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

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Abstract

This paper estimates the impact of notched driving-range-based (DRB) subsidies to consumers on Chinese electric-vehicle (EV) 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 investment decisions on the cost reduction of driving ranges by manufacturers, I find that the discontinuous incentives around the range thresholds of Chinese DRB subsidies increased the low-end EV manufacturers' probability of investing in reducing the production costs of driving ranges in 2019 by about 30 percentage points. 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 used to induce technological adoption or product upgrading.

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

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1 Introduction

This paper estimates the impact of driving-range-based (DRB) subsidies to consumers on Chinese battery-electric-vehicle (BEV)[1] manufacturers' incentives to reduce their production costs of driving ranges. Under the pressure of negative growth of automobile sales due to the 2008 financial crisis, the Chinese government implemented a package of policies in 2009 to revitalize its automobile industry through promoting the innovation by its domestic EV manufacturers.[2] The DRB subsidies to EV consumers were a crucial part of this ambition.[3] However, little is known about whether and how the DRB subsidies contribute to the 14 times increase in the Chinese EV sales in 2016-2022 and its domestic producers' newly-acquired presence in the global market in 2022. In fact, Chinese EV sales account for 65% of the global EV sales in 2022.[4] 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 only responded by installing more batteries and building smaller cars to increase driving ranges.

Using a dynamic structural model to explain and infer firms' unobserved 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, i.e. a notched subsidy scheme, increased the low-end EV manufacturers' probabilities of investing in reducing production costs of ranges in 2019 by about 30 percentage points relative to the scenarios of no subsidies. In the latter, the invest probabilities of firms most likely to invest are around 25%. This result implies that the environmental benefits and welfare gains of notched DRB subsidies are very likely larger than the estimates in existing literature that ignores this channel of reducing future production costs of ranges. The machinery built to estimate the impact on the production costs of ranges offers a possible tool for future research on devising better DRB subsidies for incentivizing cost reductions over ranges. A dynamic structural model is needed to for the aforementioned results because I need to quantify the impact of product subsidies on firms' decisions to change their state variable, the production costs of ranges.

[1]BEVs are a type of electric vehicles who relies exclusively on rechargeable battery packs, without a secondary source of propulsion such as an internal combustion engine.

[2]The announcement is aimed at new energy vehicles, which are mainly BEVs and plug-in hybrid electric vehicles. 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]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

From 2016 to 2020, EVs in China became cheaper with longer ranges and used higher-density batteries, but there was no clear trend of a decline in EV 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 cannot explain the variation. Possible explanations for the variation are different EV model characteristics such as whether it is a high-end model, manufacturers' capability of exercising market power, and manufacturers' decisions to reduce their production costs of ranges. Manufacturers can reduce their production costs by designing more energy efficient models, so that the same EV model with the same battery capacity can travel a longer distance. Manufacturers can also reduce their production costs by improving their exposure to the technological progress in batteries, such as sourcing better battery suppliers, vertically integrating with battery suppliers, or carrying out in-house R&D. 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 manufacturers' decisions to reduce the production costs of ranges. I focus on EVs because they are the most targeted EVs by Chinese DRB subsidies and have the largest sales among all the EVs.

In my structural model, heterogeneous 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 to buy a car. They differ on their price sensitivity but are otherwise the same apart from the consumer-product-year specific shocks. Manufacturers maximize their expected sum of current and discounted future profits over a finite number of periods 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 under an adaptive expectation about the aggregate market conditions and a belief that the evolution of future subsidy schemes is deterministic . If they decide to reduce the production costs, they pay an investment cost in this period. Their production costs of ranges are lower in the next period by one step with certainty and will stay at this value until further investments are made in the future periods. I assume that firms have rational expectations about the current prices and ranges and observe the current subsidy scheme, but have adaptive expectations about future aggregate market conditions, and that firms believe the subsidy schemes will decrease with an known ratio and will completely stop after a finite number of periods because predicting what happens in the current year is likely easier and more reliable than predicting what will happen in all future years with an infinite horizon. In the rapidly growing EV industry, it is likely challenging to predict what happens next year. EV manufacturers are assumed to interact in Chamberlinian monopolistic competition because the market share of EV manufacturer in my data is less than 1%.

I follow Berry et al. (1995) and Crawford et al. (2019) by assuming that unobserved consumer-model-period-specific taste shocks are independent and identically distributed so that I can use EV-model-level market shares in each year to estimate parameters of consumer preferences. One period in the structural model is one year in the data. I parameterize manufacturers' production costs as linear in ranges plus a non-parametric term that captures all the remaining factors in the marginal cost functions. The first order conditions of manufacturers' profit maximization together with EV 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 instruments following Berry et al. (1995) for both prices and ranges.

Since the driving range is an endogenous control variable, my estimation produces EV-model-year-specific cost parameters of ranges like Crawford et al. (2019). I infer manufacturers' investment decisions from whether a manufacturer release a new vehicle model or a new version of an existing model in the next period. An investment decision leads to a stochastic change in the manufacture's technology for producing ranges. A manufacturer 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 manufacturers' investment decisions and from manufacturers maximizing their expected sum of discounted profits under their beliefs about the future. The investment cost is assumed to be constant across manufacturers and time.

I estimate the investment cost by solving a non-stationary dynamic problem with a finite time horizon for each EV manufacturer. It is non-stationary because the subsidy scheme changes over time and manufacturers update their beliefs about the future. It has a finite time horizon in the sense that manufacturers make decisions based on their intertemporal profits over a finite number of periods. To solve these dynamic problems, I discretize the estimated cost parameters of ranges and assume that the space of the cost parameters is a finite set with a known bounds, that change the cost parameter of ranges follows a normal distribution with mean and variance unknown to the econometrician but known to manufacturers when they invests, and that there are only a finite amount of possible subsidy schemes. These assumptions allow me to solve for the optimal investment policies in the dynamic problems by backward recursion. To simplify the dynamic problem, I assume firms to have adaptive expectations about the future market conditions and that they interact in Chamberlinian monopolistic competition. The former captures the idea that it is difficult to accurately predict the future in the rapidly evolving EV industry, which makes it difficult to justify rational expectations. The latter is due to the low market shares of EV manufactures.

The market share of the largest EV manufacturer is less than 1% in 2016-2020. This simplifies the optimal investment policies for each manufacturer in each period to the solution to an auxiliary single-agent stationary dynamic problem. Using these optimal investment policies and the inferred investment decisions, I can estimate the investment cost using maximum likelihood estimation, similar to Rust (1987) in the sense that an outer loop searches over the parameter space and an inner loop solves the dynamic programming problem using parameters set by the outer loop. The lower bound is low enough so that no firm in my data managed to reach it. Firms do not foresee themselves surpassing this lower bound due to, for example, the difficulties in predicting the changes in the technological frontier in the future, or due to current technology bottlenecks that prevent the cost parameters from dropping below certain values.

Applying my structural model to the data, which is a newly constructed rich dataset that contains national-level vehicle model sales in 2010-2021 and the technical description of all vehicle model variations available or once available on the market,[5] I find that the existing notched investment scheme in 2019 increased the EV manufacturers' investment probabilities by up to 30 percentage points.

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 can incentivize firms to put more effort in reducing production costs and consequently creates efficiency gains.

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 no empirical evidence that the same holds in the EV market and this paper fills that 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

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

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.[6] 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.[7] 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.[8].

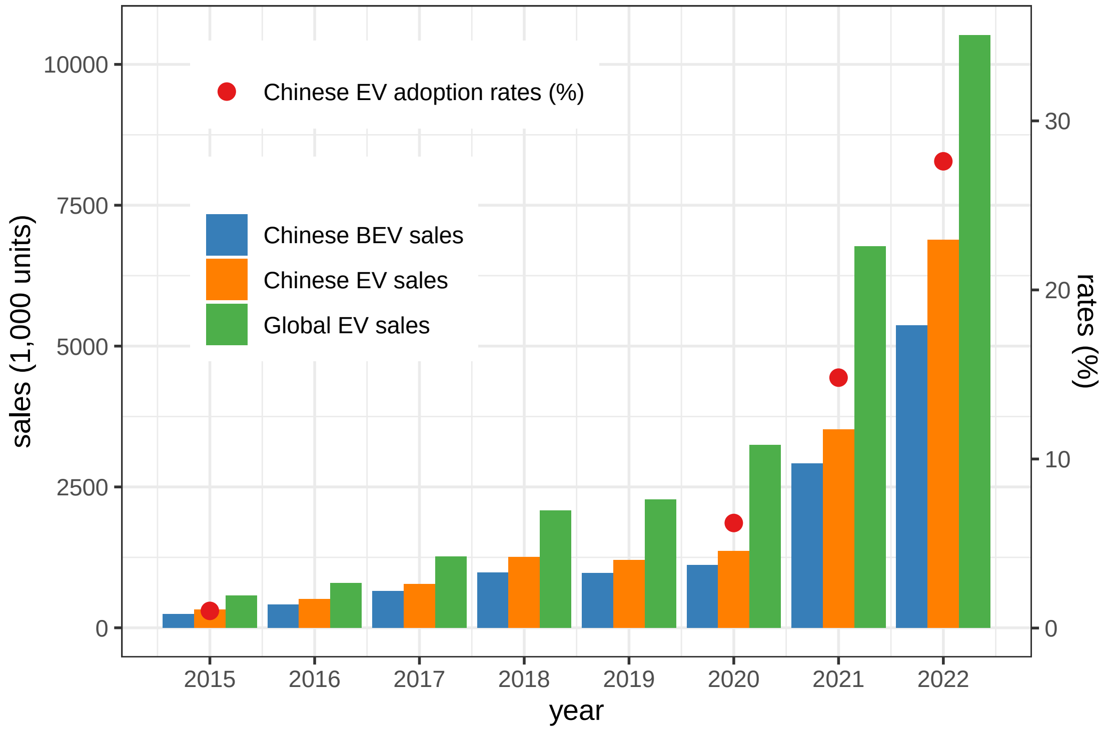
Table 1 demonstrates the range-based subsidies to consumers purchasing EVs. Here I only list the subsidies of EVs because they are the focus of this paper. It is a notched subsidy scheme because the amount of subsidies consumers receive is a discontinuous function of the driving ranges. Both the thresholds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

[6] Source: http://www.gov.cn/zwgk/2009-03/20/content_1264324.htm

[7] Source: https://www.chinanews.com.cn/ny/2010/10-13/2583130.shtml

[8] Source: http://ex.chinadaily.com.cn/exchange/partners/82/rss/channel/language/columns/v0m20b/stories/WS6389a97da31057c47eba25e3.html

Figure 1: Trends of EV and EV sales



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.

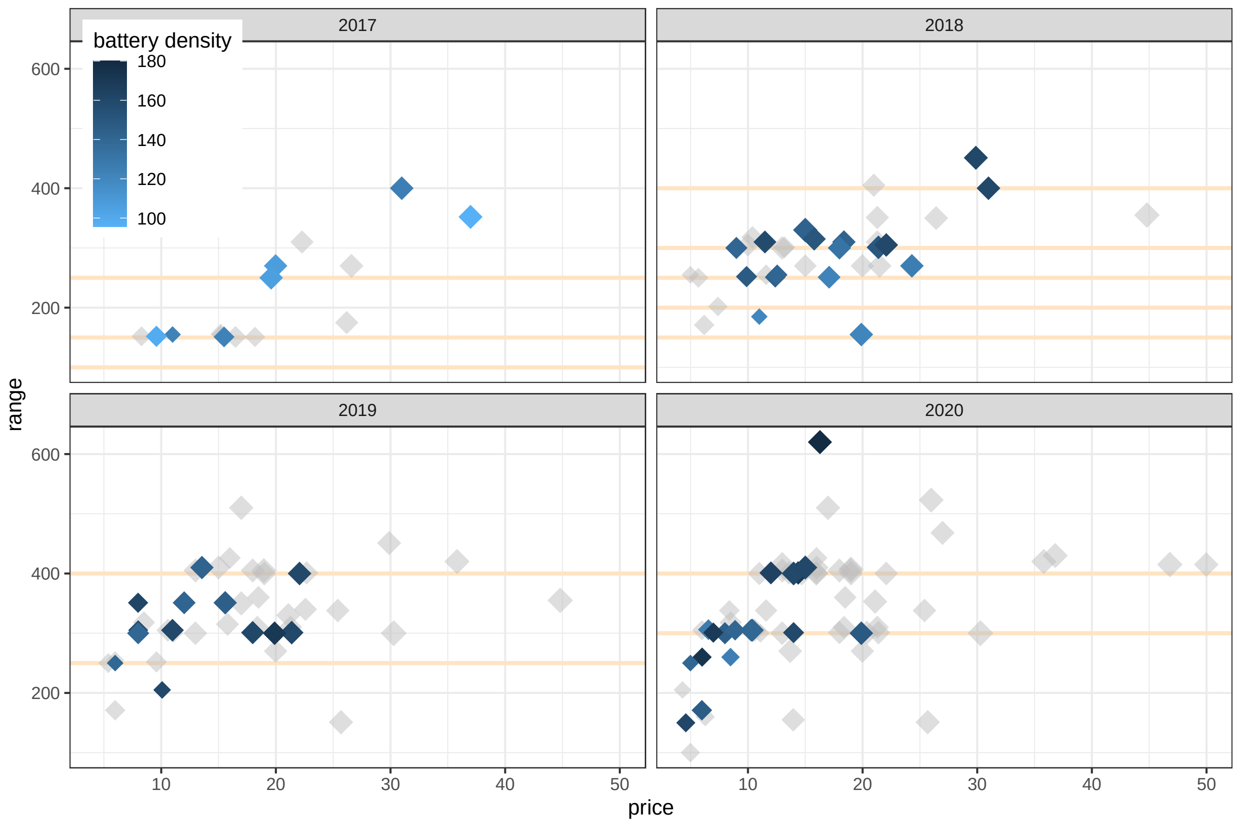
Table 1: Range-based subsidy for EVs by the central government (10,000 RMB)

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

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 demonstrates prices (10,000 RMB), ranges (km), model sizes (length (m) × 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 2: 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) × 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

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.

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

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

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) $\times$ 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.

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 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

[1] Prices and subsidies (τ) are deflated by the annual consumer price index and are in units of 10,000 RMB. Purchasing tax is also deducted in price-τ 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

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

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 5: The number of EV firms vs. the number of EV firms with new release

year	EV firms	w/ new product	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}:

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

which consists of the mean utility of purchasing this product δ_{jft} and consumer i's taste shock for this product in the year t, ϵ_{ijft}. Since consumers are homogeneous, the mean utility is product-year specific and is the same for all the consumers. I assume δ_{jft} to be:

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

where α_i and β 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 ζ_t and ι_{jf}.

$\mathbb{1}[\cdot]$ takes the value 1 if the statement inside is true and 0 otherwise. For EVs, β^R measures consumers' marginal utility of driving ranges. η is the EV fixed effect. ξ_{jft} is consumers' utility derived from product j's unobserved characteristics in the year t.

Ranges directly enter consumers' utility if it is an EV and but not if it is a combustion engine. This reflects that ranges are 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:

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

where ϵ_{i0t} is a mean-zero taste shock. All the taste shocks, ϵ_{ijft} and ϵ_{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

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

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

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

4.2 Supply

Firm f's profits at time t, π_{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 γ_{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),[9] and torque. η_{jft} captures 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 by deciding whether to pay a fixed investment cost λ for each of its products this period t, to reduce the cost parameter of ranges, $c_{jf,t+1}$, of its products next period by 1 step for sure. The cost parameter c_{jft} of range takes a value from a known finite set $\mathcal{C} = \{c_1, c_2, \cdots, c_L\}$ that satisfies $c_{l-1} < c_l$ and $\log(c_l) - \log(c_{l-1})$ constant for $l \in \{2, 3, ..., L\}$. This means the reduction in c_{jft} due to investment is lower for lower values of c_{jft}. If a model's current c_{jft} takes the value c_l and this firm invests, then in the next period, $c_{jf,t+1}$ decreases by 1 step for sure to c_{l-1}. Because c_{jft} can either stay constant or become smaller, this assumption of $\mathcal{C}$ being a finite set allows me to solve the dynamic problem using backward induction over the state space $\mathcal{C}$. Since prices and ranges are set in every period, they are static optimization problems. The first order conditions (FOCs) of prices and ranges are:

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

$$\frac{\partial \pi_{ft}}{\partial R_{jft}} = s_{jft} \left(-\frac{\partial mc_{jft}}{\partial R_{jft}} + \frac{\partial \tau(R_{jft})}{\partial R_{jft}} \right) + \sum_{k \in \mathcal{J}_{ft}} (p_{kft} - mc_{kft} + \tau(R_{kft})) \frac{\partial s_{kft}}{\partial R_{jft}} = 0 \tag{3}$$

If $\tau(\cdot)$ is a notched scheme, $\tau(\cdot)$ is discontinuous. The optimal range may not satisfy the FOC in Equation (3) 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 (3) 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.

[9] 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

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

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

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 (2) and (3) gives:

$$\begin{aligned} 0 =& 1 + \sum_{k \in \mathcal{J}_{ft}, k \neq j} (p_{kft} - mc_{kft} + \tau(R_{jft})) \cdot (-s_{kft})\mathbb{E}_i\left[\frac{\partial \delta_{ijft}}{\partial p_{ijft}}\right] \\ & + (p_{jft} - mc_{jft} + \tau(R_{jft})) \cdot (1 - s_{jft})\mathbb{E}_i\left[\frac{\partial \delta_{ijft}}{\partial p_{ijft}}\right] \quad (4) \\ 0 =& \left(-\frac{\partial mc_{jft}}{\partial R_{jft}} + \frac{\partial \tau(R_{jft})}{\partial R_{jft}}\right) + \sum_{k \in \mathcal{J}_{ft}, k \neq j} (p_{kft} - mc_{kft} + \tau(R_{jft})) \cdot (-s_{kft}\frac{1}{2}\beta^R R_{jft}^{1/2}) \\ & + (p_{jft} - mc_{jft} + \tau(R_{jft})) \cdot (1 - s_{jft})\frac{1}{2}\beta^R R_{jft}^{1/2} \quad (5) \end{aligned}$$

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

$$-c_{jft} + \tau'(R_{jft}) - \frac{\frac{1}{2}\beta^R R_{jft}^{1/2}}{\mathbb{E}_i\left[\frac{\partial \delta_{ijft}}{\partial p_{ijft}}\right]} = 0 \quad (6)$$

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

If the market share of each individual product is very close to zero, i.e. $s_{ijt} \approx 0$, which turns out to be the case in my data, the FOCs in Equations (4) and (5) can be approximated as:

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

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

$$\pi^*_{ft} \approx -\frac{\sum_{j\in\mathcal{J}_{ft}} s^*_{jft}}{\mathbb{E}_i\left[\frac{\partial\delta_{ijft}}{\partial p_{ijft}}\right]} \tag{7}$$

$$p^*_{jft} \approx -\frac{1}{\mathbb{E}_i\left[\frac{\partial\delta_{ijft}}{\partial p_{ijft}}\right]} + c_{jft}R^*_{jft} + \eta_{jft} - \tau(R^*_{jft}) \tag{8}$$

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.[10]. Since firms in my model interact in Chamberlinian monopolistic competition, firms

[10] 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)

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:

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

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

$$
c_{jft} = \bar{c}_{ft} + \nu_{jft} \text{ , where } \mathbb{E}[\nu_{jft}] = 0 \tag{9}
$$

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

and firms' responses to technology shocks (Huang et al. (2009)).

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 $\bar{m}c_{ft} = \bar{c}_{ft}\bar{R}_{ft} \cdot \mathbb{1}[\text{j is an EV}] + \bar{\eta}_{ft}$ and $\bar{\eta}_{ft}$ is the average of η_{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. Δ^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 $v_f^t(c_l)$:

$$v_{ft}^{\tilde{t}}c_l) = \mathbb{E}[\max\{U_{ft}^{\tilde{t}}(c_l, 1) + \epsilon_{ft}(1), U_{ft}^{\tilde{t}}(c_l, 0) + \epsilon_{ft}(0)\}] \tag{10}$$

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, $t \geq \tilde{t}$. $U_{ft}^{\tilde{t}}(c_l, 0)$ and $U_{ft}^{\tilde{t}}(c_l, 1)$ are the choice-specific values that satisfy

$$U_{ft}^{\tilde{t}}(c_l, 1) = -\lambda + \pi_{ft}^{\tilde{t}}(c_l) + \rho v_{ft}^{\tilde{t}}(c_{l-1}) \tag{11}$$

$$U_{ft}^{\tilde{t}}(c_l, 0) = \pi_{ft}^{\tilde{t}}(c_l) + \rho v_{ft}^{\tilde{t}}(c_l) \tag{12}$$

where λ 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. ρ is the discount factor.

Equation (10) 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:

$$\begin{aligned} \mathbb{P}(a_{ft}^{\tilde{t}}(c_l) = 1) =& \mathbb{P}(U_{ft}^{\tilde{t}}(c_l, 1) + \epsilon_{ft}(1) > U_{ft}^{\tilde{t}}(c_l, 0)) + \epsilon_{ft}(0) \\ =& \frac{\exp(U_{ft}^{\tilde{t}}(c_l, 1))}{\exp(U_{ft}^{\tilde{t}}(c_l, 1)) + \exp(U_{ft}^{\tilde{t}}(c_l, 0))} \end{aligned} \tag{13}$$

When $\bar{c}_{ft} = c_l$, the investment probability of firm f at time t in the data is $\mathbb{P}(a_{ft}^{\tilde{t}}(c_l) = 1)$.

Each period $\tilde{t}$'s auxiliary stationary problem can be solved by backwards induction from $\bar{c}_{ft} = c_1$.[11] 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 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 (10), (11), (12), and (13).

4.4 Investment probability under different subsidy scheme scenarios

Proposition 1 *Consider a case where the dynamic problem defined by Equations (10), (11), and (12) 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 π_{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

[11] 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.

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 (10), the conditional choice probability of investing is a function of the unknown investment cost λ 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:

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

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:

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

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 α_i and β 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 (2) and (3). Using the estimated $\hat{\alpha}$ and $\hat{\beta}^R$, only mc_{jft} and $\frac{\partial mc_{jft}}{\partial R_{jft}}$ are unknown in Equations (2) and (3). 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 9.

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 (10). 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 (13), 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 (3) 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:

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

6 Results

Figure 3 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 4 show the change in $\log(c_{ft})$ of firm f when release at least one new product compared to the $\log(c_{ft})$ since firm f release new product last time.

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

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 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.

FIGURE 3: The trend of $\log(c_{ft})$ of firms with new release

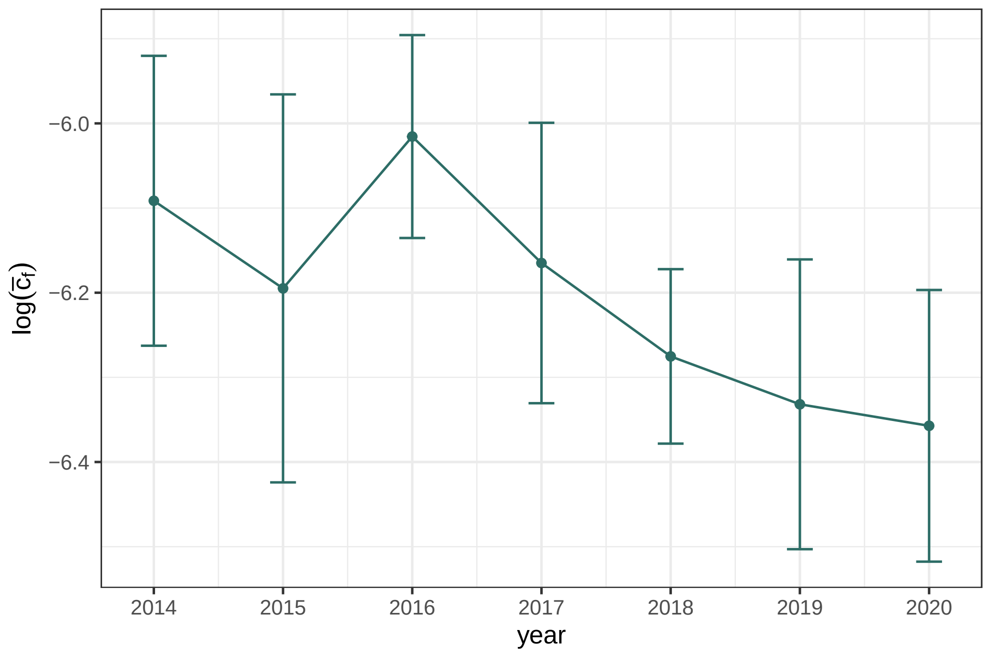


FIGURE 4: The distribution of $\log(c_{ft+1}) - \log(c_{ft})$ when there is new release

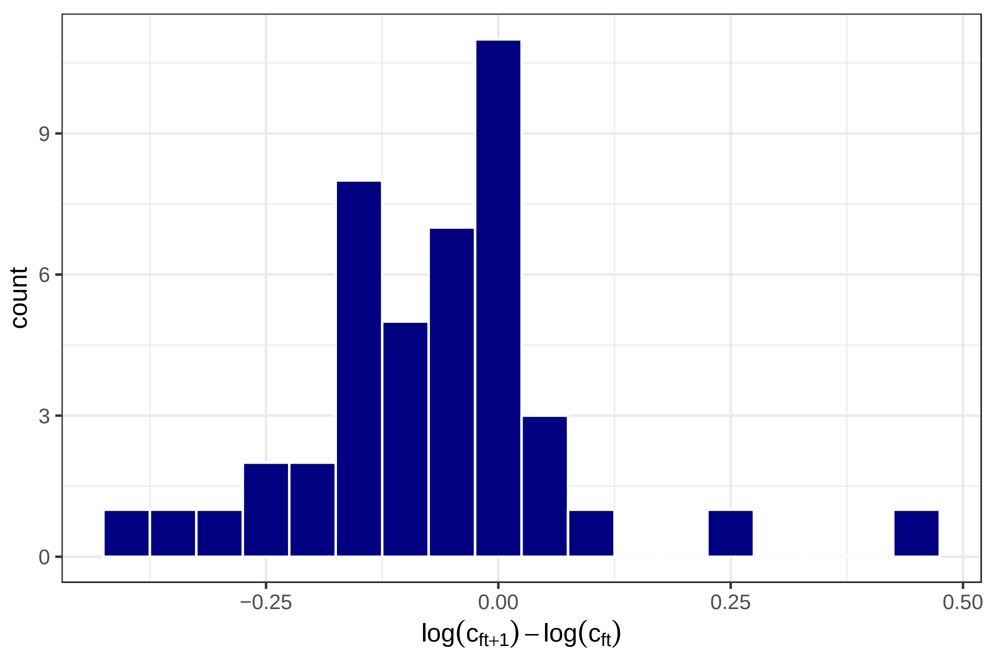


Table 6: Estimated consumer taste parameters on prices and ranges

		estimated values
β	$R^{\frac{1}{2}}$ (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]

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

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	

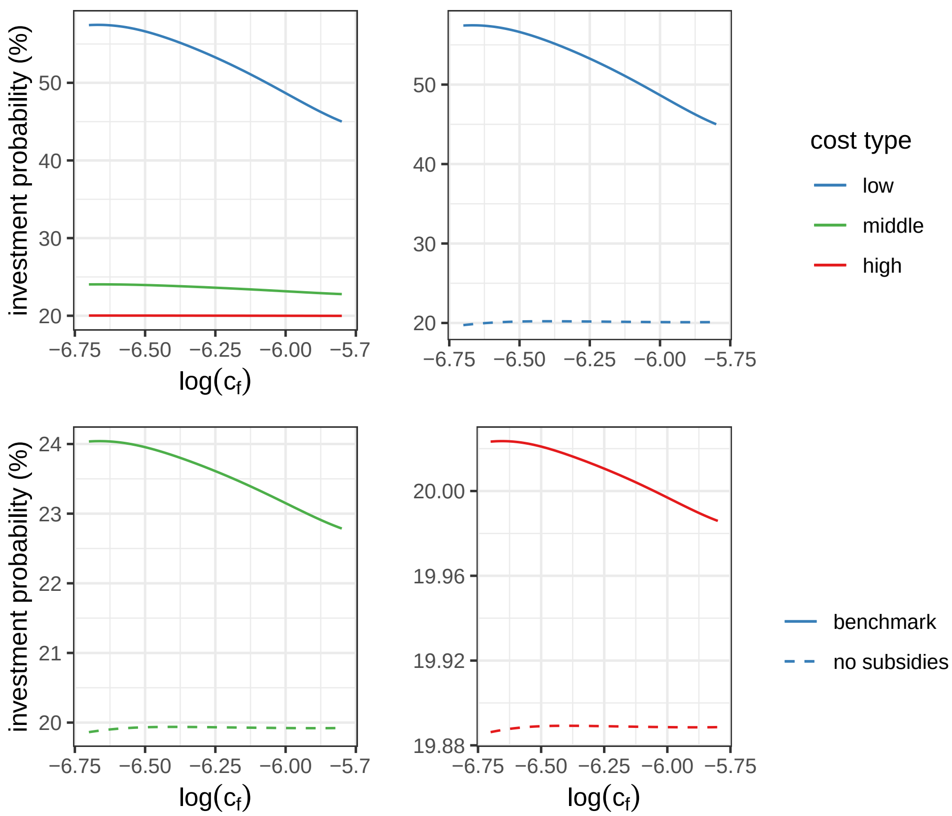
Table 8: Summary statistics of a selection of the supply-side parameters (2019)

	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	
π_f/λ (%)	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 5 shows the investment probability under the 2019 subsidies. The low cost firms both in terms of the exogenous marginal cost parameter η_{jft} and the production cost of ranges c_{ft} has the highest investment probability, which is around $50-55\%$. If the subsidies are removed, the investment probability would lower by 30 percentage points. The same pattern exists for firms with higher level of marginal costs but the decrease in investment probability is much smaller.

FIGURE 5: Investment probabilities for firms with different marginal cost type



7 Conclusion

This paper models and estimates manufacturers' incentives to reduce the production cost of ranges in response to range-based subsidies to consumers purchasing battery electric vehicles (EVs) and finds that the notched scheme increases the investment probabilities by up to 30 percentage points in 2019.

The numerical results in this paper are derived under the assumption that demand is static, in the sense that consumers' decisions about purchasing a EV last year does not affect their decisions this year. This paper also assumes that subsidies to consumers do not generate dynamic changes in demand, such as causing consumers to postpone or expedite the decisions of buying a EV. Other assumptions imposed are homogeneous consumers, adaptive expectations about the aggregate market conditions, and that investment leads to one unit of decrease in the log of the cost parameter of increasing ranges, i.e. $\log(c_l)$, with certain.

The assumption of homogeneous consumers can be relaxed by allowing the consumer taste parameters to differ across consumers and then estimate the demand side of the structural model using random-coefficient estimation as it is implemented in Berry et al. (1995). The adaptive expectation about the aggregate market conditions can be relaxed by using adaptive expectations about other EV models' range cost parameters, i.e. c_{jft}. This implies that investment decisions on one EV take into account the price and range responses of the other EVs. This adaptive expectation about the aggregate market conditions can also be replaced by rational expectation so that the investment decision is a dynamic game. Under the belief that the subsidy scheme stays constant, the auxiliary dynamic problem in each period is a stationary directional dynamic game and can be solved using the method of Iskhakov et al. (2016). The assumption that $\log(c_l)$ decreases by 1 unit with certainty if a firm invests can be relaxed by allowing the change in $\log(c_{jft})$ to follow a distribution where $\log(c_{jft})$ may decreases by more than 1 unit. Although most EVs' $\log(c_{jft})$ either decrease by one unit or do not change in 2019, there are some EVs whose $\log(c_{jft})$ decreases by more than 1 unit. Allowing stochastic improvements over c_{jft} can improve the fit of the structural model to the data in this regard. Instead of assuming that manufacturers believe the subsidy scheme never changes, firms can be assumed to have perfect foresight about future subsidy schemes. This is probably the most difficult extension because the problem of investment decisions is then non-stationary with infinite time horizon. If the adaptive expectation about the aggregate market conditions is kept, the investment decision problem is still a single-agent problem. Since the subsidy scheme in China will eventually disappear, the periods after the subsidy scheme disappears can be modeled as stationary and the periods with subsidy scheme can be solved by backward recursion.

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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 (10) using the Mcfadden surplus gives the following Bellman operators:

$$\begin{aligned}\Psi_{jf}^{t,n,l}(v) =& \pi_{jf}^{t,n}(c_l) + \log(\exp(\rho v) + \exp(-\lambda + \rho v_{jf}^{t,n}(c_{l-1}))\\ \Psi_{jf}^{t,o,l}(v) =& \pi_{jf}^{t,o}(c_l) + \log(\exp(\rho v) + \exp(-\lambda + \rho v_{jf}^{t,o}(c_{l-1}))\end{aligned}$$

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 $v_{jf}^{t,n}(c_l)$ and $v_{jf}^{t,o}(c_l)$. Rewriting Equation (13) gives:

$$\mathbb{P}(a_{jf}^t(c_l) = 1) = \frac{\exp[-\lambda + \rho(v_{jf}^t(c_{l-1}) - v_{jf}^t(c_l))]}{1 + \exp[-\lambda + \rho(v_{jf}^t(c_{l-1}) - v_{jf}^t(c_l))]}$$

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

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

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

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

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

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

Therefore, $v^{t,n}_{jf}(c_l) > \cdots > (\Psi^{t,n,l}_{jf})^3(v^{t,o}_{jf}(c_l) + \mu_{l-1}) > (\Psi^{t,n,l}_{jf})^2(v^{t,o}_{jf}(c_l) + \mu_{l-1}) > \Psi^{t,n,l}_{jf}(v^{t,o}_{jf}(c_l) + \mu_{l-1}) > v^{t,o}_{jf}(c_l) + \mu_{l-1}$, which means $\mu_{l-1} < \mu_l$ and $\mathbb{P}(a^{t,n}_{jf}(c_l) = 1) < \mathbb{P}(a^{t,o}_{jf}(c_l) = 1)$. $\blacksquare$