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The Impact of Automobile Purchase Restriction on Urban Air Quality: Experimental Evidence from Beijing, China

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ABSTRACT

It's critical for environmental governance to understand the effectiveness of policy interventions as well as their working mechanisms. This paper focuses on the vehicle license plate-based management, a sort of policy intervention understudied in environmental governance literature. Specifically, we study the automobile purchase restriction (APR), a major method of license management to address urban air pollution and traffic congestion recently launched by the authorities of China. However, limited studies have quantified the environmental impact of such purchase restriction. Based on the panel data of PM2.5 concentration in 330 cities in China during 1998-2016, this study aims to explore the causal impact of Beijing automobile purchase restriction on air quality, using the regression control method and high-dimensional data regression of machine learning. The average PM2.5 concentration did not decrease but increased because of the purchase restriction. Over time, the deterioration effect on urban air quality will not alleviate. Besides, the restriction cannot enhance urban air quality by decreasing the increase of PM2.5. Despite excluding the impact of driving restriction, the purchase restriction markedly aggravate urban air quality. This paper has some policy implications for policymakers on the impact of urban vehicle license management with caution. Hence, it is essential to promote urban economy, production, and lifestyle to attain the win-win goal of air pollution control and urban development.

KEYWORDS

Beijing; Regression control method; High-dimensional regression; Automobile purchase restriction; Environmental protection effect

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1. Introduction

As automobile consumption continues to play a driving role in China's economic growth, China's motor vehicle ownership continues to reach a new record high. In 2018, the number of motor vehicles in China reached 327 million. Compared with 2017, 2018 witnessed an increase of 2.85 million and 11.56% year-on-year. Automobile emission has been considered one of the primary reasons for urban air pollution (Wu & Li, 1999). Facing urban traffic and environmental issues due to colossal motor vehicle ownership, several cities, such as Beijing, Shanghai, Guangzhou, and Shenzhen, have issued automobile purchase restriction (APR) or driving restriction (ADR) since 1994 to alleviate traffic congestion and improve urban air quality. However, scholars and public alike have debated whether APR or ADR in China have improved air quality. [1]

As automobile consumption in China has influenced the global economic development, the policy impact of APR warrants further attention. Unlike ADR, APR attempt to alleviate urban pollution and congestion by regulating motor vehicle ownership. Thus, APR can more directly alter automobile consumption and, ultimately, affect economic growth. Indeed, automobile consumption could change China's overall consumption scenario. Since 2018, China's consumption growth has exhibited a downward trend; the total retail sales of consumer goods was 38098.7 billion RMB. The growth rate of consumer goods in China has been declining for 7 consecutive years. Among them, the growth rate of automobile consumption has declined the most, decreasing by 2.4%, implying that the decline of automobile consumption exerts a pronounced impact on overall consumption. [2]

As a major automobile country occupying 30% of the global automobile market, [3] China's automobile consumption inevitably exerts a crucial impact on the global automotive industry and, even, global economy. Thus, it is imperative to explore how to choose the best urban vehicle license management to play the role of the automobile industry in the overall consumption, while effectively protecting urban air quality.

In recent years, especially with the slowdown of China's economic growth, policymakers have noted the negative impact of APR, such as the erosion of the automobile industry and the overall economy, and, thus, attempted to change the excessive reliance on the policy. For instance, in June 2018, the Ministry of Transport of China issued "The Outline of the 13th Five-Year Plan for Urban Public Transportation," which specified that China would take multiple measures to alleviate urban traffic congestion; study and promote the charging policy for urban traffic congestion on time; cautiously adopt the vehicle control policy and avoid the policy normalization as far as possible. In April 2019, the National Development and Reform Commission of the People's Republic of China made a public response and indicated that it is currently exploring the cancellation of APR by families without vehicles. [4]

To date, studies on the environmental effect of the automobile license plate–based policy primarily focused on the research of ADR; among them, Beijing has been the leading research object (Chen et al., 2013; Sun et al., 2014; Viard & Fu, 2015; Cao et al., 2014; Yi et al., 2018). Nevertheless, relatively less attention has been paid to the environmental impact of APR. Besides, among the current nine representative cities with ADR in China (Table 1), all have also conducted APR. [5] Indeed, although APR in China have been implemented for 26 years, their environmental effect remains debatable. To date, there is a lack of a clear quantitative assessment of the improvement in air quality of APR. Hence, the research of the environmental impact of automobile license plate–based policy in China should not overlook the discussion of APR.

[1] Data source (in Chinese): http://news.ifeng.com/a/20150304/43264355_0.shtml.
[2] Data source (in Chinese): http://www.ctoutiao.com/1375975.html.
[3] Calculate from data provided by the International Automobile Manufacturers Association (http://www.oica.net/).
[4] Data source (in Chinese): http://www.chinanews.com/gn/2019/04-18/8812739.shtml.
[5] Of course, there are also cities that implement the ADR alone, such as Jinan and Lanzhou City in China.

Table 1. An overview of APR and ADR in nine representative units of China.

Units	APR	ADR[6]
	Start times	Start times
Shanghai	1994	2015
Beijing	2010	2007
Guiyang	2011	2011
Guangzhou	2012	2018
Shijiazhuang	2013	2013
Tianjin	2013	2014
Hangzhou	2014	2011
Shenzhen	2014	2015
Hainan Province	2018	/[7]

This paper differs from previous studies in three ways. First, it selects 330 cities in China to determine and evaluate the environmental impact of APR by using a quasi-natural experimental evaluation method, which can fit the "counterfactual" results of the policy in a broader scope. Second, using the regression control method (RCM) proposed by Hsiao et al. (2012) and the high-dimensional data regression under machine learning, it can correct the errors caused by endogenous policy problems and sample selectivity errors in selecting the control group units. This way, the environmental effect can be separated to more scientifically and accurately assess the net effect of APR. Third, it investigates the environmental impact from the absolute and relative, fundamental and long-term changes, to provide some useful reference for the follow-up relevant policy implementation.

To achieve the goals mentioned above, the remainder of this paper is organized as follows: Section 2 presents a literature review; Section 3 provides a description of the data, research area, and methods; Section 4 provides the basic results and robustness checks; Section 5 further empirically explores the potential impact path of APR on air quality; and Section 6 discusses conclusions and implications for the urban management practice and research.

2. Literature Review

The discussion of correlations between automobile license plate–based policy and urban environmental protection has primarily focused on ADR. The mainstream view is that the impact of ADR on air quality is not significant. A representative example of ADR is the Hoy No Circula (HNC) policy implemented in Mexico City in 1989. Regarding the environmental impact of the policy, Eskeland and Feyzioglu (1997) reported that during 1984□1993, HNC did not result in a considerable decline in the gasoline demand or motor vehicle ownership. Davis (2008) used the hourly air pollution data obtained from the monitoring station to control the covariates, such as weather conditions, by using the regression discontinuity (RD) design, but found no evidence that HNC improved air quality of Mexico City. Lin et al. (2011) explored a range of other cities, such as São Paulo and Bogota, and inferred that ADR exhibited slight and even negligible mitigation of air pollution. Chowdhury et al. (2017) reported that the policy of restricting odd-numbered license plates did not markedly decrease the PM2.5 concentration in Delhi, India. Using big data processing procedures and different estimation methods for regression discontinuous design, Huang et al. (2017) observed that ADR in Lanzhou, China, were effective in the short term but ineffective in the long term. Notably, Salas (2010) used the same data as Davis (2008) but reported that ADR could alleviate urban air pollution.

Furthermore, the deductions of relevant research on the environmental impact of Beijing ADR are also inconsistent. Using regression discontinuity to alleviate endogeneity bias, Cao et al., (2014) revealed that ADR, especially the "tail number limit," exert little effect on air quality. However, limited studies have presented the

[6] Since the introduction of the ADR, many cities have been updated, so this refers to the first implementation of the ADR.
[7] Hainan Province in China plans to increase the limit of the non-local license plates from August 1, 2019. The non-local automobiles must not travel more than 120 days on Hainan Provincial Roads.

adverse viewpoint, namely, ADR could markedly alleviate air pollution. Chen et al. (2013) used the Difference-In-Difference (DID) method to investigate that Beijing ADR in 2008, indeed, improved air quality during the Beijing Olympics Games, although the degree of air pollution increased rapidly in the first month after the Olympics Games. Moreover, Viard and Fu (2015) reported that Beijing ADR decreased air pollution by 21% during the weekly limited periods.

Overall, previous studies on the correlations between air quality and APR are relatively limited. Among them, most studies have reported that ADR exert some negligible or almost no impact on air quality, and only a few studies have suggested that the restriction could exert a significant positive impact. Despite some controversies, some studies have also provided a useful research basis for automobile license plate–based policy. Comparatively, APR do not directly affect the automobile driving strategy, and the studies of its environmental impact have not drawn considerable attention. Thus, the literature on the environmental impact of APR is usually scarce. Considering the significance of research methods, Salas (2010) revisited the work of Davis (2008) and argued that reasonable changes in the methods used (different time windows and polynomial orders) could markedly change the conclusions. Precisely, Salas (2010) used the same data as Davis (2008) to find evidence that ADR successfully alleviated air pollution. In addition, complex chain processes ranging from traffic emissions to air pollutant concentrations could be affected by various time-varying variables, such as weather, wind speed, public transport supply, fuel prices, parking fees, and taxi fares, all of which could influence the environmental effect of APR or ADR. Indeed, these factors are not likely to be covered under the traditional research framework. Notably, changes in these factors could be random and unobservable, or very difficult to control. Thus, the reliability and applicability of traditional methods using parametric functions, such as DID, remain debatable.

To more effectively separate, identify, and evaluate the net environmental impact of APR, this study collects panel data of 330 cities in China, including Beijing, between 1998 and 2016, and uses the RCM proposed by Hsiao et al. (2012), together with the high-dimensional data regression under machine learning, to simulate and examine the counterfactual results of air quality when Beijing does not implement APR.

3. Research Design, Variable Descriptions, and Dataset

3.1 Applicability of methods

In recent years, counterfactual analysis has been extensively used in the field of policy evaluation. Currently, two methods, parametric and nonparametric method, are used primarily (Ching et al., 2012). While the parametric method mainly performs empirical analysis in constructing the function of related variables from the theory, the nonparametric method relaxes the strict requirements of theoretical analysis and decreases the hypothesis dependence needed for the correct setting of function forms. Of note, the nonparametric method primarily includes regression discontinuity, propensity analysis, DID, and synthetic control method (SCM). Among them, DID and SCM apply to the situation that policy implementation only occurs in one region at a specific time, while other regions are not always subject to policy intervention. In addition, the DID method cannot solve the endogenous bias caused by unobservable factors of time-varying attributes. Although the nonobservable components are considered in the integrated control method, when the characteristic directions of the treated group are similar, especially when the equivalent is far from the convex combination of the eigenvectors of the control group, it is challenging to synthesize the control group effectively.

Hsiao et al. (2012) proposed the RCM, which is also the latest nonparametric method of panel data. Compared with DID and SCM, RCM is more flexible. In particular, RCM can allow the composite weight between control groups to be negative. By setting a constant variable, it can further modify the differences between the treatment and synthetic control groups. The basic idea of RCM is to attribute the correlation between individuals of the cross-section to the common factors that drive the change of objects. By predicting the strong correlation between the treatment and control groups, RCM can depict all common potential factors with the treatment group, thereby making this method more applicable to reality.

3.2 Model assumptions and design

Let Y_{it} denote the annual average PM2.5 concentration of Beijing ($i = 1$) and other cities ($i = 2,3,...,330$), which are generated by the following factor model:

$$Y_{it} = B_i F_t + \partial_i + \varepsilon_{it}, i = 1,2,\dots,N, t = 1,2,\dots T \tag{1}$$

where F_t is the K-dimensional time-varying common factor vector; B_i is a coefficient vector of the K-dimensional variation with the region i; ∂_i is a regional fixed effect; ε_{it} is a random disturbance satisfying the assumed condition of $E(\varepsilon_{it}) = 0$.

Assume that the implementation of Beijing APR in 2010 did not have any linkage effect on other cities i had

$$Y_{it} = Y_{it}^0, i = 2,3,\dots,N, t = 1,2,\dots,T \tag{2}$$

There is no impact on Beijing's air quality before the start of APR; we have the following:

$$Y_{1t} = Y_{1t}^0, t = 1,2,\dots,T_1 \tag{3}$$

Urban air quality has changed after the start of the policy; we have

$$Y_{1t} = Y_{1t}^1, t = T_1 + 1, T_1 + 2, \dots \tag{4}$$

Let D_{1t} denote the dummy variable of policy intervention, where $D_{1t} = 1$ if Y_1 is affected by policy intervention at time t and $D_{1t} = 0$otherwise.

Assumedly, the random factors of air quality changes of other cities are conditionally independent of the policy intervention dummy variables; we have

$$E(\varepsilon_{is}|D_{1t}) = 0, i = 2,3,\dots,N, s \geq t \tag{5}$$

We define the treatment effect of APR on Beijing's air quality as Δ_{1t} that takes the form as follows:

$$\Delta_{1t} = Y_{1t}^1 - Y_{1t}^0, t = T_1 + 1,\dots,T \tag{6}$$

where the difficulty of estimation Δ_{1t} is that Y_{1t}^1 and Y_{1t}^0 cannot be observed at the same time.

Based on the model ideas of Hsiao et al. (2012), we presupposed that air quality of different regions in the same period was affected by common factors (e.g., population, capital, and technology). Although the impact of these common factors on air quality of regions differs, some correlation exists between the cross-section data, which becomes the basis for the counterfactuals mentioned above.

Thus, we used the information of other control group individuals, which is not subject to policy intervention, by substituting F_t of function 1 with $\tilde{Y}_t^0 = (Y_{2t}^0,...,Y_{Nt}^0)$ to produce the counterfactual result Y_{1t}^0 at time $t = T_1 + 1,...,T$. More concretely, first the counterfactual value of Y_{1t}^0 obtained by the time-series data was used as follows: $\tilde{Y}_{1t}^0 = \hat{\alpha}_1 + \hat{\alpha}_2 Y_{2t}^0 + ... + \hat{\alpha}_N Y_{NT}^0$. Then, the counterfactual result $\tilde{Y}_{1t}^0$ over the whole policy evaluation period $T_1 + 1$ to T was obtained by the out-of-sample prediction of Y_{1t}^0.

We gained the estimation of the impact of APR on air quality as follows:

$$\Delta_{it} = Y_{1t} - \tilde{Y}_{1t}^0, t = T_1 + 1,\dots,T \tag{7}$$

As the number of periods used in this study is limited, its corresponding long-term treatment effect is the average net policy effect estimated, which takes the following form:

$$\frac{\sum_{t=T_1+1}^{T} \hat{\Delta}_{1t}}{T - T_1} \tag{8}$$

3.3 The synth method of the control group: high-dimensional data regression

Hsiao et al. (2012) primarily used the two-step method to select the control group units. The potential control group individuals were selected from 1, 2, 3 ... N to enter the model; then, the optimal synth weight of the control group was chosen with Akaike information criterion (AIC or AICC). This processing method is applicable to the situation that the number of the control group is not very large; however, when facing the high-dimensional dataset, namely the number of variables is much larger than the number of samples, it increases the difficulty of model selection. Furthermore, data overfitting results in markedly weakening the effect of regression analysis and prediction of the model. Hence, we chose the LASSO regression under machine learning for multifactor selection of the control group.

The basic idea of machine learning is to avoid overfitting by testing the estimation results from the training set using a setting validation set. In recent years, the high-dimensional data regression represented by LASSO is in the ascendant. The objective function of LASSO regression proposed by Tibshirani (1996) is as follows:

$$\underset{\beta}{argmin}(y - X\beta)'(y - X\beta) \ + \lambda||\beta||_1 \tag{9}$$

where λ denotes the tuning parameter of the control penalty, which can be determined with K-fold cross-validation (default is 10). Accordingly, the constraint minimum value can be used to perform penalized regression on all variable coefficients so that the regression coefficients of some variables are strictly equal to 0, thereby obtaining a sparse model. In particular, first, the sample data were randomly divided into 10 equal parts. The first subsample was reserved as a "validation set," and the remaining nine subsamples were used as a "training set" to estimate the model, following which the first subsample was predicted. Thus, we obtained the mean squared prediction error (MSPE) of the first subsample. Second, we used the second subsample as the verification set, while the other nine subsamples were used as the training set to estimate the second subsample, and the MSPE of the second subsample was calculated as well. By analogy, the MSPE of the entire sample can be obtained by summing up all subsamples. Finally, as tuning parameters were selected to minimize the MSPE of the whole sample, it has the best prediction ability. In this study, we mainly used LASSO regression and AIC or AICC criteria under ridge regression to test robustness.

3.4 Data descriptions

As the key variable in this study, PM2.5 can objectively measure air pollution in a city. The higher the PM2.5 concentration in the air, the more serious the air pollution is. Thus, there exist the PM2.5 balance panel data of 330 cities in China from 1998 to 2016, which are largely two parts of source data processed. First, we derived the data during 1998–2013 from the global PM2.5 raster data published by the Columbia University Social Economic Data and Application Center (SEDAC; Van et al., 2015) and used the ArcGIS software to parse it into the average concentration of PM2.5 years in China. Second, based on the annual average PM2.5 concentration data released by the China Urban Air Quality Platform from 2013 to 2016, we used ordinary kriging method (OKM) and ArcGIS software to vectorize them. Furthermore, the data obtained were processed by moving average for 3 years to ensure the consistency of statistical caliber.

In this study, the sample period is from 1998 to 2016, while Beijing implemented APR in 2010. Thus, we set 1998–2010 as the nonimplementation period (T1 = 13) and 2011–2016 as the implementation period (T2 = 6). Besides, T1 > T2 and T1 > 10 satisfy the basic requirement of counterfactual estimation for sample time-span.

To date, eight cities and one province in China have implemented APR. Based on the available data, we found nine regions with APR; however, Beijing is the best treatment unit for the sample period per the counterfactual research paradigm. The main reasons are as follows: (i) the start time of restriction in Shanghai and Hainan Province is not in the sample period; (ii) compared with Guiyang, Guangzhou, Shijiazhuang, Tianjin, Hangzhou, and Shenzhen, the policy forecast period of Beijing is the longest. Hence, it is more reasonable to use Beijing as the regression control analysis object in SCM.

Based on the methodological framework of Hsiao et al. (2012), we needed to fulfill two conditions when selecting the control group unit—the unit should be a good predictor of the treatment unit before Beijing APR, and an exogenous factor of Beijing restriction policy. Thus, first, in the sample period of 1998–2010, we deleted Shanghai, which has implemented the restriction; second, we assumed that the impact of the restriction is local. However, the relevant research has demonstrated a type of strong regional relationship in the changes of PM2.5 concentration in Beijing. Per the research data released by the Beijing Environment and Protection Bureau, we found that about a third of Beijing PM2.5 in 2014 and 2018 is from the transmission of adjacent regions.[8] This suggests that Tianjin and the cities under the jurisdiction of Hebei Province could benefit from the Beijing restriction policy and, thus, increase the local demand for automobiles. Meanwhile, their air environment also has some spatial spillover. Thus, based on Kline and Moretti (2014), we eliminated any other cities bordering Beijing or adjacent to Beijing, including Tianjin and 10 cities under the jurisdiction of Hebei Province,[9] to satisfy the key identification hypothesis 5 (strict cross-exogenous) in Hsiao et al. (2012).

Accordingly, we finally chose 330 cities from 1998 to 2016, with Beijing as the treatment group unit and the remaining 329 cities as the potential control group ones.

4. Basic Empirical Results and Robustness Checks

4.1 The basic environmental effect of APR

Based on the counterfactual analysis method of Hsiao et al. (2012), we used the data samples of the preimplementation of APR, as well as K-fold cross-validation method of LASSO regression under high-dimensional data to screen variables. Table 2 shows that the optimal control group comprised eight cities with good in-sample fit . These findings indicate that the predictive model chosen by K-fold cross-validation criterion performs well, and the control group and predicted counterfactuals are reasonably comparable in the posttreatment period.

Table 2. Composite weights of the optimal control group.

Control unit	Coefficient	Robust standard error	T value
Nanping	0.143	0.259	0.55
Quanzhou	-0.033	0.179	-0.19
Zhanye	2.711	0.655	4.14
Nanning	0.091	0.154	0.59
Shenlongjia	0.192	0.271	0.71
Huludao	0.194	0.182	1.07
Yangquan	0.218	0.151	1.44
Lijiang	0.592	0.455	1.30
Intercept	-11.825	5.331	-2.22

Incorporating the PM2.5 concentration of the eight cities as explanatory variables into the regression equation, Fig. 1 shows the fitting curve of 1998–2010 before the implementation of the policy. Figure 1 shows that the real and counterfactual values of the annual average PM2.5 concentration of Beijing coincide with each other and are well fitted even at some critical points. Thus. The results show that air quality of Beijing could be accurately fitted

[8] Data source (in Chinese): http://www.bjepb.gov.cn/bjhrb/xxgk/jgzn/jgsz/jjgjgszjzz/xcjyc/xwfb/832588/index.html.
[9] The cities under the jurisdiction of Hebei Province in China in this paper are Baoding, Zhangzhou, Chengde, Handan, Hengshui, Langfang, Qinhuangdao, Shijiazhuang, Tangshan, Xingtai and Zhangjiakou.

by the control group comprising the eight cities listed above.

Based on the synthetic control group shown in Table 2, we made an out-of-sample prediction for Beijing APR

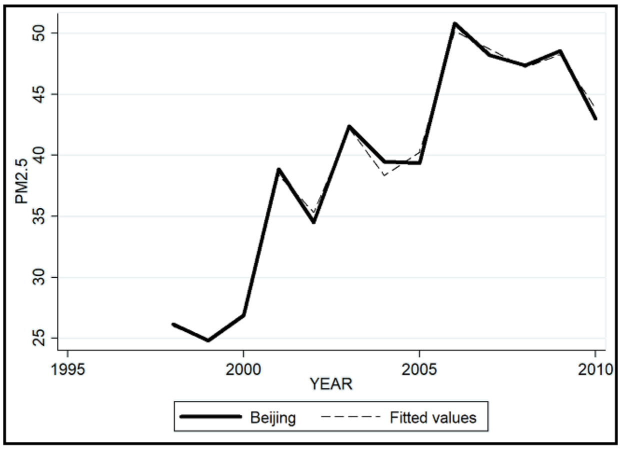

Figure 1. The real and counterfactual values of 1998–2010.

during 2011–2016. We estimated the annual average PM2.5 concentration if Beijing did not implement restriction policy; then, we obtained the real and counterfactual values of Beijing's annual average PM2.5 concentration for the entire sample period (Fig. 2). The gap between the real and counterfactual values of Beijing's annual average PM2.5 concentration was the net effect of Beijing APR.

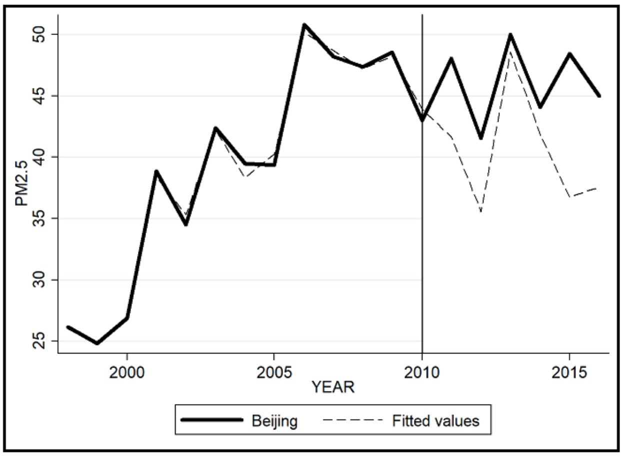

Figure 2. The real and counterfactual values of the entire period (start in 2010).

Figure 2 shows that the real annual average PM2.5 concentration in Beijing was basically higher than the counterfactual since APR were implemented in 2010, although the gap between both revealed a tortuous change. Table 3 shows that the average policy effect is 5.85, with 5% significance level, suggesting that APR would markedly contribute to the air pollution instead of improving air quality of Beijing.

4.2 Robustness checks

We resorted to some indirect justification of our estimates in this section to evaluate the credibility of above-mentioned baseline treatment effect of APR.

4.2.1 Change the start time of APR

The increase in PM2.5 concentration in Beijing could attributable to the implementation of APR, that is, it is likely that the restriction cannot effectively improve air quality in Beijing. However, whether the deteriorating effect

Table 3. The net environmental effect of APR in Beijing.

Year	Real PM2.5	Fitted PM2.5	Policy effect
2011	48.06	41.66	6.40
2012	41.55	35.54	6.01
2013	50.00	48.61	1.39
2014	44.06	41.88	2.18
2015	48.46	36.75	11.71
2016	45	37.54	7.46
Mean	46.18	40.33	5.85**
Standard error	1.29	1.96	1.53
P	–	–	0.0125

***Two-tailed statistical significance at 5% levels.*

is only an accident and whether it has no direct relationship with APR remain unclear. Thus, we attempted to construct a placebo test by randomly selecting the start time of APR, such as 2 years ahead of the real start time; that is, we set the pretreatment period of 1998–2008, while the posttreatment period of 2009–2016, and then estimated the average treatment effect (ATE) with the same method as above. At the randomly start time 2008, if the real annual average PM2.5 concentration in Beijing was markedly higher than the counterfactuals, it is established that the empirical analysis provided above is inadequate to support the environmental effect of APR.

The optimal synthetic control group (including nine regions of Nanping, Zhangye, Shenlongjia, Xiaogan, Huludao, Xilingol, Yan'an, Mianyang, and Suining) selected by multiple factors under LASSO regression also exhibited a higher fitting degree. The results indicated that the predictive ability of the optimal synthesis control group was still strong, although the implementation of the restriction was 2 years in advance.

Figure 3 shows that the entire sample period is divided into left and right parts with the boundaries of 2008. Before 2008, the optimal synthetic control group accurately fit the real annual average PM2.5 concentration data in Beijing, whereas during 2008–2016, the solid line with the real annual average PM2.5 and the dashed line with the fitted annual average PM2.5 appear alternately. Notably, the dotted line of counterfactual values and the solid line of real values basically coincided from 2008 to 2010; since 2010, the difference between the two curves became apparent. Furthermore, the difference test revealed that the ATE was –0.266 (P = 0.8) between 2008 and 2010, indicating that the treatment effect was not significant at this time. However, between 2011 and 2016, the ATE was 6.481 (P = 0.0088), which also implies that APR exerted a markedly deteriorating effect at the time only when it was actually started in 2010.

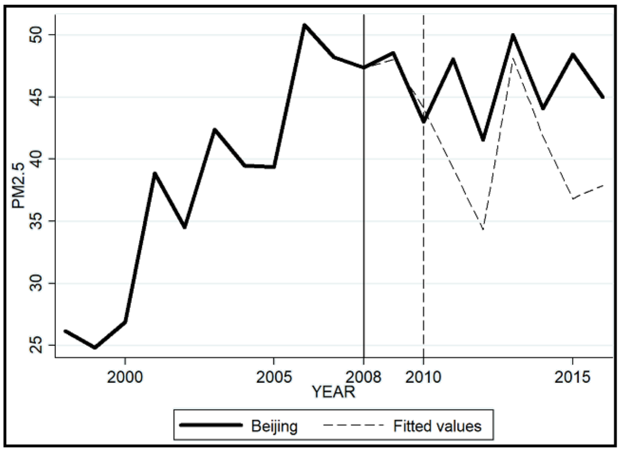

Figure 3. The real and counterfactual values of the entire period (start in 2008).

The results mentioned above suggested that the deteriorating effect of APR is significant at the time when restriction is actually started; however, it could be that it is just when this effect happened by chance in Beijing. If it can be established that other cities did not have the same policy effect at the same time, we can validate that the environmental effect of Beijing APR is neither accidental nor a national phenomenon. In other words, it establishes that the driving force of restriction for Beijing air quality is significant.

In 2018, Hainan Province implemented APR, but its motor vehicle ownership per 1000 people is very low, urban traffic pressure is small, and air quality is also among the best. Accordingly, it is markedly different from other cities with APR. Notably, APR in Hainan are not because of congestion or air pollution. Thus, we excluded the cities under the jurisdiction of Hainan Province and, in turn, conducted counterfactual tests of APR for seven cities, except Beijing, in 2010, as well as obtained ATEs of various cities (Table 4). Table 4 shows that ATEs in seven cities cannot pass the 5% significant test, thereby proving to some extent that it is the introduction of APR in 2010 that worsens air pollution in Beijing, rather than other common and contingency factors.

Table 4. The net policy effect of APR in seven cities.

City	ATE	P
Shanghai	-2.56	0.1116
Tianjin	-2.87	0.0791
Guiyang	0.325	0.3644
Guangzhou	-0.229	0.7718
Shenzhen	0.026	0.9001
Hangzhou	-0.152	0.5962
Shijiazhuang	1.441	0.1883

4.2.2 Exclude all cities that later imposed restriction on purchases

The robustness of the counterfactual analysis was restricted by the exogenous hypothesis, which needed air quality of the selected control group units to be independent of Beijing APR. Considering that the restriction could exert a certain imitative effect, we further excluded all other restriction cities in China, including Guiyang, Guangzhou, Shenzhen, Hangzhou, and cities under the jurisdiction of Hainan Province, and then reassessed the environmental impact of APR on Beijing's air quality.

Excluding the other restriction cities except for Beijing, we obtained the synthetic optimal control group of eight cities, including Nanping, Quanzhou, Zhangye, Guests, Shenlongjia, Nantong, Huludao, and Yangquan. Figure 4 shows the change trend of the real and counterfactual values of the annual average PM2.5 concentration of Beijing before and after the implementation of APR. Figure 4, left, shows that when a change of the control group occurs, the fitting degree of the new model remains very high with R2 of 0.994, suggesting the strong prediction ability of the control group. Figure 4, right, shows that after the implementation of APR, the real annual PM2.5 concentration of Beijing is above the counterfactual ones. In other words, the ATE of Beijing APR is positive. Furthermore, we found that the ATE of Beijing restriction was 6.23 (P = 0.0132), which verified that the significant impact of Beijing restriction policy on air quality could have existed even when considering the influence factors of other cities with the restriction.

4.2.3 Change in the method of selecting the control group units

Previous studies used LASSO regression to synth the optimal control group for ATE of Beijing air quality. Based on LASSO regression, we used ridge regression and AICC to determine the optimal control group. Accordingly, we obtained the optimal control group of Beijing PM2.5 concentration (comprising seven cities like Nanping, Zhangye, Guests, Shenlongjia, Huludao, Yangquan, and Lijiang). Figure 5 presents the real, counterfactual values, and the policy impact before and after the implementation of APR. Likewise, we found that APR exerted a significant deteriorating effect on air pollution in Beijing.

5. Further Analysis

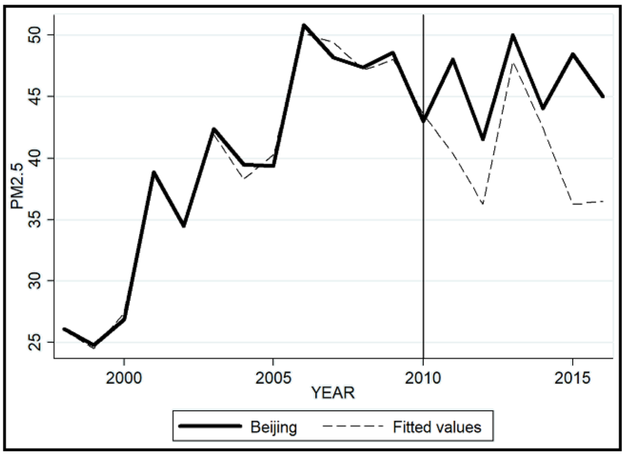

Figure 4. The real and counterfactual values (excluding the cities with the restriction).

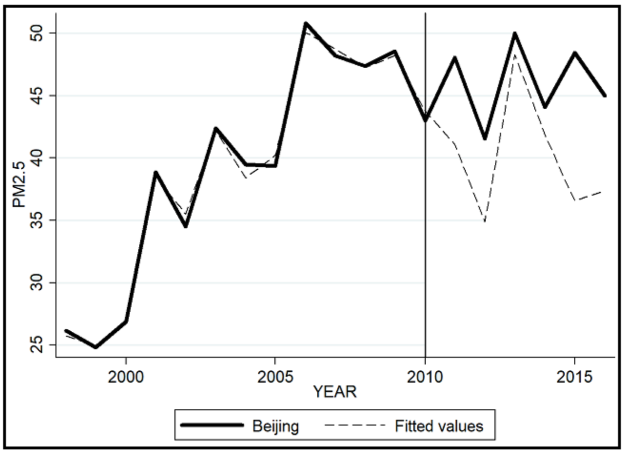

Figure 5. The real and counterfactual values (change in the selection method).

5.1 Long-term impact

We used Hsiao et al. (2012) for reference and autoregressive model (AR) to evaluate the long-term impact of APR on Beijing's air quality. Based on the information criteria, such as AIC and Bayesian Information Criterion(BIC), we found that the policy effect of Beijing APR is subject to the AR (2) model (the standard error of the estimated coefficient in parentheses of Eq. 10):

$$\underset{}{Treatment_{i,t}} = \underset{(1.1282)}{14.648} - \underset{(0.1039)}{0.234} \cdot Treatment_{i,t-1} - \underset{(0.1902)}{1.936} \cdot Treatment_{i,t-2} + \eta_t \tag{10}$$

Based on the empirical results of Eq. 10, we found that the long-term impact of the restriction on Beijing's annual average PM2.5 concentration was 4.621 (corresponding P = 0.000), suggesting that the Beijing air pollution is still exacerbating from the long-term effect, although the restriction have been implemented; this implies that if PM2.5 concentration is used as an indicator of air pollution, the continued implementation of APR will not improve air quality.

5.2 The effect of the increase of PM2.5

Previous empirical analysis revealed that Beijing APR cannot effectively lower the annual PM2.5 concentration. Then, can the restriction control air pollution by decreasing the increase of PM2.5 concentration? Thus, we analyzed the impact of APR on air pollution with the increase of PM2.5 as a key variable. Similarly, we used the counterfactual analysis proposed by Hsiao et al. (2012), along with the K-fold cross-validation method of LASSO regression. Finally, we selected six control group units (Zhangyi, Nanning, Huludao, Shizuishan, Datong, and Yangquan) whose PM2.5 growth rate was used as an explanatory variable for the change of PM2.5 in Beijing. The corresponding counterfactual equation was constructed and used for intrasample and out-of-sample prediction. Accordingly, we obtained the change of the real and counterfactual PM2.5 increase in Beijing (Fig. 6).

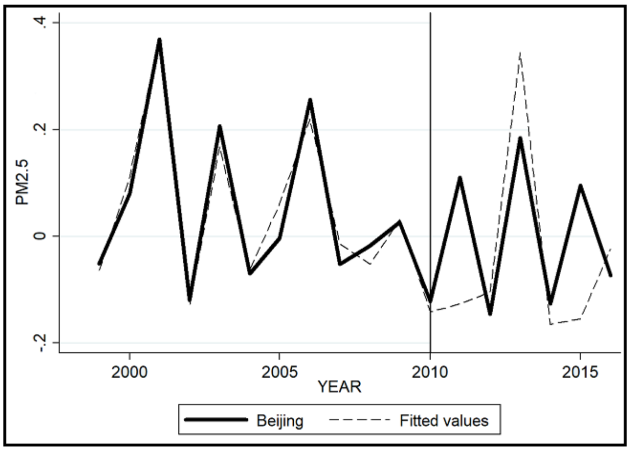

Figure 6. Fitting prediction of the increase of PM2.5 in Beijing.

Figure 6 shows that the counterfactual equation fit well before 2010 (R2 = 0.958), whereas in 2011, the gap between the counterfactual PM2.5 with a solid line and the real ones in Beijing with a solid line began to produce differences. Notably, the difference is to measure the policy impact on the increase of PM2.5 in Beijing (Fig. 7).

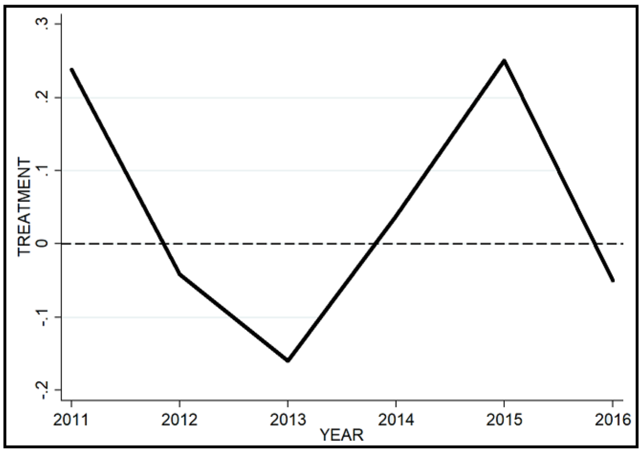

Figure 7. The net effect of Beijing APR (subject to the increase of PM2.5).

Figure 7 shows that the net policy effect markedly decreases the increase of PM2.5 at the beginning, and even negative effect appears in the middle stage. However, since 2014, some staggered changes in the increase or decrease have begun appearing. On average, the real and counterfactual PM2.5 increase was 0.007 and −0.038. In addition, the ATE of APR was 0.045; however, the policy effect did not pass the 10% significance test (P = 0.5271). Hence, there exist some reasons that APR cannot clearly improve air quality of Beijing by decreasing the increase of PM2.5 concentration.

5.3 Eliminate the environmental impact of ADR

The analysis of the automobile license plate–based policy of Beijing revealed that Beijing started APR in December 2010. Before that, four ADR explorations occurred successively as follows: (i) August 17–20, 2007, of the

Beijing Olympic Test Tournament Period; (ii) July 20–September 20, 2008, during the 2008 Beijing Olympic Games; (iii) October 11, 2008–April 10, 2009; and (iv) April 11, 2009–April 10, 2010.

Our literature review highlighted a certain environmental impact in the short term, although the studies reviewed had different conclusions on the environmental impact of APR. Correspondingly, Beijing air environment could face a dual treatment influence, including the residual impact of ADR and the environmental impact of APR. Thus, if the residual impact is not considered, a large deviation could have occurred when evaluating APR. Thus, this section attempts to separate the effect of ADR from the dual effect.

Affected by multiple policies, the general method of treatment effect assessment has major limitations. Fujiki and Hsiao (2015) reported that the net policy effect could be obtained only if one policy impact is used in sample data. Thus, we excluded the annual sample with the period 2007–2010, which might have a significant impact from Beijing ADR, and then used RCM and high-dimensional data regression under machine learning to evaluate the ATE with the remaining annual sample data. Finally, we obtained seven optimal control group units such as Nanping, Dingxi, Zhangye, Nanning, Shenlongjia, Huludao, and Ulanchabu. Table 5 shows the estimated coefficients.

Table 5. The optimal control group when eliminating ADR.

Control unit	Coefficient	Robust standard error	T value
Nanping	0.237	0.146	1.62
Dingxi	-0.232	0.065	-3.56
Zhangye	2.391	0.306	7.81
Nanning	0.086	0.085	1.02
Shenlongjia	0.515	0.108	4.76
Huludao	0.285	0.111	2.57
Ulanchabu	0.632	0.234	2.70
Intercept	-9.251	2.545	-3.63

Likewise, based on the synthetic control group shown in Table 5, we conducted an out-of-sample prediction (Table 6) and plotted the real and counterfactual values of the Beijing annual average PM2.5 of 2011–2016 sample period (Fig. 8). Then, we found that excluding the impact of ADR, although the ATE of APR was relatively decreased from 5.85 to 3.67, it was also tested by the 5% significance level. The results above suggested that despite excluding the impact of ADR, APR still could not significantly improve Beijing's air quality, namely it markedly increased the level of air pollution in Beijing.

Table 6. The net environmental effect when eliminating ADR.

Year	Real PM2.5	Fitted PM2.5	Policy effect
2011	48.06	41.54	6.52
2012	41.55	37.66	3.89
2013	50	48.84	1.16
2014	44.06	43.75	0.31
2015	48.46	41.32	7.14
2016	45	41.91	3.09
Mean	46.18	42.51	3.67**
Standard error	1.299	1.504	1.13
P	–	–	0.0224

**Two-tailed statistical significance at 5% levels.

6. Discussion and conclusions

There exist significant similarities in urban pollution problem between China and the west. Undeniably, the sharp increase in motor vehicle ownership is one of the crucial factors contributing to the continuous deterioration

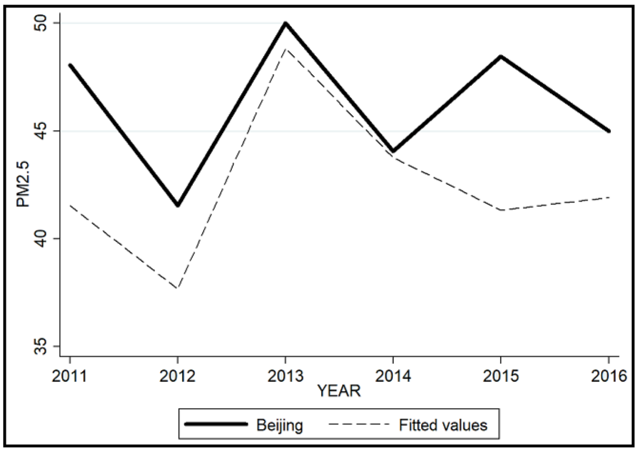

Figure 8. The real and counterfactual values when excluding ADR.

of air quality. Thus, for alleviating environment pollution, it is essential for the national or regional governments to introduce the management measures or methods of vehicles.

However, the side effect of APR could be further amplified as the economic situation changes. In recent years, China’s call for deregulation of APR is increasing because of the purpose of stimulating domestic consumption demand. Guangdong Province took the lead in promulgating the “Guangdong Province Implementing Scheme of Improving Consumption System and Mechanism” in May 2019. It was specified that the automobile lottery and bidding of Guangzhou and Shenzhen are no longer restricted and other cities can no longer introduce APR, which directly expanded the scale of automobile purchases. Then, Guangzhou also issued the corresponding supporting measures.[10] Beijing is a representative city that implemented ADR and APR earlier in China, and is also the main research object at home and abroad on the environmental impact of automobile license plate–based management. Hence, taking Beijing as an example to quantitatively evaluate the impact of APR on urban air quality in multiple dimensions, this study attempted to provide a useful reference for the future policy orientation of urban automobile management.

The findings of this study revealed that APR exerted no expected effect on alleviating urban air pollution. Instead, the average PM2.5 concentration increased considerably, and the deterioration effect will not disappear with time. Intuitively, APR could decrease the growth of motor vehicle ownership in a short time through the government rigid regulations. For instance, owing to the implementation of APR, the annual increase of automobile license plate–based policy is controlled by 240,000. Nevertheless, total motor vehicle ownership still exhibits an upward trend. Besides, the challenge for replacing old automobiles has increased because of the restriction of automobile purchase, and the likelihood of continuous use of automobiles with high pollution emission persists.

In addition, we found that APR cannot clearly improve air quality by decreasing the increase of PM2.5 concentration. The impact of APR on air quality depends on various factors. Under the premise that other factors remain unchanged, if the quota set by restriction is higher than the natural increment, the impact of APR is relatively larger. Notably, only when the motor vehicle ownership and use correlate positively, APR can play the anticipated environmental protection role. Besides, if APR cannot alter the long-term expectation of urban automobile consumption and promote the balance between supply and demand of automobiles, then, in the long term, it cannot exert the environmental protection impact by controlling the growth of automobiles. If APR are abolished, it could lead to retaliatory growth in automobile consumption, thereby resulting in greater environmental or traffic problems.

[10] Content source (in Chinese): http://m.xjqnpx.com.cn/m/view.php?aid=131636&ivk_sa_s=130828.

In this study, we tried to use three methods, including a start-up time of APR in advance, change the control group units, and choose different variable selection criteria, to conduct the robustness checks. Finally, substantial evidence supports the implementation of APR to deteriorate air quality. Moreover, we observed that even if the impact of ADR is eliminated, APR would not improve air quality of Beijing but would markedly increase the level of air pollution in Beijing.

The results imply that the impact of APR on alleviating air pollution is minimal. Thus, in the future, we should be cautious about APR. We should not only rely on unconventional means but also use the automobile market–oriented management policy selectively. For cities that have already implemented APR, it is essential to evaluate as soon as possible and timely explore the introduction of necessary alternative measures or supporting measures to decrease the policy imbalance caused by the single policy.

Of note, the breakthrough of urban air pollution control should start from the source. Based on the urban situation, the regional governments should formulate relevant policies rationally, optimize the industrial structure, upgrade the ability of scientific pollution control, and improve the economy, production, and lifestyle of the city from various angles in an all-round way, to attain the win-win goal of air pollution control and urban development.

Owing to the limitation of data availability, the time series of panel prediction data is short, which could affect the accuracy of research conclusions, although the quasi-natural experimental method was used to quantitatively assess the environmental impact of APR based on the PM2.5 data published by the Columbia University's Social Economic Data and Application Center. Moreover, the single index of PM2.5 and annual data used in this study might not fully and sensitively reflect the environmental effect of APR. In the future, as the data are further supplemented, it will further complement the effect of policy tools not tested in this study.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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