Optimal Subsidies for the Product Upgrading of Battery Electric Vehicles in China

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Abstract

This paper estimates the impact of Chinese notched driving-range-based (DRB) subsidies to consumers on Chinese battery-electric-vehicle (BEV) manufacturers' incentives to reduce their production costs of driving ranges. Chinese consumers received generous subsidies if the driving ranges were above certain thresholds. Using a dynamic structural model to infer unobserved firms' decisions on the cost reduction of driving ranges, I find that the discontinuous incentives around the range thresholds of Chinese DRB subsidies incentivized Chinese manufacturers to reduce the production costs of ranges. Compared with counterfactual linear DRB subsidies and holding the total amount of subsidies a firm receives constant, the top quartile of firms in terms of production costs in 2019 are 70 percentage points more likely to reduce their production costs of ranges under the existing notched DRB subsidies. This dynamic impact on production costs implies that the environmental benefits and welfare gains of notched DRB subsidies are very likely larger than the estimates of existing literature. It also implies that notched subsidies can be effective in inducing technological adoption or product upgrading.

Keywords: Industrial policy, product subsidy, technology catch-up, electric vehicle, dynamic discrete choice model

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1 Introduction

This paper estimates the impact of Chinese driving-range-based (DRB) subsidies to consumers on Chinese battery-electric-vehicle (BEV) manufacturers' incentives to reduce their production costs of driving ranges. The Chinese DRB subsidies are part of Chinese ambition to dominate the world auto industry with electric vehicle (EV) manufacturing, however little is known whether and how the DRB subsidies contribute to the 450 times increase in Chinese EV sales in the past decade and its domestic producers newly-acquired presence in the global market in 2022. More specifically, it is unclear whether the Chinese DRB subsidies induced Chinese EV manufacturers to actively reduce their production costs of driving ranges, such as building more energy-efficient models or improving their supply chains of batteries, or whether the manufacturers responded by only installing more batteries and building smaller cars. Using a dynamic structural model to explain and infer firms' decisions regarding the cost reduction of driving ranges, I find that Chinese DRB subsidies, which offer a generous amount of subsidies to consumers once the driving ranges are above certain range thresholds and is addressed as notched subsidy scheme in this paper, increased Chinese manufacturers' incentives to reduce the production costs of ranges. Compared with counterfactual linear DRB subsidies and holding the total amount of subsidies a firm receives constant, the top quartile of firms in terms of production costs in 2019 are 70 percentage points more likely to reduce their production costs of ranges under the existing notched DRB subsidies. This result implies that the environmental benefits and welfare gains of notched DRB subsidies are very likely larger than the estimates of existing literature where this channel of reducing future production costs of ranges is ignored. The machinery built to estimate the impact of reducing production costs of ranges can also be used to devise better or even optimal DRB subsidies to guide firms' decisions on reducing production costs of ranges, such as whether to announce future subsidy changes in advance, different menus of thresholds and subsidies, and different timelines of the subsidies.

From 2016 to 2020, BEVs in China became cheaper with longer ranges, using higher-density batteries but there was no clear trend of a decline in model sizes. Furthermore, there is large variation in prices and driving ranges in each given year and the trend of changing prices and ranges varied across models and manufacturers. Underlying changes in battery technology alone can not explain the variation. Possible explanations for the variation are consumers' heterogeneous tastes and price sensitivity, different model characteristics, firms' capability of exerting markups, and firms' decisions to reduce their production costs of ranges. Firms can reduce their production costs by improving their exposure to the technological progress in batteries, such as sourcing better battery suppliers or vertical integration of battery suppliers either via merge and acquisition or via in-house R&D. Firms can also reduce their production costs by designing more energy efficient models so that the same model with the same battery capacity can travel a longer distance. I use a dynamic structural model to disentangle the channel of a reduction in the production costs of ranges from the remaining channels so that I can quantify the impact of Chinese DRB subsidies on firms' decisions to reduce the production costs of ranges. I focus on BEVs because they are the most targeted EVs by Chinese DRB subsidies and have the largest sales among all the EVs.

In my structural model, consumers make their purchase decisions in each period based on observed and unobserved model characteristics, and unobserved consumer-model-period-specific taste shocks. They can also choose not buy a car. Manufacturers maximize their expected sum of current and discounted future profits by choosing the optimal prices and ranges in each period and make dynamic decisions on whether to reduce the production costs of ranges in the next period. If they decide to reduce the production costs, they pay an investment cost in this period. Their production costs are lower in the next period and will stay at this value until further investments are made in future periods.

I follow Berry et al. (1995) and Crawford et al. (2019) to assume that unobserved consumer-model-period-specific taste shocks are independent and identically distributed so that I can use model-level market shares in each year to estimate parameters of consumer preferences. To capture consumers' heterogeneous tastes and price sensitivity, I model consumers' utitlity using random coefficients so that the preference parameters are consumer specific. I follow Crawford et al. (2019) to parametrize firms' production costs as log-linear in the endogenous control variables prices and ranges squared, and exogenous observed and unobserved model characteristics. The first order conditions of firms' profits maximization together with model prices and consumers' preference parameters give the estimated production cost functions. To account for endogeneity caused by the unobserved model characteristics in both demand and supply, I construct instrument variables following Berry et al. (1995).

Since the range is an endogenous control variable, my estimation produces model-year-specific cost parameters of ranges. I infer firms' investment decisions from the changes in the cost parameters of ranges. A reduction in a firm' cost parameters this period means that the firm invests in reducing the production cost of ranges in the previous period. A firm invests when the increase in its expected discounted sum of future profits is larger than the investment cost. The investment cost is unobserved and is estimated from the inferred investment decisions and that firms maximize their expected sum of discounted profits. The investment cost is assumed to be constant across firms and time. To ease the computation burden, I discretize the estimated cost parameters of ranges and assume that the space of the cost parameters to be a finite set with a known lower bound. The lower bound and the discrete state space allow me to solve for the optimal investment decisions in my dynamic game using backward induction. Solving an infinite-horizon game recursively over a finite set of state space when the transition of state variables is unidirectional follows Iskhakov et al. (2016). Using dynamic optimization to estimate parameters of a dynamic game is similar in spirit to Rust (1987). I set the lower bound lose enough so that firms won't be able to reach it in the near future. The intuition behind this known and lose lower bound is that predicting plausible technology frontier over 50 or 100 years is difficult and most of time firms cannot foresee new technology in the distant future. In this finite space of cost parameters, a firm's cost parameter of ranges in the next period improves by one unit when it invests in the current period.

Applying my structural model to the data which is a newly constructed rich dataset that contains national-level model sales in 2010-2021 and the technical description of each model variations available or once available on the market,[1] I find that firms with lower production cost of ranges have higher probability to invest in reducing the production costs. Compared with a counterfactual linear scheme and holding the total amount of subsidies constant, the current notched DRB subsidies improve firms' incentives to reduce the production costs of ranges the most when the range thresholds under the current notched DRB subsidies are binding, for example, the firm at the top quartile in terms of production costs of ranges and also where the threshold constraint start to bind is about 70 percentage points more likely to invest.

This paper provides the first empirical evidence that notched attribute-based subsidies can produce efficiency gains. Existing literature on attribute-based subsidies, such as Ito and Sallee (2018) and Jia et al. (2022), almost universally criticizes notched subsidy schemes for the distortions they create around the thresholds and therefore recommend against notched ones for the sake of efficiency. My results show that the discontinuity in firms' profits around the thresholds incentivize firms to try harder to reduce production costs and consequently creates efficiency gains.

This paper contributes to the literature of industrial policies on innovation and technological progress by providing empirical evidence on whether and how support on the demand side can encourage innovation and technological upgrading. Studies have shown that reducing the costs of investment can support R&D (Takalo et al. (2013) and Criscuolo et al. (2019)) because this increases the gains to investment. In theory, such an increase can also be achieved by promoting demand. The field experiments in Bold et al. (2022) show that

[1] The sources are Chezhu Home (`https://www.16888.com`) and Auto Home (`https://www.autohome.com.cn`)

higher demand can encourage farmers' technological adoptions, suggesting that policies targeting the demand side can be effective. However, there is no empirical evidence that the same holds in the EV market and this paper fills in the gap.

The methodological contribution of this paper is to combine Berry et al. (1995) and Crawford et al. (2019)'s model for structurally estimating demand and supply using aggregate data, such as automobile models' annual sales at the national level rather than individual consumer's decisions, with the literature of dynamic discrete choice models (Rust (1987), Bresnahan and Reiss (1991), Ericson and Pakes (1995), Abbring et al. (2018)) where estimators of dynamic decisions are estimated using data on individual decisions, so that one can do counterfactual analysis that involves dynamic decision making without observing the dynamic decisions.

The remainder of the paper is organized as follows. I present historical background and stylized facts in Section 2. I then introduce the model and demonstrate theoretical results in Section 3. I explain the estimation procedure in Section 4 and describe the data set in Section 5. Results are provided in Section 6. Section 7 concludes.

2 Historical background and stylized facts

3 Model

We start with the static part of the model which is similar to the setup in Berry et al. (1995) and Crawford et al. (2019).

3.1 Demand

Consumers maximize their indirect utility by deciding whether to purchase a car and which car model to purchase if they decide to purchase one. If consumer i chooses to buy a model j from firm f in the year t, the indirect utility from such purchase is U_{ijft}, which consists of the mean utility of purchasing this model δ_{ijft} and the consumer i's taste for this model in the year t, ϵ_{ijft}. The mean utility is the mean utility for consumer i and different consumers may have different mean utility from the same model in the same because of heterogeneous consumer tastes and price sensitivity. If the consumer chooses not to purchase a car, the indirect utility is U_{i0t}, whose mean utility is normalized to 0 and the taste shock for not to purchase a car is ϵ_{i0t}. ϵ_{ijft} and ϵ_{i0t} are independent and identically distributed and are Type

I extreme values with mean zero.

$$\begin{cases} U_{ijft} = \delta^{ijft} + \epsilon_{ijft} & \text{for product } j \text{ from manufacturer } f \text{ at time } t \\ U_{i0t} \quad = \epsilon_{i0t} & \text{otherwise} \end{cases}$$

where δ_{ijft} is assumed to be:

$$\delta_{ijft} = \alpha_i * p_{jft} + \beta_i * x_{jft} + \xi_{jft}$$

The subscript i of α and β reflects heterogeneous price sensitivity and heterogeneous tastes of model characteristics. x_{jft} includes size, power-weight ratio, torque, luxury level, whether released this year, years the model exists in the data, model and year two-way fixed effects. For EV cars, x_{jft} also include driving ranges and consumer i's preference parameter of ranges is β_i^c. If a model is not qualified for subsidies because it does not meet the requirements of subsidies, $\tau_{jft} = 0$.

Demand for product j from firm f in the year t is

$$N_t \cdot \mathbb{E}_i \left[\frac{exp(\delta_{ijft})}{1 + \sum_{j,f} exp(\delta_{ijft})} \right]$$

where N_t is the total amount of households in the year t, which is my measure of all the consumers who consider whether to buy a car in the year t. The expectation $\mathbb{E}_i$ is over the distribution of consumers. This product's market share is

$$s_{jft} = E_i \left[\frac{exp(\delta_{ijft})}{1 + \sum_{j,f} exp(\delta_{ijft})} \right]$$

3.2 Supply

Firm f's profits at time t, π_{ft}, are the sum of all its products' profits. The set of firm f's products at time t is $\mathcal{J}_{ft}$.

$$\pi_{ft} = \sum_{j \in \mathcal{J}_{ft}} N_t s_{jft}(p_{jft} - mc_{jft} + \tau(R_{jft}))$$

where N_t is the total amount of household, s_{jft} is its product i's market share and p_{jft} is the price and τ_{jft} is the subsidy. I parametrize the marginal production as log-linear in ranges squared if it is a BEV, observed and unobserved covariates that affect production costs.

$$mc_{jft} = \exp(c_{jft}R_{jft}^2 + \mu * w_{jft} + \eta_{jft})$$

where w_{jft} represents the observed covariates, which include power-weight ratio, size, luxury level, mpg(e) and torque. η_{jft} is the unobserved model characteristics that affect production costs.

Firms maximize the sum of their current and discounted expected future profits by choosing the optimal prices and ranges in each period, and deciding whether to pay a fixed amount of investment cost for a product this period to reduce the production cost parameter of ranges in the next period, $c_{jf,t+1}$. The cost parameter of range c_{jft} takes value from a known finite set $\mathcal{C} = \{c_1, c_2, \cdots, c_L\}$ that satisfies $c_{l-1} < c_l$ for $l \in \{2, 3, ..., L\}$. If a model's current c_{jft} takes the value c_l and this firm invests, then in the next period, $c_{jf,t+1} = c_{l-1}$ Because c_{jft} can either stay constant or become smaller, this assumption of $\mathcal{C}$ being a finite allows me to solve the dynamic problem using backward induction over the state variable c_{jft}. Since prices and ranges are set in every period, they are static optimization problems. The first order conditions of prices and ranges are:

$$\begin{aligned}
\frac{\partial \pi_{ft}}{\partial p_{jft}} =& s_{jft} + \sum_{k \in \mathcal{J}_f} (p_{kft} - mc_{kft} + \tau(R_{kft})) \frac{\partial s_{kft}}{\partial p_{jft}} = 0 \\
\frac{\partial \pi_{ft}}{\partial R_{jft}} =& - s_{jft} \left(\frac{\partial mc_{jft}}{\partial R_{jft}} + \frac{\partial \tau(R_{jft})}{R_{jft}} \right) + \sum_{k \in \mathcal{J}_f} (p_{kft} - mc_{kft} + \tau(R_{kft})) \frac{\partial s_{kft}}{\partial R_{jft}} = 0
\end{aligned}$$

3.3 Firms' optimal choices

In order to provide an analytical solution to firms' dynamic decisions on reducing the production cost parameters of ranges, c_{jft}, I assume away consumer' heterogeneous tastes on observed model characteristics and heterogeneous price sensitivity, i.e. $\alpha_i = \alpha$, $\beta_i = \beta$, and $\beta_i^c = \beta^c$, but maintain the unobserved consumer-model-firm-year specific taste shocks, ϵ_{ijft}. I will use simulation to demonstrate these results for heterogeneous consumers.

Market shares under homogeneous tastes on observed model characteristics and price sensitivity are:

$$s_{jft} = \frac{exp(\delta_{jft})}{1 + \sum_{j,f} exp(\delta_{jft})}$$

And response of market shares to changes of model prices and ranges are:

$$\frac{\partial s_{kjt}}{\partial d_{jft}} = \begin{cases} -s_{kft}s_{jft}\frac{\partial \delta_{jft}}{\partial d_{jft}} \text{ , if } k \neq j \\ (1-s_{jft})s_{jft}\frac{\partial \delta_{jft}}{\partial d_{jft}} \text{ , if } k = j \end{cases}$$

and $d_{ift} \in \{p_{ift}, R_{ift}\}$, $\frac{\partial \delta_{ift}}{\partial p_{ift}} = \alpha$, $\frac{\partial \delta_{ift}}{\partial R_{ift}} = \beta^R$.

Since firms set prices and ranges in each period, the optimal prices and ranges at time t maximize the profits at time t and satisfy the following first order conditions:

$$\begin{aligned} 0 =& 1 + \sum_{k \in \mathcal{J}_{ft}, k \neq j} (p_{kft} - mc_{kft} + \tau(R_{jft})) \cdot (-s_{kft}\alpha) \\ &+ (p_{jft} - mc_{jft} + \tau(R_{jft})) \cdot (1 - s_{jft})\alpha \\ 0 =& -\left(\frac{\partial mc_{jft}}{\partial R_{jft}} + \frac{\partial \tau(R_{jft})}{R_{jft}}\right) + \sum_{k \in \mathcal{J}_{ft}, k \neq j} (p_{kft} - mc_{kft} + \tau(R_{jft})) \cdot (-s_{kft}s_{jft}\beta^R) \\ &+ (p_{jft} - mc_{jft} + \tau(R_{jft})) \cdot (1 - s_{jft})\beta^R \end{aligned}$$

The optimal ranges satisfy the following equation:

$$-2c_{jft}R^*_{jft} + \tau'(R^*_{jft}) - \frac{\beta^R}{\alpha} = 0$$

If the market share of each individual car model is very close to zero, i.e. $s_{ijt} \approx 0$, which turns out to be the case in my data, the right side of the first order conditions are approximated as:

$$\begin{aligned} 0 \approx& 1 + (p_{jft} - mc_{jft} + \tau(R_{jft})) \cdot \alpha \\ 0 \approx& -\left(\frac{\partial mc_{jft}}{\partial R_{jft}} + \frac{\partial \tau(R_{jft})}{R_{jft}}\right) + (p_{jft} - mc_{jft} + \tau(R_{jft}))\beta^R \end{aligned}$$

So firm j's optimal profits and optimal prices are approximately

$$\pi^*_{ft} \approx -\frac{\sum_{j \in \mathcal{J}_{ft}} s^*_{jft}}{\alpha} \tag{1}$$

$$p^*_{jft} \approx -\frac{1}{\alpha} + c_{jft}(R^*_{jft})^2 + \mu * w_{jft} + \eta_{jft} - \tau(R^*_{jft}) \tag{2}$$

where s^*_{jft} is the market share when all the firms choose their optimal prices and ranges.

Firm j will invest in reducing the c_{jft} of its product j at time t if the discounted sum of expected profits from model j is higher if it invests. The underlying assumption is that firm j do not internalize the impact of investing in one of its product on its other products. Therefore the value of product j at $c_{jft} = c_l$ for firm f, $v_{jft}(\vec{c}_t, I_t)|_{c_{jft}=c_l}$, is:

$$\begin{aligned} v_{jft}(\vec{c}_t, I_t)|_{c_{jft}=c_l} = \max\{ & -\lambda + \pi_{jft}(\vec{c}_t, I_t)|_{c_{jft}=c_l} + \epsilon_{jft}(1) + \rho * \mathbb{E}_t[v_{jft+1}(\vec{c}_{t+1}, I_{t+1})|_{c_{jft+1}=c_{l-1}}], \\ & \pi_{jft}(\vec{c}_t, I_t)|_{c_{jft}=c_l} + \epsilon_{jft}(0) + \rho * \mathbb{E}_t[v_{jft+1}(\vec{c}_{t+1}, I_{t+1})|_{c_{jft+1}=c_l}]\} \end{aligned}$$

$\vec{c}_t$ is the vector of c_{jft} for all the firms and all the models at time t, i.e. $\vec{c}_t = \{c_{jft}\}_{j\in\mathcal{J}_{ft}, f\in\mathcal{F}_t}$. $\mathcal{F}_t$ is the set of all the firms at time t. λ is the investment cost. $\epsilon_{jft}(0)$ and $\epsilon_{jft}(1)$ are Type-I extreme-value shocks and are independent and identically distributed. ρ is the discount factor. I_t represents the information available to all the firms at time t, which includes the current subsidy scheme, and all the other exogenous observed and unobserved model characteristics, i.e. $\{w_{jft}, \eta_{jft}, x_{jft}, \xi_{jft}\}_{j\in\mathcal{J}_{ft}, f\in\mathcal{F}_t}$. $\mathbb{E}_t$ is expectation about next period's equilibrium and about next period's information set I_{t+1} condition on this period's information I_t. I assume that firms' expect the subsidy scheme and the observed and unobserved model characteristics to stay constant over time and are capable of solving the dynamic programming problem when predict other firms behavior. I define $U_{jft}(\vec{c}_t, I_t, 0)$ and $U_{jft}(\vec{c}_t, I_t, 1)$ as the choice-specific value that satisfy:

$$v_{jft}(\vec{c}_t, I_t)|_{c_{jft}=c_l} = \max\{U_{jft}(\vec{c}_t, I_t, 1)|_{c_{jft}=c_l} + \epsilon_{jft}(1), U_{jft}(\vec{c}_t, I_t, 0)|_{c_{jft}=c_l} + \epsilon_{jft}(0)\}$$

Under the assumption about firms' expectation, the dynamic problem at time t becomes a stationary problem. In each period t, firms' optimal decision is a solution to a stationary dynamic programming problem based on the information set realized at time t. However, the realized information set I_t can be different in each period, for example the realized subsidy scheme can differ in each period or the exogenous model characteristics can change over time. This means the stationary dynamic programming problem attached to each period can be different. Therefore, firms' actual investment decisions in each period is the first-period optimal decisions of each period's auxiliary dynamic programming problem. I denote variables from period t's auxiliary dynamic programming problem by superscript t, and the time periods inside the dynamic programming problem by subscript r. By construction, $r \geq t$.

$$\begin{aligned} U^t_{jf}(\vec{c}_r, 1)|_{c_{jfr}=c_l} &= -\lambda + \pi^t_{jfr}(\vec{c}_r)|_{c_{jfr}=c_l} + \rho * \mathbb{E}^t_r[v_{jfr+1}(\vec{c}_{r+1})|_{c_{jfr+1}=c_{l-1}}] \\ U^t_{jf}(\vec{c}_r, 0)|_{c_{jfr}=c_l} &= \pi^t_{jfr}(\vec{c}_r)|_{c_{jfr}=c_l} + \rho * \mathbb{E}^t_r[v_{jfr+1}(\vec{c}_{r+1})|_{c_{jfr+1}=c_l}] \\ v^t_{jf}(\vec{c}_r)|_{c_{jfr}=c_l} &= \max\{U^t_{jf}(\vec{c}_r, 1)|_{c_{jfr}=c_l} + \epsilon_{jf}(1), U^t_{jf}(\vec{c}_r, 0)|_{c_{jfr}=c_l} + \epsilon_{jf}(0)\} \end{aligned}$$

Each period t's auxiliary stationary problem can be solved by backwards induction from

$c_{jft} = c_1$ as explained in Iskhakov et al. (2016).[2] This also produces firms' optimal investment decisions at time t.

3.4 An illustrative example of two single-product firms for solving the dynamic problem

This section demonstrates how to solve the auxiliary dynamic programming for firms at time t in a simple setup of two single-product firms, j and m. Since firms do not internalize the impact of investing in one of its product on the profits of its other products, the solution explained in this section is applied to multiple multi-product firms. I drop the model subscript i because firm j and m are single-product.

Following Iskhakov et al. (2016), I use backward recursion over the space of firms range production cost c_{jr} and c_{mr}, in the sense that I start with $(c_{jr}, c_{mr}) = (c_1, c_1)$ and then move backwards to $(c_{jr}, c_{mr}) = (c_2, c_1)$ and $(c_{jr}, c_{mr}) = (c_1, c_2)$, and then move backward to $(c_{jr}, c_{mr}) = (c_2, c_2)$. This process continues until all the possible realization of (c_{jr}, c_{mr}) for $c_{jr}, c_{mr} \in \mathcal{C}$ are covered.

When $(c_{jr}, c_{mr}) = (c_1, c_1)$, there is no investment decision possible because it is at the boundary of $\mathcal{C}$. Because firms expect subsidy scheme and exogenous model characteristics to stay constant, the value for firm j and m are:

$$v_j(c_1, c_1) = \frac{\pi_j^{*t}(c_1, c_1)}{1-\rho} \approx -\frac{s_j^{*t}(c_1, c_1)}{(1-\rho)\alpha} \tag{3}$$

$$v_m(c_1, c_1) = \frac{\pi_m^{*t}(c_1, c_1)}{1-\rho} \approx -\frac{s_m^{*t}(c_1, c_1)}{(1-\rho)\alpha} \tag{4}$$

The approximation follows from Equation (1). The superscript t means the equilibrium market shares $s_j^{*t}(c_1, c_1)$ and $s_m^{*t}(c_1, c_1)$ are calculated using the subsidy scheme and exogenous model characteristics at time t. There is no subscript r because the problem is stationary under my assumption about firms' expectations.

Move one step backwards, I will solve the situation where $(c_{jr}, c_{mr}) = (c_1, c_2)$ and $(c_{jr}, c_{mr}) = (c_2, c_1)$, and then solve the situation where $(c_{jr}, c_{mr}) = (c_2, c_2)$.

When $(c_{jr}, c_{mr}) = (c_1, c_2)$, j doesn't invest because j is at the boundary but m can still

[2] There is no investment decision to be made at $c_{jft} = c_1$ but the continuation value of $c_{jft} = c_1$ is needed to solve the optimal investment decisions at $c_{jft} = c_2$. The backward induction is over the space of the state variables because this is a non-stationary infinite-horizon problem and the state variable c_{jft} can only change in one direction.

invest.

$$v_m(c_1,c_2) = \pi_m(c_1,c_2) + \max\{\epsilon_m(0) + \rho v_m(c_1,c_2), -\lambda + \epsilon_m(1) + \rho v_m(c_1,c_1)\} \tag{5}$$

The optimal strategy for m at (c_1,c_2) is:

$$a_m(c_1,c_2) = \begin{cases} 1, \text{ if } -\lambda + \epsilon_m(1) + \rho v_m(c_1,c_1) \geq \epsilon_m(0) + \rho v_m(c_1,c_2) \\ 0\text{ , otherwise} \end{cases}$$

Firm j does not observe firm m's $\epsilon_m(0)$ and $\epsilon_m(1)$ in the current period.

$$\begin{aligned} v_j(c_1,c_2) =& \pi_j(c_1,c_2) + \rho\mathbb{E}[v_j(c_1,c_m')] \\ =& \pi_j(c_1,c_2) + \rho(\mathbb{P}[a_m(c_1,c_2)=1]\cdot v_j(c_1,c_1) + \mathbb{P}[a_m(c_1,c_2)=0]\cdot v_j(c_1,c_2)) \quad (6) \\ =& \pi_j(c_1,c_2) + \rho\mathbb{P}[\epsilon_m(1)-\epsilon_m(0) \geq \rho v_m(c_1,c_2) + \lambda - \rho v_m(c_1,c_1)]\cdot v_j(c_1,c_1) + \quad (7) \\ & \rho\mathbb{P}[\epsilon_m(1)-\epsilon_m(0) < \rho v_m(c_1,c_2) + \lambda - \rho v_m(c_1,c_1)]\cdot v_j(c_1,c_2) \end{aligned}$$

$\mathbb{P}[\cdot]$ indicates the probability of the statement inside is true. I first solve $v_m(c_1,c_2)$ as a fixed point to Equation (5) using $v_m(c_1,c_1)$ calculated in Equation (4). Use $v_m(c_1,c_2)$, I calculate the probability of $a_m(c_1,c_2)=1$ and $a_m(c_1,c_2)=0$ before $\epsilon_m(0)$ and $\epsilon_m(1)$ are realized. These together with $v_j(c_1,c_1)$ from Equation 3 allow me to solve $v_j(c_1,c_2)$ as a fixed point of Equation 6.

Similarly, I can solve $v_j(c_2,c_1)$, $a_j(c_2,c_1)$, and $v_m(c_2,c_1)$. When $(c_j,c_m)=(c_2,c_2)$, both firms can invest.

$$\begin{aligned} v_j(c_2,c_2) =& \pi_j(c_2,c_2) + \max\{\epsilon_j(0) + \rho\mathbb{E}_j[v_j(c_2,c_m')], -\lambda + \epsilon_j(1) + \rho\mathbb{E}_j[v_j(c_1,c_m')]\} \\ =& \pi_j(c_2,c_2) + \max\{\epsilon_j(0) + \rho\cdot(v_j(c_2,c_1)\cdot\mathbb{P}[a_m(c_2,c_2)=1] + v_j(c_2,c_2)\cdot(1-\mathbb{P}[a_m(c_2,c_2)=1])), \\ & -\lambda + \epsilon_j(1) + \rho\cdot(v_j(c_1,c_1)\cdot\mathbb{P}[a_m(c_2,c_2)=1] + v_j(c_1,c_2)\cdot(1-\mathbb{P}[a_m(c_2,c_2)=1]))\} \\ v_m(c_2,c_2) =& \pi_m(c_2,c_2) + \max\{\epsilon_m(0) + \rho\mathbb{E}_m[v_m(c_j',c_2)], -\lambda + \epsilon_m(1) + \rho\mathbb{E}_m[v_m(c_j',c_1)]\} \\ =& \pi_m(c_2,c_2) + \max\{\epsilon_m(0) + \rho\cdot(v_m(c_1,c_2)\cdot\mathbb{P}[a_j(c_2,c_2)=1] + v_m(c_2,c_2)\cdot(1-\mathbb{P}[a_m(c_2,c_2)=1])), \\ & -\lambda + \epsilon_m(1) + \rho\cdot(v_m(c_1,c_1)\cdot\mathbb{P}[a_j(c_2,c_2)=1] + v_m(c_2,c_1)\cdot(1-\mathbb{P}[a_j(c_2,c_2)=1]))\} \end{aligned}$$

and

$$a_j(c_2, c_2) = \begin{cases} 1, \text{ if } -\lambda + \epsilon_j(1) + \rho \mathbb{E}_j[v_j(c_1, c'_m)] \geq \epsilon_j(0) + \rho \mathbb{E}_j[v_j(c_2, c'_m)] \\ 0 \text{ , otherwise} \end{cases}$$

$$a_m(c_2, c_2) = \begin{cases} 1, \text{ if } -\lambda + \epsilon_m(1) + \rho \mathbb{E}_m[v_m(c'_j, c_1)] \geq \epsilon_m(0) + \rho \mathbb{E}_m[v_m(c'_j, c_2)] \\ 0 \text{ , otherwise} \end{cases}$$

so

$$\begin{aligned} \mathbb{P}[a_j(c_2, c_2) = 1] =& \mathbb{P}[\epsilon_j(1) - \epsilon_j(0) \geq \rho \mathbb{E}_j[v_j(c_2, c'_m)] + \lambda - \rho \mathbb{E}_j[v_j(c_1, c'_m)]] \\ \mathbb{P}[a_m(c_2, c_2) = 1] =& \mathbb{P}[\epsilon_m(1) - \epsilon_m(0) \geq \rho \mathbb{E}_m[v_m(c'_j, c_2)] + \lambda - \rho \mathbb{E}_m[v_m(c'_j, c_1)]] \end{aligned}$$

The solution is a fixed point to this system of equations.

The backward induction then move on to solve the case of (c_1, c_3), (c_3, c_1), then (c_2, c_3) and (c_3, c_2), and then (c_3, c_3). I continue this process till all the possible realization of (c_j, c_m) are considered.

3.5 Changes in profits due to investment under notched and linear subsidy schemes

It is difficult to analytically derive the explicit formula of changes in the investment probability because of the strategic interactions among firms. However, if the increase in profits from invest is lower under one scheme, the incentive for investment should also be lower under this scheme. The differences in incentives between a notched scheme and a linear scheme should be the largest when firms invest out of the binding threshold constraint under the notched scheme. For the ease of demonstration, I continue using the 2-firm setup as in the section above and drop the covariates x and w. To capture the biggest differences in investment incentives, I will look at changes in profits between two time periods that are not adjacent, i.e. there may be multiple periods between these two periods. The notched scheme, denoted as (a, τ_n), has a threshold a so that models with driving range above a is qualified for subsidies τ_n. I compare it to a linear scheme where a model with range R receives subsidies $\mu_t R$. μ_t is the linear parameter under the linear scheme and is set to the value so that the total amount of subsidies is the same as the notched scheme in each period.

In the first period, denoted as t_1, both firms' state variables, c_j and c_m, are so low that their optimal choices is to choose a range that is below the threshold of the notched scheme,

a. They receive zero subsidies and the optimal ranges R^*_{j1} and R^*_{m1} are:

$$R^*_{j1} = -\frac{\beta^R}{2c_{j1}\alpha}$$
$$R^*_{m1} = -\frac{\beta^R}{2c_{m1}\alpha}$$

Since neither firm receives subsidies under the notched scheme, the linear scheme's μ_1 at t_1 is set to $\mu_1 = 0$.

When both of the firms' market shares are 0, their optimal prices and profits, as derived in Equation (2) and Equation (1), are approximately:

$$p^*_{j1} \approx -\frac{1}{\alpha} + c_{j1} \cdot (R^*_{ji})^2$$
$$\pi^*_{j1} \approx -\frac{s^*_{j1}}{\alpha}$$
$$p^*_{m1} \approx -\frac{1}{\alpha} + c_{m1} \cdot (R^*_{mi})^2$$
$$\pi^*_{m1} \approx -\frac{s^*_{m1}}{\alpha}$$

The equilibrium market shares are approximately:

$$s^*_{j1} \approx \frac{\exp\left(-1 + \alpha \cdot c_{j1}\left(\frac{\beta^R}{2c_{j1}\alpha}\right)^2 - \frac{(\beta^R)^2}{2c_{j1}\alpha}\right)}{1 + \sum_{f\in\{j,m\}} \exp\left(-1 + \alpha \cdot c_{f1}\left(\frac{\beta^R}{2c_{f1}\alpha}\right)^2 - \frac{(\beta^R)^2}{2c_{f1}\alpha}\right)} = \frac{\exp\left(-1 - \frac{(\beta^R)^2}{4c_{j1}\alpha}\right)}{1 + \sum_{f\in\{j,m\}} \exp\left(-1 - \frac{(\beta^R)^2}{4c_{f1}\alpha}\right)}$$
$$s^*_{m1} \approx \frac{\exp\left(-1 + \alpha \cdot c_{m1}\left(\frac{\beta^R}{2c_{m1}\alpha}\right)^2 - \frac{(\beta^R)^2}{2c_{m1}\alpha}\right)}{1 + \sum_{f\in\{j,m\}} \exp\left(-1 + \alpha \cdot c_{f1}\left(\frac{\beta^R}{2c_{f1}\alpha}\right)^2 - \frac{(\beta^R)^2}{2c_{f1}\alpha}\right)} = \frac{\exp\left(-1 - \frac{(\beta^R)^2}{4c_{m1}\alpha}\right)}{1 + \sum_{f\in\{j,m\}} \exp\left(-1 - \frac{(\beta^R)^2}{4c_{f1}\alpha}\right)}$$

Since $\mu_1 = 0$, the optimal prices, ranges, and profits under the linear scheme is the same.

In the period t_2, which may be several periods after t_1, c_{j2} and c_{m2} are small enough so that both firms' optimal ranges under the notched scheme (a, τ_n) are the interior solution

$$R^{n*}_{j2} = -\frac{\beta^R}{2c_{j2}\alpha}$$
$$R^{n*}_{m2} = -\frac{\beta^R}{2c_{m2}\alpha}$$

and $R^{n*}_{j2}, R^{n*}_{m2} > a$. Without loss of generality, I assume $c_{j2} < c_{m2}$. The total amount of subsidies firms receive are

$$\tau_n \sum_{f \in \{j,m\}} s_{f2}^{n*}$$

where s_{f2}^{n*} for $f \in \{j,m\}$ denotes the equilibrium market share. The linear scheme's μ_2 in t_2 satisfies:

$$\mu_2 \sum_{f \in \{j,m\}} R_{f2}^{l*} s_{f2}^{l*} = \tau_n \sum_{f \in \{j,m\}} s_{f2}^{n*}$$

where s_{f2}^{l*} and R_{f2}^{l*} is the equilibrium market share under the linear scheme μ_2, and s_{f2}^{n*} is the equilibrium market share under the notched scheme (a, τ_n).

The equilibrium market shares under the notched scheme (a, τ_n) are approximately:

$$s_{j2}^{n*} \approx \frac{\exp\left(-1 - \frac{(\beta^R)^2}{4c_{j2}\alpha} - \alpha\tau_n\right)}{1 + \sum_{f \in \{j,m\}} \exp\left(-1 - \frac{(\beta^R)^2}{4c_{f2}\alpha} - \alpha\tau_n\right)}$$

$$s_{m2}^{n*} \approx \frac{\exp\left(-1 - \frac{(\beta^R)^2}{4c_{m2}\alpha} - \alpha\tau_n\right)}{1 + \sum_{f \in \{j,m\}} \exp\left(-1 - \frac{(\beta^R)^2}{4c_{f2}\alpha} - \alpha\tau_n\right)}$$

and the profits are approximately:

$$\pi_{j2}^{n*} \approx -\frac{s_{j2}^{n*}}{\alpha}$$

$$\pi_{m2}^{n*} \approx -\frac{s_{m2}^{n*}}{\alpha}$$

Under the linear scheme μ_2, i.e. models with range R is qualified for subsidies $\mu_2 R$ in period t_2, the market shares are approximately:

$$s_{j2}^{l*} \approx \frac{\exp\left(-1 - \frac{(\mu_2\alpha - \beta^R)^2}{4c_{j2}\alpha}\right)}{1 + \sum_{f \in \{j,m\}} \exp\left(-1 - \frac{(\mu_2\alpha - \beta^R)^2}{4c_{f2}\alpha}\right)}$$

$$s_{m2}^{l*} \approx \frac{\exp\left(-1 - \frac{(\mu_2\alpha - \beta^R)^2}{4c_{m2}\alpha}\right)}{1 + \sum_{f \in \{j,m\}} \exp\left(-1 - \frac{(\mu_2\alpha - \beta^R)^2}{4c_{f2}\alpha}\right)}$$

and profits under the linear scheme are approximately:

$$\pi_{j2}^{l*} \approx -\frac{s_{j2}^{l*}}{\alpha}$$

$$\pi_{m2}^{l*} \approx -\frac{s_{m2}^{l*}}{\alpha}$$

The differences in the increase of profits for firm j and m between t_1 and t_2 under the two schemes are:

$$(\pi^{n*}_{j2} - \pi^{*}_{j1}) - (\pi^{l*}_{j2} - \pi^{*}_{j1}) = \pi^{n*}_{j2} - \pi^{l*}_{j2} \approx -\frac{s^{n*}_{j2} - s^{l*}_{j2}}{\alpha}$$
$$(\pi^{n*}_{m2} - \pi^{*}_{m1}) - (\pi^{l*}_{m2} - \pi^{*}_{m1}) = \pi^{n*}_{m2} - \pi^{l*}_{m2} \approx -\frac{s^{n*}_{m2} - s^{l*}_{m2}}{\alpha}$$

Proposition 1 *If the amount of subsidy an individual firm receives is constant and none-zero under a notched scheme (a, τ) and a linear scheme μ, the firm's profits are higher under the notched scheme.*

Proof.

■

4 Estimation

5 Data

We collect sales data from Chezhu Home (https://www.16888.com) and technical description from both Chezhu Home (https://www.16888.com) and Auto Home (https://www.autohome.com.cn). We collect more variables about new energy vehicles using the Lists of Recommended New Energy Vehicles (hereafter the NEV Lists) published by the Chinese government multiple times a year. This provides important variables for new energy vehicles (hereafter NEV) not reported by Chezhu Home and Auto Home. These variables includes the battery energy density (the ratio between battery capacity and battery weight) and fuel efficiency. These variables are required when calculating each model's subsidy value. The NEV Lists relevant for our study are those published in 2017-2020, in total 49 lists.

In addition to direct purchase subsidy, the exemption of purchasing tax influences consumers significantly. We use the Lists of NEVs Eligible for Purchasing Tax Exemption (hereafter the NEVPTE List) and the Lists of NEVs Removed from the NEVPTE Lists (hereafter the RNEVPTE List). These lists are also published by the Chinese government multiple times a year. The lists we collect cover 2016-2020. There are 32 NEVPT Lists and 10 RNEVPTE Lists.

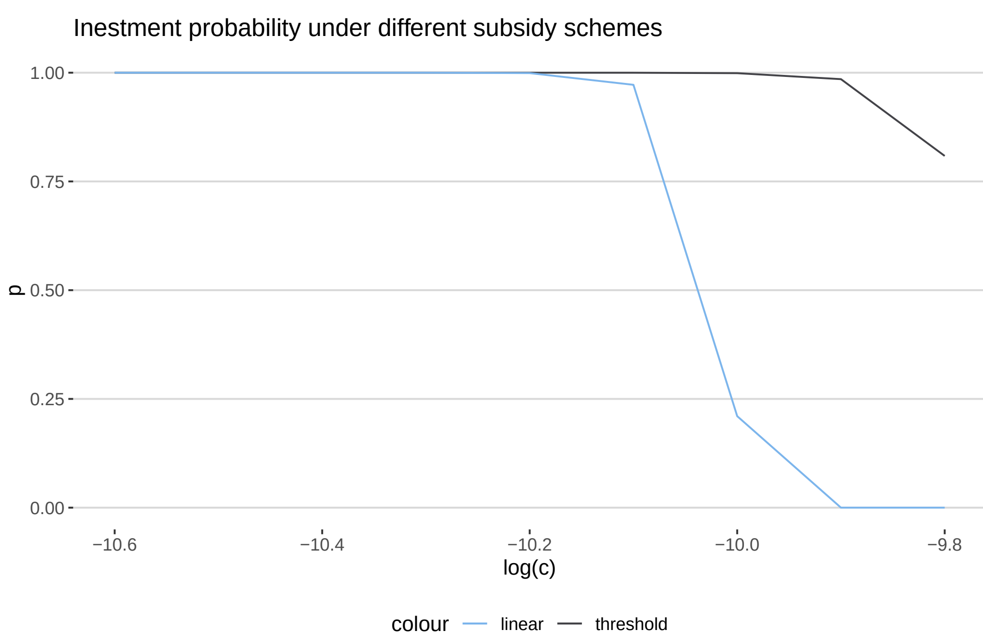
We do not observe the exact amount of subsidy per transaction but we collect the formula announced by the Chinese government to calculate the subsidy. We extract the formula from all the government announcements that dictate how much subsidy is granted what what kind of NEVs. We track the government announcement from 2010 till 2020 and collect the formula for both the subsidy by the central government and the local government.

We use the city-level year book and the Seventh Census to collect the population of the 21 most important cities for NEV consumption.

We also collect data on electricity price and gasoline price. According to the State Grid Corporation of China, the monopoly electricity supplier in China, the electricity price remains at 0.542 RMB/kwh during our sample. We acquire national average of 92 gasoline for 2014-2021 from globalpetrolprices.com and the 92 and 95 gasoline, and diesel price for Beijing and Shanghai in 2010-2021 from https://data.eastmoney.com/cjsj/oil_default.html.

Our data on charging stations and charging poles are from the report of China Electric Vehicle Charging Infrastructure Promotion Alliance (EVCIPA). It consists of national-level and province-level number of charging stations and poles from 2018 till 2021.

6 Results



7 Conclusion

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Appendix

A Data preparation

We need to merge all the data collected from various source into one panel data. Each observation is a model-year-month. The variables including monthly sales, technical descriptions such as horse power, whether eligible for subsidy, the value of subsidy if it is eligible, whether eligible for purchase tax exemption, the price of electricity and gasoline, the number of charging poles or charging stations. The biggest challenge is merge sales data, subsidy info, purchase tax info, and technical description. In this section, we will talk about how this merge is carried out.

A.1 Merge NEVPTE List, RNEVPTE List, and the NEV List

We first convert the lists published by government into data format. These lists share the same model identity. For each of three list groups, we treat observations as redundant if the same model ID in the same year-month appears more than once. Among the redundant observations, we keep the observation with the least number of missing variables, the smallest size, and the smallest weight. We merge based on model ID and use variables shared by the three groups of lists to check the merging is correct. More specifically, the lists all report manufacture name, model type, weight. We first check whether the manufacture names and model types are the same. Next we check whether weight are close enough, i.e. less than 10% difference. We call the merged data subsidy-purchase-tax data (SPT).

A.2 Merge sales, SPT, and the technical description data

We first take the sales data collected from Chezhu Home. Using model names to match the technical description data collected from Chezhu Home and Auto Home. We first use exact matching and the apply fuzzy matching for those unmatched by the exact matching. We then repeat the same process to match with SPT. Sales data is at the model level but the technical description data is at the model-variation level. Meaning, for each model, there are multiple variation in our technical description data. We keep the variation that has the least amount of missing variables, the lowest price, and the smallest sizes, weight, and horse power, following the practice of Berry et al. (1995). For the unmatched observation, we check whether the unmatching is due to incorrectly recorded names and correct them manually if needed.

A.3 Summary stats

TABLE 1

year	sales Merged	sales Scrapped	sales web	gap merged and scrapped	gap scrapped and web
2010	7,763	11,040	13,758	0.300	0.200
2011	12,019	14,316	14,473	0.160	0.010
2012	12,844	16,455	15,494	0.220	-0.060
2013	20,481	21,135	17,929	0.030	-0.180
2014	21,856	22,424	19,701	0.030	-0.140
2015	21,755	22,322	21,146	0.030	-0.060
2016	23,304	23,788	24,377	0.020	0.020
2017	20,237	20,689	24,718	0.020	0.160
2018	19,523	19,858	23,710	0.020	0.160
2019	17,403	17,834	21,444	0.020	0.170
2020	15,761	16,311	20,178	0.030	0.190
2021	13,612	13,843	21,482	0.020	0.360