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How Consumers Respond to the Phase-Out of Attribute-Based Subsidies: Evidence from the Chinese Electric Vehicle Market *

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This paper examines consumer responses to the 2020 phase-out of electric vehicle (EV) subsidies in China using a Difference-in-Differences (DD) strategy with monthly sales data. We uncover heterogeneous responses across different EV models, with significant impacts observed in the group facing a two-stage subsidy reduction. Moreover, evidence of forward-looking behavior indicates consumers adjusted their purchasing decisions in anticipation of future subsidy cuts. These findings highlight the significance of nuanced policy design in fostering sustainable EV adoption.

Key Words: Industrial policy; Difference-in-Differences; Inter-temporal effects; Electric vehicle market.

JEL Classification Numbers: D12, L52.

1. INTRODUCTION

Since 2015, the Chinese electric vehicle (EV) market has consistently maintained its leading position, experiencing sustained growth at an annual rate of 70%. By 2018, China had surpassed significant milestones, having sold 1.1 million EVs, a figure exceeding the US market by over

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threefold and constituting more than 55% of global EV sales (Guo and Xiao, 2023). This growth was greatly facilitated by the government's initiation of consumer subsidies for EVs in 2009, which played a pivotal role in driving domestic EV adoption. By March 2019, the central government had allocated approximately 96.84 billion CNY in financial subsidies for EVs. Nevertheless, since 2017, these subsidies have gradually diminished, prompting important questions about how consumers will react to their phase-out. Understanding and analyzing consumer responses are essential steps in informing relevant policy design.

The EV subsidies in China are attribute-based. Attribute-based Subsidies (ABS) provide subsidies tied to product attributes, a strategy adopted by many governments to support the EV market. Different countries link subsidy amounts to various vehicle attributes, such as driving range in China and Japan, battery capacity in the U.S. and India, and vehicle size and weight in South Korea (Barwick et al. 2024). In China, subsidies are determined by driving range and are tiered with multiple cutoff points, favoring vehicles with greater driving range.

While subsidies have significantly boosted the adoption of domestic EVs in the Chinese market, the government began gradually reducing subsidies in 2017. This reduction was primarily driven by considerations of technological progress. The phase-out plans for subsidies exhibited variation by model, with EVs possessing shorter driving ranges subject to more substantial reductions in subsidy support. In April 2020, the government announced a phase-out plan for subsidies in the upcoming year, which varied for different types of EVs. Some EVs experienced a 50% reduction in subsidy between April 23rd and July 22nd, followed by complete subsidy withdrawal after July, which is referred to as the *withdrawal* group in our paper. Others experienced a slight subsidy reduction (approximately 10% compared to previous subsidies), and these EVs are termed the *reduction* group in our paper.

Our paper investigates consumers' response to the 2020 phase-out plan for EV subsidies. Reduced or withdrawn purchase subsidies for EVs lead to a price change, triggering the substitution effect. We aim to understand how the substitution effect comes into play for the EVs affected by the policy change and whether there is heterogeneity in consumers' responses to these affected EVs. Additionally, we explore the presence of inter-temporal effects on sales resulting from the policy change.

The 2020 phase-out plan presents an ideal setting to examine these questions. Firstly, it introduces varying levels of subsidy reduction across different EV types, allowing us to analyze consumer responses to different subsidy reduction levels. Secondly, the phase-out plan unfolds gradually for EVs in the *withdrawal* group in two distinct periods: subsidies decrease by 50% between April 23rd and July 22nd, followed by complete cessation after July. This two-stage process enables us to investigate whether consumers exhibit forward-looking behavior and explore potential inter-temporal effects of subsidy variations.

Passenger vehicles, being durable goods, prompt forward-looking consumers to consider not only current choices but also the utility of a current or future purchase. The phase-out plan prompts consumers to expect future prices for these EVs to rise relative to current prices. Consequently, forward-looking consumers planning to purchase a car later in the year may be motivated to make their purchases in advance, before July. In our study, we aim to examine the presence of inter-temporal effects on sales resulting from the policy change.

We develop theoretical models to examine consumer responses to the 2020 phase-out plan. Our models are grounded in the standard exogenous differentiation model with linear demands, supported by the Quasilinear Quadratic Utility Model as the underlying micro-foundation. Our analysis addresses two primary aspects of consumer behavior. First, we investigate how consumers respond to differential subsidy reductions among various types of EVs. Second, we explore the presence of inter-temporal effects resulting from the policy change.

Utilizing data on national monthly sales of all electric passenger vehicles in 2020, we employ a Difference-in-Differences (DD) strategy to identify the causal effects of subsidy policy changes and to test our theoretical hypotheses. Specifically, we analyze the relative variations in monthly sales between the periods before and after the policy change for car models affected by subsidy reduction or withdrawal, compared to those unaffected.

We observe heterogeneity in responses to policy changes across models. Consumers are highly responsive to the policy change in the *withdrawal* group, showing a significantly negative impact on monthly sales. Conversely, there is little responsiveness to the policy change in the *reduction* group. EVs in the *withdrawal* group experience the most substantial subsidy reduction during this policy change. Consequently, the relative prices of these EVs to other models increase significantly. This substitution effect prompts consumers to switch to other models or even consider the outside option of not purchasing any car, thereby reducing the likelihood of purchasing EVs in the group.

We then provide evidence suggesting the presence of inter-temporal effects of the policy change: consumers are forward-looking, weighing the utility of current versus future purchases. In April, EVs in the *withdrawal* group faced a 50% subsidy reduction, diminishing consumers' incentives to purchase these EVs. However, consumers anticipated further subsidy cuts in July. Consequently, they expected future prices for these EVs to rise relative to current prices. This prompted forward-looking consumers planning to purchase a car later in the year to make their purchases in advance, before July.

Our paper contributes to the extensive literature on subsidies' impacts on the EV market, such as the studies on hybrid vehicles in the United States (Beresteanu and Li, 2011) and electric vehicle adoption in Norway (Springel, 2021). Additionally, Guo and Xiao, (2023) find that while subsidies enhance Chinese EV adoption, they may impede technological advancement. Furthermore, Barwick et al. (2024) analyze attribute-based subsidies (ABS) in the Chinese EV market, demonstrating that ABS improve product quality and mitigate quantity distortions more effectively than uniform subsidies.

Our paper contributes to the recent literature on dynamic demand estimation. Seminal work by Gowrisankaran and Rysman (2012) emphasizes the importance of modeling dynamics in consumer demand and offers a tractable framework for analyzing dynamic decisions. A growing body of literature explores various industries (Bayer et al., 2016; De Groote and Verboven, 2019; Hu et al., 2023; Schiraldi, 2011). For instance, Hu et al. (2023) develop a structural model of dynamic demand to examine price elasticity in the Chinese EV market, capturing inter-temporal elasticity. While existing papers rely on structural models, our study focuses on providing reduced-form evidence of inter-temporal effects in consumers' demand.

Finally, our paper contributes to the study on the automobile market in China, including Barwick et al. (2021); Li (2018); Xiao and Ju (2014). While much of the literature examines consumer demand and welfare using structural models, our study analyzes consumer demand response through Difference-in-Differences (DD) estimations.

The remaining sections of the paper are organized as follows. Section 2 introduces the policy background of the Chinese EV market and the subsidy policy. Section 3 develops theoretical models to examine consumer responses to the subsidy phase-out plan. Section 4 describes the data. Section 5 discusses the estimation strategy adopted in the paper, along with our identifying assumptions. Section 6 examines the heterogeneous effects on sales of the policy change across different EVs. Section 7 provides evidence of the inter-temporal effects, and Section 8 concludes the paper.

2. POLICY BACKGROUND

The Chinese government has placed significant emphasis on the EV market, implementing plans and objectives to bolster this industry since 2009. On September 8, 2010, during the State Council's executive meeting, the electric vehicle industry was earmarked as one of China's seven key strategic emerging sectors. Subsequently, in 2012, the State Council issued the

"Energy Saving and New Energy Vehicle Industry Development Plan (2012-2020)" to further propel the growth of the EV sector. In 2020, the State Council released the plan for 2021-2025, establishing targets such as reducing the average electricity consumption of electric passenger cars to 12.0 kWh per 100 km and aiming for electric vehicles to constitute approximately 20% of total new car sales.

The primary policy adopted by the government to promote this industry is through consumer subsidies. At the time of purchase, consumers pay the post-subsidy price, while subsidies are then allocated to automakers either quarterly or annually by the government (Barwick et al. 2024). Starting from 2009, the Chinese central government introduced consumer subsidies in designated pilot cities, including Changchun, Hangzhou, Hefei, Shanghai, and Shenzhen. By 2014, these programs had extended to 88 cities before being implemented nationwide in 2016. The subsidies are attribute-based and notched, determined by the driving range. For battery electric vehicles (BEVs), they are tiered with multiple cutoff points, favoring those with greater driving range. Plug-in hybrid electric vehicles (PHEVs) receive a uniform subsidy across models, contingent on a minimum range of 50km. Starting from 2017, the government gradually reduced the subsidies, with a 20% reduction in 2017 and 2018, followed by a further 50% reduction in 2019. By March 2019, the central government had cumulatively issued financial subsidies of approximately 96.84 billion CNY for electric vehicles.

In April 2020, the government announced the phase-out plan for subsidies in the upcoming year. The phase-out plans vary for different types of EVs. The first group, termed the *subsidy withdrawal* group in our paper, includes BEVs with a driving range between 250km and 300km. Consumers purchasing these BEVs between April 23rd and July 22nd, 2020, which is termed the transition period, would receive a subsidy of 9K CNY, representing a 50% reduction from the previous subsidies. After July 22nd, 2020, consumers no longer received any subsidies upon purchasing this type of BEVs.

The second group, termed the *subsidy reduction* group in our paper, includes BEVs with a driving range greater than 300km and PHEVs with a driving range greater than 50km. Starting from April 23rd, 2020, these cars experienced a slight subsidy reduction (approximately 10% compared to the previous subsidies). This reduced subsidy level remained in effect until the end of the year. Please refer to Figure 1 for more details about this policy change.

The phase-out plan in 2020 presents an ideal scenario for studying demand response. Firstly, the magnitude of subsidy reduction varies across different types of EVs. The *withdrawal* group faces a 50% reduction in subsidies between April 23rd and July 22nd, while in the mean time the *reduction* group experiences a slight decrease of 10% compared to previous

FIG. 1. Changes of Subsidy Policy in 2020

		Withdrawal Group	*Reduction* Group			*Control* Group
Before	Before April, 2020	250≤R<300	300≤R<400	R>400	R>50	Others
	BEVs	18,000 CNY	18,000 CNY	25,000 CNY	/	/
	PHEVs	/	/	/	10,000 CNY	/
Transition	Start in May, 2020	250≤R<300	300≤R<400	R>400	R>50	Others
	BEVs	9,000 CNY	16,200 CNY	22,500 CNY	/	/
	PHEVs	/	/	/	8,500 CNY	/
After	Start in August, 2020	250≤R<300	300≤R<400	R>400	R>50	Others
	BEVs	0 CNY	16,200 CNY	22,500 CNY	/	/
	PHEVs	/	/	/	8,500 CNY	/

*Note: R = Range per Charge (km)

subsidies. This variation allows us to investigate how consumers respond to different levels of subsidy reduction.

Secondly, the phase-out plan for the *withdrawal* group unfolds gradually, comprising two distinct periods. Between April 23rd and July 22nd, subsidies decrease by 50%, followed by a complete cessation of subsidies after July 22nd. This two-stage process enables us to examine whether consumers exhibit forward-looking behavior and explore potential intertemporal effects of subsidy variations.

3. THEORETICAL MODELS

In this section, we develop theoretical models to examine consumer responses to the 2020 phase-out plan. Our analysis focuses on two key dimensions of consumer behavior. First, we explore how consumers react to the differential subsidy reductions among various types of EVs, specifically examining the *withdrawal* group and the *reduction* group. Second, we investigate whether there exists an inter-temporal effect resulting from the policy change.

3.1. Exogenous Differentiation Model with Linear Demands

Our models are based on the standard exogenous differentiation model with linear demands, with the Quasilinear Quadratic Utility Model providing the corresponding micro-foundation. These models were initially developed and extensively utilized by Richard E. Levitan and Martin Shubik in the 1960s. The Quasilinear Quadratic Utility Model was also independently introduced by Spence (1976) and Dixit (1979). Recent applications of these models include studies by Calzolari and Denicolo (2015) and Edelman and Wright (2015). For a detailed discussion of these models, please refer to Choné and Linnemer (2020).

We follow the framework by Wright (2008). Consider a utility function for a representative consumer who derives utility from two products, with the consumed amount q_1 and q_2. The utility function is:

$$U(q_1, q_2) = \alpha(q_1 + q_2) - \frac{\beta}{2}(q_1^2 + q_2^2 + 2\gamma q_1 q_2). \tag{1}$$

The consumer chooses q_1 and q_2 to maximize their utility net of the expenditure on the goods:

$$\max_{q_1, q_2} \left[U(q_1, q_2) - p_1 q_1 - p_2 q_2\right]. \tag{2}$$

This offers a convenient method to parameterize the level of competition among products. In particular, the inverse demand functions are represented as $p_i = \alpha - \beta(q_i + \gamma q_j)$, where $0 \leq \gamma < 1$ serves as a measure of the degree of product differentiation. A higher value of γ indicates a greater degree of substitutability between the two products.

Throughout the paper we assume that prices are such that all q_i are positive. By maximizing the above utility function, the demand functions for q_1 and q_2 are:

$$q_1 = \frac{\alpha(1-\gamma) - (p_1 - \gamma p_2)}{\beta(1-\gamma^2)}, \tag{3}$$

$$q_2 = \frac{\alpha(1-\gamma) - (p_2 - \gamma p_1)}{\beta(1-\gamma^2)}. \tag{4}$$

3.2. Subsidy Reductions on the *Withdrawal* and *Reduction* Groups

EVs in the *withdrawal* group face significantly larger subsidy reductions compared to those in the *reduction* group: The *withdrawal* group experiences a 50% subsidy reduction between April 23rd and July 22nd, followed by complete withdrawal thereafter. In contrast, EVs in the *reduction* group encounter a modest 10% decrease in subsidies compared to previous levels.

In our model, the price of EVs in the *withdrawal* group is denoted by p_1, and for the *reduction* group, it is denoted by p_2. A larger subsidy reduction corresponds to a greater price increase for consumers. Assuming p_1 increases to $p_1 + \delta_1$ and p_2 increases to $p_2 + \delta_2$, where $\delta_1 > \delta_2 > 0$.

According to equations (3) and (4), the new quantities q_1' and q_2' after the price changes are:

$$q_1' = \frac{\alpha(1-\gamma) - [(p_1+\delta_1) - \gamma(p_2+\delta_2)]}{\beta(1-\gamma^2)},$$
$$q_2' = \frac{\alpha(1-\gamma) - [(p_2+\delta_2) - \gamma(p_1+\delta_1)]}{\beta(1-\gamma^2)}.$$

The change in q_1 is given by:

$$q_1' - q_1 = \frac{-(\delta_1 - \gamma\delta_2)}{\beta(1-\gamma^2)}.$$

Given that $\delta_1 > \delta_2$ and $0 < \gamma < 1$, we have $\delta_1 - \gamma\delta_2 > 0$ and hence $q_1' < q_1$. It indicates that the demand for EVs in the *withdrawal* group will fall after the subsidy reductions.

Next, consider the demand change in q_2, which is given by:

$$q_2' - q_2 = \frac{-(\delta_2 - \gamma\delta_1)}{\beta(1-\gamma^2)}.$$

Given that $\delta_1 > \delta_2$ and $0 < \gamma < 1$, the sign of $\delta_2 - \gamma\delta_1$ depends on the value of γ: (i) If γ is sufficiently small, $\delta_2 - \gamma\delta_1$ can be positive; (ii) if γ is sufficiently large (but still less than 1), $\delta_2 - \gamma\delta_1$ can be negative; (iii) if γ is at a certain level where $\delta_2 = \gamma\delta_1$, then $q_2' - q_2 = 0$, implying $q_2' = q_2$. Thus, when γ is at a certain level, the quantity q_2 may remain stable ($q_2' = q_2$). Based on our model, we propose the following hypothesis:

Hypothesis 1: The demand for EVs in the *withdrawal* group will decrease following the subsidy reductions. However, for EVs in the *reduction* group, the change in demand depends on the degree of substitutability (γ). When the level of substitutability is such that $\delta_2 = \gamma\delta_1$, demand will remain unchanged.

Intuitively, EVs in the *withdrawal* group experience the most substantial subsidy reduction magnitudes during this policy change. Consequently, the relative prices of these EVs to other models increase significantly. This prompts consumers to switch to other models or even consider the outside option of not purchasing any car, thereby reducing the likelihood of purchasing EVs in the *withdrawal* group.

On the other hand, EVs in the *reduction* group experience a much slighter reduction compared to the *withdrawal* group. Consequently, while the relative prices of the *reduction* group to the *withdrawal* group decrease, the relative prices of the *reduction* group to other cars (including the outside option) increase. This ambiguity in relative prices predicts an uncertain substitution effect. Some consumers may opt to switch from the *withdrawal* group to the *reduction* group due to the decreasing relative prices, while others, particularly those highly price-sensitive, may decide against purchasing EVs altogether due to the increased relative prices compared to the outside option. Therefore, under certain conditions of differentiation among EVs, the demand for EVs in the *reduction* group remains unchanged.

3.3. Inter-temporal Effects

Passenger vehicles are always considered as durable goods, prompting forward-looking consumers to weigh not only current choices but also the utility of both immediate and future purchases. The policy announced in April implemented subsidy reductions for EVs in the *withdrawal* group in two stages: a 50% reduction starting in April, followed by complete withdrawal after July. We denote the period between April and July as Period 1, and the period after July as Period 2.

Do inter-temporal effects exist in consumers' responses to this policy change? In other words, are consumers forward-looking in evaluating both current and future purchases? We employ the exogenous differentiation model with linear demands described in Section 3.1 to address these questions. In this context, the price and quantity consumed of EVs in the *withdrawal* group in Period 1 are denoted by p_1 and q_1, while in Period 2, they are denoted by p_2 and q_2. The degree of substitutability γ captures the time discount effect for consumers.

If inter-temporal effects are present and consumers are forward-looking, the demand for EVs in the *withdrawal* group during both Period 1 and Period 2 is described by equations (3) and (4). Consumers optimize their utility by considering both current and future purchases. However, if consumers are myopic, they optimize their utilities based solely on current consumption. In Period 1, consumers' utility function includes only q_1 but not q_2, while in Period 2, it includes only q_2 but not q_1. The first-order conditions in this case are equivalent to those in equation (3) and (4) with $\gamma = 0$.

Now we consider the effects of price changes on the quantities. Note that EVs in the *withdrawal* group face a 50% reduction in subsidies starting in April, followed by complete withdrawal after July. In our model, we assume that the price increases by δ_1 in Period 1 and by δ_2 in Period 2, where $\delta_2 > \delta_1 > 0$.

If consumers are forward-looking (i.e. $\gamma > 0$), the changes in quantities would be:

$$\Delta q_1 = q_1' - q_1 = \frac{-\delta_1 + \gamma\delta_2}{\beta(1 - \gamma^2)},$$

$$\Delta q_2 = q_2' - q_2 = \frac{-\delta_2 + \gamma\delta_1}{\beta(1-\gamma^2)}.$$

The quantity consumed in Period 1 depends on the time discount effect γ. When $\gamma = \frac{\delta_1}{\delta_2}$, $\Delta q_1 = 0$, indicating no change in consumption in Period 1. However, the quantity consumed in Period 2, q_2, will decrease as $\gamma < \frac{\delta_2}{\delta_1}$. If consumers are myopic (i.e. $\gamma = 0$), we have

$$\Delta q_1 = q_1' - q_1 = -\delta_1/\beta < 0, \qquad \Delta q_2 = q_2' - q_2 = -\delta_1/\beta < 0.$$

Hence, the quantities q_1' and q_2' in Periods 1 and 2 will decrease.

Observing that q_1 remains unchanged after the policy change suggests that consumers are forward-looking, indicating an inter-temporal effect of the policy change. Therefore, we propose Hypothesis 2:

Hypothesis 2: If consumers are forward-looking, the quantity consumed in Period 1 (between April and July) remains unchanged by the policy change when the time discount effect reaches a certain level. Conversely, if consumers are myopic, the quantity consumed in Period 1 decreases.

Intuitively, in April, EVs in the *withdrawal* group faced a 50% subsidy reduction, reducing consumers' incentives to purchase these EVs. However, consumers anticipated further subsidy cuts in July, expecting future prices for these EVs to rise relative to current prices. Consequently, forward-looking consumers planning to purchase a car later in the year were motivated to make their purchases in advance, before July. This interplay of temporal and inter-temporal effects could counteract each other, potentially leading to insignificant changes in quantities between April and July.

4. DATA

Our dataset consists of the national sales of all the electric passenger vehicles in China for every month in 2020. The electric vehicles include Battery Electric Vehicles (BEVs), Plug-In Hybrid Electric Vehicles (PHEVs) and Fuel Cell Electric Vehicles (FCEVs)[1]. We have 804 vehicle models in our sample. For each model, we observe its make, model name, fuel type, size, brand country of origin, driving range and Manufacturer's Suggested Retail Price (MSRP). The observations in our sample are at the model-month level, totaling 9,648 observations.

Our sales data are gathered through information from the Compulsory Third Party (CTP) insurance of new vehicles. The CTP insurance is

[1] For technical definition of vehicle types, see:
https://www.transportation.gov/rural/ev/toolkit/ev-basics/vehicle-types

mandatory for all vehicles in China before they can be driven, usually obtained at the time of vehicle purchase. This ensures that the collected sales data serve as a reliable proxy for actual sales figures.

The Ministry of Industry and Information Technology issued an official document listing eligible car models and their corresponding model codes for the price subsidy[2]. Each car model in our dataset is identified by a unique model code, enabling us to associate the model with its subsidy status as determined by the government.

TABLE 1.

Summary Statistics

	Mean	**SD.**	**Min.**	**Median**	**Max.**
Treat[1]	0.731	0.443	0	1	1
Monthly Sales[2]	47.73	143.7	0	1	1,671
Price[3]	25.62	26.67	5.00	17.50	200.0
BEV[4]	0.769	0.420	0	1	1
PHEV[5]	0.228	0.420	0	0	1
Foreign	0.072	0.258	0	0	1
Seats	4.781	0.932	2	5	9
Size[6]	2581	291.5	1,560	2,655	3,200
# of Car Models					804
N					9,648

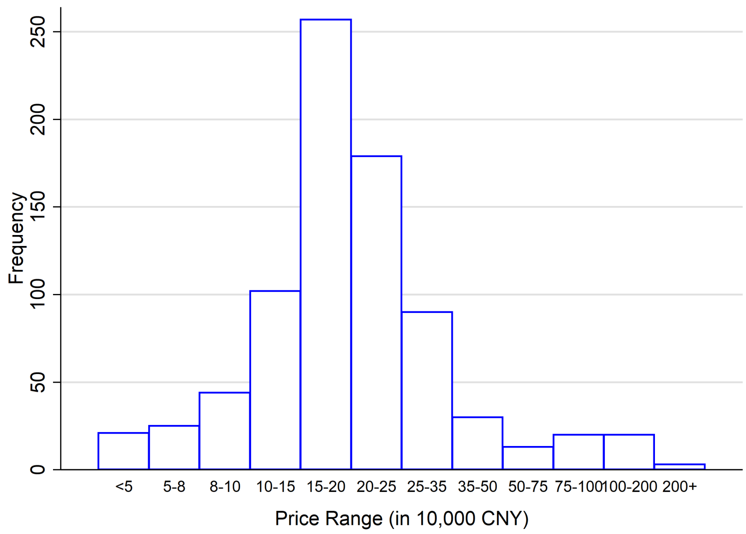
1 Treat = Car models that belong to either *subsidy withdrawal* group or *subsidy reduction* group;
2 Monthly Sales = Number of a particular model of cars that was sold across the country;
3 Price = Manufacturer's Suggested Retail Price (MSRP), measured in thousands of 2020 US Dollar;
4 BEV = Battery Electric Vehicle;
5 PHEV = Plug-In Hybrid Electric Vehicle;
6 Size = Measured by wheelbase, which is the horizontal distance (in inches) between the centers of the front and rear wheels on the same side of a vehicle.

Table 1 presents summary statistics for our dataset. In 2020, approximately 880,000 new electric passenger cars were purchased in China, averaging to 73,000 cars per month. On an individual model basis, the average monthly sales figure is 47.73 cars, although this varies significantly depending on the model. As mentioned earlier, the dataset comprises 12-month balanced panels of monthly sales data for a total of 804 car models, with over 70% of the models directly impacted by either subsidy reduction or withdrawal. This proportion remains consistent when measured by sales, with 74% of total sales impacted by either subsidy reduction or withdrawal.

[2]For an example document, see:
https://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057585/n3057589/c7627190/part/7627202.pdf

Figure 2 depicts the distribution of MSRP for the models in the dataset. Cars' prices can be broadly categorized as low, median, and expensive. Low-priced cars range from 50,000 to 150,000 CNY, median-priced cars from 150,000 to 350,000 CNY, and expensive ones typically exceed 500,000 CNY. The average price for models in our data is approximately 256,000 CNY. After the policy change in April 2020, the typical price subsidy for BEVs with the driving range between 300 km and 400km was 16,200 CNY, and for PHEVs with the driving range greater than 50km, it was 85,000 CNY. These subsidies amount to approximately 3% to 6% of the average MSRP, respectively.

FIG. 2. Distribution of Price Ranges



BEVs dominate China's electric vehicle market. In 2020, they constituted over 75% of EV models or 77% of EV sales, which is three times higher than PHEV sales. Table 2 compares the characteristics of BEVs and PHEVs. In China, BEVs have notably lower prices and smaller sizes compared to PHEVs. BEVs in China are predominantly manufactured by domestic companies, with only a small fraction of models (6%) and sales (3%) contributed by foreign brands.

5. EMPIRICAL STRATEGY

We employ a Difference-in-Differences (DD) strategy to identify the causal effects of subsidy policy changes. Specifically, we analyze the relative vari-

TABLE 2.

Comparisons of Specifications between BEV and PHEV

	BEV[4]	**PHEV**[5]	**B−P**
Monthly Sales[1]	32.80	38.00	−5.20
	(106.8)	(118.3)	(5.14)
Price[2]	31.91	69.88	-37.97^{***}
	(22.78)	(65.87)	(1.77)
Foreign	0.036	0.176	-0.140^{***}
	(0.187)	(0.381)	(0.012)
Seats	4.687	5.135	-0.448^{***}
	(0.952)	(0.700)	(0.043)
Size[3]	100.0	110.1	-10.108^{***}
	(11.99)	(4.94)	(0.55)

1 Monthly Sales = Number of a particular model of cars that was sold across the country;
2 Price = Manufacturer's Suggested Retail Price (MSRP), measured in thousands of 2020 US Dollar;
3 Size = Measured by wheelbase, which is the horizontal distance (in inches) between the centers of the front and rear wheels on the same side of a vehicle.
4 BEV = Battery Electric Vehicle;
5 PHEV = Plug-In Hybrid Electric Vehicle;

ations in monthly sales between the pre-change and post-change periods for car models affected by subsidy reduction and withdrawal, in contrast to those unaffected.

Our main estimating equation is presented as follows:

$$MonthlySales_{it} = \alpha_i + \lambda_t + \beta Treat_i \times Post_t + \epsilon_{it}, \tag{5}$$

where i and t index car models and time periods, respectively, spanning the twelve months of 2020. The outcome variable $MonthlySales_{it}$ is the national monthly sales of car model i at time t. The binary variable $Treat_i$ equals 1 if car model i is subject to subsidy changes and 0 otherwise. Similarly, $Post_t$ equals 1 for periods following the implementation of subsidy changes on April 23, 2020, and 0 otherwise. Additionally, the equation incorporates fixed effects for both car models and time periods, denoted by α_i and λ_t, respectively. The error term ϵ_{it} accounts for idiosyncratic shocks to monthly sales.

The coefficient of interest in Equation (5), β, estimates the impact of subsidy changes on national monthly sales. Specifically, the estimated coefficient $\widehat{\beta}$ measures the change in national monthly sales experienced by the car models that are subject to reduction of government subsidy (relative to those that are not) after the changes went into effect after April

2020 (relative to before). A negative coefficient indicates a decrease in monthly sales for car models affected by subsidy policy changes following the reduction in government subsidy post-April 2020.

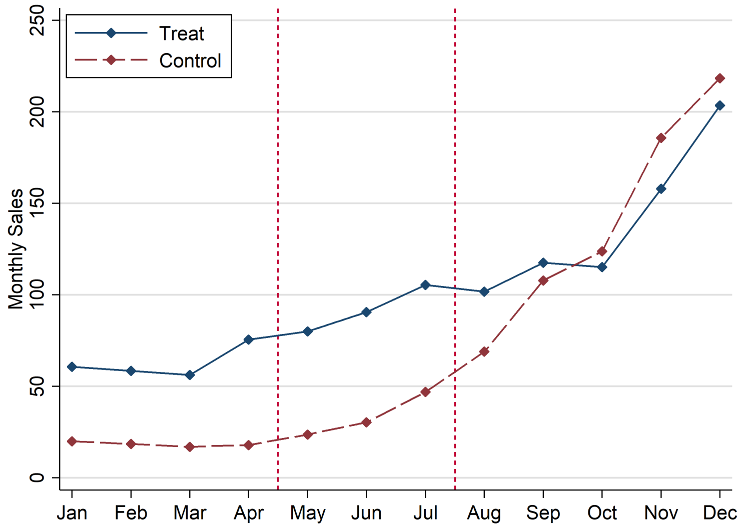
Our estimation approach inherits both the advantages and potential drawbacks of standard two-way fixed effects DD estimators. The car model specific effects α_i control for all time invariant factors that differ between car models. The time period fixed effects control for any monthly seasonal patterns of national car sales that affect all car models similarly. A fundamental identifying assumption underlying the fixed effects estimation of Equation (5) is the conditional mean independence of the intervention variable $Treat_i \times Post_t$, expressed as:

$$E(MonthlySales_{0it}|\alpha_i,\ \lambda_t,\ Treat_i \times Post_t) = E(MonthlySales_{0it}|\alpha_i,\ \lambda_t). \tag{6}$$

Here, $MonthlySales_{0it}$ represents the potential monthly sales of car model i during period t if unaffected by subsidy policy changes. This assumption posits that, after accounting for car model and time-specific effects, both the selection of the treatment group $Treat_i$ and the timing of policy changes $Post_t$ are independent of other factors influencing potential monthly sales. The validity of this exogeneity assumption is partially supported by the following two facts: First, subsidy eligibility and intensity are predetermined by car technical specifications that are designed by manufactures prior to year 2020 and time-invariant during our sample period. Second, the new policy, stipulating the phaseout of subsidy, was applicable to all car models in the market and officially announced and became effective on 23rd April 2020. As the government announcement states that, the subsidy policy adjustment is driven primarily by considerations of technological progress and economies of scale, which are highly manufacture-specific (and hence car model-specific) and invariant in the short run. Thus, conditional on car model and time-specific effects, the intervention $Treat_i \times Post_t$ is arguably independent of other determinants of monthly sales.

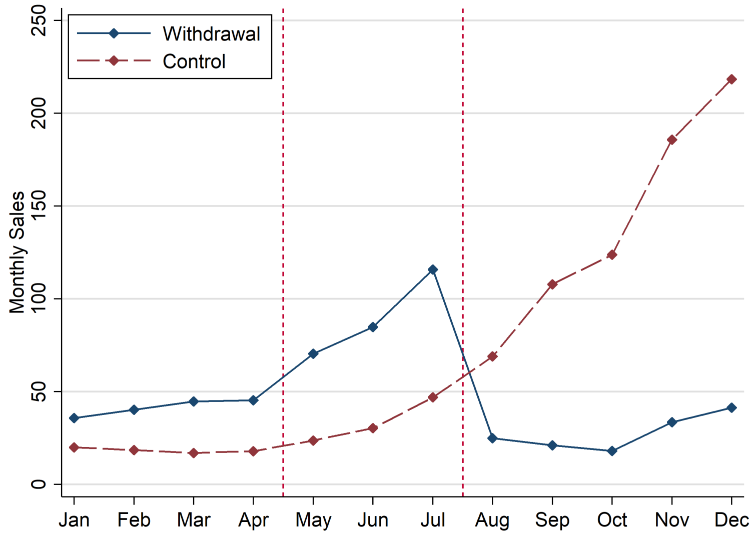
Another important identifying assumption implied by the specification of equation (5) is the parallel trend assumption, $E(MonthlySales_{0it}|\alpha_i,\ \lambda_t) = \alpha_i + \lambda_t$. The trends of potential monthly sales for the car models in the treatment group (affected by subsidy changes) are parallel to those for the car models in the control group(unaffected by subsidy changes). Since our sample includes multiple periods before the subsidy policy changes, the parallel trend assumption can be visually inspected. Figure 3 displays average monthly sales for the treatment and control groups, indicating a substantial reduction in the sales gap following the subsidy withdrawal, suggesting a potential treatment effect of the policy change. The subsidy reduction became effective as of April 23rd 2020. Later on, after July 22nd 2020, the car models that no longer meet the 2020 standard faced complete subsidy withdrawal. The two incidences are marked by vertical dashed lines in red. Noted that the average sales for car models in the treatment group are significantly higher than their counterparts, but the trends for the treatment group and the control group were quite parallel prior to the subsidy withdrawal, after which the gap between the treatment group and the control group had contracted considerably, suggesting potential treatment effect of the policy change.

FIG. 3. Trends in Average Monthly Sales (Treatment vs. Control)



Moreover, as elucidated in Section 2, the extent of subsidy phaseout varies across car models, allowing further categorization of the treatment group into two subsets: the *withdrawal* group and the *reduction* group. Figure 4 illustrates the average monthly sales for the *withdrawal* group and the control group. Prior to the policy changes in April, the trend for withdrawal group is higher than and almost parallel to that for the control group. In the transition period from May to July 2020, the car models in the *withdrawal* group experienced 50% reduction in subsidy. Interestingly, the trend gap between the withdrawal and control groups had actually increased rather than decreased. Subsequently, with complete subsidy withdrawal after July 2020, the average monthly sales for the withdrawal group decline sharply and remain stagnant. The rich time series variations in monthly sales across control and treatment groups offer valuable insights into market responses to price changes and underlying mechanisms.

FIG. 4. Trends in Average Monthly Sales (Withdrawal vs. Control)



In addition to the simple DD method, we explore variations in treatment effects across time periods by estimating a dynamic treatment effects regression model:

$$MonthlySales_{it} = \alpha_i + \lambda_t + \sum_{\substack{k=1 \\ k\neq 4}}^{12} \beta_k Treat_i \times I(t = k) + \epsilon_{it}$$

where $I(t = k)$ indicates whether the observation occurs in month k, and β_k captures the treatment effect during time period k. This dynamic treatment effect model allows us to formally test the parallel trend assumption and investigate changes in treatment effects over time.

6. EFFECTS OF THE POLICY CHANGE ON SALES

In this section, we examine how consumers respond to the phase-out of subsidies using the estimation strategy outlined in Section 5, employing various specifications.

Initially, we assess the overall effects of the policy change on sales by considering all car models affected by the policy change as the *treatment* group. Subsequently, we empirically test our Hypothesis 1 by delving deeper into consumer responses to different levels of subsidy reduction and leveraging the variation in subsidy reduction magnitudes across the *withdrawal* group and the *reduction* group.

6.1. Overall Effects of the Policy Change

We begin by analyzing the overall effects of the policy change on sales, treating all car models affected by the policy change as the *treatment* group. This includes EVs in the *withdrawal* group, which experienced a 50% subsidy reduction after April and subsidy withdrawal after July, as well as EVs in the *reduction* group, which encountered a 10% subsidy reduction after April. We then assign all other models to the control group and estimate the DD regression.

The left column in Table 3 presents the estimated overall effect on monthly sales. The results indicate that the policy had insignificant impact on the monthly sales of models in the treatment group.

TABLE 3.

Treatment Effect on Monthly Sales (Baseline)

	Monthly Sales[1]	**Monthly Sales**[1]
Treat[4]**×Post**	8.864	
	(19.18)	
Withdraw[2]**×Post**[5]		-72.65^{**}
		(27.72)
Reduction[3]**×Post**		−11.11
		(29.01)
Model FE	Yes	Yes
Time FE	Yes	Yes
# of Car Models	804	804
N	9,648	9,648

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard error (in parentheses) are clustered on model-level.
1 Monthly Sales = Number of a particular model of cars that was sold across the country;
2 Withdraw = Car models that belong to *subsidy withdrawal* group;
3 Reduction = Car models that belong to *subsidy reduction* group;
4 Treat = Group were affected by either of treatment types.
5 The variable *Post* is a binary variable that takes the value of 1 for observations occurring after April, and 0 otherwise.

The lack of significant estimates for the overall effects of the policy change might seem surprising. However, by treating all car models affected by the policy change as the *treatment* group, the results overlook potential heterogeneity in responses to policy changes across models. Therefore, in the next subsection, we explore consumer responses in greater detail by examining different levels of subsidy reduction. This approach leverages the variation in subsidy reduction magnitudes across the *withdrawal* group and the *treatment* group.

6.2. Heterogeneity in Treatment Effects

To test our Hypothesis 1 and examine the heterogeneous treatment effects on sales resulting from the policy announced in April 2020, we distinguish between the *withdrawal* group and the *treatment* group as different treatment types in the DD specification. The control group comprises all models unaffected by the policy change, i.e., all cars except those in the *withdrawal* group or *reduction* group.

The results in the right column of Table 3 indicate that the policy announced in April has a significantly negative impact on monthly sales for the *withdrawal* group. EVs in this group experienced a 50% subsidy reduction after April, followed by subsidy withdrawal after July, encountering the most substantial subsidy reduction magnitudes during this policy change. Our findings show that compared to models unaffected by the policy, the policy results in a 72.65 decrease in the number of car sales per month for the model in the *withdrawal* group. We consider the effect size to be substantial, especially considering that the average monthly sales figure is 47.73 for each model in our sample. In contrast, the effect for the *reduction* group is insignificant, explaining the insignificant result when estimated by pooling treatment types together.

In sum, there exists heterogeneity in responses to policy changes across models. Consumers demonstrate high responsiveness to the policy change in the *withdrawal* group, whereas they exhibit little responsiveness to the policy change in the *reduction* group. These findings are consistent with our Hypothesis 1.

Intuitively, when purchase subsidies for EVs are reduced or withdrawn, it leads to a price change, making affected EVs more expensive. EVs in the *withdrawal* group face significant subsidy reductions, sharply increasing their relative prices compared to other models. This prompts consumers to consider alternatives or even refrain from purchasing a car, reducing demand for EVs in this group.

EVs in the *reduction* group experience milder subsidy cuts than the *withdrawal* group. While their relative prices compared to the *withdrawal* group decrease, their prices relative to other cars rise, creating uncertainty in consumer substitution. Some may switch from the *withdrawal* to the *reduction* group due to lower relative prices, while others may abstain from EV purchases due to higher prices compared to other options. Thus, depending on EV differentiation levels, demand for EVs in the *reduction* group may remain stable.

6.3. Robustness Checks

To estimate the heterogeneous treatment effects, our control group comprises all cars unaffected by the policy change announced in April, including those produced by foreign manufacturers. These foreign car models are typically high-end and expensive, and have not been subsidized by the Chinese government. One concern is the comparability of these high-end foreign car models with the domestic cars in our DD regressions.

As a robustness check, we re-estimate the heterogeneous treatment effects on sales using a sample excluding foreign manufacturers, while retaining cars made by joint-venture companies.

Table 4 presents the estimation results, which align with those in Table 3. Thus, our baseline findings remain robust even after excluding models made by foreign makers.

TABLE 4.

Treatment Effect on Monthly Sales (Withdrawal vs. Control, Excluding Foreign Makers)

	Monthly Sales[1]	**Monthly Sales**[1]
Treat[4] $\times$**Post**	-51.36	
	(37.31)	
Withdraw[2] $\times$**Post**[5]		-100.4^{**}
		(37.63)
Reduction[3] $\times$**Post**		-38.90
		(38.86)
Model FE	Yes	Yes
Time FE	Yes	Yes
# of Car Models	746	746
N	8,952	8,952

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard error (in parentheses) are clustered on model-level.
1 Monthly Sales = Number of a particular model of cars that was sold across the country;
2 Withdraw = Car models that belong to *subsidy withdrawal* group;
3 Reduction = Car models that belong to *subsidy reduction* group;
4 Treat = Group were affected by either of treatment types.
5 The variable *Post* is a binary variable that takes the value of 1 for observations occurring after April, and 0 otherwise.

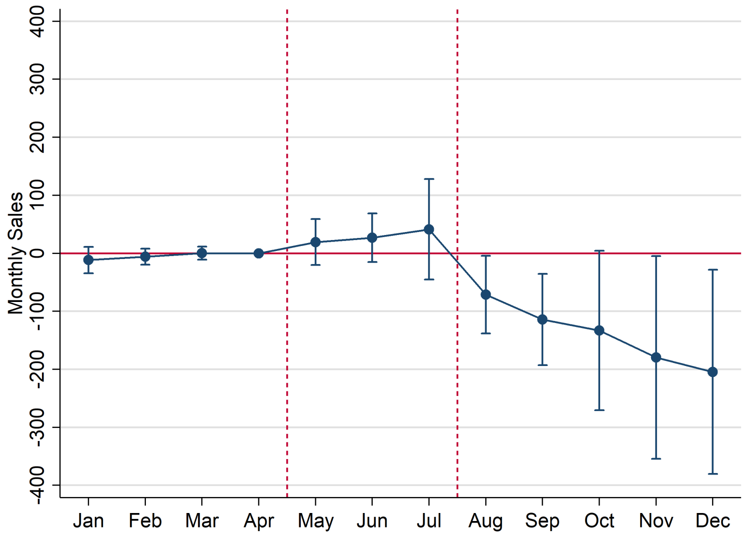
7. INTER-TEMPORAL EFFECTS

In this section, we investigate the presence of inter-temporal effects in consumers' responses to the policy change. Passenger vehicles are typically regarded as durable goods, prompting forward-looking consumers to not only consider current choices, but also weigh the utility of a current or future purchase. The policy announced in April reduced subsidies for EVs in the *withdrawal* group in two stages: a 50% reduction after April, followed by complete withdrawal after July. How might consumers react to a subsidy scheme with a dynamic feature? In the following subsections, we aim to address this question and present evidence of the existence of inter-temporal effects.

7.1. Evidence from the Dynamic Treatment Effects

To examine the inter-temporal effects and empirically test Hypothesis 2, we start by analyzing the dynamic treatment effects on monthly sales, with the *withdrawal* group as the treatment group and the control group comprising cars unaffected by the policy change. Figure 5 displays the results, with confidence intervals calculated at a 99% level. Prior to April, the estimated effects validate the "parallel trend" assumption, strengthening the credibility of our empirical approach. We find a notable and negative impact on monthly sales after July, with the effect size increasing over time. However, between April and July, we observe no significant effect on monthly sales of models in the *withdrawal* group.

FIG. 5. Dynamic Treatment Effects on Monthly Sales (Withdrawal vs. Control, Baseline)

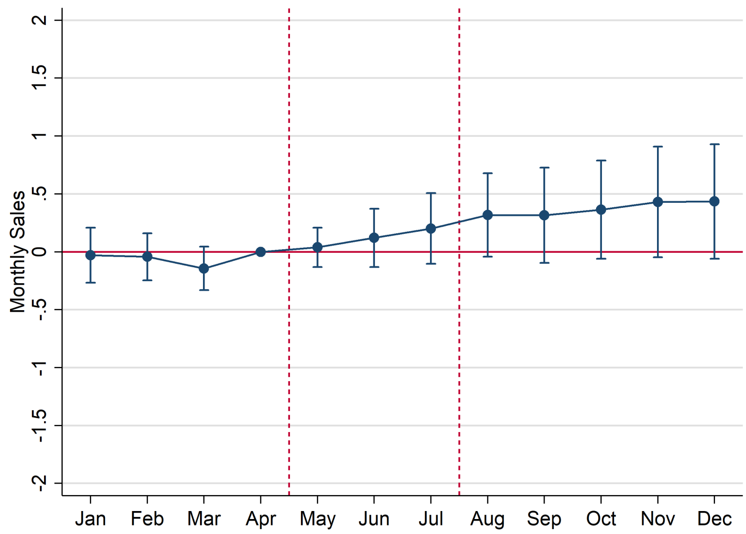


The results may appear puzzling at first glance. Despite the subsidy reductions being of equal magnitude in April and July, why do we observe no significant effects between April and July, but a substantial and negative impact after July? We interpret these findings as evidence of inter-temporal effects, which is consistent with Hypothesis 2 of our theoretical model.

In April, EVs in the *withdrawal* group encountered a 50% subsidy reduction, diminishing consumer incentives for purchasing these vehicles. Anticipating additional subsidy cuts in July, consumers expected future prices of these EVs to rise relative to current prices. As a result, forward-looking consumers intending to buy later in the year were spurred to make their purchases ahead of time, before July. These dynamics of temporal and inter-temporal effects could offset each other, potentially resulting in insignificant changes in quantities between April and July.

We also analyze the dynamic treatment effects on monthly sales, with the *reduction* group as the treatment group and the control group comprising cars unaffected by this policy change. Figure 6 presents the dynamic treatment effects on monthly sales with 99% confidence intervals. Again, the results indicate consistent insignificant impacts of the policy change across time periods, consistent with the results of the DD regression. There are no inter-temporal effects for this group because the policy announced in April immediately reduced the subsidy for these EVs by 10%, with no further changes until the end of the year. Consequently, consumers expected the prices for the *reduction* group to remain relatively stable throughout the year.

FIG. 6. Dynamic Treatment Effects on Monthly Sales (Reduction vs. Control)



7.2. Evidence from the DD Estimation

To provide further evidence of the existence of inter-temporal effects, we conduct the following DD estimation:

$$MonthlySales_{it} = \alpha_i + \lambda_t + \beta Withdrawal_i \times Trans_t + \gamma Reduction_i \times Trans_t + \epsilon_{it}$$

where $Withdrawal_i$ and $Reduction_i$ indicate the *withdrawal* group and the *reduction* group respectively. $Trans_t$ indicates observations occurring during the transition period between April and July. To facilitate interpretation, we constrain the sample post-April, thereby excluding any comparison before the subsidy reduction.

TABLE 5.

Treatment Effect on Monthly Sales(Withdrawal vs. Reduction vs. Control)

	Monthly Sales[1]
Withdrawal[2]**×Trans**[4]	169.8***
	(43.41)
Reduction[3]**×Trans**	32.23
	(41.73)
Model FE	Yes
Time FE	Yes
# of Car Models	804
N	6,432

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard error (in parentheses) are clustered on model-level.
1 Monthly Sales = Number of a particular model of cars that was sold across the country;
2 Withdraw = Car models that belong to *subsidy withdrawal* group;
3 Reduction = Car models that belong to *subsidy reduction* group;
4 The variable $Trans$ is a binary variable that takes the value of 1 for observations occurring before July, and 0 otherwise.

As discussed in the previous subsection, the two-stage phaseout design for the *withdrawal* group could induce inter-temporal effects: Consumers may anticipate higher prices after July and opt to purchase cars in advance. In contrast, the policy design for the *reduction* group would not have this inter-temporal effect, as consumers expect relatively stable prices. If inter-temporal effects exist for the *withdrawal* group, we would observe a significantly positive estimate of β and an insignificant estimate of γ. Table 5 presents the estimation results. The estimated coefficient $\widehat{\beta}$ is 169.8 and statistically significant (with a standard error of 43.41), while the estimated coefficient $\widehat{\gamma}$ is 32.23 and statistically insignificant (with a standard error of 41.73). These findings suggest the presence of inter-temporal effects specifically for the *withdrawal* group.

8. CONCLUSION

In summary, our study investigates how consumers respond to the 2020 phase-out plan for EV subsidies in China. We find that consumers show varying degrees of responsiveness to the subsidy changes, with significant impacts observed in the group facing subsidy withdrawal. Additionally, we identify forward-looking behavior among consumers, who adjust their purchasing decisions in anticipation of future subsidy cuts.

These findings underscore the importance of considering both temporal dynamics and subsidy levels in policy design. By shedding light on consumer behavior and market dynamics, our study provides valuable insights for policymakers navigating the evolving landscape of EV subsidies and sustainability initiatives.

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