The Impact of Car Restriction Measures on the Consumption of Self-brand Automobiles in China

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Abstract: Based on the license plates registration data, this paper investigates the impact of vehicle purchase and automobile driving restriction on the proportion of self-owned brand automobiles in newly-sold cars in major cities of China during this period. After solving the endogenous problem through regression discontinuity design regression, this paper finds that the automobile purchase restriction policy had a significant negative impact on the consumption of self-brand automobiles, while the automobiles driving restriction policy had no significant impact on the proportion of self-brand automobiles or the total number of newly sold cars. However, compared with other factors at city and time level, the purchase restriction policy was not the main reason for the decline of the proportion of self-brand automobiles. In addition, this paper also confirms that the regional characteristics of Chinese automobile consumption were very obvious.

1. Introduction

Under the background of the continuous improvement of urbanization level and the sharp increase of the number of motor vehicles in urban areas in China, many cities in China have introduced automobile purchase restriction (purchase restriction for short) and vehicle driving restriction rule. In August 2007, Beijing implemented a five-day policy of vehicle driving restrictions, becoming the first city in China to restrict traffic. From November 2008, Beijing vehicle driving restriction began to operate normally. Since then, many mega-cities have begun to implement vehicle restriction policies. By December 2015, 10 main big cities across China, including Beijing, Lanzhou, Guiyang, Hangzhou, Chengdu, Changchun, Wuhan, Harbin, Tianjin and Nanchang, have implemented a normalized motor vehicle restriction policy for local license plates. Although the specific policy arrangements are different in different places, the restricted areas of each city are all urban centers and main roads; each city adopts the tail number rotation restriction method, which ensures the fairness of the policy for different vehicles within the city.

The automobile purchase restriction policy aims at controlling the excessive growth of motor vehicles in urban areas and alleviating traffic congestion and air pollution. Beijing has been using a license plate lottery system to curb the city's traffic since January 1, 2011. Up till December 2015, seven cities across the country, Shanghai, Beijing, Guiyang, Guangzhou, Tianjin, Hangzhou and

Shenzhen, have implemented various forms of restriction policies on car purchases. At present, the main measures to restrict purchase include two ways: namely, license plate lottery system adopted by Beijing and auction used by Shanghai. The other five cities have combined the two methods. Chen et al used the unbalanced panel data of three cities of Hangzhou, Tianjin and Guangzhou to prove that the time cost and the money cost of the two ways tend to be balanced[1]. Therefore, we no longer consider the relevant issues of different forms of purchase restriction policies in different cities.

The purpose of the restriction policy was to alleviate traffic congestion and air pollution, but it inevitably had a certain impact on consumers' choice of car purchase and automobile market. On the one hand, vehicle driving restriction measures might increase consumers' willingness to buy a second car and vehicle purchase restriction directly restrict the annual increment of cars in the region, affecting the automobile market total quantity. On the other hand, the policy increased the additional cost of newly purchased vehicles, might change consumers' purchase preferences, and might also affect the structure of the automobile market. Among them, the impact on the self-brand automobile market is an important issue.

Relevant stakeholders have put forward their own views on the policy. As for the purchase restriction, Chinese Automobile Industry Association leaders has publicly proposed that the purchase restriction policy implemented by several major cities in China has affected the development of self-owned brands. They publicly said that in Beijing, Shanghai and Guangzhou, where the economic development level is relatively high, the self-owned brands have in fact been marginalized and the market share has dropped by more than 50%. In addition, Yang et al noted that the unit price of automobile sales in Beijing increased by 14% in 2003-2010 before the implementation of the purchase restriction policy, but increased by 28% in the first year (2011) of the purchase restriction policy[2]. However, Yang did not make any further analysis of this phenomenon. In terms of restriction policy, Wang et al. found that after the implementation of the vehicle driving restriction in Beijing, the turnover of cars with unit price less than 80,000 yuan in the used car market doubled and the price increased by 15%. Wang et al. attributed this to the restriction policy, which encouraged citizens to buy a second car at a low price to avoid restriction[3].

However, these views are only based on the simple comparison of data differences before and after the policy. In fact, this simple comparison is not convincing enough, and has endogenous problems: cities with restrictions on purchasing are cities with higher income levels, so consumers naturally prefer high-level models or to buy another car; with the development of economy, residents' preferences for purchasing cars also changed. Therefore, we still need to eliminate endogenous problems through empirical methods and analyze the direction and extent of policy impact.

2. Literature Review

At present, there are few empirical studies on the impact of urban restrictions on automobile consumption. Davis L W used the 1989 Mexico City natural experiment of "driving less than one day a week" event, and found that the restriction policy led to a significant increase in car sales, which encouraged residents to buy another car. [4] However, Davis's research does not involve the structure of the automobile market. Xiao J et al. used the IV method to study the purchase restriction policy, and found that the Shanghai license plate auction policy increased the average purchase price by 8450 RMB, and made consumers more inclined to buy high-level vehicles and SUVs, which was not conducive to independent brand manufacturers[5].

However, there are some problems in the existing research, especially in dealing with endogenous and other problems. For example, in order to eliminate the endogenous problem of automobile price and market share, Xiao et al. chose the observable parameters of automobile and the number of cities automobile brands entering as the instrumental variables. However, in reality, the location of dealers is the result of automobile enterprises' self-selection based on strategies, rather than exogenous decision.

Currently, most of the existing empirical studies focus on the impact of policies on air quality, traffic congestion and the total volume of the automobile market, while few studies focus on the impact of policies on the structure of the automobile market. In addition, Chinese studies only focused on the impact of policies on Beijing and Shanghai, and there is a certain disconnect with the reality. Ma C pointed out that the regional characteristics of China's automobile consumption are obvious[6]. Therefore, it is doubtful whether the conclusions of the existing studies can be extended to other cities.

In order to separate the various influencing factors and solve the endogenous problems, this paper will use regression discontinuity design(RDD) to analyze the impact of restriction policy on the self-owned brand automobiles. Angrist and Paschke (2008) pointed out that regression discontinuity was an appropriate method when the influence of driving variable on dependent variable has "breakpoints"[8]. The basic idea is that the proportion of self-owned brand cars in automobile market develops smoothly with economic development and consumers' purchase preferences. As an exogenous factor, the announcement and implementation of the policy has changed consumers' behavior of buying cars in a short, resulting in a breakpoint in the proportion. Through regression discontinuity design, we can separate the influence of policy change, an exogenous factor, from other factors, and accurately estimate the impact of restriction policy.

Regression discontinuity design requires that individual behavior can not affect the value and distribution of configuration variables. This paper takes time as a configuration variable, and time is an obvious exogenous variable, which eliminates a source of errors in estimation results. As for the choice of policy breakpoints, since the policies that have been issued but have not been put into practice can also affect the willingness of residents to buy cars, taking this effect into account, this paper takes the time of policy announcement as a threshold.

In addition, in order to guide consumers to buy new energy vehicles, many cities have made policy arrangements to promote new energy vehicles and relaxed the relevant requirements of restrictions on new energy vehicles purchase. Yeh S [9], Hao et al. [10] pointed out that this inclined policy reduces the cost of consumers' car purchases, and will increase the sales share of new energy vehicles. Due to the limitation of data that do not differentiate automobiles according to their energy types, it is impossible to make modification. However, in the sample time range, due to policy protection, self-owned brand automobiles obviously occupied a dominant position in the new energy vehicles, and the "new energy automobile directory" in cities was obviously partial towards self-owned brand automobiles. Therefore, this fact will make the parameter estimation error direction positive, which will only strengthen the analysis conclusion of this paper. That is to say, if there is no biased policy arrangement, the restriction policy will have a greater negative impact on the sales of self-brand automobiles.

3. Model Establishment

3.1. Data Selection

We could only collect the detailed monthly license number data of passenger vehicles of all brands in each city from January 2011 to December 2015 from public channel, but luckily the time span is the policy-intensive launch period.

This data detailed to the brand and model can truly reflect the purchasing situation of end-users in various cities. There are 137 passenger car brands in the data set, including 51 self-owned brands and 86 non-independent brands (imports, joint ventures, etc.).

Due to the limited time span of the data, in order to ensure that policy breakpoints can be included in the data scope, this paper only selects city where at least one policy was published during January 2011 to December 2015 and excludes other cities from the research scope. Therefore, this paper chooses seven cities data for research. The policy announcement time of each city is shown in Table 1.

Table 1: Time of Policy Publication for Sample Cities.

City	Announcement time of purchase restriction policy	Announcement time of driving restriction policy
Guiyang	July 2011	October 2011
Chengdu	NA	April 2012
Guangzhou	June 2012	NA
Tianjin	December 2013	March 2014
Hangzhou	March 2014	October 2011
Harbin	NA	September 2014
Shenzhen	December 2014	NA

Note: Information comes from the official website of the different cities

3.2. Data Selection

At present, there are three methods widely used in the evaluation of policy effectiveness: instrumental variable(IV) method, DID method and regression discontinuity design(RDD). In addition, adding policy dummy variable to OLS regression is also feasible. Among them, instrumental variable method requires higher exogenous nature of IV, and it is difficult to find appropriate instrumental variables; DID method needs to find control groups with similar conditions, but the fact that the regional characteristics of automobile consumption are obvious makes the search very difficult. Compared with OLS, RDD can separate the part of time trend from the part of impact of policy implementation and reflect the impact of policy on automobile market by estimating local Average Treatment Effect (LATE). Therefore, this paper chooses the RDD to build the econometric model. All the sample cities did not announce the restriction policies at the same time, and there was a certain time interval between them. This provides usage conditions for RDD.

Angrist and Paschke mentioned the RDD method with changing time. According to this method, the LATE ρ can be estimated by the following regression equation when there is only one sample city and no control variable:

$$p_t = c + \rho D_t + f(D,t) + \lambda_t + u_t \tag{1}$$

$$f(D,t) = \sum_{k=1}^{n} \gamma_{0k} \tilde{t}^{\,k} + \sum_{k=1}^{n} \gamma_{1k} D_t \tilde{t}^{\,k} \tag{2}$$

p_t is the percentage of self-brand automobiles newly sold in the city in the month t; D_t is the dummy variable of the driving or purchase restriction policy. After the policy announcement, D_t is 1; before that, D_t is 0. $f(D,t)$ is the time trend function, indicating the trend of the proportion of newly sold self-brand automobiles over time before and after the policy breakpoint. $\tilde{t} = t - t_0$ is the difference between time t and the month t_0 of the policy implementation. γ_{0k} is the regression coefficient of higher order polynomial of time term. γ_{1k} is the regression coefficient of higher order polynomial of policy-time interaction term. λ_t is the time-fixed effect. c and u_t are intercept term and the error term respectively. This regression equation can also be used to test whether there is a time-varying trend in the proportion of newly sold self-owned brand cars: if we can not deny the original assumption that $\gamma_{11}=\gamma_{12}=...=\gamma_{1n}=0$, we can believe that the time trend before and after the policy had not changed. That is, the policy only affects the dependent variable once at the breakpoint, and the function images on the left and right sides of the breakpoint are roughly parallel. If γ_{1k} is not zero significantly, it shows that the time trend has changed before and after the policy breakpoint, and the function image is unparallel. n is the order of this higher order polynomial $f(D,t)$, proper value of n can better separate the influence of time trend from policy breakpoint effect and improve the accuracy of estimation. In the following article, we will discuss the selection of polynomial order n.

Equation (1) is for the case of only one sample city. Because we use the urban cities panel data, we will also add the fixed effect at the urban level (represented by the city dummy variables) to control the regional automobile consumption impact. Pettersson and Lidbom believe that it is more advantageous to add time and individual fixed effects in RDD, because adding them can omit the steps of adding various covariates and help to improve the accuracy of estimation[12]. It is also obvious that from the theme of this study, adding time-fixed effect can also distinguish time influence factors from other factors. Therefore, this paper chooses to add the fixed effect at the individual and time levels. Furthermore, we chooses to control the fixed effect of year rather than the fixed effect of month, because from the realistic background, the automobile is not a fast consumable which is updated every month and the degree of freedom will be seriously damaged if we control monthly fixed effect. It has been proved that adding a fixed effect factor can reduce the standard deviation of the estimated coefficients and improve the validity of the estimation results.

As to whether other control variables need to be added, it is generally considered that they are not needed in a well-designed RDD regression. Because the control variables are continuous in time, there is no breakpoint of them at the policy breakpoint. In this paper, the factors affecting different consumers' decision-making on car purchasing are continuously changing in time and the government's decision-making on restricting car purchase is suddenly published. Therefore, in order to simplify the analysis, this paper chooses not to add other control variables in the initial model, but we will make sensitivity analysis on the situation of adding control variables. To sum up, the RDD regression model is as follows:

$$p_{it} = c + \rho D_t + f(D,t) + a_i + \lambda_t + u_{it} \tag{3}$$

$$f(D,t) = \sum_{k=1}^{n} \gamma_{0k} \tilde{t}^k + \sum_{k=1}^{n} \gamma_{1k} D_t \tilde{t}^k \tag{4}$$

$$p_{it} = \beta_0 + \rho D_t + f(D,t) + u_{it} + \alpha_2 city2 + \alpha_3 city3 + ... + + \alpha_7 city7 + \beta_2 year2012 + ... + \beta_5 year2015 \tag{5}$$

3.3. Selection of Optimal Time-Width and Polynomial Order

In the RDD regression design, choosing the appropriate bandwidth is the key to construct the partial random experiment. At present, in the design of RDD regression, the widely used time-width selection methods include CCT (Calonico, etc. put forward) [13], IK (Imbens and Kalyanaraman put forward) [14] and CV (Ludwig and Miller put forward)[15]. This paper attempts to use these three methods to select bandwidth: for the purchase restriction policy, the optimal bandwidth reported by the three methods is 16.4 months, 17 months and 46 months; for the driving restriction policy, the optimal bandwidth reported by the three methods is 17.4 months, 18.3 months and 43 months respectively. These bandwidths seem to have reached the theoretical optimum, but they will pose serious problems to the estimation in this paper: if we choose bandwidths that exceed the time difference between the two policies (that is to say cover another policy breakpoint), the effect of one policy may be misclassified into another. Therefore, this paper adopts the following processing methods: for cities with two policy breakpoints, the data outside the other breakpoint is set as missing values. This approach ensures that there are only two different policy states in the data set. Taking Tianjin as an example, in the analysis of the purchase restriction policy, the data from March 2014 and beyond are set as missing values. In the analysis of the driving restriction policy, the data before December 2013 are set as missing values. At the same time, in the fourth part (estimation results and robustness test), we report the estimation results under different bandwidth.

On the problem of how to choose the order n of polynomials, previous research usually use Akaike Information Criterion (AIC) to choose the order[16], or to study the estimation results under different orders as robustness test. In this paper, we calculate AIC of regression equation (5) under the condition that n ranges from 1 to 8.

The results are as follows:

Table 2: Polynomial order selection.

	D = purchase restriction		D=driving restriction	
n	$\hat{\sigma}^2$	AIC	$\hat{\sigma}^2$	AIC
1	4.673	337.029	3.136	269.164
2	4.686	339.629	3.142	271.607
3	4.697	342.136	3.151	274.271
4	4.637	341.359	3.116	273.68
5	4.675	345.121	3.128	276.571
6	4.612	344.191	3.135	279.09
7	4.566	344.026	3.139	281.386
8	4.562	345.836	3.133	282.942

Note: $AIC = N\ln(\hat{\sigma}^2) + 2(n+1)$ represents Akaike information criterion statistic, $\hat{\sigma}^2$ refers to the squared standard error of the model.

As can be seen from the table above, no matter the policy is purchase restriction or driving restriction, the AIC values of the first-order and second-order models are smaller and similar. According to AIC principle, we should choose the regression equation based on the first or second order formula. In fact, because the amount of data used is relatively limited, if the polynomial order used is too high, there may be over-fitting problem. Therefore, in the next part, we will report the regression results of polynomial order 1 and 2 respectively, to verify the robustness.

4. Equation Estimation and Robustness Test

4.1. Purchase Restriction Estimation

Table 3 lists the estimated results when the bandwidth adopts 42, 30 and 18 months, and the order of regression equation (5) is 1 and 2 respectively. Table 4 gives the estimated results of all variables when the order is 1 and 2 (Due to space constraints, only specific results at 42 months of bandwidth are reported).

Table 3: Summary of RDD Estimation Results of Purchase Restriction Policy.

Bandwidth	$n = 1$	$n = 2$
42 months	-4.365**	-3.427**
	(1.276)	(0.911)
30 months	-4.187**	-3.782**
	(0.961)	(1.352)
18 months	-4.554**	-3.573*
	(1.021)	(1.328)

Table 4: Estimated results under the purchase restriction policy (bandwidth = 42 months).

Variable	$n = 1$	$n = 2$
Purchase restriction policy D	-4.365**	-3.427**
	(1.276)	(0.911)
Time difference $\tilde{t}$	0.418**	0.365*
	(0.113)	(0.137)
$\tilde{t}^2$	-	-0.001
	-	(0.003)
Interactive term of policy and time difference $D\tilde{t}$	0.072	-0.001
	(0.066)	(0.265)
Squared interactive term of policy and time difference $D\tilde{t}^2$	-	0.005
	-	(0.005)
Dummy variables of cities		
Guangzhou	-27.982***	-27.843***
	(2.319)	(2.652)
Hangzhou	-16.713***	-16.544***
	(0.379)	(0.558)
Shenzhen	-12.177***	-12.067***
	(0.831)	(0.930)
Guiyang	-8.346**	-8.336**
	(2.458)	(2.648)
Dummy variable of year		
2012	-7.411***	-7.560***
	(0.657)	(0.871)
2013	-10.730***	-10.702***
	(1.517)	(1.990)
2014	-13.272***	-13.245***
	(1.902)	(2.333)
2015	-15.824**	-15.879**
	(4.265)	(4.650)

Note: The brackets in the table above represent the robust standard deviation of urban level clustering; ***, ** and * represented $p < 0.01$, $p < 0.05$, $p < 0.1$ respectively, and the dummy variable base groups are Tianjin City and 2011 year respectively.

As can be seen from the table above, under different bandwidth and regression equation order, the effect of purchase restriction policy on the proportion of self-brand cars is at the significant level of 5%, and the proportion of self-brand cars at breakpoints of policy decreased by an average of around 3.43-4.55%. There is no significant difference in the estimation and significance of coefficients under different conditions, which shows the robustness of the results. At the same time, no matter what regression equation is used, the regression coefficient of the interaction term of policy and time difference is not significant. It can be concluded that the purchase restriction policy only changed the residents' purchase preference at the policy breakpoint once, but could not change the overall time trend. In addition, most dummy variables of cities are very significant at the level of 1%, which confirms the view that the regional characteristics of automobile consumption are strong. It is worth noting that dummy variables of years have a significant negative impact on the proportion of self-brand cars, and with the passage of years, the degree of negative impact (absolute value of estimated regression coefficient) was increasing, indicating that the market competitiveness of self-brand cars in sample cities indeed decreased year by year. Comparing the absolute value of different coefficients, it is obvious that the negative impact of city and year is much larger than that of policy.

It can be concluded that although the purchase restriction policy had a negative impact on the market competitiveness of self-brand automobiles, it is unreasonable to attribute the decline of market share of self-brand automobiles to the purchase restriction policy. The fixed effects at the urban and time levels, that is the economic development and income increase, etc., had a significantly greater negative impact on self-brand automobiles. It also shows the necessity of using RDD and eliminating endogenous problems in analysis.

4.2. Driving Restriction Estimation

Table 5 lists the estimated results when the bandwidth is 44, 30 and 18 months, the order of regression equation (5) is 1 and 2, and the restriction policy is the treatment variable. Table 6 gives the estimation results of all variables when bandwidth is 44 months.

Table 5: Summary of the results of RDD regression estimation of driving restriction policy.

Dependent variable: Percentage of newly sold self-owned brand automobile		
Bandwidth(month)	$n = 1$	$n = 2$
44	-3.535	-3.219
	(2.298)	(3.711)
30	-3.138	-2.893
	(3.432)	(4.137)
18	-3.204	-4.757
	(3.421)	(4.268)

Table 6: Estimated results under the driving restriction policy (bandwidth = 44 months).

	Dependent variable: Percentage of newly sold self-owned brand cars	
Variables	$n = 1$	$n = 2$
Driving restriction policy D	-3.535	-3.219
	(2.298)	(3.711)
Time difference $\tilde{t}$	0.155	0.195
	(0.080)	(0.341)
$\tilde{t}^2$	-	0.001
	-	(0.006)
Interactive term of policy and time difference $D\tilde{t}$	0.179*	0.047
	(0.069)	(0.342)
Squared interactive term of policy and time difference $D\tilde{t}^2$	-	0.001
	-	(0.006)
Dummy variables of cities		
Tianjin	-4.994***	-4.871***
	(0.790)	(0.718)

Chengdu	-13.899***	-13.902***
	(1.827)	(2.038)
Hangzhou	-19.059***	-19.006***
	(2.469)	(2.737)
Guiyang	-2.008	-2.061
	(2.270)	(2.503)
Dummy variable of the year		
2012	-2.837**	-2.701
	(0.932)	(1.276)
2013	-5.492*	-5.090*
	(2.048)	(2.365)
2014	-8.721**	-8.622**
	(2.867)	(3.104)
2015	-9.771**	-9.774*
	(3.390)	(3.557)

Note: The brackets in the table above represent the robust standard deviation of urban level clustering; ***, ** and * represented $p < 0.01$, $p < 0.05$, $p < 0.1$ respectively, and the dummy variable base groups are Harbin City and 2011 year respectively.

As can be seen from the table, under the control of the fixed effect of years and cities, the driving restriction policy did not significantly affect the proportion of self-brand cars or changed consumers' purchase preferences. At the same time, the results also show that the fixed effect of region and time still had a significant impact.

This result contradicts the existing research opinion that the policy of driving restriction would encourage residents to buy another car with lower price, which has a positive effect on self-brand automobiles. A reasonable assumption is that people who buy a second car are relatively rich and price-insensitive. If so, then the driving restriction policy will have a significant positive impact on the total sales of automobiles. In order to verify this conjecture, this paper uses the method of clear RDD to analyze the data of automobile sales in each sample city within 60 months since 2011, table 7 shows the results. It suggests that the effect of driving restriction policy on automobile sales is not significant; even after controlling the resident population and the area of built-up area, this effect is still not significant. From regression results, driving restriction policy had not brought about significant growth in car sales, which indicates that the role of driving restriction in encouraging residents to buy a second car may not be obvious.

Table 7: Estimated results under the driving restriction policy.

	Dependent variable: Monthly car sales	
Bandwidth(month)	$n = 1$	$n = 2$
44	-482.060	-2991.036
	(2013.757)	(2453.014)
30	-1513.487	-3807.719
	(2552.252)	(3250.213)
18	-2884.319	-4171.275
	(1960.062)	(2525.915)

bandwidth = 44 months	Dependent Variable: Monthly car sales	
Variables	$n = 1$	$n = 2$
Driving restriction policy D	-482.060	-2991.036
	(2013.757)	(2453.014)

Time difference $\tilde{t}$	195.534	527.248
	(144.921)	(422.520)
$\tilde{t}^2$	-	7.716
	-	(7.303)
Interactive term of policy and time difference $D\tilde{t}$	209.713	-15.104
	(191.366)	(403.073)
Squared interactive term of policy and time difference $D\tilde{t}^2$	-	-10.027
	-	(8.330)
Dummy variables of cities		
Tianjin	505.518	89.605
	(1730.563)	(2006.211)
Chengdu	16562.620**	16611.12**
	(3931.284)	(3794.593)
Hangzhou	4694.632	3960.539
	(4101.482)	(4060.490)
Guiyang	-14549.520**	-15178.500**
	4809.897	(4687.891)
Dummy variable of the year		
2012	-1975.757	-1518.034
	(1547.719)	(1834.448)
2013	-2560.532	-2480.067
	(2766.364)	(3168.054)
2014	-1803.470	-2002.417
	(3780.101)	(3591.580)
2015	-5917.568	-6011.108
	(5050.477)	(4662.604)

Note: The brackets in the table above represent the robust standard deviation of urban level clustering; ***, ** and * represented $p < 0.01$, $p < 0.05$, $p < 0.1$ respectively, and the dummy variable base groups are Harbin City and 2011 year respectively.

5. Conclusions and Prospects

The empirical analysis of this paper shows that the purchase restriction policy has significantly changed the consumers purchase preference, making the proportion of new self-brand cars reduced by about 3.43% - 4.55%, and this effect is significant at the 5% level. However, its influence is far less than that of the urban economy and time development factors. Purchase restriction policy was not the main reason for the decline of the proportion of newly sold self-owned brand cars in sample cities. To increase the share of self-owned brand cars in cities with high economic level, it is necessary to enhance their own performance and competitiveness.

Besides, by using the method of clear RDD regression, this paper finds that the policy of driving restriction had no significant effect on the proportion of self-brand cars and the number of new cars sold. The view that "driving restriction encourages residents to buy second cars" is not significant in the sample. However, considering that the impact of restriction policy may lag behind, the validity of this conclusion needs to be further explored through more detailed data.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there is no conflict of interest.

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