Online Appendix

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

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A Theoretical Model

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

From Equation (A3), we know

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

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

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

where $z_1(\boldsymbol{x})$ and $z_2(\boldsymbol{x})$ are the partial derivatives with respect to the first and second element of $\boldsymbol{x}$. If the policy attribute z is linear in $\boldsymbol{x}$, the partial derivatives are constant, z_1 and z_2. Then, we

can express the firm's best response to subsidies as follows:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Based on Equation (A9), we know

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

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

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

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

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

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

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

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

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

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

where $SNB = B(\boldsymbol{x}) - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x})$. As t increases, $\boldsymbol{x}^z(t)$ deviates further from the private best choice, $\boldsymbol{x}^o$, reducing $B(\boldsymbol{x}) - C(\boldsymbol{x})$. Therefore, the greater the subsidy intensity t is, the smaller the quantity is achievable in the product market by Lemma 1. Thus, if the budget constraint is bind-

ing, which leaves a positive markup $P - C(\boldsymbol{x}) + \phi \cdot e(\boldsymbol{x}) > 0$, then $dSNB/dt$ should be positive. Figure 3 (a) shows where $dSNB/dt > 0$ holds on the best-response line. The second-best product design "$\boldsymbol{x}^z_{\text{with}BC=R}$" lies between "$\boldsymbol{x}^z_{\text{w/o BC}}$" and $\boldsymbol{x}^o$ to satisfy $dSNB/dt > 0$.

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

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

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

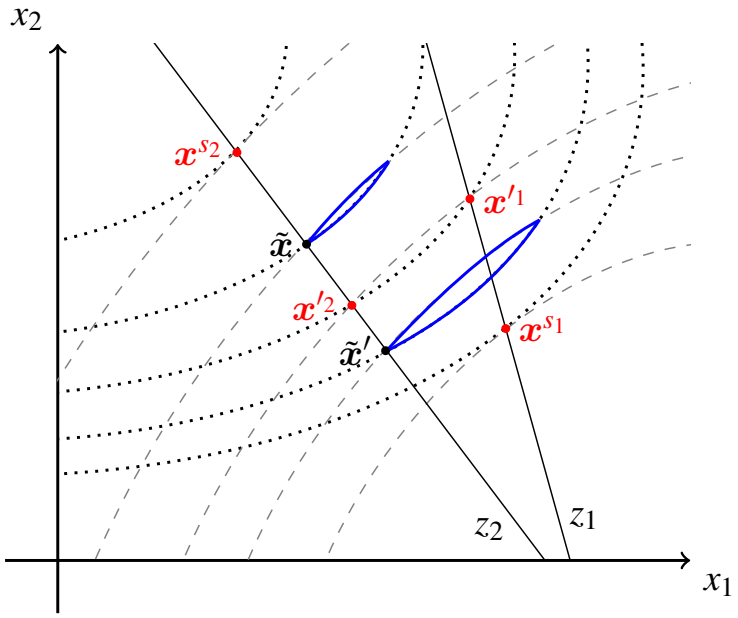
[34] Let's explore the meaning of dQ/dt. An increase in t leads to a decrease in k in Equation (A10), thereby reducing Q. Since $\tilde{P}$ is a function of $b + k$, we can express the planner's budget constraint as $b \cdot Q(\tilde{P}(b+k)) = R$. If we denote $\tilde{Q}(.) = Q(\tilde{P}(.))$ and the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

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

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

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

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



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

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

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

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

ple, suppose $\tilde{\boldsymbol{x}}'$ is the second-best given (R, z_2), then $z_1 \succ_R z_2$ since the z_1 line passes through the blue lens generated from $\tilde{\boldsymbol{x}}'$.

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

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

Recall the definition of social welfare:

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

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

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

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

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

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

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

lows:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

The last three terms in the above equation are similar to those in Equation (A15) for the monopoly case. The first term, which is new for the oligopoly case, represents the welfare impact of changes in subsidy distributions across heterogeneous products. Because products exhibit different levels

of the policy attribute, the regulator's choice of t affects how much subsidy expenditure is distributed across the products. Therefore, an ABS plays three distinct roles when there are multiple products in the market: i) distribution of subsidies, ii) product design change, and iii) sales promotion. In other words, the choice of t should take into account its impact on the subsidy allocations across products as well as balancing externalities and market power considerations.

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

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

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

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

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

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

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

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

B Institutional Background and Sample Construction

B.1 Policy Background

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

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

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

B.2 Sample Construction

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

behavior at the two extremes - purchasing excessively cheap or expensive models.

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

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

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

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

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

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

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

C Counterfactual Analysis

C.1 Environmental Impacts

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

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

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

emissions of local pollutants for renewable energy generation.

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

C.2 Accident Externalities

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

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

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

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

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

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

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

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

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

C.3 Simulation Algorithm for New Equilibrium

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

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

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

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

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

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

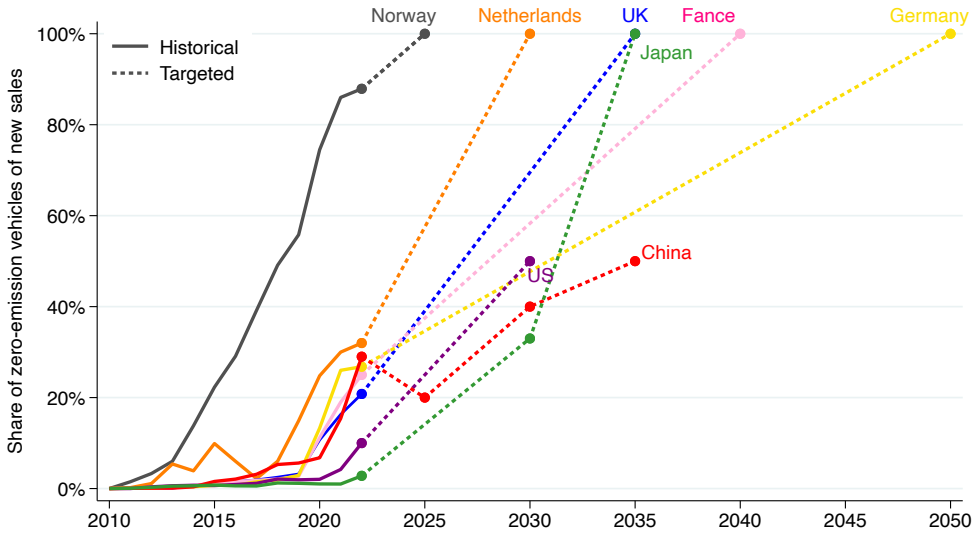
[Step 1] While fixing the demand derivatives Δ_P, Δ_k, and Δ_w, find the necessary changes in one attribute $\boldsymbol{dx}$ to make the corresponding first-order conditions satisfied, given the fixed demand derivatives, by solving the following equation:

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

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

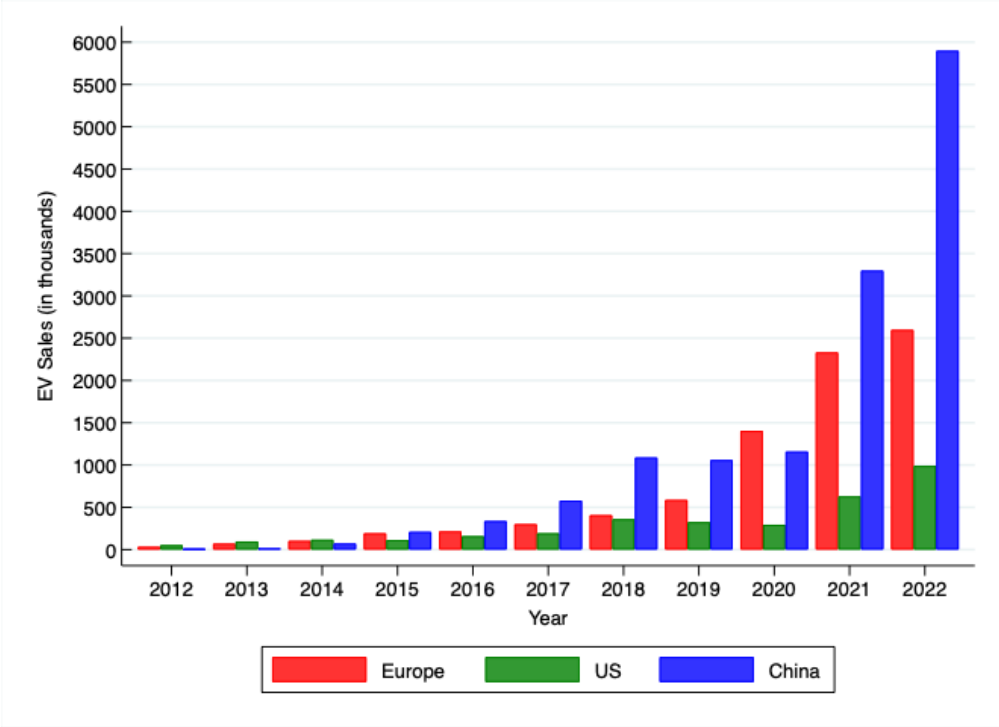
D Figures & Tables

Figure A2: ZEV Targets and Market Shares by Country



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

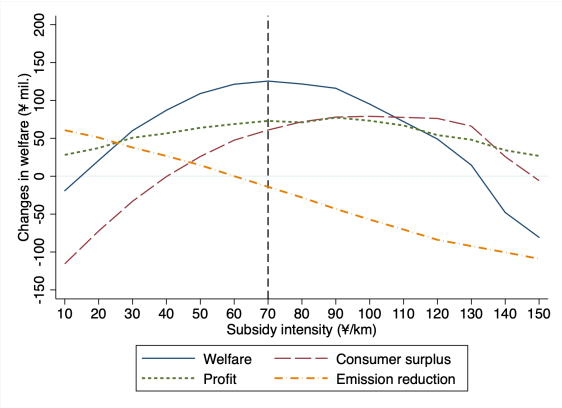
Figure A3: Global EV Sales by Region 2012-2022



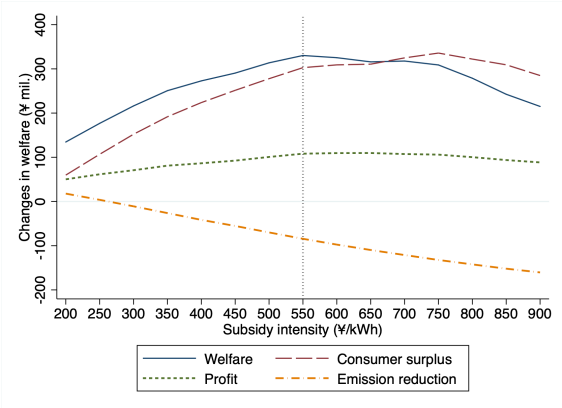
Notes: Annual sales of new EVs (including both BEVs and PHEVs) by country and region. China, Europe and the U.S. accounted for over 95% of global EV sales during the data period. Source: International Energy Agency.

Figure A4: Welfare Changes and Subsidy Intensity t

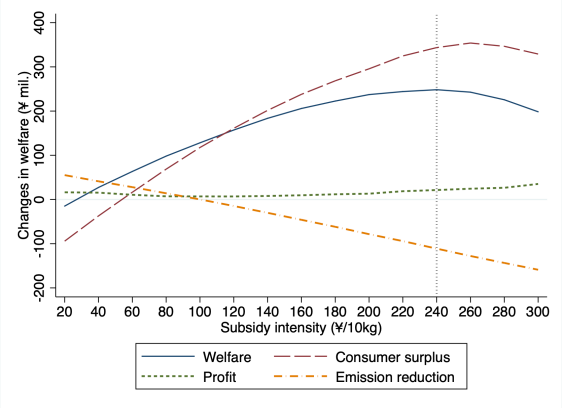
(a) Based on Driving Range



(b) Based on Battery Capacity



(c) Based on Net Vehicle Weight



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

Table A1: Average Price of Domestic EVs by Range Groups

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

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

Table A2: Emissions Intensity from ICEs and EVs

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

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

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

Table A3: Optimal Base Subsidy T and Subsidy Intensity t

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

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

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

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

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

Table A5: BEV Sales and Subsidy Distribution

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

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

Table A6: Welfare Impacts of ABS with Accident Externalities

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

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

Table A7: Welfare Impacts of ABS Holding Product Attribute Fixed

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

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