# Range-Based Subsidies and Product Upgrading of Electric Vehicles in China *

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**Abstract**

This paper estimates the impact of Chinese subsidies to consumers on electric-vehicle (EV) manufacturers' incentives to reduce production costs of driving range. Chinese consumers received subsidies of 16% to 64% of EV market prices if the driving range is above specific thresholds. I find that EV manufacturers respond to the thresholds and that the discontinuous values of subsidies around the thresholds increased the probability of high-market-share manufacturers investing in cost reduction by 25-35 percentage points. This increase more than doubled the investment probability compared to scenarios without subsidies, suggesting that the range-based consumer subsidies encouraged technology adoption and product upgrading.

**Keywords:** Industrial policy, product subsidy, technology adoption, product upgrading, electric vehicle

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# 1 Introduction

This paper estimates the impact of Chinese driving-range-based (DRB) subsidies to consumers on the incentives to reduce production costs of the range by electric-vehicle (EV) manufacturers. Under the pressure of negative growth of automobile sales due to the 2008 financial crisis, the Chinese government introduced subsidies to EV consumers in 2009 to promote innovation by its domestic EV manufacturers. These subsidies were based on the range in order to incentivize EV manufacturers to produce long-range EVs, and were substantial, ranging from 16% to 64% of the market prices for EVs with a long enough range so that they are affordable to consumers. Since then, Chinese domestic EV manufacturers have changed the historical perception of Chinese automobile manufacturers as lower-quality producers and inferior to established foreign brands, and have became major players in the world EV industry. Chinese EV sales increased 14 times in 2016-2022, accounting for 65% of the global EV sales in 2022, and expanded into overseas markets such as the UK and Belgium.[1] In spite of this achievement, it remains unclear whether the DRB subsidies generated sustained affordability and a sustained longer range after the subsidies are phased out, in the sense that whether EV manufacturers responded by reducing the production costs of the range rather than merely installing more batteries. This distinction matters, as it determines the long-term efficacy and justification for these subsidies, which, given their high expense, are intended as temporary support for manufacturers.

Using data on the universe of Chinese passenger EVs in 2012-2020 and the variation across years in the range thresholds, above which an EV is qualified for the DRB subsides, I document that the range of new EVs clustered around and moved with those thresholds. In other words, EV manufacturers chose their product attributes in response to the subsidies. In addition, the DRB subsidies and EV prices declined while EV sales increased over time. This implies that the EV products demonstrated sustained affordability and a sustained longer range. To understand whether the DRB subsidies contributed to the sustained improvement in affordabil-

[1] Sources: https://www.marklines.com, https://www.ev-volumes.com/, and http://ex.chinadaily.com.cn/exchange/partners/82/rss/channel/language/columns/v0m20b/stories/WS6389a97da31057c47eba25e3.html

ity and the range, I build and estimate a structural model where manufacturers can respond to the subsidies by installing more batteries (a static decision) and by investing in reducing future production costs of the range (a dynamic decision). The production costs and investment costs are estimated using model-based inference. My estimates show that the DRB subsidies, especially the discontinuous values of subsidies around the thresholds, increased the probability of low-cost manufacturers investing in cost reduction by 25-35 percentage points. These low-cost manufacturers have high market shares due to their low prices, and improvements in their products affect the majority of consumers.

Manufacturers with different production costs of range set their price and range differently. The DRB subsidies increase demand disproportionately more for long-range EVs and therefore raise their profits more. Since manufacturers with low production costs of range are more likely to produce long-range EVs, the DRB subsidies can make investing in cost reduction more attractive. The EV manufacturers are modeled as competing a la Chamberlinian monopolistic competition because these firms' market shares are less than 2% and on average 0.1%. The main competition is to attract consumers from gasoline producers rather than compete among themselves. By modeling heterogeneous consumers making vehicle-purchase decisions to maximize their static temporal utility, the structural model can predict the gains to profits when manufacturers invest to reduce their production costs of range in the next period and how these gains would change with and without the DRB subsidies. I do not observe decisions on cost reduction and its investment costs. I assume that whenever a manufacturer has at least one new product in this period, which is either a new vehicle model or a new release of an existing vehicle model, the manufacturer invested in the cost reduction in the previous period. Assuming that manufacturers maximizing profits over a finite number of periods, the structural model can predict, for a given value of investment costs, the likelihood of a manufacturer investing in the cost reduction. Matching the model-predicted investment likelihood to the one in data provides an estimate of the investment costs, similar to the nested-fixed point algorithm used in Rust (1987). Together with estimates of the remaining parameters of the demand and supply side following Berry et al. (1995) and Crawford et al. (2019), I quantify the counterfactual changes in manufacturers' investment probability if the DRB subsidies are removed.

Manufacturers solve their profit maximization problem under adaptive expectations about future aggregate market conditions and the belief that the future subsidy scheme will subside at a constant rate and terminate in a known year. This termination year are drawn from news reports, which pins down the subsiding constant rate. As for the current market conditions, they form rational expectations. Predicting what happens in the current period is easier than predicting the future, especially in the rapidly evolving EV industry, which makes it difficult to justify that manufacturers make decisions based on rational expectations about the future. Due to Chamberlinian monopolistic competition, manufacturers only need to form expectations about future aggregate market conditions in stead of the decisions of each individual manufacturer.

The data used in this paper is a rich dataset constructed from multiple sources. The key part includes national vehicle-level monthly sales and model-variation-level prices as well as more than 100 other observed vehicle characteristics. Subsidies are calculated based on the subsidy formulas announced by the government. Since EVs eligible for the subsidies are usually eligible for Value-Added Tax (VAT) exemptions, I collect information on which vehicle models are exempted from VAT.

This paper provides the empirical evidence that including eligibility thresholds in attribute-based subsidies can produce efficiency gains by incentivizing product upgrading. Existing literature on attribute-based subsidies, such as Ito and Sallee (2018) and Jia et al. (2022), almost universally criticizes the discontinuity generated by eligibility thresholds in subsidy schemes because these thresholds create distortions in attribute choices. My results show that the discontinuity in firms' profits around the thresholds can incentivize firms below the thresholds to put more effort in reducing production costs so as to jump over the threshold.

This paper contributes to the literature on the effects of industrial policies on innovation and technological progress by providing empirical evidence on whether and how subsidies on the demand side can encourage innovation and technological upgrading. Studies have shown that reducing the costs of investment can raise R&D (Takalo et al. (2013) and Criscuolo et al. (2019)) because this increases the net returns to investment. In theory, such an increase in net returns can also be achieved by promoting demand. The field experiments in Bold et al. (2022) show that higher demand can encourage farmers' technological adoptions, suggesting that policies targeting the demand side can be effective. However, there is little empirical evidence whether the same holds in the EV market. Although there are recent papers studying the EV subsidies to Chinese consumer (Jia et al. (2022) on their static impact on product attributes, Hu et al. (2023) on the impact of phasing out the subsidies on increasing sales, Guo and Xiao (2023) on the static impact on technology adoption), none of them take into account the subsidies' dynamic impact on product upgrading, which, as shown in this paper, turns out to provide opposite implications to those in static settings.

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)) where structural model primitives of dynamic decisions are estimated using data on observed individual decisions, so that one can do dynamic counterfactual analysis using firm-level data and market-level demand data.

The remainder of the paper is organized as follows. I present historical background and stylized facts in Section 2 and describe the dataset in Section 3. I then introduce the model and demonstrate theoretical results in Section 4. I explain the estimation procedure in Section 5. Results are provided in Section 6. Section 7 concludes. Appendix explains how I merge data from multiple sources to one panel.

# 2 Historical background and stylized facts

China's ambition of improving its global presence in automobile manufacturing dates back to the 1980s. Despite a large amount of resources spent in the automobile industry, China was far from gaining prominence in the global automobile manufacturing until the 2020s. Under the pressure of reduced automobile sales due to the shocks from the 2008 financial crisis, China decided in 2009 to pursue its ambition by promoting electric vehicle (EV) manufacturing, especially the innovation by domestic EV manufacturers.[2] To achieve this goal, the Chinese government unleashed a series of industrial policies. One important part of these policies was offering a series of generous range-based subsidies to consumers with the aim of stimulating the domestic EV manufacturers' product upgrading.[3] Since then, Chinese domestic EV sales started to grow at an increasing rate. The sales increased more than 20 times in 2015-2022, reaching 65% of the global EV sales in 2022. The Chinese adoption rate, i.e. the ratio of new EV sales to total new vehicle sales, increased from 1% in 2015 to 28% in 2022 (Figure 1). Li et al. (2022) shows that this rapid growth of the EV sales in China was largely due to the generous consumer subsidies. Furthermore, Chinese domestic EV manufacturers also started to gain a global presence in recent years. For example, Chinese EV export almost doubled in 2022 compared with 2021.[4].

Table 1: Range-Based Subsidy for EV (10,000 RMB)

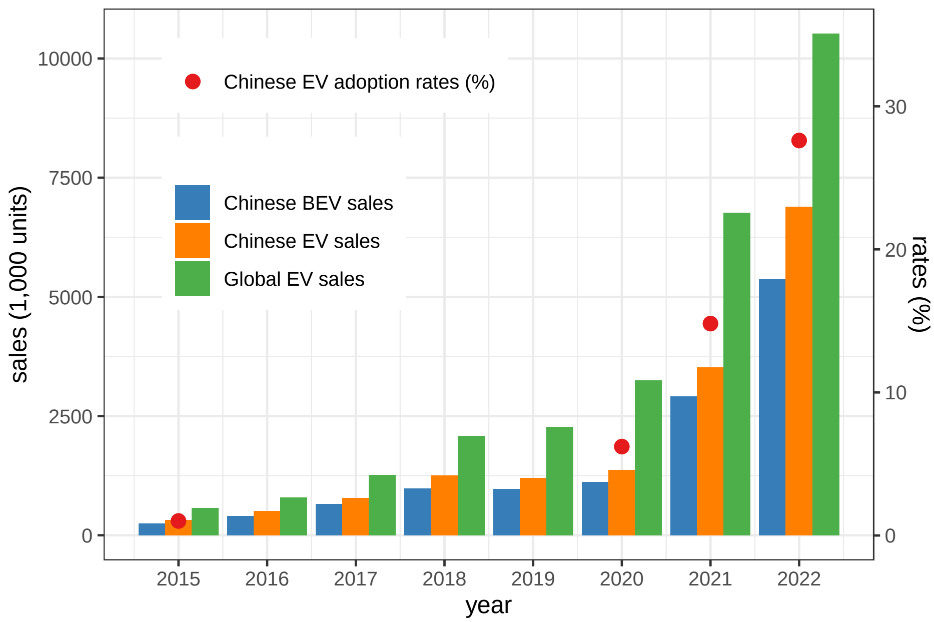
| range (km) | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|---|---|
| $[0, 100)$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $[100, 150)$ | 2.5 | 2 | 0 | 0 | 0 | 0 | 0 |
| $[150, 200)$ | 4.5 | 3.6 | 1.5 | 0 | 0 | 0 | 0 |
| $[200, 250)$ | 4.5 | 3.6 | 2.4 | 0 | 0 | 0 | 0 |
| $[250, 300)$ | 5.5 | 4.4 | 3.4 | 1.8 | 0 | 0 | 0 |
| $[300, 400)$ | 5.5 | 4.4 | 4.5 | 1.8 | 1.62 | 1.3 | 0.91 |
| $[400, \infty)$ | 5.5 | 4.4 | 5 | 2.5 | 2.25 | 1.8 | 1.26 |
| Average price | 19.6 | 19.5 | 16.8 | 16.8 | 16.2 | 16.4 | — |

Notes: The average exchange rate to USD during this period is about 6.5.

Table 1 demonstrates the range-based subsidies to consumers purchasing EVs. Here I only list the subsidies of EVs because they are the focus of this paper. It is a notched subsidy scheme because the amount of subsidies consumers receive

[2]Source: http://www.gov.cn/zwgk/2009-03/20/content_1264324.htm
[3]Source: https://www.chinanews.com.cn/ny/2010/10-13/2583130.shtml
[4]Source: http://ex.chinadaily.com.cn/exchange/partners/82/rss/channel/language/columns/v0m20b/stories/WS6389a97da31057c47eba25e3.html

Figure 1: Trends of EV Sales and EV Adoption Rates




Notes: Adoption rates are the ratios of new EV sales to total new vehicle sales. EVs and EVs include both passenger cars and commercial cars.
Source: The Chinese annual sales of EVs and EVs in 2015 are from CAAM and in 2016-2022 are from www.marklines.com. Chinese adoption rate in 2015 is calculated by the author using the Chinese EV sales from CAAM mentioned above and the total Chinese vehicle sales from www.marklines.com. The adoption rates in 2020 are from www.ce.cn. Those in 2021 and 2022 are from CPCA. Global EV sales are from www.ev-volumes.com.

is a discontinuous function of the driving ranges. Both the thresholds of the driving ranges and the amount of subsidies for a given threshold change over time. In general, the thresholds become higher and the subsidies become smaller. While the subsidies that consumers receive decline in 2016-2021, the annual sales of EV in China increases as shown in Figure 1.

Figure 2 shows the distribution of new EVs released in each year and the thresholds of each year's subsidies. It shows that the range of new EVs clustered around and moved with the thresholds. It also shows that the distribution of the range is shifting to the right, i.e. new vehicles have a longer range in more recent years,

Figure 2: Trends of EV Range and DRB Subsidy Thresholds

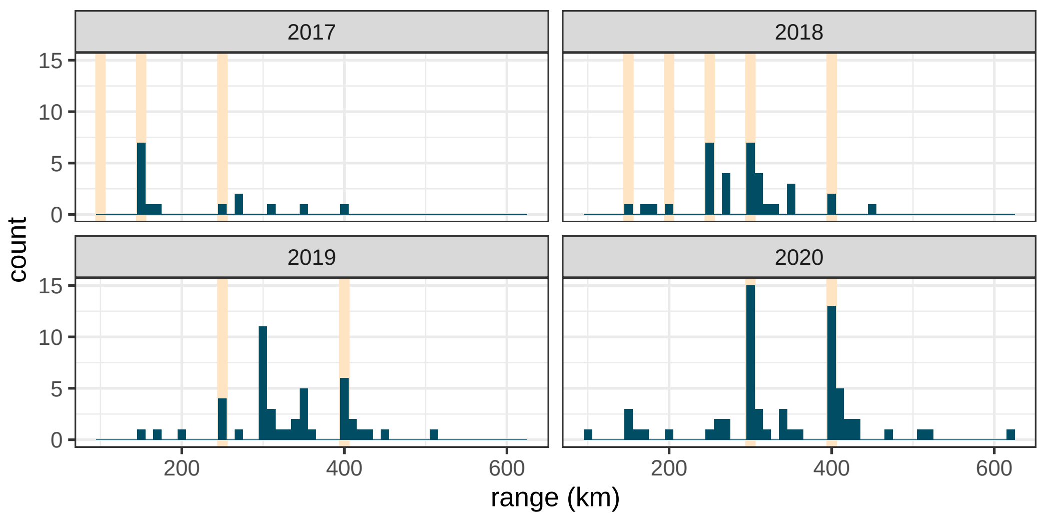
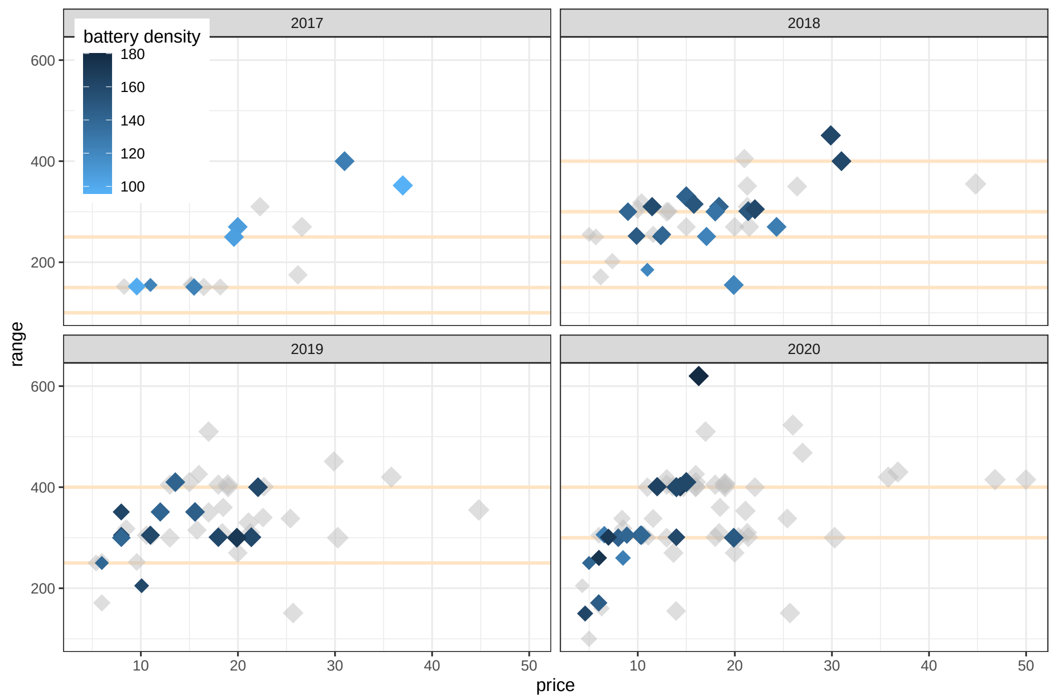


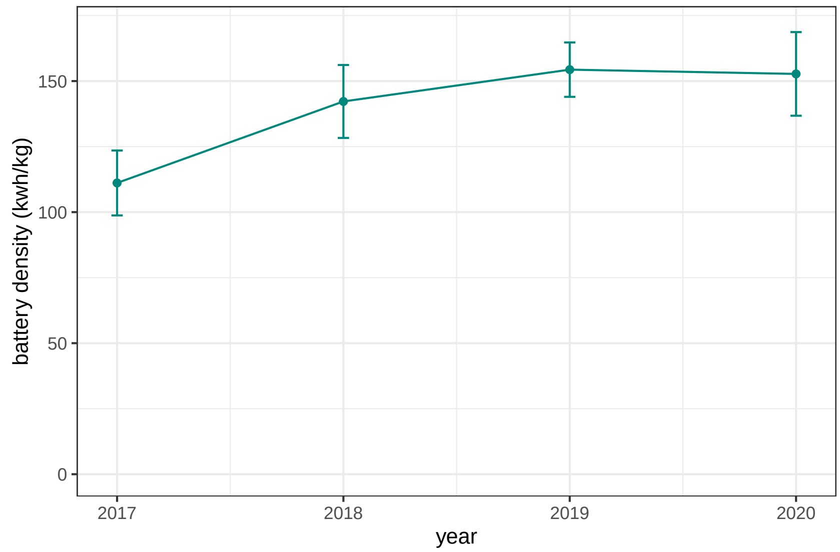

Figure 3 demonstrates prices (10,000 RMB), ranges (km), model sizes (length (m) $\times$ width (m)), and battery density (battery capacity/battery weight (wh/kg)) of new EV models or new releases of existing EV models in 2017-2020. I do not include 2016 because there were too few EV models. The orange lines are the thresholds introduced in that year. Each diamond represents a EV model. This figure shows that EV models become cheaper with longer ranges, higher-density batteries, but almost no change in sizes, and that there is large variation in the trend of prices and ranges over the years. Figure 4 gives a closer look at the trend in battery density and Figure 5 shows that there is no significant change in the battery capacity.

Figure 3: Trends of EV Attributes in China



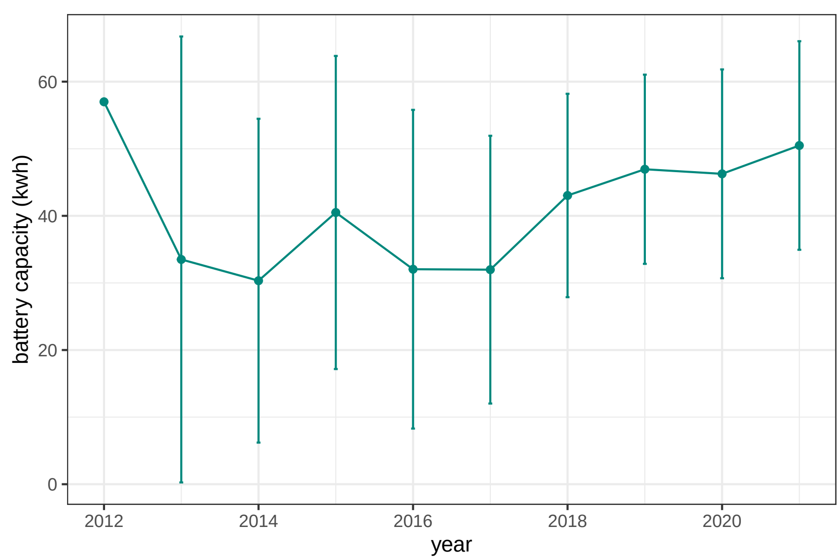

Notes: Battery density is the unit of kw/kg. Ranges are in the unit of km. Prices are measured in 10,000 RMB. The sizes of the diamonds are the sizes of the EV model which are measured as length (m) $\times$ width (m). The color gray means no information on battery density is available. Orange lines are the range thresholds of the notched subsidy scheme introduced in that year.
Source: Auto Home

Figure 4: Trend of Battery Densities Among EVs Sold in Each Year




Notes: The whiskers are standard deviations.

Figure 5: Trend of Battery Capacity Among EVs Sold in Each Year




Notes: The whiskers are standard deviations.

There are several possible reasons behind the large variation: differences in EV model characteristics other than ranges, different markups in the model prices, and different production costs of ranges. Examples of different production costs of ranges are how energy efficient are the designs of models in the sense that whether a model with the same size can travel over a longer distance, and different access to existing battery technology. In the next two sections, I will build a model that takes into account all these channels and disentangle the channel of differences in production costs of ranges from the remaining channels and then quantify how firms' production costs of ranges respond to the consumer subsidies.

# 3 Data

I 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). Additional variables about EVs, such as battery energy density (the ratio between battery capacity and battery weight), are collected using the Lists of Recommended New Energy Vehicles (hereafter the NEV Lists) published by the Chinese government in 2017-2020, which are in total 49 lists. These variables are required when calculating each product's subsidy value.

In addition to the direct purchase subsidy, the exemption of purchasing tax is also an important factor for consumers' purchase decisions. I 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) published by the Chinese government in 2016-2020 to decide whether a product receives tax exemption in a year. There are 32 NEVPT Lists and 10 RNEVPTE Lists in 2016-2020. The tax exemption is considered when estimating the demand parameters.

I do not observe the exact amount of subsidy per transaction, but I collect the formulas for calculating subsidies announced by the Chinese government in 2010-2020 and then calculate the subsidies using product characteristics accordingly. I take the number of households and consumer price index in each year in 2010-2020 from the Chinese Year Books.

According to the State Grid Corporation of China, the monopolistic electricity supplier in China, the electricity price remains at 0.542 RMB/kwh during my sample. I use the prices of 92 and 95 gasoline, and diesel in Beijing 2010-2021 from https://data.eastmoney.com/cjsj/oil_default.html to approximate the national average prices.

Table 2: Summary Statistics of the Entire Sample (2010-2020)

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| price [1] | 2,138 | 11.57 | 6.75 | 3.04 | 7.37 | 13.85 | 53.80 |
| power/weight (kw/kg) | 2,138 | 0.10 | 0.01 | 0.05 | 0.09 | 0.11 | 0.17 |
| cost per km (RMB) | 2,138 | 0.40 | 0.11 | 0.05 | 0.33 | 0.46 | 0.91 |
| size ($m^2$) [2] | 2,138 | 8.24 | 0.71 | 5.30 | 7.79 | 8.72 | 10.27 |
| torque (N·m) | 2,138 | 200.61 | 61.88 | 88 | 150 | 240 | 553 |
| luxury level[3] | 2,138 | 13.57 | 20.24 | 1 | 4.0 | 14.4 | 151 |

Notes: Each observation is a model-year.
[1] Prices are deflated by the annual consumer price index and are in units of 10,000 RMB.
[2] Size is measured using length (m) × width (m).
[3] Luxury level is an index constructed as the sum of several dummy covariates such as whether the vehicle model has a rain sensor or a key-less start.

I limit my sample to passenger vehicles with no more than 5 doors and include only EVs and gasoline vehicles. Table 2 shows the summary statistics of all the products in my sample in 2010-2020. The observation unit is a model in a year. Table 3 shows the summary statistics of EVs. Since there were no passenger EVs before 2012 in my data, Table 3 only covers 2012-2020. The data described in Table 2 and Table 3 is used for the estimation in the static part. Table 4 gives the summary statistics for EVs in 2019. There were 44 EV products in 2019. To simplify the estimation in the dynamic part, I use only firms in 2019 for that part of the estimation.

Table 5 shows the number of EV firms in each year, the number of EVs firms with at least a new product, and the average number of new products across the EV firms in a year.

Table 3: Summary Statistics of EVs (2012-2020)

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| range (km) | 171 | 304.38 | 94.16 | 80.00 | 255.00 | 380.00 | 620.00 |
| price[1] | 171 | 14.15 | 7.29 | 3.35 | 8.79 | 17.25 | 39.03 |
| price$-\tau$[1] | 171 | 13.24 | 7.56 | 2.27 | 7.37 | 16.79 | 39.03 |

Notes:
[1] Prices and subsidies ($\tau$) are deflated by the annual consumer price index and are in units of 10,000 RMB. Purchasing tax is also deducted in price-$\tau$ if the product is eligible for tax exemption.

Table 4: Summary Statistics of EVs (2019)

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| range (km) | 44 | 330.64 | 72.04 | 151 | 300 | 400 | 510 |
| price [1] | 44 | 13.47 | 6.61 | 4.31 | 8.71 | 16.92 | 35.86 |
| price$-\tau$[1] | 44 | 12.44 | 7.20 | 2.27 | 6.46 | 15.40 | 35.86 |

Notes:
[1] Prices and subsidies ($\tau$) are deflated by the annual consumer price index and are in units of 10,000 RMB. Purchasing tax is also deducted in price-$\tau$ if the product is eligible for tax exemption.

Table 5: The Number of EV Firms vs. the Number of EV Firms with At Least One New Release

| Year | EV Firms | w/ New Products | Average Number of New Products |
|---|---|---|---|
| 2012 | 1 | 0 | |
| 2013 | 2 | 1 | 1 |
| 2014 | 3 | 2 | 1 |
| 2015 | 3 | 2 | 1.50 |
| 2016 | 7 | 6 | 1.33 |
| 2017 | 15 | 12 | 1.42 |
| 2018 | 34 | 26 | 1.54 |
| 2019 | 44 | 20 | 1.95 |
| 2020 | 62 | 17 | 2.18 |

# 4 Model

We start with the static part of the structural model which is similar to the setup in Berry et al. (1995) and Crawford et al. (2019). Starting from this section, a manufacturer is called a firm. To separate the usage of model as a vehicle model from the usage as a structural model, a vehicle model will henceforth be called a product.

## 4.1 Demand

Consumers maximize their indirect utility by deciding whether to purchase a product, i.e. a car, and which product to purchase if they decide to purchase one. If consumer $i$ chooses to buy a product $j$ from firm $f$ in the year $t$, the indirect utility from such a purchase is $U_{ijft}$:

$$U_{ijft} = \delta_{jft} + \epsilon_{ijft} \ , \quad \text{for product } j \text{ from manufacturer } f \text{ at time } t$$

which consists of the mean utility of purchasing this product $\delta_{jft}$ and consumer $i$'s taste shock for this product in the year $t$, $\epsilon_{ijft}$. I assume $\delta_{jft}$ to be:

$$\delta_{jft} = \begin{cases} \alpha_i p_{jft} + x'_{jft}\beta + (\beta^R R_{jft}^{\frac{1}{2}} + \eta)\mathbb{1}[\text{j is EV}] + \xi_{jft} + \zeta_t + \iota_{jf} \ , \text{if } R_{jft} \geq \underline{R}_t \\ -\infty \ , \text{otherwise} \end{cases}$$

where $\alpha_i$ and $\beta$ are parameters of consumers' price sensitivity and tastes for observed model characteristics, $x_{jft}$. $\alpha_i \in \{\alpha^H, \alpha^L\}$. Model-and-year two-way fixed effects are $\zeta_t$ and $\iota_{jf}$. $\mathbb{1}[\cdot]$ takes the value 1 if the statement inside is true and 0 otherwise. For EVs, $\beta^R$ measures consumers' marginal utility of driving ranges. $\eta$ is the EV fixed effect. $\xi_{jft}$ is consumers' utility derived from product $j$'s unobserved characteristics in the year $t$. $\underline{R}_t$ is the threshold below which consumers won't purchase an EV, i.e. $-\infty$ utility. This reflects consumers' range anxiety.

The range directly enters consumers' utility if it is an EV and but not if it is a combustion engine. This reflects that the range is one of the main concerns for EV consumers but not the case for combustion engine consumers. However, consumers' utility may still change when shifting from combustion engine vehicles to

EVs even after controlling for EVs' ranges. To account for this, I include a fixed effect for EV.

If the consumer chooses not to purchase a product or, in other words, chooses an outside option, the indirect utility is $U_{i0t}$ with mean normalized to 0:

$$U_{i0t} \quad = \epsilon_{i0t} \ , \quad \text{for the outside option}$$

where $\epsilon_{i0t}$ is a mean-zero taste shock. All the taste shocks, $\epsilon_{ijft}$ and $\epsilon_{i0t}$, are independent and identically distributed type-I extreme value with mean zero.

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 number of households in the year $t$, which is my measure of the number of consumers considering whether to purchase a car in the year $t$ and, if so, which model to purchase. This measure of the total number of consumers is the same as Berry et al. (1995). This product's market share is

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

## 4.2 Supply

Firm $f$'s profits at time $t$, $\pi_{ft}$, are the sum of all its products' profits:

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

where $\mathcal{J}_{ft}$ is the set of firm $f$'s products at time $t$, $N_t$ is the total amount of household, $s_{jft}$ is product $j$'s market share, $p_{jft}$ is the price, and $\tau(R_{jft})$ is the subsidy product $j$ receives. $\tau(\cdot)$ represents the subsidy scheme that firms face and it specifies the amount of subsidy a product can receive based on its range $R_{jft}$. The marginal cost functions are parametrized as linear in the endogenous range plus an non-parametric term $\gamma_{jft}$ to capture all the remaining factors in the marginal cost functions:

$$mc_{jft} = c_{jft}R_{jft} \cdot \mathbb{1}[\text{j is an EV}] + \gamma_{jft}$$

If a model is a gasoline vehicle, then $\mathbb{1}[\text{j is a EV}] = 0$ and range $R_{jft}$ does not enter the marginal cost functions. The vector $w_{jft}$ represents the observed covariates, which include power-weight ratio, size, luxury level, miles per gallon (equivalent),[5] and torque. $\eta_{jft}$ captures the unobserved model characteristics that affect production costs.

Since prices and ranges are set in every period, they are static optimization problems. The first order conditions (FOCs) of prices and ranges are:

$$\frac{\partial \pi_{ft}}{\partial p_{jft}} = s_{jft} + \sum_{k \in \mathcal{J}_{ft}} (p_{kft} - mc_{kft} + \tau(R_{kft})) \frac{\partial s_{kft}}{\partial p_{jft}} = 0 \tag{1}$$

$$\frac{\partial \pi_{ft}}{\partial R_{jft}} = s_{jft} \left( -\frac{\partial mc_{jft}}{\partial R_{jft}} + \frac{\partial \tau(R_{jft})}{\partial R_{jft}} \right) + \sum_{k \in \mathcal{J}_{ft}} (p_{kft} - mc_{kft} + \tau(R_{kft})) \frac{\partial s_{kft}}{\partial R_{jft}} = 0 \tag{2}$$

If $\tau(\cdot)$ is a notched scheme, $\tau(\cdot)$ is discontinuous. The optimal range may not satisfy the FOC in Equation (2) because $\frac{\partial \tau(R_{jft})}{\partial R_{jft}}$ does not exist at the thresholds. For notched schemes, $\frac{\partial \tau(R_{jft})}{\partial R_{jft}} = 0$ when $R_{jft}$ is not at the thresholds. Therefore, for notched scheme, I first find the ranges that satisfy the Equation (2) where $\frac{\partial \tau(R_{jft})}{\partial R_{jft}} = 0$. These solutions are called interior solutions. If these interior solutions' ranges are smaller than the thresholds, I calculate the profits at these interior solutions' ranges and the profits if firms set their ranges at the range thresholds, i.e. the corner solution. The one that gives higher profits is the optimal range.

Using the market shares from the demand model, I can derive the responses of market shares to changes in prices and ranges:

[5]Miles per gallon (mpg) is the distance, measured in miles, that a gasoline car can travel per gallon of fuel. Miles per gallon equivalent (mpge) is the electric vehicle version of mpg, which is measured as the distance an EV can travel on 33.7kWh of electricity

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

and $d_{jft} \in \{p_{jft}, R_{jft}\}$, $\frac{\partial \delta_{jft}}{\partial p_{jft}} = \mathbb{E}_i\left[\frac{\partial \delta_{ijft}}{\partial p_{ijft}}\right]$, $\frac{\partial \delta_{jft}}{\partial R_{jft}} = \frac{1}{2}\beta^R R_{jft}^{-1/2}$.

Combining the formulas for $\frac{\partial s_{kjt}}{\partial p_{jft}}$ and $\frac{\partial s_{kjt}}{\partial R_{jft}}$ with Equations (1) and (2) gives:

$$\begin{aligned} 0 =& 1 + \sum_{k \in \mathcal{J}_{ft}, k \neq j} (p_{kft} - mc_{kft} + \tau(R_{jft})) \cdot (-s_{kft})\mathbb{E}_i\left[\frac{\partial \delta_{ijft}}{\partial p_{ijft}}\right] \\ &+ (p_{jft} - mc_{jft} + \tau(R_{jft})) \cdot (1 - s_{jft})\mathbb{E}_i\left[\frac{\partial \delta_{ijft}}{\partial p_{ijft}}\right] \qquad (3) \\ 0 =& \left(-\frac{\partial mc_{jft}}{\partial R_{jft}} + \frac{\partial \tau(R_{jft})}{\partial R_{jft}}\right) + \sum_{k \in \mathcal{J}_{ft}, k \neq j} (p_{kft} - mc_{kft} + \tau(R_{jft})) \cdot (-s_{kft}\frac{1}{2}\beta^R R_{jft}^{1/2}) \\ &+ (p_{jft} - mc_{jft} + \tau(R_{jft})) \cdot (1 - s_{jft})\frac{1}{2}\beta^R R_{jft}^{1/2} \qquad (4) \end{aligned}$$

Combining these two equations and using the parametric form of marginal costs gives:

$$-c_{jft} + \tau'(R_{jft}) - \frac{\frac{1}{2}\beta^R R_{jft}^{1/2}}{\mathbb{E}_i\left[\frac{\partial \delta_{ijft}}{\partial p_{ijft}}\right]} = 0 \qquad (5)$$

where $\tau'(R^*_{jft}) = \frac{\partial \tau(R_{jft})}{\partial R_{jft}}$.

Due to Chamberlinian monopolistic competition, the FOCs in Equations (3) and (4) can be expressed as:

$$\begin{aligned} 0 =& 1 + (p_{jft} - mc_{jft} + \tau(R_{jft})) \cdot \mathbb{E}_i\left[\frac{\partial \delta_{ijft}}{\partial p_{ijft}}\right] \\ 0 =& -\left(\frac{\partial mc_{jft}}{\partial R_{jft}} + \frac{\partial \tau(R_{jft})}{R_{jft}}\right) + (p_{jft} - mc_{jft} + \tau(R_{jft}))\frac{1}{2}\beta^R R_{jft}^{1/2} \end{aligned}$$

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

$$\pi^*_{ft} = -\frac{\sum_{j\in\mathcal{J}_{ft}} s^*_{jft}}{\mathbb{E}_i\left[\frac{\partial\delta_{ijft}}{\partial p_{ijft}}\right]} \tag{6}$$

$$p^*_{jft} = -\frac{1}{\mathbb{E}_i\left[\frac{\partial\delta_{ijft}}{\partial p_{ijft}}\right]} + c_{jft}R^*_{jft} + \gamma_{jft} - \tau(R^*_{jft}) \tag{7}$$

where $s^*_{jft}$ is the market share when all the firms choose their optimal prices $p^*_{jft}$ and ranges $R^*_{jft}$. From these equations, it can be seen that firms' optimal profits, prices, and ranges in each period are functions of $\vec{c}_t$, which is the vector of all the models' $c_{jft}$ at time $t$, and all the remaining model characteristics. Since the remaining model characteristics are exogenous and taken as given, we express the optimal profits, prices, and ranges as $\pi^*_t(\vec{c}_t)$, $p^*_t(\vec{c}_t)$, and $R^*_t(\vec{c}_t)$.

In the next section, I will explain firms' investment decisions on reducing the cost parameters of ranges. Since all the profits, prices, ranges in the next section are the optimal values, I drop the $*$ in the notation.

## 4.3 Firms' dynamic investment problems

Firm $f$ will invest if the expected returns to investment according to firm $f$'s belief about the future market conditions are higher than the costs of investment. The returns to investment for $f$ are the increase in the sum of all its product's expected discounted profits over $T$ periods. Firms are assumed to have adaptive expectations and interact in Chamberlinian monopolistic competition. In each period, firms update their beliefs about the future.

I deviate from rational expectations in dynamic games to avoid equilibrium and identification problems of dynamic games among heterogeneous agents with rational expectations. The deviation is also due to the difficulties in justifying that firms can perfectly predict the infinite future in the rapidly involving EV industry because firms lack the necessary information or capabilities, similar to the discussions in Pesaran (1989) in a more general context. In fact, it is sometimes difficult to even predict what happens next year in the EV industry. For example, it has been reported that the changes in Chinese EV subsidies came out as surprises to firms in some years. Therefore, firms in the EV industries likely make decisions based on intuitive predictions, and I assume their expectations to be adaptive. In standard adaptive expectations, future values are believed to be a linear function of historical values.[6]. Since firms in my model interact in Chamberlinian monopolistic competition, firms only need to form belief about the aggregate market conditions, or more precisely, the total number of households (my measurement of the market size) and the EV adoption rates defined as the ratio of EVs purchases out of all the vehicles purchases. I use past total number of households and the EV adoption rates to predict the future values. Under the adaptive expectation and Chamberlinian monopolistic competition, firms investment problems become single-agent dynamic programming problem.

Putting the dynamic part and the static part of the structural model together, firms' beliefs about other products' prices and ranges in the current period are rational expectations, whereas beliefs about the future are adaptive expectations. The intuition behind these assumptions about firms' beliefs is that predicting what happens in the current year is likely easier and more reliable than predicting what will happen in all future years. In addition, assuming rational expectations is a common practice in static empirical structural models, and adaptive expectations are a widely-used alternative to rational expectations to guarantee existence of a unique equilibrium.

Firm j maximizes the expected discounted sum of profits over T number of periods based on their beliefs about the future:

$$\max_{\{\vec{p}_{ft},\vec{R}_{ft},I_{ft}\}_{t=0,\cdots,T}} \mathbb{E}\left[\sum_{t=1}^{T} \rho^{t-1}(\pi_{ft}(\vec{p}_{ft},\vec{R}_{ft},\vec{c}_{ft}|\vec{p}_t,\vec{R}_t,\vec{c}_t) - \lambda \cdot I_{ft})\right]$$
$$\text{s.t. } \pi_{ft} = \sum_{j\in\mathcal{J}_{ft}} N_t s_{jft}(p_{jft} - mc_{jft} + \tau(R_{jft}))$$
$$mc_{jft} = c_{jft}R_{jft} \cdot \mathbb{1}[\text{j is an EV}] + \gamma_{jft}$$

where $\vec{p}_{ft}$, $\vec{R}_{ft}$, and $\vec{c}_{ft}$ are the vectors of firm $f$'s products' prices, ranges, and pro-

[6] Adaptive expectations are widely used in studies on inflation and monetary policies as well some applications for oligopoly (Okuguchi (1970) studies stability of oligopoly equilibrium under adaptive expectation) and firms' responses to technology shocks (Huang et al. (2009)).

duction costs per km of ranges, i.e. $c_{jft}$ at time $t$. $\vec{p}_t$ and $\vec{R}_t$ are the vectors of prices and ranges of all the products at time $t$. In other words, there is a non-stationary finite horizon dynamic problem for each firm in each period. The observed investment decisions are the decisions in the first periods of all these auxiliary stationary dynamic problems.

I assume that the product-level technology $c_{jft}$ is determined by the firm-level $\bar{c}_{ft}$ technology plus a shock $\nu_{jft}$:

$$c_{jft} = \bar{c}_{ft} + \nu_{jft} \text{ , where } \mathbb{E}[\nu_{jft}] = 0 \tag{8}$$

I discretize the space of $\bar{c}_{ft}$ as $\bar{c}_{ft} \in \mathcal{C} = \{c_1, c_2, \cdots, c_L\}$, which satisfies $c_{l-1} < c_l$ and $\log(c_l) - \log(c_{l-1})$ constant for $l \in \{2, 3, ..., L\}$.

The firm level market share is the sum of all its products' market share, i.e. $\bar{s}_{ft} = \sum_{j\in\{\sqcup} s_{jft}$. The firm-level range $\bar{R}_{ft}$ is the its products' average range weighted by each product's market share. The firm-level price index $\bar{p}_{ft}$ is the value that satisfies the following equation:

$$\sum_{j\in\mathcal{J}_{ft}} s_{jft}(p_{jft} - mc_{jft} + \tau(R_{jft})) = \bar{s}_{ft}(\bar{p}_{ft} - \bar{m}c_{ft} + \tau(\bar{R}_{ft}))$$

where $\bar{m}c_{ft} = \bar{c}_{ft}\bar{R}_{ft} \cdot \mathbb{1}[\text{j is an EV}] + \bar{\gamma}_{ft}$ and $\bar{\gamma}_{ft}$ is the average of $\gamma_{jft}$ for $j \in \mathcal{J}_{ft}$.

When the firm decides to invest, the change in firm-level technology $\log(\bar{c}_{ft})$ follows a normal distribution $\mathcal{N}(\Delta^c, \sigma)$. The investment decision is taken at the firm-level:

$$\log(\bar{c}_{f,t+1}) = \begin{cases} \log(\bar{c}_{ft}) & I_{ft} = 0 \\ \log(\bar{c}_{ft}) - \Delta^c + \iota_{f,t+1} & I_{ft} = 1 \end{cases}$$

where $\iota_{f,t+1} \sim \mathcal{N}(0, \sigma)$ and is i.i.d. $\Delta^c$ includes technological changes due to firms' own efforts and the common trend.

Denote the value of firm $f$ at time $t$ under $f$'s belief formed at time $\tilde{t} < t$ in the relevant auxiliary stationary dynamic problem by $v^t_f(c_l)$:

$$v^{\tilde{t}}_{ft}c_l) = \mathbb{E}[\max\{U^{\tilde{t}}_{ft}(c_l, 1) + \epsilon_{ft}(1), U^{\tilde{t}}_{ft}(c_l, 0) + \epsilon_{ft}(0)\}] \tag{9}$$

where $\bar{c}_{ft} = c_l$. The superscript $\tilde{t}$ indicates the time when a belief is formed whereas the subscript $t$ indicate the time the value function describe. By construction, $t \geq \tilde{t}$. $U^{\tilde{t}}_{ft}(c_l, 0)$ and $U^{\tilde{t}}_{ft}(c_l, 1)$ are the choice-specific values that satisfy

$$U^{\tilde{t}}_{ft}(c_l, 1) = -\lambda + \pi^{\tilde{t}}_{ft}(c_l) + \rho v^{\tilde{t}}_{ft}(c_{l-1}) \tag{10}$$

$$U^{\tilde{t}}_{ft}(c_l, 0) = \pi^{\tilde{t}}_{ft}(c_l) + \rho v^{\tilde{t}}_{ft}(c_l) \tag{11}$$

where $\lambda$ is the investment cost. $\epsilon_{ft}(0)$ and $\epsilon_{ft}(1)$ are type-I extreme-value shocks with mean zero and are independent and identically distributed across time and products. The expectation is taken over these choice-specific shocks. $\rho$ is the discount factor.

Equation (9) is the Bellman equation of this auxiliary problem. The first part in the maximization is the value of investment, and the second part is that of no investment. Firms will invest when the first part is larger than the second part:

$$\begin{aligned}\mathbb{P}(a^{\tilde{t}}_{ft}(c_l) = 1) =& \mathbb{P}(U^{\tilde{t}}_{ft}(c_l, 1) + \epsilon_{ft}(1) > U^{\tilde{t}}_{ft}(c_l, 0)) + \epsilon_{ft}(0) \\ =& \frac{\exp(U^{\tilde{t}}_{ft}(c_l, 1))}{\exp(U^{\tilde{t}}_{ft}(c_l, 1)) + \exp(U^{\tilde{t}}_{ft}(c_l, 0))}\end{aligned} \tag{12}$$

When $\bar{c}_{ft} = c_l$, the investment probability of firm $f$ at time $t$ in the data is $\mathbb{P}(a^{\tilde{t}}_{ft}(c_l) = 1)$. Each period $\tilde{t}$'s auxiliary stationary problem can be solved by backwards induction from $\bar{c}_{ft} = c_1$.[7] This also produces the optimal investment decisions, which are used to calculate the investment probabilities in the auxiliary stationary problem and the investment probabilities in the data.

At $c_1$, since there is no further reduction possible and prices and ranges of all the other products are constant according to firms' beliefs, value of $c_1$ under the belief

[7]There is no investment decision to be made at $c_1$ but the continuation value of $c_1$ is needed to solve the optimal investment decisions at $c_2$. The backward induction is over the space of the state variables.

formed at time $t$ by firm $f$ is:

$$v_{ft}^{\tilde{t}}(c_1) = \frac{\pi_{ft}^{\tilde{t}}(c_1)}{1-\rho}$$

$\pi_{ft}^{\tilde{t}}(c_1)$ is the profits of $f$ under the belief formed by $f$ at $\tilde{t}$ if $c_{ft} = c_l$. For $1 < l \leq L$, $v_{ft}^{\tilde{t}}(c_l)$, $U_{ft}^{\tilde{t}}(c_l, 0)$, $U_{ft}^{\tilde{t}}(c_l, 1)$, and $\mathbb{P}(a_{ft}^{\tilde{t}}(c_l) = 1)$ can be solved by backward recursion according to Equations (9), (10), (11), and (12).

## 4.4 Investment probability under different subsidy scheme scenarios

**Proposition 1** *Consider a case where the dynamic problem defined by Equations* (9)*,* (10)*, and* (11) *with the state space* $\{c_1, c_2, \cdots, c_L\}$ *is implemented under two subsidy schemes called* $n$ *and* $o$*. These subsidy schemes can be linear, notched, or no subsidy. Denote the value functions* $v_{jf}^t$*, the profits* $\pi_{jf}^t$*, and investment probability* $\mathbb{P}(a_{jf}^t = 1)$ *under the scheme* $n$ *as* $v_{jf}^{t,n}$*,* $\pi_{jf}^{t,n}$*, and* $\mathbb{P}(a_{jf}^{t,n} = 1)$*, and under the scheme* $o$ *as* $v_{jf}^{t,o}$*,* $\pi_{jf}^{t,o}$*, and* $\mathbb{P}(a_{jf}^{t,o} = 1)$*. Then for* $c_l \in \{c_2, \cdots, c_L\}$*, the following results hold:*

- *if* $\pi_{jf}^{t,n}(c_l) - \pi_{jf}^{t,0}(c_l) = (1-\rho)(v_{jf}^{t,n}(c_{l-1}) - v_{jf}^{t,0}(c_{l-1}))$*, then* $\mathbb{P}(a_{jf}^{t,n}(c_l) = 1) = \mathbb{P}(a_{jf}^{t,o}(c_l) = 1)$*;*

- *if* $\pi_{jf}^{t,n}(c_l) - \pi_{jf}^{t,0}(c_l) < (1-\rho)(v_{jf}^{t,n}(c_{l-1}) - v_{jf}^{t,0}(c_{l-1}))$*, then* $\mathbb{P}(a_{jf}^{t,n}(c_l) = 1) > \mathbb{P}(a_{jf}^{t,o}(c_l) = 1)$*;*

- *if* $\pi_{jf}^{t,n}(c_l) - \pi_{jf}^{t,0}(c_l) > (1-\rho)(v_{jf}^{t,n}(c_{l-1}) - v_{jf}^{t,0}(c_{l-1}))$*, then* $\mathbb{P}(a_{jf}^{t,n}(c_l) = 1) < \mathbb{P}(a_{jf}^{t,o}(c_l) = 1)$*.*

*In other words, the investment probability under the scheme* $n$ *is larger than the one under the scheme* $o$ *if the difference in the current profits is small enough compared to the difference in the value of investment.*

The proof of Proposition 1 is in Appendix B. When firms' profits are increased, this affects investment probabilities through both the value of investing and the value of not investing. Higher profits at a $c$ lower than the current $c$ means a higher value for investment. However, higher profits at the current $c$ imply a higher value for not investing. The investment probability is higher when switching from one scheme to another if the increase in the value for investing is higher than the increase in the value for not investing. As Proposition 1 shows, this is equivalent to comparing the increase in the values for investing with the increase in the current period profits. This proposition also shows that increasing the profits is not the key to boost investment, the key is the disproportionally larger increase in the profits gained from investment, or in other words, the profits at a lower $c$, which can be reached at some point in the future through investment.

This proposition also implies that not all the subsidy scheme can increase investment probabilities. Therefore, in Section 6, I will compare the investment probabilities under the notched scheme implemented in China in 2019 to a counterfactual scenario of no subsidies to evaluate the impact of the notched scheme on investment probabilities.

# 5 Estimation

The setup of the model allows me to first estimate the static part of the model, i.e. the demand side and the static part of the supply side. This estimates all the demand parameters and the marginal cost functions, and it closely follows Berry et al. (1995) and Crawford et al. (2019). I then discretize the cost parameter of ranges, $c_{ft}$ which is already estimated when estimating the marginal cost functions. Solving the dynamic problem in Equation (9), the conditional choice probability of investing is a function of the unknown investment cost $\lambda$ because all the other parameters have been estimated in the static part. I then use maximum likelihood estimation to find the value of the investment cost that maximizes the inferred investment decisions. The first part of this section describes the estimation procedure in the static part and the second part explains the dynamic part.

## 5.1 The static part

According to the structural model, the mean utility of product $j$ at time $t$ is:

$$\delta_{jft} = \alpha_i p_{jft} + x'_{jft}\beta + \beta^R R^{\frac{1}{2}}_{jft} \cdot \mathbb{1}[\text{j is a EV}] + \eta \mathbb{1}[\text{j is an EV}] + \xi_{jft} + \zeta_t + \iota_{jf}$$

Then the market share of model $j$ from firm $f$ at time $t$ is:

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

The market share in logarithms relative to the outside option is:

$$\ln(s_{jft}) - \ln(s_{0t}) = \alpha_i p_{jft} + x'_{jft}\beta + \beta^R R^{\frac{1}{2}}_{jft} \cdot \mathbb{1}[\text{j is a EV}] + \eta \mathbb{1}[\text{j is an EV}] + \xi_{jft} + \zeta_t + \iota_{jf}$$

The left-hand side and the $p_{jft}$ and $x_{jft}$ from the right-hand side are known from data. I use the instruments constructed by Berry et al. (1995) to account for the endogeneity of prices and ranges, and estimate $\alpha_i$ and $\beta$ using the generalized method of moments (GMM). $x_{jft}$ includes size, power-weight ratio, cost per km, torque, luxury level, whether released this year, and years the model exists in the data. Cost per km measures the expenditure on fuel per kilometer travelled, which reflects the fuel efficiency. The luxury level is a numerical indicator that sums over several dummy variables, such as whether a product contains a rain sensor or has a key-less start.

I estimate $mc_{jft}$ and $\frac{\partial mc_{jft}}{\partial R_{jft}}$ using the first-order conditions of firms' profit maximization in Equations (1) and (2). Using the estimated $\hat{\alpha}_i$ and $\hat{\beta}^R$, only $mc_{jft}$ and $\frac{\partial mc_{jft}}{\partial R_{jft}}$ are unknown in Equations (1) and (2). I follow Crawford et al. (2019) to calculate $\widehat{mc}_{jft}$ and $\widehat{\frac{\partial mc_{jft}}{\partial R_{jft}}}$ using matrix inversion. Since the marginal cost functions is $mc_{jft} = c_{jft}R_{jft} + \gamma_{jft}$, $\frac{\partial mc_{jft}}{\partial R_{jft}}$ satisfies:

$$\frac{\partial mc_{jft}}{\partial R_{jft}} = c_{jft}$$

Thus, the estimated $\hat{c}_{jft}$ is:

$$\hat{c}_{jft} = \left(\widehat{\frac{\partial mc_{jft}}{\partial R_{jft}}}\right)$$

$\hat{c}_{jft}$ is then used to estimate $\bar{c}_{ft}$ using Equation 8.

To prepare for the estimation in the dynamic part, I discretize the estimated $\bar{c}_{ft}$ in logarithms over a grid whose lower bound $\log(c_1)$ is the lowest value of $\bar{c}_{ft}$ in my sample in the year 2012-2020 minus 1.8, the upper bound $\log(c_L)$ is the largest value of $\bar{c}_{ft}$ plus 0.1, and the distance between two adjacent grid points are 0.1. The estimated $\log(\bar{c}_{ft})$ is discretized to the closest grid point. If a firm has one or more new product this period, I infer that this firm invested in the previous period.

## 5.2 The dynamic part

The investment cost, the only parameter estimated in this part, is estimated using the investment decisions only in 2019 to simplify the estimation in the dynamic part. I do not model entry and exit of firms and products, though entry and exit is common in the EV industry in 2012-2020. I acknowledge that entry and exit can possibly affect the estimated investment cost. The estimation in this paper takes the set of firms and products in 2019 as exogenous. Therefore, the estimated investment cost should be interpreted as the average investment cost among the products that are still available next year and under the assumption that entry and exit is exogenous.

As explained in Section 4.3, the investment decision by firm $f$ in period $t$ under firm $f$'s belief formed at $t$ is the optimal choice in the first period of its auxiliary stationary dynamic problem as defined in Equation (9). Solving this problem following the steps explained in Section 4.3, gives the investment probability for firm $f$ at time $t$ in the data. Denote the choice of investing for firm $f$ by firm $f$ at time $t$ in the data as $a_{ft}(\bar{c}_{ft})$. When $\bar{c}_{ft} = c_l$, the investment probability $\mathbb{P}(a_{ft}(c_l) = 1) = \mathbb{P}(a^t_{ft}(c_l) = 1)$ is given in Equation (12), which is a function of the unknown investment cost.

I do not use the investment decisions of products whose ranges are less than 5 km away from the notched thresholds because, as explained in Section 4, the FOC in Equation (2) likely does no hold for these products and these products' inferred

$\log(c_{jft})$s are biased downward, which will also affect the estimated $\log(\bar{c}_{ft})$. The estimated investment cost $\hat{\lambda}$ maximizes the log-likelihood function of investment decisions for all the products in 2019:

$$\hat{\lambda} = \arg\max_{\lambda} \sum_{f,t} \{\hat{a}_{ft} \cdot \ln(\mathbb{P}[\hat{a}_{ft}(\bar{c}_{ft}) = 1|\lambda]) + (1 - \hat{a}_{ft}) \cdot \ln(\mathbb{P}[\hat{a}_{ft}(\bar{c}_{ft}) = 0|\lambda])\}$$

To reduce the computation burden, I discretize the exogenous part of marginal costs $\bar{\gamma}_{ft}$, or in other words, marginal costs net of costs on the range, at the firm-level to three levels.

## 5.3 Firms' Beliefs About Future Market Conditions

Under Chamberlinian monopolistic competition and the logit demand, it is sufficient to specify firms' beliefs about the future total household number, future vehicle purchase rates and EV adoption rates (EV sales/vehicle sales) instead of choices of each firm. I assume that firms' beliefs about these future values to follow the trajectory of historical values as shown in Figure 6 and 7. Future household number increase at the the average growth rate in the past 10 years. In terms of the time trend of the exogenous part in consumers' indirect utility and marginal costs, I take the average growth rates in my estimates over time.

Figure 6: Vehicle Purchase Rate

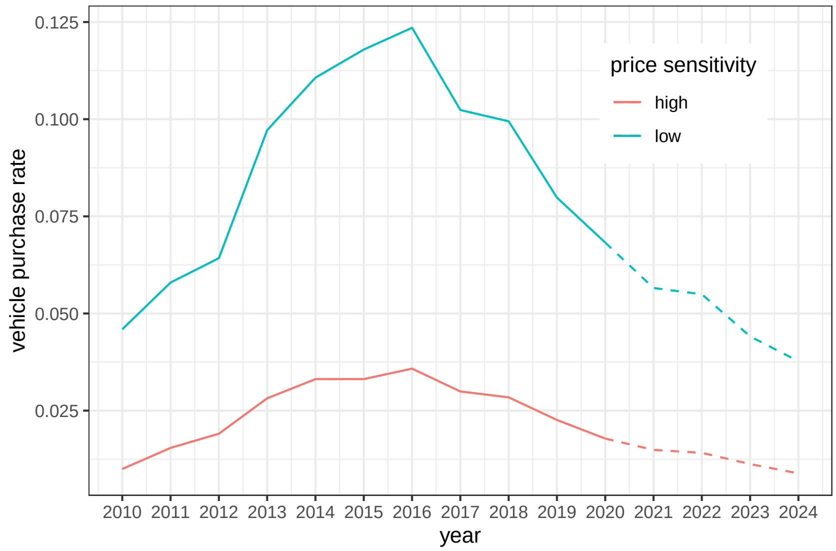



Figure 7: EV Adoption Rate

# 6 Results

Figure 8 shows the trend of the average log$(c_{ft})$ from 2014 till 2020 for firms with new releases. The brackets represent standard deviations. Generally speaking, the production cost per kilometer declines. Figure 9 show the change in log$(c_{ft})$ of firm $f$ when release at least one new product compared to the log$(c_{f\cdot})$ since firm $f$ release a new product last time, i.e. $-\Delta^c + \iota_{ft}$. Figure 10 show the time trend of the exogenous part of the indirect utility, i.e. net of the part due to the price and the range. The average growth is used to predict its future values. Figure 11 shows the exogenous part of the marginal costs, i.e. net of the costs on the range. To reduce computation burden, this value is discretized to three levels using the 10th, 50th, and 90th percentiles. Since the 10th and 50th percentiles are likely driven by entry and exit, I use the growth rate of the 90th percentile to predict the future values for all three levels.

Figure 8: The Trend of log$(c_{ft})$ of Firms with New Release

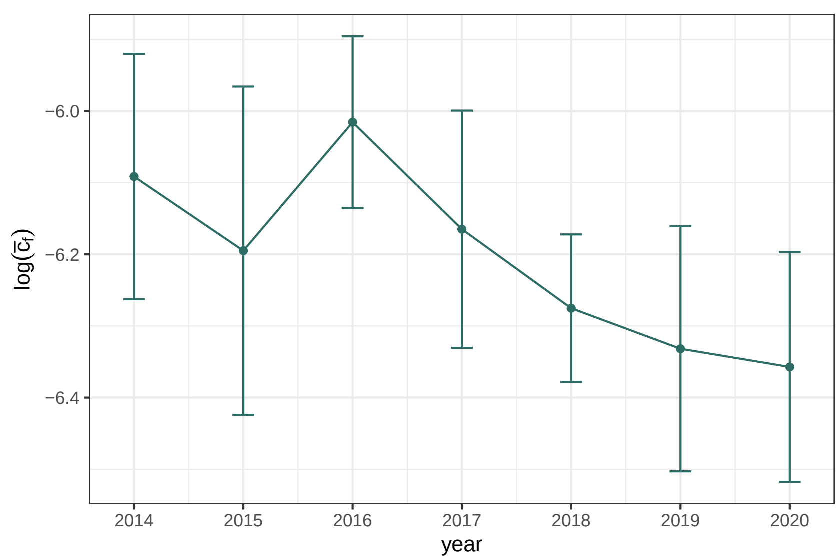



Table 6 displays the consumer taste parameters that include consumers' price sensitivity and the marginal utility from the observed product characteristics. Table 7 demonstrates the distribution of the estimated own price elasticities both in the full sample, i.e. including gasoline vehicles and EVs, and in the sample of EVs

Figure 9: The Distribution of $\log(\bar{c}_{ft+1}) - \log(\bar{c}_{ft})$ When There Is A New Release

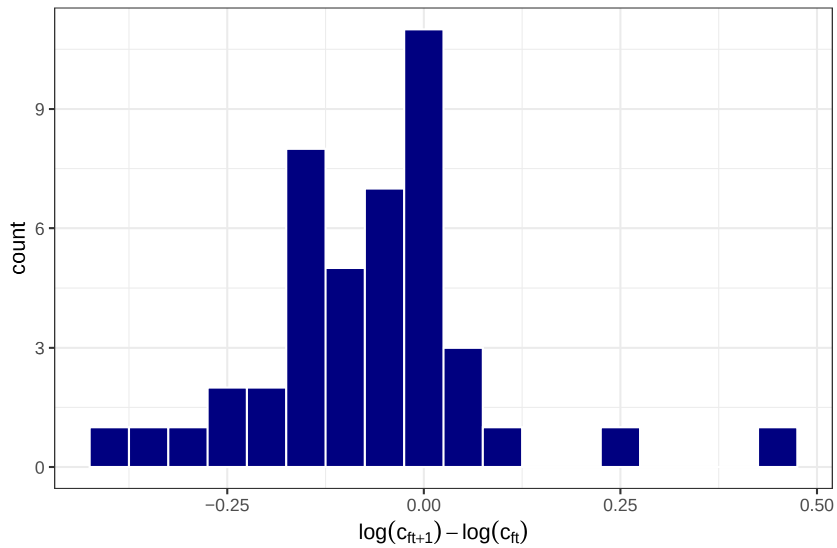



Figure 10: The Exogenous Part of the Indirect Utility: $\bar{\omega}_{ft}$

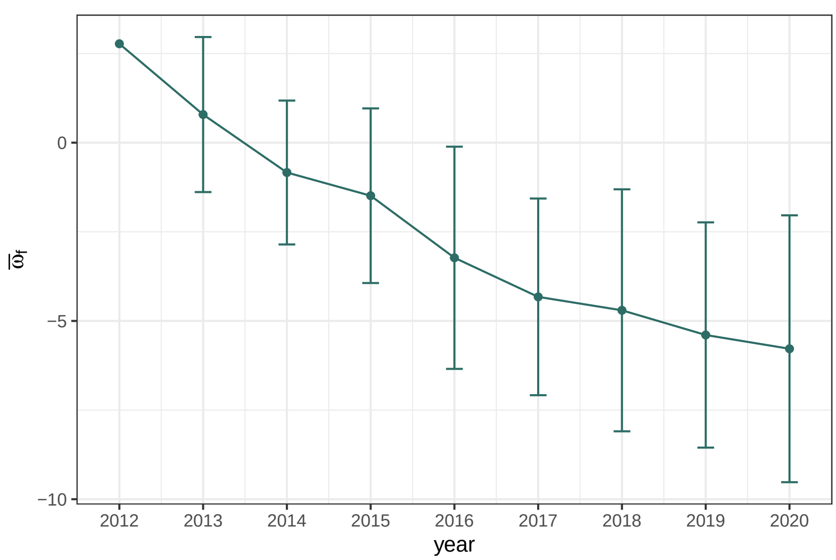
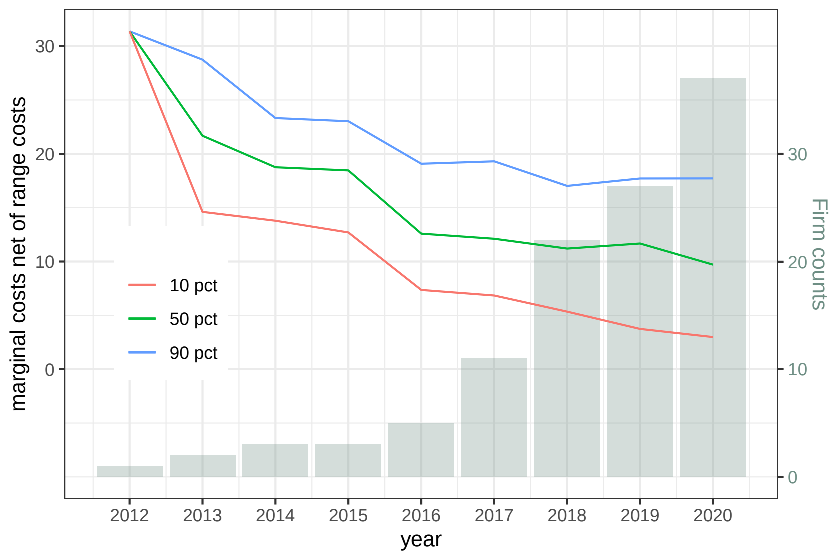


Figure 11: The Marginal Costs Net of Range Costs: $\bar{\eta}_{ft}$




only. For $90\%$ of the products, the EV products have higher own price elasticities than those in the full sample.

Table 6: Estimated Consumer Taste Parameters on Prices and Ranges

| | | estimated values |
|---|---|---|
| $\beta$ | $R^{\frac{1}{2}}$ (100 km) | 3.01 [1.58] |
| | power-weight ratios (kw/kg) | 45.59 [11.98] |
| | cost per km (RMB/km) | 6.09 [5.80] |
| | size ($m^2$) | 1.23 [0.58] |
| | luxury level | 0.04 [0.02] |
| | EV | -4.98 [5.73] |

Notes: Standard errors are in the brackets. Model-year two-way fixed effects are included. All the parameters except $\beta^R$ are estimated using the entire dataset, i.e. including both gasoline vehicle models and EVs. $\beta^R$ only uses EVs.

The estimated investment cost is 53 billion RMB. The first two rows in Table 8 display the distributions of the EVs' estimated range cost parameters in logarithms in 2019 and the ratios between the estimated profits and the estimated investment

Table 7: Summary Statistics of Estimated Own Price Elasticities

| | Mean | St. Dev. | min | Pctl(10) | Pctl(25) | Median | Pctl(75) | Pctl(90) | max |
|---|---|---|---|---|---|---|---|---|---|
| $\frac{\partial \log(s_{jft})}{\partial \log(p_{jft})}$ (full sample) | $3,272$ | 5.70 | 3.62 | 2.39 | 3.39 | 4.67 | 6.81 | 10.41 | |
| $\frac{\partial \log(s_{jft})}{\partial \log(p_{jft})}$ (EV) | 171 | 6.78 | 3.87 | 2.39 | 3.77 | 6.39 | 8.59 | 11.27 | |

cost. On average, the investment cost is about 180 ($\frac{100}{0.057}$) times larger than the annual profits. The third row reports the markups of the EVs, showing that EVs' markups are between 1.16 and 1.30 in 2019.

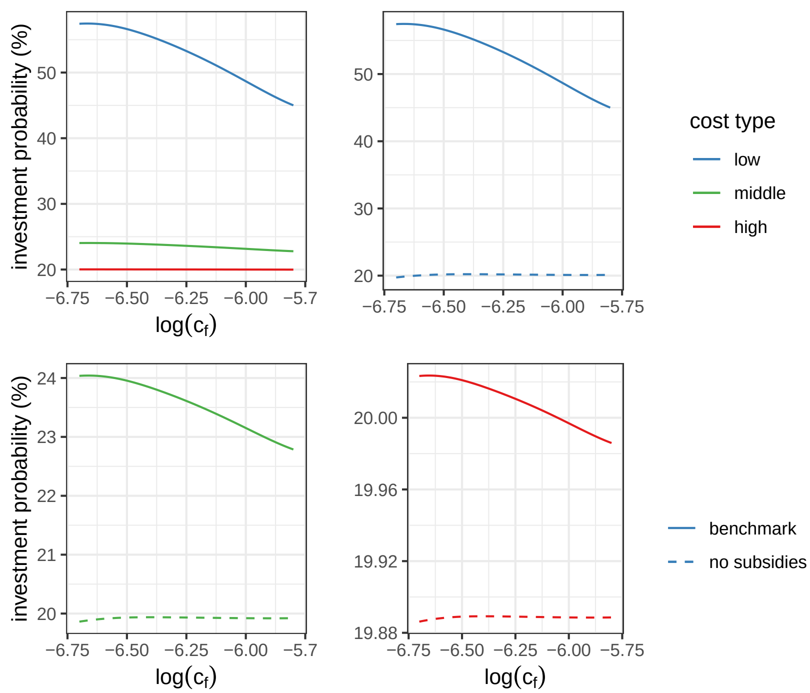
Table 8: Summary Statistics of a Selection of the Supply-Side Parameters (2019)

| | Mean | St. Dev. | min | Pctl(10) | Pctl(25) | Median | Pctl(75) | Pctl(90) | max |
|---|---|---|---|---|---|---|---|---|---|
| $p_j/mc_j$ | 44 | 1.27 | 0.19 | 1.12 | 1.15 | 1.19 | 1.31 | 1.45 | |
| $\pi_f/\lambda$ (%) | 27 | 7.82 | 13.82 | 0.16 | 0.38 | 2.13 | 7.29 | 21.29 | |
| log($c_f$) | 27 | -6.32 | 0.13 | -6.47 | -6.43 | -6.32 | -6.28 | -6.18 | |

## 6.1 Counterfactuals

The upper-left figure in Figure 12 shows the investment probability under the 2019 subsidies. The low cost firms both in terms of the exogenous marginal cost parameter $\bar{\gamma}_{ft}$ and the production cost of ranges $\bar{c}_{ft}$ has the highest investment probability, which is around $50$-$55$%. If the subsidies are removed, the investment probability would be lowered by $25$-$35$ percentage points. The same pattern exists for firms with higher level of marginal costs but the decrease in investment probability is much smaller.

Figure 12: Investment Probabilities for Firms with Different Marginal Cost Types



# 7 Conclusion

This paper models and estimates manufacturers' incentives to reduce the production cost of range in response to driving-range-based (DRB) subsidies to EV consumers and finds that the subsidies increased the investment probabilities by 25-35 percentage points for low-cost manufacturers in 2019. The method developed in this paper can be used to study other counterfactual scenarios, such as linear subsidy schemes or schemes with a different time line. It can also be used to study whether manufacturers should receive more or less information about future subsidy schemes. The dynamic channel identified in this paper suggests that the environmental benefits and welfare gains of DRB subsidies are very likely larger than the estimates of existing literature where this dynamic channel has been ignored.

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# Appendix

## A Data preparation

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

### A.1 Merging NEVPTE List, RNEVPTE List, and the NEV List

I first convert the NEVPTE List, RNEVPTE List, and the NEV List published by the government from text format into data format. I treat observations in these lists as redundant if the same model ID number in the same year-month appears more than once in a list. Among the redundant observations, I keep the observation with the lowest number of missing variables, the smallest size, and the smallest weight. Because these lists use the same model ID numbers, I merge them based on model ID numbers and use variables shared by the lists to check whether the merging is correct. More specifically, the lists all report manufacturer's name, model type, and weight. I first check whether the manufacturer's names and model types are the same. Next I check whether weights are close enough, i.e. less than $10\%$ apart. I call the merged data "subsidy-purchase-tax" (SPT) data.

### A.2 Merging sales, SPT, and the technical description data

I first take the sales data collected from Chezhu Home. I use model names to match the technical description data collected from Chezhu Home and Auto Home. I first use exact matching and then apply fuzzy matching for those unmatched by the exact matching. I 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. Therefore, for each model, there are multiple entries in our technical description data. I keep the entry that has the lowest 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 observations, I check whether the failures of matching is due to incorrectly recorded names and correct them manually if needed.

### A.3 Summary stats

Table 9 shows the differences in annual aggregate sales between my raw data, my merged data, and sales announced by the government.

Table 9: Differences in Aggregate Annual Sales Caused by Data Collection and Data Cleaning

| year | sales merged | sales scraped | sales web | gap merged and scraped | gap scraped 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 |

Notes:
- Gap merged and scraped = 1-sales merged/sales scraped
- Gap scraped and web = 1-sales scraped/sales web

## B Proof of Proposition 1

**Proof.** Define $\mu_l \equiv v_{jf}^{t,n}(c_l) - v_{jf}^{t,o}(c_l)$ and $\theta_l \equiv \pi_{jf}^{t,n}(c_l) - \pi_{jf}^{t,o}(c_l)$. Rewriting the Bellman equations in (9) using the Mcfadden surplus gives the following Bellman operators:

$$\Psi^{t,n,l}_{jf}(v) = \pi^{t,n}_{jf}(c_l) + \log(\exp(\rho v) + \exp(-\lambda + \rho v^{t,n}_{jf}(c_{l-1}))$$
$$\Psi^{t,o,l}_{jf}(v) = \pi^{t,o}_{jf}(c_l) + \log(\exp(\rho v) + \exp(-\lambda + \rho v^{t,o}_{jf}(c_{l-1}))$$

for $l = 2, \cdots, L$. Since these Bellman operators are contraction mappings defined over a space of bounded functions with a finite state space, they all have a unique fixed point by the contraction mapping theorem. I denote the fixed points as $v^{t,n}_{jf}(c_l)$ and $v^{t,o}_{jf}(c_l)$. Rewriting Equation (12) gives:

$$\mathbb{P}(a^t_{jf}(c_l) = 1) = \frac{\exp[-\lambda + \rho(v^t_{jf}(c_{l-1}) - v^t_{jf}(c_l))]}{1 + \exp[-\lambda + \rho(v^t_{jf}(c_{l-1}) - v^t_{jf}(c_l))]}$$

This shows the sign of $\mathbb{P}(a^{t,n}_{jf}(c_l) = 1) - \mathbb{P}(a^{t,o}_{jf}(c_l) = 1)$ is the same as the sign of $[v^{t,n}_{jf}(c_{l-1}) - v^{t,n}_{jf}(c_l)] - [v^{t,o}_{jf}(c_{l-1}) - v^{t,o}_{jf}(c_l)]$. Because $[v^{t,n}_{jf}(c_{l-1}) - v^{t,n}_{jf}(c_l)] - [v^{t,o}_{jf}(c_{l-1}) - v^{t,o}_{jf}(c_l)] = [v^{t,n}_{jf}(c_{l-1}) - v^{t,o}_{jf}(c_{l-1})] - [v^{t,n}_{jf}(c_l) - v^{t,o}_{jf}(c_l)] = \mu_{l-1} - \mu_l$, the sign of $\mathbb{P}(a^{t,n}_{jf}(c_l) = 1) - \mathbb{P}(a^{t,o}_{jf}(c_l) = 1)$ is the same as the sign of $\mu_{l-1} - \mu_l$.

Evaluating the Bellman operator $\Psi^{t,n,l}_{jf}(v)$ at $v = v^{t,o}_{jf}(c_l) + \mu_{l-1}$ gives:

$$\begin{aligned}
\Psi^{t,n,l}_{jf}(v^{t,o}_{jf}(c_l) + \mu_{l-1}) =& \pi^{t,n}_{jf}(c_l) + \log[\exp(\rho(v^{t,o}_{jf}(c_l) + \mu_{l-1})) + \exp(-\lambda + \rho v^{t,n}_{jf}(c_{l-1}))] \\
=& \pi^{t,n}_{jf}(c_l) + \log[\exp(\rho(v^{t,o}_{jf}(c_l) + \mu_{l-1})) + \exp(-\lambda + \rho(v^{t,o}_{jf}(c_{l-1}) + \mu_{l-1}))] \\
=& \pi^{t,n}_{jf}(c_l) + \log[\exp(\rho v^{t,o}_{jf}(c_l)) + \exp(-\lambda + \rho v^{t,o}_{jf}(c_{l-1}))] + \rho\mu_{l-1} \\
=& \pi^{t,n}_{jf}(c_l) - \pi^{t,o}_{jf}(c_l) + v^{t,o}_{jf}(c_l) + \rho\mu_{l-1} \\
=& v^{t,o}_{jf}(c_l) + \theta_l + \rho\mu_{l-1}
\end{aligned}$$

The second equation uses the definition of $\mu_{l-1}$, and the third equation brings the common $\rho\mu_{l-1}$ out of the log operator. The fourth equation uses the fact that $v^{t,o}_{jf}(c_l)$ is the fixed point of $\Psi^{t,o,l}_{jf}(v)$.

If $\pi^{t,n}_{jf}(c_l) - \pi^{t,0}_{jf}(c_l) = (1-\rho)(v^{t,n}_{jf}(c_{l-1}) - v^{t,0}_{jf}(c_{l-1}))$, i.e. $\theta_l = (1-\rho)\mu_{l-1}$, then

$$\Psi^{t,n,l}_{jf}(v^{t,o}_{jf}(c_l) + \mu_{l-1}) = v^{t,o}_{jf}(c_l) + (1-\rho)\mu_{l-1} + \rho\mu_{l-1} = v^{t,o}_{jf}(c_l) + \mu_{l-1}$$

So $v_{jf}^{t,o}(c_l)+\mu_{l-1}$ is a fixed point of $\Psi_{jf}^{t,n,l}(v)$. Since $\Psi_{jf}^{t,n,l}(v)$ has a unique fixed point, it must be $v_{jf}^{t,o}(c_l)+\mu_{l-1}$. So $\mu_{l-1}=\mu_l$ and $\mathbb{P}(a_{jf}^{t,n}(c_l)=1)=\mathbb{P}(a_{jf}^{t,o}(c_l)=1)$.

If $\pi_{jf}^{t,n}(c_l)-\pi_{jf}^{t,0}(c_l)<(1-\rho)(v_{jf}^{t,n}(c_{l-1})-v_{jf}^{t,0}(c_{l-1}))$, i.e. $\theta_l<(1-\rho)\mu_{l-1}$, then

$$\Psi_{jf}^{t,n,l}(v_{jf}^{t,o}(c_l)+\mu_{l-1})<v_{jf}^{t,o}(c_l)+(1-\rho)\mu_{l-1}+\rho\mu_{l-1}=v_{jf}^{t,o}(c_l)+\mu_{l-1}$$

Therefore, $v_{jf}^{t,n}(c_l)<\cdots<(\Psi_{jf}^{t,n,l})^3(v_{jf}^{t,o}(c_l)+\mu_{l-1})<(\Psi_{jf}^{t,n,l})^2(v_{jf}^{t,o}(c_l)+\mu_{l-1})<\Psi_{jf}^{t,n,l}(v_{jf}^{t,o}(c_l)+\mu_{l-1})<v_{jf}^{t,o}(c_l)+\mu_{l-1}$, where $v_{jf}^{t,o}(c_l)$ is the fixed point of $\Psi_{jf}^{t,n,l}(v)$. This means $v_{jf}^{t,o}(c_l)+\mu_{l-1}>v_{jf}^{t,n}(c_l)$, so $\mu_{l-1}>\mu_l$ and $\mathbb{P}(a_{jf}^{t,n}(c_l)=1)>\mathbb{P}(a_{jf}^{t,o}(c_l)=1)$.

If $\pi_{jf}^{t,n}(c_l)-\pi_{jf}^{t,0}(c_l)>(1-\rho)(v_{jf}^{t,n}(c_{l-1})-v_{jf}^{t,0}(c_{l-1}))$, i.e. $\theta_l>(1-\rho)\mu_{l-1}$, then

$$\Psi_{jf}^{t,n,l}(v_{jf}^{t,o}(c_l)+\mu_{l-1})>v_{jf}^{t,o}(c_l)+(1-\rho)\mu_{l-1}+\rho\mu_{l-1}=v_{jf}^{t,o}(c_l)+\mu_{l-1}$$

Therefore, $v_{jf}^{t,n}(c_l)>\cdots>(\Psi_{jf}^{t,n,l})^3(v_{jf}^{t,o}(c_l)+\mu_{l-1})>(\Psi_{jf}^{t,n,l})^2(v_{jf}^{t,o}(c_l)+\mu_{l-1})>\Psi_{jf}^{t,n,l}(v_{jf}^{t,o}(c_l)+\mu_{l-1})>v_{jf}^{t,o}(c_l)+\mu_{l-1}$, which means $\mu_{l-1}<\mu_l$ and $\mathbb{P}(a_{jf}^{t,n}(c_l)=1)<\mathbb{P}(a_{jf}^{t,o}(c_l)=1)$. ■