Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Terminated local subsidy on electric vehicle adoption during the COVID-19 pandemic: The case of Chongqing City

Xiang Zhang a,b,⁎, Xiaoming Hu a,b,⁎, Liang Qi c

a School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China
b Sustainable Development Research Institute for Economy and Society of Beijing, Beijing 100081, China
c China Automotive Technology & Research Center Co., Ltd., 68# Xianfeng East Road, Dongli District, Tianjin 300300, China

ARTICLE INFO

Keywords:
Subsidy cessation
The COVID-19 pandemic
Policy evaluation
Revised synthetic control method
Electric vehicle

ABSTRACT

Chongqing, one of the four municipalities directly under the Central Government in China, terminated local subsidies for electric vehicles (EVs) on June 26, 2019. Shortly after the termination, EV adoption in China was affected by the coronavirus disease (COVID-19) pandemic. However, little research studies on whether the terminated local subsidy has a lasting impact on EV adoption, especially during the pandemic. Using EV adoption data from Chongqing and 44 other cities in China, this study aims to fill this gap by first proposing a new method to estimate the unobservable data of the treated unit in the preintervention periods to obtain accurate results. This study then also estimates unobservable data for more conservative results. The findings show that the terminated subsidy has had a significant positive impact on EV adoption during the COVID-19 pandemic compared to the situation where a local subsidy was never provided. The results show that in Chongqing, during the first five months of the pandemic, terminated local subsidy helped reduce the loss of EV adoption by approximately 3141 units when accurately estimated, and approximately 1696 units when more conservatively estimated. These findings help to understand the role of subsidies both during implementation and after their termination.

1. Introduction

Many countries provide subsidies of various forms to promote the use of electric vehicles (EVs). In 2020, major countries spent 14 billion US dollars in EV subsidies [1]. China has implemented incentive-based subsidy policies in pilot cities since 2009 and has expanded covering the entire country since 2016. This has promoted EV adoption in China remarkably. Since 2015, China has ranked number one in the world in terms of EV adoption. EV adoption refers to the purchase and use of electric vehicles by both institutions and individuals [2,3]. However, excessive subsidies may lead to local protectionism, subsidy dependence problems, and financial pressure [4,5]. Hence China terminated local purchase subsidies for EVs except for electric buses on June 26, 2019 [4].

Shortly after the local subsidy termination, EV adoption in China encountered the coronavirus disease (COVID-19) pandemic. In response to the pandemic, governments adopted prevention and control measures, such as quarantine and restrictions on external borders, non-essential businesses, and travel [6,7] that lasted several months, affecting the production, circulation, and consumption of EVs [8].

Compared with the situation where there has never had a subsidy, will the once existed subsidy have different impacts on EV adoption, especially during the pandemic? The answer to this question is important because, on the one hand, it could reveal policy effectiveness after a subsidy is terminated, especially during the COVID-19 pandemic; on the other hand, it could help formulate more accurate subsidy phasing out or cessation strategies to cope with the pandemic and other market challenges. However, earlier research focused on evaluating the effectiveness of existing subsidy policies, (cf. [9,10]). Ignorance of subsidy termination may lead to underestimating the overall effectiveness of incentive policies, and may bias future subsidy strategies.

We answer the above question with a case study of Chongqing City.

⁎ Corresponding author. 5# Zhong-guan-cun South Street, Haidian District, Beijing 100081, China.
E-mail addresses: xiangzhang@bit.edu.cn (X. Zhang), 3120215805@bit.edu.cn (X. Hu), qiliang@catarc.ac.cn (L. Qi).
1 The first two authors (i.e. Xiang Zhang and Xiaoming Hu) contribute equally to this study.
2 In this study, the local subsidies refer to economic incentives announced and implemented by local provincial and municipal government agencies to subsidize consumers for the promotion of EVs. Not all cities provided local subsidies in China.

https://doi.org/10.1016/j.energy.2022.124891
Received 9 October 2021; Received in revised form 16 July 2022; Accepted 18 July 2022
Available online 4 August 2022
0360-5442/© 2022 Elsevier Ltd. All rights reserved.
Chongqing has provided local subsidies since 2009, with a target to promote 1150 EVs by the end of 2011. From 2016, local subsidies have been provided to EVs that meet the standards,\(^5\)\(^6\)\(^7\). Their local purchase subsidies\(^8\) were terminated on June 26, 2019 \[^4\]. Shortly after termination, Chongqing announced prevention and control measures owing to COVID-19. Adoption of EVs in Chongqing dramatically dropped from the previous month,\(^9\) with a monthly decrease rate of 78.43% in February 2020.

The difference between EV adoptions under the terminated- and never-subsidy conditions can reveal the impact of once-existent subsidy on EV adoption, especially during the pandemic. We adopt a counterfactual framework design to analyze the outcome of EV adoption during the pandemic to uncover the difference. If a sample city had local subsidy before the pandemic and terminated it thereafter, then EV adoption in that city falls under the terminated-subsidy condition; if a sample city has never had local subsidy during the study period, then it falls under the never-subsidy condition.

A widely used method is the synthetic control method (SCM). However, the traditional SCM cannot be directly used because the never-subsidized EV adoption data prior to COVID-19 cannot be observed in the treated unit. Thus, we design two ways of estimating the treated unit’s data. First, we propose a new method of estimating the data of the treated unit that was unobservable in preintervention periods to get more accurate results. Second, we also estimate unobservable data for more conservative results. The results show that although the local subsidy provided by Chongqing has been terminated, it has lasting positive impact on local EV adoption by reducing the loss of EV adoption during the first five months of the pandemic by approximately 3141 units when accurately estimated, and 1696 units when conservatively estimated.

The rest of this paper is organized as follows. Section 2 presents the literature review. Section 3 proposes the new method and describes the data and samples. The impact of the terminated subsidy on EV adoption during the pandemic is analyzed in Section 4. Finally, Section 5 discusses the results and draws conclusions of the study.

2. Literature review

Earlier studies on policy effectiveness mainly focused on evaluating the effectiveness of existing incentive policies. Zhang and Bai \[^5\] proposed and adopted a policy dependency mapping method to reveal the incentive policy system for EV adoption in China. Ma et al. evaluated the incentive policies of six license plate-restricted cities in China from 2011 to 2016 \[^9\]. The results show that subsidy policy positively impacted EV adoption. However, Qiu et al.’s evaluation of incentive policies in the pilot cities shows that subsidy policy did not significantly impact EV adoption during 2014–2015 \[^10\]. One reason might be subsidy fraud behavior at that time. Policy evaluation studies of 50 states in the United States found that economic incentive policies, including tax rebates or credits, could significantly increase the number of EV registrations \[^11,12\].

Some studies noted local subsidy termination in China. Ji et al. studied the dynamic evolution of EV industry under the gradual cancellation and non-cancellation of subsidy scenarios using simulation \[^13\]. Basu et al. showed that subsidy cessation will lead to a substantial decline in China’s EV market share by more than 40% \[^14\]. Lu et al. using survey data studied the effect of several alternative incentive policies on EV adoption after subsidies ceased and found significantly negative impacts on consumers’ EV purchase probability from the removal of purchase subsidy \[^15\]. However, due to different research focus, they did not consider whether terminated subsidies have a lasting effect.

Some studies have analyzed the impacts of the pandemic on the EV industry \[^16,17\]. Owing to the different research focus, these studies did not empirically assess subsidy termination, nor the joint influence of subsidy termination and the pandemic on EV adoption.

This study uses Chongqing as a case to demonstrate the lasting influence of the terminated subsidy on EV adoption which differs from earlier research that focused on the evaluation of existing EV policy. Furthermore, this study proposes a method for estimating the data of the treated unit that was unobservable in the pre-intervention periods.

3. Data and methodologies

3.1. Data and samples

Monthly EV adoption panel data for 45 cities from January 2019 to June 2020 were obtained from the China Automotive Technology and Research Center Co. Ltd. We selected Chongqing as the treated unit for the counterfactual analysis because Chongqing was one of the first cities to provide local subsidy and once provided local subsidy\(^7\) from January to June 26, 2019. Also, the Chengdu-Chongqing region is one of the four major urban agglomerations for EV adoption in China. EV adoption in the city ranked at the 17th among all Chinese cities in 2019. The control units were 44 cities with no municipal purchase subsidies during the study period. They were selected in order of their 2019 EV adoption ranking, ranging from high to low. The EV adoption for the 45 cities is presented in Appendix 1.

Local subsidy policies were collected from open channels and the official websites of relevant local government agencies (e.g., the local Development and Reform Commission and the Local Bureau of Statistics).

Following the COVID-19 outbreak in 2020, most provincial Health Commissions initiated the first-level Public Health Emergency Response on January 24 and 25, 2020; various provinces and subordinate cities adopted its restriction measures. Hence, we took February 2020 as the time when EV adoption in various cities began to suffer because of the pandemic. Later, in May 2020, some places started to initiate necessary measures to resume production. Hence, we collected data up to the end of June 2020 to avoid unnecessary intervention.

The outcome variable in this study was the monthly EV adoption in thousands of units per city. The predictor variables included gasoline price \[^9\], air temperature, natural logarithm of monthly per capita disposable income (InPCDI), and Nitrogen Dioxide (NO\(_2\)) \[^18\]. Their

\(^2\) Chongqing Science and Technology Bureau, Chongqing Municipal Bureau of Finance. Measures and Procedures for the Implementation of Financial Subsidies for the Purchase of New Energy Vehicles in Chongqing (for Trial Implementation) (No. Yukewifa (2009)147), October 12, 2009.

\(^3\) City Office of Chongqing Municipal People’s Government. The Implementation Opinions on Accelerating Promotion of the Application of New Energy Vehicles (No. Yufubanfa (2016)260), December 16, 2016.

\(^4\) Chongqing Municipal Finance Bureau, Chongqing Municipal Commission of Economy and Information. The Circular on Financial Subsidy Policies for Promotion and Application of New Energy Vehicles in 2017 (No. Yucaichanye (2017)188), July 10, 2017.

\(^5\) Chongqing Municipal Finance Bureau. The Circular on Financial Subsidy Policies for Promotion and Application of New Energy Vehicles in 2018 (No. Yucaichanye (2018)52), April 24, 2018.

\(^6\) Chongqing Municipal Finance Bureau, Chongqing Municipal Commission of Economy and Information, Chongqing Municipal Bureau of Energy. The Circular on Printing and Issuing the Financial Subsidy Policies for Promotion and Application of New Energy Vehicles in 2019 (No.Yucaigui (2019)10), May 28, 2019.

\(^7\) Chongqing Municipal Finance Bureau, Chongqing Municipal Commission of Economy and Information, Chongqing Municipal Bureau of Energy. The Circular on Printing and Issuing the Financial Subsidy Policies for Promotion and Application of New Energy Vehicles in 2019 (No.Yucaigui (2019)10), May 28, 2019.
descriptions are presented in Table 1. Two lagged EV adoption (i.e., the 9th and 12th month adoption) were also used as predictor variables in the synthetic process.

3.2. The proposed estimation method

Suppose the EV adoption outcome, \( Y \), can be observed in the \( t \)th city in the \( t \)th month, where \( t = 1, \ldots, n + 1 \) and \( t = 1, \ldots, T \); \( T \) is defined as the intervention point, which represents the month when COVID-19 began (i.e., February 2020). Without loss of generality, suppose the first city is Chongqing. The \( n + 1 \) cities all suffered from COVID-19 after \( T \). The difference was that Chongqing, as the treated unit, once issued local subsidy and was under the terminated-subsidy condition after \( T \). The other \( n \) cities as the control units had not issued subsidy and were under the never-subsidy condition.

To assess the intervention effects of the terminated subsidy during the pandemic, we need to know the differences between Chongqing’s EV adoption under both the terminated- and never-subsidy conditions, \( Y^n_t \) and \( Y^0_t \), respectively. According to the SCM, Chongqing should not be intervened by the terminated subsidy before COVID-19. However, Chongqing was exposed to the terminated subsidy before the COVID-19 pandemic, and the counterfactual EV adoption \( Y^0_t \) in Chongqing that had not provided local subsidy could not be observed. Therefore, we designed two scenarios (Scenario 1 and 2) and estimated the relevant adoption \( Y^{11}_{t^1} \) and \( Y^{01}_{t^1} \) in pre-intervention periods to approximate \( Y^0_{t^1} \), as shown in Fig. 1.

In Scenario 1, we aimed to estimate the data of EV adoption \( Y^1_{t^1} \) under the no-subsidy condition to approximate \( Y^0_{t^1} \). The no-subsidy condition means that the city did not implement an EV subsidy in the current period and does not emphasize whether it has ever issued one. This adoption \( Y^{11}_{t^1} \) was obtained by applying a separate SCM using data from January to December 2019.

In the separate SCM, let \( T_0 \) be the intervention point, which represents the month when local subsidy was terminated. The city was in the intervention period when \( 1 < t < T_0 \) because Chongqing had provided local subsidy from January to June 2019. When \( T_0 < t < T \), Chongqing no longer provided local subsidy. This differs from the traditional SCM which defines the intervention period after the intervention point.

Using the treated unit Chongqing and the 44 untreated units during the pre-intervention periods, we fitted the synthetic adoption of the treated unit under the no-subsidy condition during the entire analysis period. The pre-intervention EV adoption data was used in the SCM to select matching cities and corresponding weights that could best reflect the changing trend of Chongqing’s adoption from the donor pool, thereby constructing a synthetic Chongqing that was “not exposed to the intervention.” See Appendix 2 for the SCM results plot, treatment effect, and placebo test. The matching results showed that if Chongqing did not issue a municipal subsidy policy from January to June 2019, its counterfactual adoption could be reproduced through the combination of the three cities of Foshan, Jinan, and Guiyang, as shown in Table 2. The weights of the other cities in the donor pool were all assigned zero.

Using the matching cities and weights, the specific synthetic adoption under the no-subsidy condition were calculated. The results are presented in Table 3. The results show that if Chongqing had not implemented the local subsidy policy from January to June 2019, the city’s EV adoption would have decreased by 9,673, of which 6562 vehicles would have been lost in June alone. This shows that the subsidy had a positive effect on EV adoption during its existence.

The synthetic Chongqing EV adoption obtained by the separate SCM (in Table 3) is \( Y^{11}_{t^1} \) under the no-subsidy condition. We then used it to approximate \( Y^0_{t^1} \). However, \( Y^{11}_{t^1} \) under the no-subsidy condition was larger than the EV adoption \( Y^0_{t^1} \) under the never-subsidy condition in pre-intervention periods. Thus, when using \( Y^{11}_{t^1} \) to substitute into the SCM, the gap between the synthetic and actual adoption was relatively

| Table 1: Main predictor variables. |
|-----------------------------------|
| Variables | Definition | Data processing | Data sources |
|----------|------------|-----------------|--------------|
| gasoline price | monthly average gasoline price released by each province | weighted average gasoline price | Eastmoney http://data.eastmoney.com/cjsj/oil_default.html; Jintou Network http://lishi.tianqi.com |
| lnPCDI | natural log value of monthly per capita disposable income | obtained by taking the natural logarithm of the average of quarterly disposable income per capita | local Bureau of Statistics and local investigation team of National Bureau of Statistics |
| temperature | monthly average minimum air temperature | - | - |
| NOx | monthly NOx contents in air | - | - |
| PM2.5 | daily contents of PM2.5 in air | - | - |
smaller than reality. Thus, the positive effect of the terminated subsidy during COVID-19 was relatively underestimated. Therefore, the positive effect we found was an approximation and was smaller than the true value.

In Scenario 2, we aimed to use the actual EV adoption \( Y_{it}^{2nd} \) under the terminated-subsidy condition to approximate \( Y_{it}^{1st} \). Since \( Y_{it}^{2nd} \) was larger than \( Y_{it}^{1st} \) in Scenario 1, the gap between the synthetic and actual adoption was relatively smaller than in Scenario 1. Thus, the positive effect of the terminated subsidy during the pandemic was relatively smaller than in Scenario 1. We defined the impact of the terminated subsidy measured in Scenario 2 as a conservative result.

After obtaining \( Y_{it}^{2nd} \), we used it and the control units under the never-subsidy condition in the pre-intervention periods for fitting. Then we estimated the synthetic adoption of Chongqing that had never issued subsidy by applying the SCM [19,20].

### 3.3. The models

In this study, the following model (1) estimated the counterfactual synthetic adoption \( Y_{it}^{0} \) when Chongqing was not subject to intervention.

\[
Y_{it}^{0} = \delta_i + \theta t_i + Z_i \lambda_i + \epsilon_{it}, \quad t = 1, \ldots, T
\]

Among them, \( \delta_i \) is an unknown common factor, which has the same effect on all individuals. \( Z_i \) is a \((K \times 1)\) vector of observable covariates, and \( \theta t_i \) is a \((1 \times T)\) vector of unknown parameters. \( \lambda_i \) is a \((1 \times F)\) vector of unobserved common factors, and \( \mu_{it} \) is an \((F \times 1)\) vector of unobserved regional fixed effects. \( \epsilon_{it} \) is an unobserved temporary shock with a mean value of zero at the city level.

To estimate the impact of a local subsidy on EV adoption in Chongqing, it was necessary to estimate the EV adoption \( Y_{it}^{1st} \) when Chongqing had not implemented the local subsidy policy. Abadie et al. proposed to consider an \((n \times 1)\) weight vector \( W = (w_2, \ldots, w_{n+1}) \) satisfying \( w_j \geq 0, j = 2, \ldots, n + 1, \) and \( w_2 + \ldots + w_{n+1} = 1 \) [19]. Each weight vector \( W \) represented a synthetic control of the first city. By weighting the variable value of each control unit, we can have the following model (2):

\[
\sum_{j=2}^{n+1} w_j Y_{it} = \delta_i + \theta_t \sum_{j=2}^{n} w_j Z_j + \lambda_i \sum_{j=2}^{n+1} w_j \beta_j + \sum_{j=2}^{n+1} w_j \epsilon_{it}.
\]  

Suppose there is a weight vector \( W^* = (w_2^*, \ldots, w_{n+1}^*) \), such that

\[
\sum_{j=2}^{n+1} w_j^* Y_{it} = Y_{t1}, \quad \sum_{j=2}^{n+1} w_j^* Z_j = Z_1.
\]

If \( \sum_{j=2}^{n+1} \lambda_j^* \alpha^*_j \) is nonsingular, then

\[
\sum_{j=2}^{n+1} w_j^* Y_{it} = \sum_{j=2}^{n+1} w_j^* \beta_j + \sum_{j=2}^{n+1} w_j^* \epsilon_{it}^* - \sum_{j=2}^{n+1} w_j^* (\epsilon_{it}^* - \epsilon_{it}^1) - \sum_{j=2}^{n+1} w_j^* (\epsilon_{it}^1 - \epsilon_{it}^2).
\]

When the period before the intervention was long enough, Eq. (4) approached zero. Therefore, the counterfactual result of the first city exposed to the intervention could be approximated by a synthetic control group,

\[
\tilde{Y}_{it}^{0} = \sum_{j=2}^{n+1} w_j^* Y_{it}.
\]

Hence, the policy intervention effect of the first city exposed to the intervention can be expressed as follows:

\[
\tilde{Y}_{it} = Y_{it} - \sum_{j=2}^{n+1} w_j^* Y_{it}, \quad t = 1, \ldots, T_{t1} - 1.
\]

The key to find \( \tilde{Y}_{it} \) was to find the weight vector \( W^* \) that made Eq. (3) hold. Let \( X_1 \) be the \((M \times 1)\) vector of pre-intervention characteristics for

### Table 2
Matching cities and weights of Chongqing.

| City     | Weights |
|----------|---------|
| Foshan   | 0.289   |
| Jinan    | 0.365   |
| Guiyang  | 0.347   |

### Table 3
Actual and synthetic EV adoption of Chongqing.

| Month      | Jan 2019 | Feb  | Mar  | Apr  | May  | Jun  | Jul  | Aug  | Sep  | Oct  | Nov  | Dec 2019 |
|------------|----------|------|------|------|------|------|------|------|------|------|------|---------|
| Actual     | 1299     | 490  | 1170 | 405  | 853  | 6987 | 498  | 425  | 88   | 99   | 202   | 158     |
| Synthetic  | 291      | 132  | 224  | 120  | 339  | 425  | 88   | 99   | 202  | 158  | 175   | 144     |
| Differences| 1008     | 358  | 946  | 285  | 514  | 6562 | 410  | 326  | 284  | 251  | 368   | 798     |

Fig. 1. The proposed estimation method.
the treated units, and $X_0$ be the $(M \times N)$ vector of pre-intervention characteristics for the untreated units. The weight $W$ was determined by minimizing the distance between $X_1$ and $X_0W$:

$$
\min \|X_0 - X_0W\| = \min \sqrt{(X_1 - X_0W)^T V(X_1 - X_0W)},
$$

subject to $w_1 \geq 0, \ldots, w_{n+1} \geq 0$, $w_2 + w_3 + \ldots + w_{n+1} = 1$.

Among them, $V$ is an $(M \times N)$ symmetric and positive semidefinite matrix. We adopted the SCM [19] to obtain the optimal $V$, so that the synthetic city can approximate the changing trajectory of EV adoption in Chongqing in pre-intervention periods.

4. Impacts of terminated local subsidy

In this section, we analyze the terminated local subsidy’s impact using data from July 2019 to June 2020. As intervention effects are evaluated in two scenarios as analyzed in Section 3.2, we assessed the influences first, under Scenario 1 in Section 4.1, and second, under Scenario 2 in Section 4.2. The results in Sections 4.1 and 4.2 show the intervention of the terminated subsidy on EV adoption during the pandemic. The relevant placebo test results are reported in Section 4.3.

4.1. Intervention effects under scenario 1

Chongqing’s EV adoption data under the no-subsidy condition in the pre-intervention periods were used as $Y_{10}$ in the SCM. The matching cities that best reflected the adoption trend and corresponding weights were estimated from the donor pool, as shown in Table 4. The weights reported in Table 4 show that if Chongqing had not issued a subsidy policy, its counterfactual adoption could have been reproduced through the combination of five cities, i.e., Foshan, Zhuhai, Maanshan, Liaocheng, and Mianyang. The weights of the other cities in the donor pool were all assigned zero.

The differences between the synthetic EV adoption if Chongqing had not issued subsidy and the actual EV adoption were obtained, as illustrated in Fig. 2. The solid line represents the actual EV adoption in Chongqing, and the dashed line represents the synthetic adoption trend. Before the COVID-19 outbreak (July 2019 to January 2020), the synthetic EV adoption trajectory in Chongqing almost overlapped with that of the actual EV adoption, showing that the matching cities participating in the fitting well represented the EV adoption trend in Chongqing where there had been no subsidy. The gap between the solid and dashed lines from February to June 2020 constitutes the additional loss in EV adoption during the pandemic if no subsidy had existed in Chongqing.

Fig. 3 shows the treatment effect on Chongqing. The treatment effect is the difference between the actual EV adoption and synthetic EV adoption in Chongqing. It reflects the impacts of the terminated subsidy on EV adoption during COVID-19.

Synthetic EV adoption was calculated as per matching results and weights, as shown in Table 5. The results showed that Chongqing would have lost an additional 3141 cumulative units in EV adoption during the pandemic if the city had not provided local subsidy. The relevant placebo test was conducted, and the results are presented in Section 4.3.

4.2. Intervention effects under scenario 2

Here Chongqing’s actual EV adoption data under the terminated-subsidy condition in pre-intervention periods were used as $Y_{20}$ in the SCM. The matching cities are shown in Table 6. The weights reported in Table 6 show that if Chongqing had not issued the subsidy policy, its counterfactual adoption could have been reproduced through the combination of four cities, which are Foshan, Jinan, Jining, and Guiyang. The weights of the other cities in the donor pool were all assigned zero.

The differences between the synthetic EV adoption if Chongqing had not issued subsidy and the actual EV adoption in Chongqing under the terminated-subsidy condition were obtained and are illustrated in Fig. 4. The treatment effect of Chongqing is illustrated in Fig. 5. Similar to the results in Section 4.1, the results in Figs. 4 and 5 show that actual EV adoption was significantly higher than synthetic EV adoption during the pandemic.

Synthetic EV adoption was calculated as per matching results and weights, as shown in Table 7. The results showed that Chongqing would lose an additional 1696 cumulative units during the first five months of the pandemic if the city had not provided local subsidy. This results a conservative estimate due to $Y_{20}^{CE}$. For details, see Section 3.2. The relevant placebo test was carried out and the results are presented in Section 4.3.

We compared the intervention results of the terminated subsidy on
EV adoption during the pandemic in Sections 4.1 and 4.2, as shown in Fig. 6. The upper solid line represents the intervention effect on EV adoption in Scenario 1 and the lower dashed line represents the intervention effect on EV adoption in Scenario 2. In Scenario 1, we estimated accurate intervention data, and in Scenario 2, we estimated conservative intervention data. The cumulative adoption of the two lines from February to June 2020 corresponded to 3141 and 1696, respectively. The difference between the two lines for each month is the estimated intervention difference between the two scenarios.

4.3. Placebo test results

To test whether the analysis results in previous Sections 4.1 and 4.2 were reliable, placebo tests were performed. This study took each city in the donor pool as the hypothetical treated unit in turn, treated the original treated unit as part of the control units and used the SCM to estimate the "intervention effect." By comparing the differences in treatment effect between the actual and hypothetical treated unit, we can know whether the actual policy intervention is reliable. If a large gap existed between the treatment effect of the hypothetical and actual treated units in the placebo test, it indicated that the intervention results obtained were effective.

4.3.1. A. Placebo test results under Scenario 1

The results of the placebo test under Scenario 1 are shown in Fig. 7. The solid orange line represents the treatment effect of Chongqing, and the dashed gray ones represent the treatment effect of several control cities. The treatment effect of Chongqing from February to June 2020 (during COVID-19) was significantly larger than that of the control cities. The error measured by the placebo test was 2.63%. In other words, there was only a 2.63% probability of such a large gap between the synthetic and actual EV adoption in Chongqing. Thus, the change in Chongqing’s EV adoption was significant at the 5% level, and the evaluation results obtained using the SCM were reliable.

4.3.2. B. Placebo test results under Scenario 2

The result of the placebo tests under Scenario 2 are shown in Fig. 8. The solid orange line represents the treatment effect of Chongqing, and the dashed gray ones represent the treatment effect of the several control cities. The treatment effect of Chongqing from February to June 2020 (during COVID-19) was significantly larger than that of the control cities. The error measured by the placebo test was 2.63%. Thus, the change in Chongqing’s EV adoption was significant at the 5% level, and the evaluation results obtained using the SCM were reliable.

5. Discussion and concluding remarks

Earlier studies on subsidy termination claim that subsidy removal leads to reduced production and consumption of target goods and...
negatively impacts the capital market [21]. Few studies have focused on whether terminated subsidies have lasting influences. In this study, we evaluated the influence of terminated subsidy on EV adoption during the pandemic. When using SCM, we designed two ways of estimating the unobservable treated unit’s data in the pre-intervention periods. We first proposed a new method for estimating the unobservable data of the treated unit for accurate results. We then also estimate unobservable data for more conservative results.

We found that compared with the situation where there had never been a local subsidy, the once-existed local subsidy policy had lasting positive influences on EV adoption, especially during the pandemic. Taking Chongqing as an example, our results show that the once existed subsidy reduced the loss of EV adoption by approximately 3141 units when accurately estimated, and approximately 1696 units when conservatively estimated during the first five months of the pandemic.

To the best of our knowledge, there is no literature that can be directly compared to our findings. Nevertheless, parts of our findings are consistent with literature. Our study shows Chongqing’s local subsidy played a positive role during its existence, which helped promote 9673 additional EVs from January to June 2019. Earlier studies also show that purchase subsidy has significant positive impacts on EV adoption (e.g. Ref. [9]). Our findings show that the removal of local subsidy in Chongqing led to a dramatic drop in EV adoption. Using the stated preference survey data, Lu et al. found similar results that consumer’s EV purchase probability decreased from 47.52% to 12.43% when the per unit subsidy of 32,500 was removed [15].

Our findings also generate important implications for policy making and assessment in the future. First, local subsidy has a lasting positive influence after cessation in addition to the positive influence during its existence. The lasting positive influences alleviate to a certain degree the negative impacts of the pandemic on EV adoption. Hence future policy assessment is recommended to consider the lasting influences of the terminated subsidy. Second, local governments that have not provided subsidies need to consider additional measures if they want to achieve the same EV adoption level during the pandemic.

This paper considers air temperature, gasoline price, per capita disposable income, and NO\textsubscript{2} content in the air in the prediction of EV adoption.
adoption. However, the influential factors of EV adoption are complex, including geographical location and local industry development, to name a few. In the future, more factors can be considered to make the research results more comprehensive. In addition, a large sample of data can be collected to further reveal and verify the influence of subsidy termination.

Credit author statement

Xiang Zhang: Conceptualization, Research design, Methodology, Data analysis, Writing – review and revision, Supervision, Funding acquisition. Xiaoming Hu: Conceptualization, Research design, Methodology, Data collection and analysis, Software, Writing – original draft and revision. Liang Qi: Data collection, Writing – revision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgments

The authors acknowledge support received from the National Natural Science Foundation of China (Nos. 71872012 and 71521002), and Special Fund of the Beijing Municipal Commission of Education (No. 20162139016 and the following Funds).

Appendix 1

Table A1
The 45 sample cities and description of monthly EV adoption from January 2019 to June 2020 (in 1000 EVs)

| city               | id  | Mean values | Std. Dev. | Min.  | Max.  |
|--------------------|-----|-------------|-----------|-------|-------|
| Chongqing in Scenario 1 | 1   | 0.466       | 0.450147  | 0.088 | 1.332 |
| Chongqing in Scenario 2 | 1   | 0.718583    | 0.370375  | 0.157 | 1.332 |
| Qingdao            | 2   | 0.67275     | 0.251829  | 0.127 | 1.09  |
| Baoding            | 3   | 0.177333    | 0.078924  | 0.004 | 0.295 |
| Weifang            | 4   | 0.23375     | 0.256845  | 0.009 | 0.989 |
| Shijiazhuang       | 5   | 0.384667    | 0.143614  | 0.039 | 0.578 |
| Foshan             | 6   | 0.526833    | 0.331482  | 0.151 | 1.167 |
| Dezhou             | 7   | 0.084833    | 0.037351  | 0.047 | 0.183 |
| Jinan              | 8   | 0.601083    | 0.432997  | 0.058 | 1.558 |
| Zhongshan          | 9   | 0.1295      | 0.086275  | 0.012 | 0.369 |
| Jinghua            | 10  | 0.352667    | 0.17958   | 0.066 | 0.697 |
| Jinan              | 11  | 0.4335      | 0.284269  | 0.012 | 1.153 |
| Guiyang            | 12  | 0.238833    | 0.108303  | 0.022 | 0.388 |
| Jiaxing            | 13  | 0.223167    | 0.14884   | 0.024 | 0.561 |
| Huizhou            | 14  | 0.262917    | 0.140337  | 0.016 | 0.603 |
| Xingtai            | 15  | 0.173667    | 0.075637  | 0.013 | 0.307 |
| Linyi              | 16  | 0.194167    | 0.094944  | 0.011 | 0.413 |
| Handan             | 17  | 0.15075     | 0.066424  | 0.014 | 0.289 |
| Langfang           | 18  | 0.10975     | 0.054892  | 0.008 | 0.225 |
| Heze               | 19  | 0.227083    | 0.113042  | 0.023 | 0.491 |
| Yangtai            | 20  | 0.136       | 0.056686  | 0.008 | 0.208 |
| Dalian             | 21  | 0.131083    | 0.077717  | 0.012 | 0.337 |
| Guangzhou          | 22  | 0.150917    | 0.057135  | 0.081 | 0.243 |
| Zhubai             | 23  | 0.137833    | 0.120419  | 0.004 | 0.387 |
| Zibo               | 24  | 0.122       | 0.058147  | 0.014 | 0.257 |
| Maanshan           | 25  | 0.032667    | 0.017834  | 0.003 | 0.063 |
| Zaozhuang          | 26  | 0.134417    | 0.080127  | 0.000 | 0.306 |
| Binhai             | 27  | 0.098417    | 0.036833  | 0.019 | 0.138 |
| Zunyi              | 28  | 0.099583    | 0.043968  | 0.007 | 0.171 |
| Fuyang             | 29  | 0.084083    | 0.044259  | 0.003 | 0.168 |
| Xinzhou            | 30  | 0.079       | 0.080289  | 0.005 | 0.268 |
| Dongying           | 31  | 0.074167    | 0.037973  | 0.022 | 0.168 |
| Wusunqi            | 32  | 0.050417    | 0.03766   | 0     | 0.157 |
| Liaocheng          | 33  | 0.08275     | 0.049688  | 0.004 | 0.195 |
| Mianyang           | 34  | 0.095917    | 0.041908  | 0.02  | 0.186 |
| Weihai             | 35  | 0.061917    | 0.027138  | 0.007 | 0.116 |
| Shiyian            | 36  | 0.060838    | 0.0968    | 0.003 | 0.257 |
| Rizhao             | 37  | 0.070333    | 0.040433  | 0.005 | 0.167 |
| Yichang            | 38  | 0.14083    | 0.164485  | 0     | 0.502 |
| Qianxinan          | 39  | 0.0615      | 0.02895   | 0.014 | 0.111 |
| Yinchuan           | 40  | 0.059167    | 0.029064  | 0.005 | 0.11  |
| Taian              | 41  | 0.061167    | 0.039669  | 0.003 | 0.126 |
| Suzhou             | 42  | 0.059667    | 0.039401  | 0.002 | 0.156 |
| Luonsanhu          | 43  | 0.039167    | 0.021523  | 0.006 | 0.09  |
| Hengshui           | 44  | 0.06575     | 0.041196  | 0.005 | 0.164 |
| Jincheng           | 45  | 0.073417    | 0.04204   | 0.002 | 0.155 |
Appendix 2

The comparison between actual and synthetic EV adoption in Chongqing is shown in Figure A1. In Figure A1, the trajectory of synthetic EV adoption in Chongqing almost overlapped with the actual adoption before the intervention of local subsidy (July to December 2019). This shows that the control cities could well express Chongqing’s adoption that was not exposed to the intervention. The treatment effect of Chongqing is shown in Figure A2.

The placebo test result is displayed in Figure A3. The orange line represents the treatment effect of Chongqing, and the gray line represents the treatment effects of the control cities. The treatment effect of Chongqing from January to June was significantly larger than those of the control cities. The error probability measured by the placebo test for Chongqing was 2.5%, there was only a 2.5% probability of such a big gap in adoption, as with synthetic and actual Chongqing. In other words, the change in EV adoption of Chongqing was significant at the 5% level, so the policy evaluation result obtained by using the SCM was reliable.

---

(1) Before using the SCM to analyze Chongqing, the four cities of Baoding, Zhongshan, Qingdao, and Xinzhou in the donor pool (44 cities) were excluded. When performing the placebo test, city that exceeded Chongqing’s Root Mean Square Prediction Error (RMSPE) value by more than 1 time was excluded (i.e., Weifang). RMSPE measures the degree of fit between a city and its synthetic cities. The above two steps showed that the probability of such a big gap in adoption like synthetic and real Chongqing is 1/40, or 2.5%, in these 45 cities.
Fig. A3. Placebo test to obtain $\gamma^*_k$ in Section 3.2.

References

[1] IEA. EV outlook 2021 - accelerating ambitions despite the pandemic. Paris, France: the International Energy Agency; 2021.
[2] MoF, MoST. The circular on launching the pilot demonstration program for Energy saving and new Energy vehicles No.Caijian[2009]6. Beijing: Ministry of Finance, Ministry of Science and Technology; 2009.
[3] MoF, MoST, MIIT, and NDRC.. The circular on launching the pilot program for subsidizing the private purchasers of new Energy vehicles No.Caijian[2010]230. Beijing: Ministry of Finance, Ministry of Science and Technology, Ministry of Industry and Information Technology, National Development and Reform Commission; 2010.
[4] MoF, MoST, MIIT, NDRC. The circular on further improvement of financial subsidy policy for the promotion and application of new Energy vehicles No.Caijian[2019] 138. Beijing: Ministry of Finance, Ministry of Science and Technology, Ministry of Industry and Information Technology, National Development and Reform Commission; 2019.
[5] Zhang X, Bai X. Incentive policies from 2006 to 2016 and new energy vehicle adoption in 2010–2020 in China. Renew Sustain Energy Rev 2017;70:24–43.
[6] Cheng C, Barceló J, Hartnett AS, Kubinec R, Messerschmidt L. COVID-19 government response event dataset (CoronaNet v.1.0). Nat Human Behav 2020;4(7):756–68.
[7] Hale T, Angrist N, Goldszmidt R, Kira B, Peretherick A, Phillips T, et al. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nat Human Behav 2020;4(7):756–68.
[8] Bhagwati J, Ramaswami VK. Domestic distortions, tariffs and the theory of optimum subsidy. J Polit Econ 1963;71(1):44–50.
[9] Ma SC, Fan Y, Feng L. An evaluation of government incentives for new energy vehicles in China focusing on vehicle purchasing restrictions. Energy Pol 2017;110: 609–18.
[10] Qiu YQ, Zhou P, Sun HC. Assessing the effectiveness of city-level electric vehicle policies in China. Energy Pol 2019;130:22–31.
[11] Jenn A, Springel K, Gopal AR. Effectiveness of electric vehicle incentives in the United States. Energy Pol 2018;119:349–56.
[12] Wei S, Coffman M, La Croix S. Do electric vehicle incentives matter? Evidence from the 50 U.S. states. Res Pol 2018;47(9):1601–10.
[13] Ji SF, Zhao D, Luo RJ. Evolutionary game analysis on local governments and manufacturers’ behavioural strategies: impact of phasing out subsidies for new energy vehicles. Energy 2019;189:116064.
[14] Bao A, Mazumdar T, Raj SP. Indirect network externality effects on product attributes. Market Sci 2003;22(2):209–21.
[15] Lu T, Yao E, Jin F, Yang Y. Analysis of incentive policies for electric vehicle adoptions after the abolishment of purchase subsidy policy. Energy 2022;239: 122136.
[16] Kanda W, Kivimaa P. What opportunities could the COVID-19 outbreak offer for sustainability transitions research on electricity and mobility? Energy Res Soc Sci 2020;68:101666.
[17] Nundy S, Ghosh A, Mesloub A, Albaqawy GA, Alnaim MM. Impact of COVID-19 pandemic on socio-economic, energy-environment and transport sector globally and sustainable development goal (SDG). J Clean Prod 2021;312:127705.
[18] Song C, Wu L, Xie Y, He J, Chen X, Wang T, et al. Air pollution in China: status and spatiotemporal variations. Environ Pollut 2017;227:534–47.
[19] Abadie A, Diamond A, Hainmueller J. Synthetic control methods for comparative case studies: estimating the effect of California’s tobacco control program. J Am Stat Assoc 2010;105(490):493–505.
[20] Abadie A, Gardeazabal J. The economic costs of conflict: a case study of the Basque Country. Am Econ Rev 2003;93(1):113–32.
[21] Liu C, Liu Y, Zhang D, Xie C. The capital market responses to new energy vehicle (NEV) subsidies: an event study on China. Energy Econ 2022;105:105677.