit (emissions reduction relative to alternative models), firm price, and average subsidies (in ¥10,000). In 2016, BYD's BEV model Denza, which was heavier than two tons, has a negative environmental impact due to its low energy efficiency relative to alternative models.

Table 7: Optimal Base Subsidy T and Subsidy Rate t

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

Notes: This table shows the per-unit fixed transfer and incentive rate pairs of linear subsidies based on driving range, battery capacity, and weight. For each subsidy slope, the level of transfer is determined to maintain the government subsidy expenditure unchanged. The fourth column highlighted in red displays the welfare-maximizing pairs.

Table 8: Welfare Changes from Counterfactual Policy Designs in 2017

		Changes from the Current Policy			
		Range	Capacity	Weight	Uniform
Total welfare (in ¥mil.)		135.7	349.4	266.1	-101.9
Consumer surplus		90.6	417.0	453.7	-226.2
Emissions	CO_2	11.5	73.9	105.9	-57.4
	PM	0.3	1.6	2.2	-1.1
	NOx	1.9	9.4	11.9	-7.4
	SO_2	0.6	1.2	4.8	-0.3
	All pollutants	13.2	86.2	124.8	-65.6
Firm Profit	BEV	73.0	108.2	21.4	16.0
	PHEV	-0.9	-5.1	-3.6	3.8
	ICV	-13.8	-84.6	-80.7	38.8
	Total Profit	58.3	18.3	-62.9	58.6

Notes: The unit is ¥million in 2017 for all cells. The results are the changes under the four counterfactual scenarios relative to the observed policy. The first three uses the linear design based on driving range, battery capacity, and vehicle weight, respectively. The fourth counterfactual scenario is a uniform subsidy across all EV models. The total subsidies are held the same under these counterfactual scenarios as that under the observed policy.

ONLINE APPENDICES

Appendix A: Theoretical Model

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

A.1 Socially Optimal Attributes and Price

The social welfare consists of consumer surplus, producer surplus, and externality:

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

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 $\boldsymbol{x}$. The first-order conditions for welfare-maximizing are given by:

$$
\begin{aligned}
&[P] \qquad P^* - C(\boldsymbol{x}^*) + \phi \cdot e(\boldsymbol{x}^*) = 0 \\
&[x_k] \quad B_k(\boldsymbol{x}^*) - C_k(\boldsymbol{x}^*) + \phi \cdot e_k(\boldsymbol{x}^*) = 0 \ \text{ for } \ i = 1, 2, ..., K.
\end{aligned}
$$

A.2 Proof of Proposition 1

Proof: Under the perfect targeting ($z = e$), the private first-order condition Equation (6) 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), the social planner attains socially optimal pricing $P^e(T^*,\ \phi) = P^*$ as well.

A.3 Two Market Failures and One Policy Instrument

If the subsidy rate $t = 0$, the social planner cannot achieve the first best by varying the base subsidy T since firm's attribute choices cannot be affected by the subsidies. In other words, the product design remains inefficient with the presence of externality. On the other hand, let's suppose the base subsidy $T = 0$ and the social planner searches for the optimal subsidy rate t. Then, there remains the positive markup after the financial incentive, i.e., $P^z(0,t) - C(\boldsymbol{x}^z(t)) + t \cdot z(\boldsymbol{x}^z(t)) > 0$. The first-order condition of the social planner's problem of searching optimal subsidy rate t is:

$$\begin{aligned}
\frac{dSW(P,\ \boldsymbol{x})}{dt} &= SW_P(P,\ \boldsymbol{x})\frac{dP}{dt} + \sum_k SW_k(P,\boldsymbol{x})\frac{dx_k}{dt} \\
&= (P - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x}))\underbrace{[Q_P(P,\boldsymbol{x})\frac{dP}{dt} + \sum_k Q_k(P,\boldsymbol{x})\frac{dx_k}{dt}]}_{dQ/dt} \\
&\quad + Q(P,\boldsymbol{x})\underbrace{[\sum_k (B_k(\boldsymbol{x}) - C_k(\boldsymbol{x}) + \phi \cdot e_k(\boldsymbol{x}))]}_{dSNB/dt} \\
&= \underbrace{(P - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x}))\frac{dQ(P,\boldsymbol{x})}{dt}}_{\text{Extensive margin}} + \underbrace{Q(P,\ \boldsymbol{x})\frac{dSNB(\boldsymbol{x})}{dt}}_{\text{Intensive margin}} = 0.
\end{aligned}$$

The first term of the last line captures how the subsidy rate t affects the social welfare through the extensive margin by changing the output level. The second term shows the impact of the subsidy rate through the intensive margin by changing the product design. In the competitive market, the subsidy rate, $t = \phi$, is the socially optimal under perfect targeting because both the extensive margin and the intensive margin would be zero: $P^{e,\phi} - C(\boldsymbol{x}^{e,\phi}) + \phi \cdot e(\boldsymbol{x}^{e,\phi}) = 0$, and $dSNB(\boldsymbol{x}^{e,\phi})/dt = 0$.

With the presence of market power, however, the subsidy rate, $t = \phi$, is not socially optimal even if the social planner can perfectly target the externality. The subsidy rate under perfect targeting maximizes the per-unit social net benefit (i.e. $dSNB(\boldsymbol{x}^{e,\phi})/dt = 0$). But, it does not maximize the entire social welfare due to the presence of the market power:

$$\frac{dSW(P^{e,\phi},\ \boldsymbol{x}^{e,\phi})}{dt} = (P^{e,\phi} - C(\boldsymbol{x}^{e,\phi}) + \phi \cdot e(\boldsymbol{x}^{e,\phi}))\frac{dQ(P^{e,\phi},\ \boldsymbol{x}^{e,\phi})}{dt} \neq 0 \ \text{ at } \ t = \phi.$$

Where there are two market failures, externality and market power, the subsidy rate t alone cannot achieve the socially optimal outcomes ($\boldsymbol{x}^*$ and P^*) because no subsidy rate t can satisfy Equations (3) and (4) simultaneously.

A.4 Imperfect Targeting and the Second-Best Policy

Suppose the regulator provides subsidies based on a policy attribute z that differs from the externality e. Further assume that subsidies follow a two-part structure $T + t \cdot z(\boldsymbol{x})$. For graphical illustration, we restrict the number of basis attributes to two. We specify the private welfare loss as a quadratic function and assume the policy attribute z to be linear in $\boldsymbol{x}$. These two assumptions allow us to depict the iso-net-benefits curves as ellipses and firm's best response to subsidies as a straight line. Recall that the private net benefit is $B(\boldsymbol{x}) - C(\boldsymbol{x})$ is highest at $\boldsymbol{x}^o$ and any deviation from it incurs private welfare losses as a quadratic function:

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

From Equation (6), we know

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

Thus, $\boldsymbol{x}^z(t)$ should satisfy the 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. We can express the firm's best response to subsidies as follows:

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

If there is no incentive (i.e. $t = 0$), the deviation $\Delta\boldsymbol{x}^z(t)$ become zero and the agent chooses $\boldsymbol{x}^z(t) = \boldsymbol{x}^o$. If $t \neq 0$, the private choice differs from $\boldsymbol{x}^o$, and a higher subsidy or tax result in a greater distortions in attribute choices. We denote the direction of the distortions by $d\vec{x_z}$.

The solid line in Figure 2 (a) shows the collection of points available to the planner when it perfectly targets the externality. By offering subsidy rate ($t > 0$) or levying a tax ($t < 0$), the social planner can select any point on the extended line of the directional vector with the origin at $\boldsymbol{x}^o$. The desirable characteristic, $\boldsymbol{x}^*$ is on the line. In reality, however, the planner may not be able to perfectly target e but instead use the policy attribute z to approximate the externality. Then, the optimal attributes can be achieved and the social planner can try to induce the (second-best) attributes that are closest to the first best $\boldsymbol{x}^*$ in terms of the social welfare.

The dashed curves in Figure 2 show the contour lines representing the level of social welfare/benefit. Because e is assumed to be linear in $\boldsymbol{x}$, the social benefit, $B(\boldsymbol{x})-C(\boldsymbol{x})+\phi e(\boldsymbol{x})$, has strictly convex contour sets as the private benefit, $B(\boldsymbol{x})-C(\boldsymbol{x})$, does. But, the social benefit has the peak at $\boldsymbol{x}^*$ while the private benefit reaches the peak at $\boldsymbol{x}^o$. The second-best attributes $\boldsymbol{x}^s$ can be found at the tangent point between the extended line of $d\vec{x_z}$ and an iso-social-benefit curve.

A.5 Proof of Lemma 1

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 (5). Using the fact that $\boldsymbol{x}^z(t)$ does not depend on Equation (5), we can rewrite the firm's pricing decision separately as follows:

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

Without loss of generality, we can switch the decision variable from P to $\tilde{P}=P-B(\boldsymbol{x}^z(t))$. Then, the problem becomes

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

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.

$$\max_{\tilde{P}}(\tilde{P}+k+b)\ Q(\tilde{P}). \tag{A1}$$

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

$$\text{FOC}:\quad Q\big(\tilde{P}^*(b,k)\big)+(\tilde{P}^*(b,k)+k+b)\ Q'\big(\tilde{P}^*(b,k)\big)=0, \tag{A2}$$

$$\text{SOC}:\quad \underbrace{2Q'\big(\tilde{P}^*(b,k)\big)+(\tilde{P}^*(b,k)+k+b)\ Q''\big(\tilde{P}^*(b,k)\big)}_{\text{denoted by } S(b,k)}<0. \tag{A3}$$

Taking the partial derivative of Equation (A2) 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 (A3), we know

$$\frac{\partial \tilde{P}^*(b,k)}{\partial b} = \frac{\partial \tilde{P}^*(b,k)}{\partial k} < 0. \tag{A4}$$

Write the equilibrium quantity as $Q(b,k) = Q(\tilde{P}^*(b,k))$, Equation (A4) 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

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

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 $b < b'$ should be true, leading to $Q(b,k) > Q(b',k')$.

A.6 Proof of Proposition 2

Proof: Rewrite the social planner's problem under the budget constraint:

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

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

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

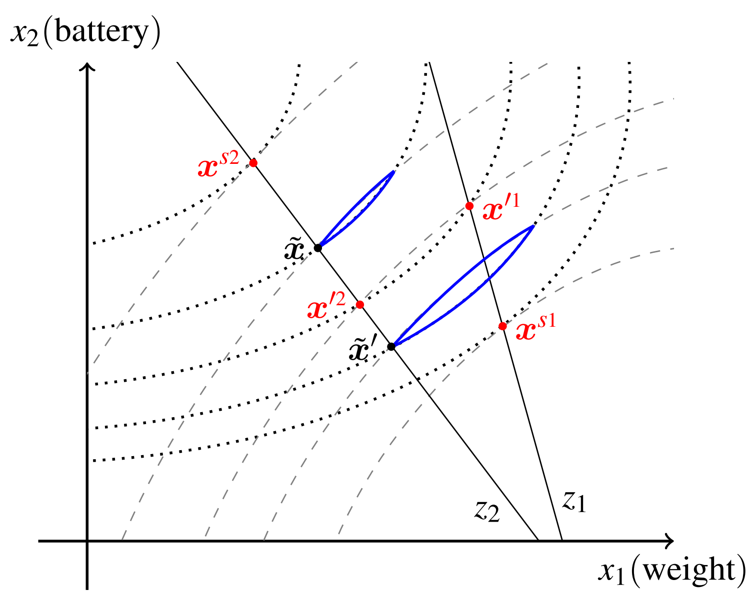
where $SNB = B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$. As t increases, $\boldsymbol{x}^z(t)$ deviates further from the private best choice ($\boldsymbol{x}^o$) reducing $B(\boldsymbol{x}) - C(\boldsymbol{x})$. Therefore, the greater the subsidy rate t is, the smaller the quantity is achievable in the product market by Lemma 1. Thus, if the budget constraint is binding, leaving a positive markup $P - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x}) > 0$, then $dSNB/dt > 0$. Figure 4 (a) shows where $dSNB/dt > 0$ holds on the best-response line. The second-best product design should lie between "$\boldsymbol{x}^s$ w/o BC" and $\boldsymbol{x}^o$.

A.7 Proof of Proposition 3

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 4 (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 policy line passes through $\boldsymbol{x}'$. By Proposition 2, there exists a unique budget level R that makes $\boldsymbol{x}'$ as the second-best choice. Also, there is a unique t^R that encourage the firm to choose $\boldsymbol{x}'$ given the policy attribute z'. Lastly, there exists a unique T^R that satisfies the budget constraint for given t^R and R. Then, the constructed policy triad (T^R, t^R, z') achieves $\boldsymbol{x}' = \boldsymbol{x}^{z'}(t^R)$ and it is socially optimal by Proposition 3 i).

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 $\boldsymbol{x}^{s2}$ to be the second-best choice is greater than that for $\boldsymbol{x}^{s1}$.

Proof of iii): We provide Figure A1 to demonstrate this statement. Suppose (R^1, z^1) makes $\boldsymbol{x}^{s1}$ the second-best attribute bundle while $\boldsymbol{x}^{s2}$ 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. By Proposition 2, there exist 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 following Proposition 2. Therefore, if we can show $R'^1 = R'^2$, we have $R^2 > R'^2 = R'^1 > R^1$.

If a budget level R is greater than R'^2, the planner prefers z_2 to z_1 (denoted by $z_2 \succ_s z_1$). For instance, suppose $\tilde{\boldsymbol{x}}$ is the second-best choice given (R, z_2). $\tilde{\boldsymbol{x}}$ should be closer to $\boldsymbol{x}^*$ since $R > R'^2$. Then, the z_1 line does not pass the blue lens created by $\tilde{\boldsymbol{x}}$, and thus $z_2 \succ_s z_1$. On the other hand, if R is less than R'^2, the planner prefers z_1 to z_2. For example, if $\tilde{\boldsymbol{x}}'$ is the second-best given (R, z_2), then $z_1 \succ_s z_2$ since the z_1 line passes through the blue lens from $\tilde{\boldsymbol{x}}'$. Thus, we have $R \geq R'^2$ if and only if $z_2 \succsim_s z_1$. By the similar logic, we can show $R \geq R'^1$ if and only if $z_2 \succsim_s z_1$. These two statements imply $R'^1 = R'^2$

Denote $R' = R'^1 = R'^2$. We know z_1 represents the best policy attribute when the budget level is equal to R^1. z_2 is the best attribute when the budget level is equal to R^2, where R^2 is larger than R_1. The above discussion tells us that there exist the budge level $R' \in (R^1, R^2)$ with which the planner is indifferent between z_1 and z_2. Lastly, the planner prefers z_1 to z_2 (z_2 to z_1) if the budget is less (more) than R'.

A.8 Product-specific Subsidy with Differentiated Products

Consider two heterogeneous goods $j = 1, 2$ with benefit B_j, marginal cost C_j, and demand $Q_j\big(B_1 - P_1,\ B_2 - P_2\big)$. The planner chooses the per-unit subsidies b_1 and b_2 to maximize the social welfare subject to a budget constraint, $b_1 Q_1 + b_2 Q_2 = R$. First, assume two goods are independent for a moment: $Q_j\big(B_1 - P_1,\ B_2 - P_2\big) = Q_j(B_j - P_j)$. Then, the social welfare is equal to

$$SW = \sum_{j=1}^{2} \int_0^{Q_j(B_j - P_j)} B_j - Q_j^{-1}(s) - P_j ds + \big(P_j - C_j\big) Q((B_j - P_j).$$

Given a per-unit subsidy b_j and $k_j = B_j - C_j$, we can formulate firm's problem as in Equation (A1), and the markup $M_j(b_j, k_j)$ satisfies Equation (A2). The social planner's problem can be written as:

$$\max_{b_1, b_2} \mathscr{L}\left(b_1, b_2 | k_1, k_2\right) = SW\left(b_1, b_2 | k_1, k_2\right) + \lambda \Big(R - b_1 Q_1\big(k_1 - M_1(b_1, k_1)\big) - b_2 Q_2\big(k_2 - M_2(b_2, k_2)\big)\Big).$$

The first order conditions of the planner's problem become:

$$[b_i] \quad -M_j(b_j, k_j) \cdot Q_j' \cdot \frac{\partial M_j(b_j, k_j)}{\partial b_j} - \lambda \Big(Q_j\big(k_j - M_j(b_j, k_j)\big) - b_j \cdot Q_j' \cdot \frac{\partial M_j(b_j, k_j)}{\partial b_j})\Big) = 0 \quad \text{for} \quad j = 1, 2$$

$$[\lambda] \quad R - b_1 Q_1\big(k_1 - M(b_1, k_1)\big) - b_2 Q_2\big(k_2 - M(b_2, k_2)\big) = 0.$$

Appendix B: Environmental Impact Calculations

The baseline emission intensity (g/km) for gasoline models and BEVs are provided in Table A2. CO_2 emissions per km by each vehicle model is calibrated based on Huo et al. (2013) which measure 'fuel-cycle' CO_2 emissions of EVs and gasoline vehicles by taking into account differences in the fuel source of electricity generation across provinces in China.

For local emissions (PM, SO_2, and NO_x) from ICVs, we use Tailpipe Emission Standard Level 5 or Fuel Standard level 5/6. For EVs, we obtain the information on emission intensity from China Emissions Accounts for Power Plants (Tang et al., 2020). The lifetime travel distance of vehicles is assumed to be 200,000km. To monetize the damage from total emissions, the social cost of CO_2 is assumed to be \$42 per ton based on 3% discount rate from the US Intergovernmental Working Group.[30] The cost of each local pollutant is from Parry et al. (2014). Because electricity is generated primarily from coal in China, EVs' environmental advantage compared to ICVs is significantly compromised. For instance, when the fuel efficiency of EV and ICV is 0.2kWh/km and 0.08L/km, respectively, EVs generate even more CO_2 per km than ICVs as in in North and Northeast provinces.

[30] https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html.

Appendix C: Simulation Algorithm for New Equilibrium

This appendix provides details on the simulation algorithm. In our model, an equilibrium outcome is the set of prices and attributes that satisfies firms' first-order conditions. We introduce the following matrix notations in order to write the first-order conditions concisely.

$$M_x = \begin{pmatrix} \frac{\partial mc_1}{\partial x_1} & 0 & \cdots & 0 \\ 0 & \frac{\partial mc_2}{\partial x_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \\ 0 & 0 & & \frac{\partial mc_J}{\partial x_J} \end{pmatrix}, \quad M'_x = \begin{pmatrix} \frac{\partial^2 mc_1}{\partial x_1^2} \cdot q_1 & 0 & \cdots & 0 \\ 0 & \frac{\partial^2 mc_2}{\partial x_2^2} \cdot q_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \\ 0 & 0 & & \frac{\partial^2 mc_J}{\partial x_J^2} \cdot q_J \end{pmatrix}, \quad dFC_x = \begin{pmatrix} \frac{\partial FC_1}{\partial x_1} \\ \frac{\partial FC_2}{\partial x_2} \\ \vdots \\ \frac{\partial FC_J}{\partial x_J} \end{pmatrix}.$$

for $x = k$ and w. The first-order conditions can be written as:

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

where dOP implies the derivatives of the operating profit. The first order conditions do not hold with the initial prices and product attributes if there is any policy change. Our goal is to find a set of prices and attributes that make dOP be equal to dFC in an equilibrium.

[Step 1] Fix the demand derivatives (Δ_x for $x = P$, k, and w) and let each firm deviate to the best response given others' price and attribute choices. Denote the deviations by $\boldsymbol{dP}$, $\boldsymbol{dk}$, and $\boldsymbol{dw}$, and they should satisfy the following conditions:

$$\begin{aligned} dOP_P &+ [\qquad\quad (\Omega \otimes \Delta_P) + (\Omega \otimes \Delta_P)^t \quad]\, \boldsymbol{dP} \\ &+ [\qquad\quad (\Omega \otimes \Delta_k) - (\Omega \otimes \Delta_P)^t M_k]\, \boldsymbol{dk} \\ &+ [\qquad\quad (\Omega \otimes \Delta_w) - (\Omega \otimes \Delta_P)^t M_w]\, \boldsymbol{dw} \simeq \boldsymbol{0} \end{aligned} \tag{A5}$$

$$\begin{aligned} dOP_k &+ [\qquad -M_k (\Omega \otimes \Delta_P) + (\Omega \otimes \Delta_k)^t \quad]\, \boldsymbol{dP} \\ &+ [-M'_k \; -M_k (\Omega \otimes \Delta_k) - (\Omega \otimes \Delta_k)^t M_k]\, \boldsymbol{dk} \\ &+ [\qquad -M_k (\Omega \otimes \Delta_w) - (\Omega \otimes \Delta_k)^t M_w]\, \boldsymbol{dw} \simeq dFC_k + \phi_2^k \boldsymbol{dk} \end{aligned} \tag{A6}$$

$$\begin{aligned} dOP_w &+ [\qquad -M_w (\Omega \otimes \Delta_P) + (\Omega \otimes \Delta_w)^t \quad]\, \boldsymbol{dP} \\ &+ [\qquad -M_w (\Omega \otimes \Delta_k) - (\Omega \otimes \Delta_w)^t M_k]\, \boldsymbol{dk} \\ &+ [-M'_w \; -M_w (\Omega \otimes \Delta_w) - (\Omega \otimes \Delta_w)^t M_w]\, \boldsymbol{dw} \simeq dFC_w + \phi_2^w \boldsymbol{dw} \end{aligned} \tag{A7}$$

$$\quad ① \qquad\qquad ② \qquad\qquad\qquad ③ \qquad\qquad\qquad\qquad ④$$

The first (①) and last components (④) represent the change in the slopes of the marginal costs and fixed costs, respectively. The second components (②) stem from the change in sales, while the third components (③) come from the change in markups. The detailed derivation of Equation (A5), (A6), and (A7) is organized in Appendix.

The three sets of equations include also the three sets of unknowns. Thus, by solving the system of linear equations, we can obtain the optimal deviations of individual firms, $\boldsymbol{dP}$, $\boldsymbol{dk}$, and $\boldsymbol{dw}$ easily. Note that the equations have $\simeq$ instead of $=$, which is because the equations linearly approximate the impact of the deviations on dOP and dFC although they are not linear in price and attributes. Therefore, the equations do not hold if the changes in price and attributes are large. The update in price and attributes should be small enough during the actual implementation of the algorithm.

[Step 2] Update $\boldsymbol{Q}$, $\boldsymbol{mc}$, and Δ_x (for x = P, k, and w) with the new $\boldsymbol{P}$, $\boldsymbol{k}$, and $\boldsymbol{w}$. Although we updated the prices and vehicle attributes by solving Equation (A5), (A6), and (A7), the first order conditions still do not hold because we fixed the demand derivatives in **Step 1** and also, the deviations are the optimal changes for individual firms, given other firms' choices. Therefore, we need to repeat the updates until no firms want to deviate from the current price and attribute choices.

[Step 3] Repeat **Steps 1** and **2** until the algorithm converges.

As implementing the algorithm, we add another assumption that firms change an attribute only based on a single set of first order conditions corresponding to the attribute. In other words, the firms changes the prices by considering only the optimality condition of price. Also, the change of battery capacity (weight) is determined only by the first order condition of capacity (weight). This assumption simplifies Equation (A5), (A6), and (A7) to

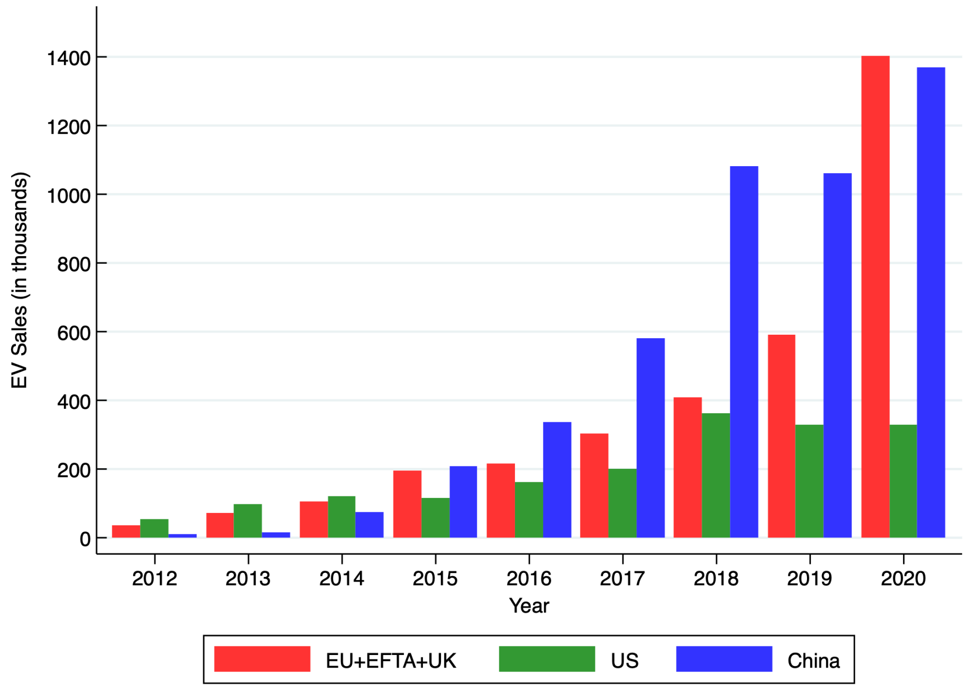
$$\begin{aligned}
dOP_P &+ [\qquad (\Omega \otimes \Delta_P) + (\Omega \otimes \Delta_P)^t \qquad]\, \boldsymbol{dP} \simeq \boldsymbol{0} \\
dOP_k &- [\, M_k' + M_k\,(\Omega \otimes \Delta_k) + (\Omega \otimes \Delta_k)^t M_k \,]\, \boldsymbol{dk} \simeq dFC_k + \phi_2^k \boldsymbol{dk} \\
dOP_w &- [\qquad M_w(\Omega \otimes \Delta_w) + (\Omega \otimes \Delta_w)^t M_w \,]\, \boldsymbol{dw} \simeq dFC_w + \phi_2^w \boldsymbol{dw}
\end{aligned}$$

This simplification of firm's decision on the attribute changes has two advantages. The first and obvious advantage is to reduce the burden of solving the system of linear equations in each iteration. Because now each set of first order conditions determines the deviation of the corresponding attribute independently, computation of $\boldsymbol{dP}$, $\boldsymbol{dk}$, and $\boldsymbol{dw}$ is easier.

The second and more important reason of the simplification is that the updates of attributes are much smaller now, making the algorithm more stable. For example, consider Equation (A5). Intuitively, a firm can raise price if it installs a larger battery or increases the vehicle size. On the other hand, when the firm lowers price, it tends to decrease the battery capacity or the size to reduce the production costs. So, it is likely that $\boldsymbol{dk}$ and $\boldsymbol{dw}$ have the same sign with $\boldsymbol{dP}$. Provided that the Δ_k and Δ_w have the opposite directions with Δ_p, therefore, the impact of the battery capacity change, $[(\Omega \otimes \Delta_k) - (\Omega \otimes \Delta_P)^t M_k]\ \boldsymbol{dk}$, and the vehicle weight change, $[(\Omega \otimes \Delta_w) - (\Omega \otimes \Delta_P)^t M_w]\ \boldsymbol{dw}$, partially offsets that of the price change, $[(\Omega \otimes \Delta_P) + (\Omega \otimes \Delta_P)^t]\ \boldsymbol{dP}$. As a result, Equation (A5), creates larger updates $\boldsymbol{dP}$, $\boldsymbol{dk}$, and $\boldsymbol{dw}$ as the solutions. The similar logic applies to Equation (A6) and (A7) as well. Because the equations represent the choices of individual firms with other firms' decisions as given, getting the exact solutions each iteration is not necessary. Rather, the direction of the updates, which must narrows the gap between dOP and dFC, is more crucial to approach to the equilibrium, and it can be obtained using the simplified version of the equations.

Appendix D: Figures & Tables

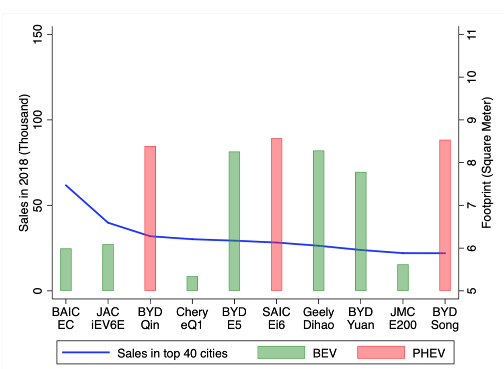
Figure A2: Global EV Sales 2012-2020



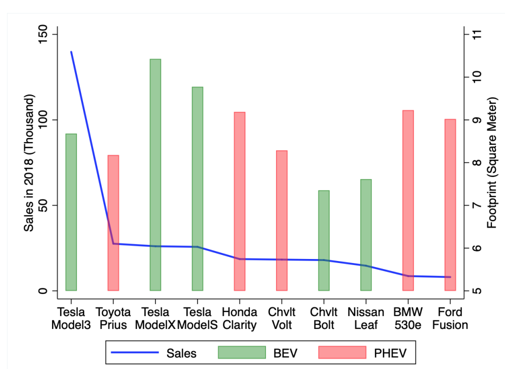
Note: New EV sales (including both BEVs and PHEVs) by country and region. Source: International Energy Agency, and the European Automobile Manufacturers' Association.

Figure A3: Top 10 EVs in China and US in 2018

(a) China EV Size



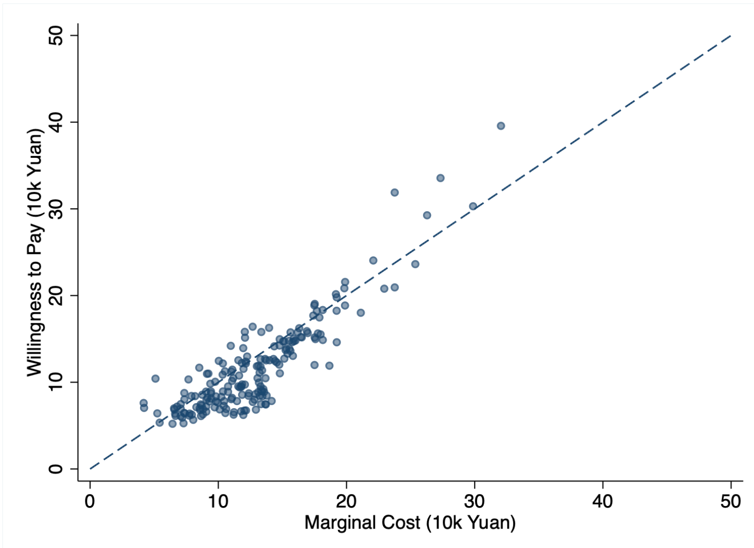
(b) USA EV Size



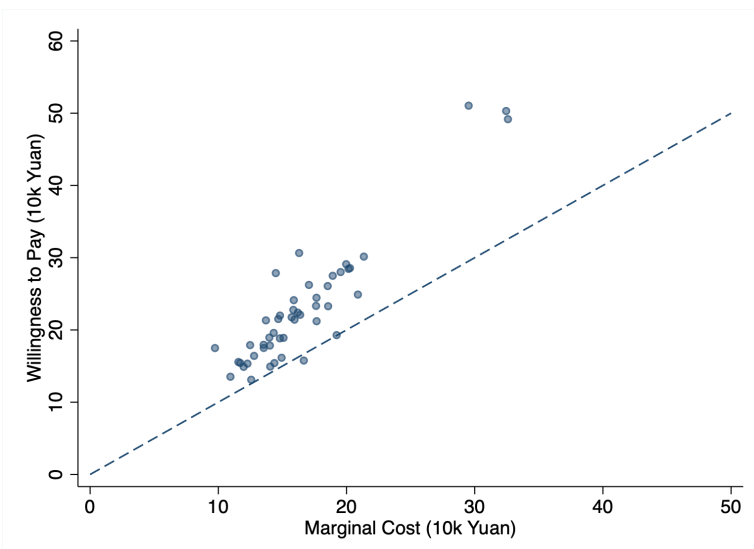
Notes: The figure compares the top 10 most popular EV (including both BEV and PHEV) models in China and the US. The left vertical axis and the blue line in each graph show the 2018 sales. The right vertical axis and the bars show the footprint (length by width) of each model. The green and red color represent BEV and PHEV, respectively.

Figure A4: Willingness to Pay and Marginal Costs by Model

(a) BEVs



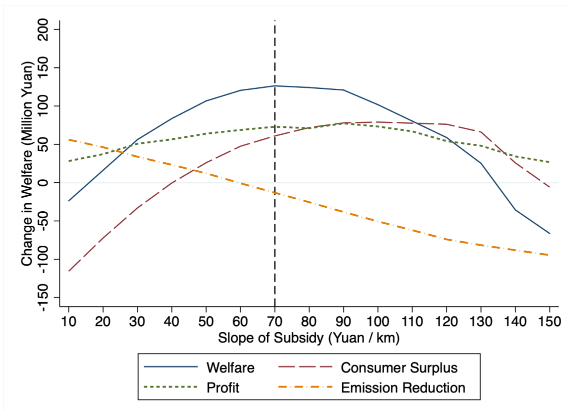
(b) PHEVs



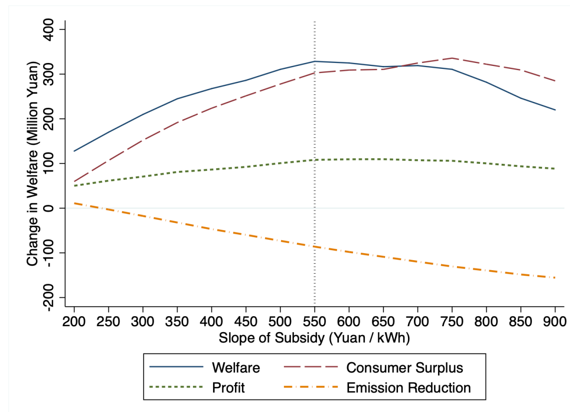
Notes: The figures depict the willingness to pay (y-axis) and the marginal costs (x-axis) of BEVs and PHEVs sold from 2015 to 2018. The dashed lines represent the 45-degree line. More than half of BEV models are under the 45-degree line, suggesting the willingness to pay being lower than the marginal costs.

Figure A5: Welfare Change and Slope of Linear Subsidy in 2017

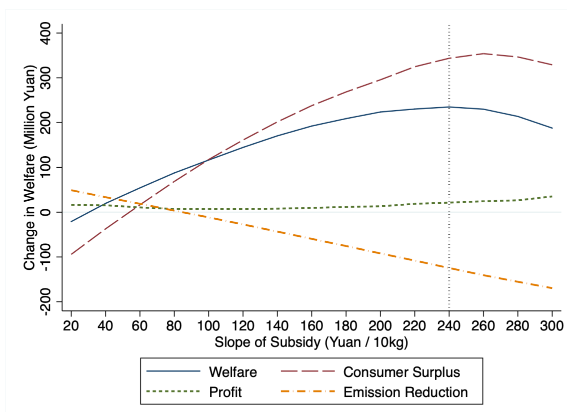
(a) Based on Driving Range



(b) Based on Battery Capacity



(c) Based on Net Weight



Notes: The horizontal axis represent the incentive rate of linear subsidies based on driving range, battery capacity, and net weight. The vertical axis shows the change in welfare compared to the original level of welfare under the actual subsidy program. The total welfare is divided into consumer surplus, firm profit, and benefit from emission reduction. The government expenditure for the BEV subsidy is maintained constant. The vertical dotted lines indicate the optimal slope of the linear subsidies that maximizes the welfare in the BEV marekt.

Table A1: Average Price of Domestic EVs by Range Groups

Type	Range	2013	2014	2015	2016	2017	2018
BEV	≥ 80km	¥170,800 (20.5%)	¥139,300 (23.9%)	¥114,133 (27.6%)			
	≥ 100km	¥267,450 (13.1%)	¥234,900 (14.2%)	¥238,350 (13.2%)	¥234,900 (10.6%)		
	≥ 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%)
	≥ 200km		¥227,567 (20.9%)	¥241,233 (18.7%)	¥234,233 (19.2%)	¥168,521 (21.4%)	¥121,773 (20.5%)
	≥ 250km			¥268,267 (20.1%)	¥249,495 (22.0%)	¥196,027 (22.4%)	¥159,662 (21.3%)
	≥ 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%)
	≥ 400km			¥319,900 (16.9%)	¥319,900 (17.2%)	¥319,900 (13.8%)	¥215,588 (23.2%)
PHEV	≥ 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 ICVs and EVs

Emission (g/km)		Min	Mean	Max	Source
ICV	CO_2	240.16	248.00	250.98	Huo et al. (2013)
	NOx	0.0600	0.0600	0.0600	Tailpipe Emission Standard Level 5
	PM	0.0045	0.0045	0.0045	Tailpipe Emission Standard Level 5
	SO_2	0.0016	0.0016	0.0016	Fuel Standard Level 5/6
BEV	CO_2	17.07	205.81	287.97	Huo et al. (2013)
	NOx	0.0438	0.0597	0.0884	China Emissions Accounts for Power Plants
	PM	0.0036	0.0069	0.0120	China Emissions Accounts for Power Plants
	SO_2	0.0186	0.0426	0.1086	China Emissions Accounts for Power Plants

Notes: The values are the emission amount from ICVs and BEVs when the fuel efficiency of ICVs is 8L/100km and energy efficiency of BEVs is 20kWh/100km. Thus, the emission amount varies across vehicles with different fuel/energy efficiency. For PHEVs, we assume miles driven on electricity counts for 55% of the total. Lastly, the emission amount varies across cities in China, except for the local pollutants from ICVs.

Table A3: Attribute Choices and Market Outcomes for BEV Models in 2017

Range groups	Attributes/outcomes	Observed	Counterfactual Scenarios			
			Range	Capacity	Weight	Constant
(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Net weight (10kg)	77.9	79.2	81.1	85.2	80.3
	Battery capacity (kWh)	18.9	17.1	17.4	16.1	16.0
	Driving range (km)	152.2	139.8	139.6	126.9	131.9
$150 \leq D_j \leq 155$	MSRP	12.5	12.2	12.6	12.7	11.9
	Marginal cost	9.2	8.9	9.1	9.2	8.8
$(\lambda_j > 0)$	Markup	2.2	2.2	2.3	2.2	2.1
	Central subsidy	3.67	3.45	3.30	3.41	3.73
	Sales	3673	3468	2940	2853	4324
	WTP	8.3	8.2	8.7	8.6	7.7
	# of cases			15		
	Net weight (10kg)	96.5	94.1	96.1	103.3	96.5
	Battery capacity (kWh)	24.1	28.7	29.3	23.3	24.1
	Driving range (km)	175.9	206.5	208.3	163.9	175.8
$155 < D_j < 250$	MSRP	13.4	13.9	14.3	14.0	13.4
	Marginal cost	10.0	10.4	10.7	10.5	10.0
$(\lambda_j = 0)$	Markup	2.2	2.2	2.3	2.3	2.2
	Central subsidy	3.67	3.92	3.95	3.85	3.73
	Sales	3368	3311	3253	3251	3469
	WTP	8.3	8.8	9.2	9.1	8.4
	# of cases			18		
	Net weight (10kg)	121.9	125.5	128.8	137.6	127.8
	Battery capacity (kWh)	41.4	36.3	37.0	32.2	32.7
	Driving range (km)	251.3	215.9	216.4	178.0	191.4
$250 \leq D_j \leq 255$	MSRP	21.0	20.2	20.6	20.2	19.6
	Marginal cost	15.7	14.9	15.4	15.2	14.4
$(\lambda_j > 0)$	Markup	3.3	3.3	3.2	3.1	3.2
	Central subsidy	4.49	3.98	4.37	4.67	3.73
	Sales	1448	1426	1621	1811	1420
	WTP	14.4	14.2	14.4	13.9	13.8
	# of cases			9		
	Net weight (10kg)	133.0	130.9	135.2	143.4	129.9
	Battery capacity (kWh)	48.4	59.1	58.6	46.2	49.2
	Driving range (km)	310.3	378.7	370.9	286.1	318.7
$155 < D_j < 250$	MSRP	24.7	25.9	26.4	25.8	24.7
	Marginal cost	17.8	18.9	19.3	18.7	17.6
$(\lambda_j = 0)$	Markup	4.5	4.5	4.5	4.6	4.6
	Central subsidy	4.49	5.12	5.50	4.81	3.73
	Sales	1725	1868	2046	2096	1368
	WTP	18.1	19.2	19.0	19.2	19.1
	# of cases			14		

Notes: The marginal cost, markup, subsidy, and WTP are all in ¥10k. The first column organizes the attributes of 2017 models under the current policy. The next four columns present firms' attribute decisions and market outcomes under the four counterfactual scenarios. Columns (4-6) use linear subsidies based on driving range, battery capacity, and vehicle weight while column (7) uses a constant subsidy.

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

Fuel Type	Attributes/outcomes	Observed	Counterfactual Scenarios			
			Range	Capacity	Weight	Constant
(1)	(2)	(3)	(4)	(5)	(6)	(7)
PHEV	Net weight (10kg)	166.4	166.4	166.3	166.3	166.5
	Battery capacity (kWh)	14.1	14.0	14.0	14.0	14.1
	Driving range (km)	70.3	70.2	70.0	70.1	70.3
	MSRP	24.3	24.3	24.2	24.2	24.3
	Marginal cost	15.6	15.6	15.6	15.6	15.6
	Markup	4.9	4.9	4.9	4.9	4.9
	Central subsidy	1.94	1.94	1.94	1.94	1.94
	Sales	3711	3709	3703	3705	3717
	WTP	23.7	23.3	23.3	23.7	23.3
	# of cases	19				
ICV	Net weight (10kg)	143.9	143.9	143.9	143.9	143.9
	MSRP	14.4	14.4	14.4	14.4	14.4
	Marginal cost	9.0	9.0	9.0	9.0	9.0
	Markup	2.7	2.7	2.7	2.7	2.7
	Sales	23608	23612	23618	23618	23600
	WTP	16.2	16.2	16.1	16.1	16.1
	# of cases	330				

Notes: The marginal cost, markup, subsidy, and WTP are all in ¥10k. The first column organizes the attributes of 2017 models under the current policy. The next four columns present firms' attribute decisions and market outcomes under the four counterfactual scenarios. Columns (4-6) use linear subsidies based on driving range, battery capacity, and vehicle weight while column (7) uses a constant subsidy.

Table A5: BEV sales and Central Subsidy Distribution

		Observed	Counterfactual Scenarios			
			Range	Capacity	Weight	Constant
(1)	(2)	(3)	(4)	(5)	(6)	(7)
WTP < ¥120k	BEV sales	92695	-3503	-12692	-13364	10857
	Central subsidy (¥10k)	3.70	0.00	-0.07	-0.10	0.03
WTP > ¥120k	BEV sales	60198	1228	5680	7430	-4517
	Central subsidy (¥10k)	4.37	0.20	0.55	0.32	-0.63
Total central subsidy expenditure (¥10k)		633,359	633,238	632,923	633,405	633,660

Notes: This table divides BEVs into high-quality models (WTP > ¥120k) and low-quality models (WTP < ¥120k) using the willingness to pay under the current policy. The central subsidy represents the average subsidy for each group. The first column shows the BEV sales and central subsidies in 2017 under the current policy. The next four columns present the changes in BEV sales and subsidies under the counterfactual scenarios.