Can Driving-Restriction Policies Alleviate Traffic Congestion? A Case Study of Beijing, China

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Research Article

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Title page

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Abstract

With ongoing urbanization, traffic congestion and the air pollution it induces are worsening. Using a system dynamics approach, this study constructed a driving-restriction policy model to explore the effects of different stages of policy implementation on variables such as traffic congestion, emissions, and parking demand. Medium- and long-term dynamic simulation showed that the effect of the policy was obvious in the initial stage but gradually weakened in the medium term, leading to a “fading” effect on emission reduction and traffic-congestion alleviation; a “rebound” effect was even observed at the end of the simulation. Thus, the policy will not effectively reduce traffic congestion in the long term and will induce a new demand for car purchases, resulting in paradoxical effects, which will aggravate parking demand, congestion, and pollution. Yet, it was also found that introducing penalty policies and an air pollution charging fee could weaken the paradoxical effects and compensate for some defects of the policy. Such strategies could help reduce emissions, traffic congestion, parking demand, the number of illegal trips, and the overall number of vehicle trips. These findings can provide not only a theoretical basis for further research but also practical guidance for policy improvement.

Key words: Driving restriction; system dynamics; degree of parking demand; paradoxical effect; combined strategy

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With ongoing urbanization, traffic congestion and the air pollution it induces are worsening. Using a system dynamics approach, this study constructed a driving-restriction policy model to explore the effects of different stages of policy implementation on variables such as traffic congestion, emissions, and parking demand. Medium- and long-term dynamic simulation showed that the effect of the policy was obvious in the initial stage but gradually weakened in the medium term, leading to a "fading" effect on emission reduction and traffic-congestion alleviation; a "rebound" effect was even observed at the end of the simulation. Thus, the policy will not effectively reduce traffic congestion in the long term and will induce a new demand for car purchases, resulting in paradoxical effects, which will aggravate parking demand, congestion, and pollution. Yet, it was also found that introducing penalty policies and an air pollution charging fee could weaken the paradoxical effects and compensate for some defects of the policy. Such strategies could help reduce emissions, traffic congestion, parking demand, the number of illegal trips, and the overall number of vehicle trips. These findings can provide not only a theoretical basis for further research but also practical guidance for policy improvement.

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1. Introduction

As China's urbanization levels continue to rise, traffic congestion and its induced air pollution are becoming increasingly serious (Wu et al. 2017; Hubbell et al. 2018). Although government departments have adopted various policies to alleviate traffic congestion (e.g., traffic-restriction policy, different working hour measures), the effects have been very limited (Xiao et al. 2019; Liu et al. 2018).

Many studies have investigated ways to ease traffic congestion. Studying public attitudes about traffic-congestion charges in Stockholm, Eliasson (2014) found that attitudes became dramatically more positive, changing from two-thirds against to more than two-thirds in favor. Börjesson and Kristoffersson (2015), studying traffic-congestion charges in Gothenburg, found that deciding to levy charges mainly depended on support from political parties—which mainly depends on the current system setting and the control of income—while depending to a lesser extent on public support and the benefits of reducing congestion. Peng and Zhang (2017), meanwhile, examined synthesizing the management of megalopolis transportation, which includes analyzing the causes of traffic congestion, forecasting and managing congestion, and analyzing the effects of policy. These studies provide some useful decision-making references for managing urban traffic congestion.

In recent years, some large cities in China have implemented a driving-restriction policy to cope with severe urban congestion. Public attitudes about the policy are varied. On the one hand, supporters believe the policy can effectively reduce the number of motor vehicle trips, alleviate congestion, and reduce vehicle emissions (Liu et al. 2016a; Gu et al. 2017; Zhao et al. 2018). On the other hand, some studies have revealed the negative effects of the driving-restriction policy (Liu et al. 2016b; Xu et al. 2015). For example, Zhang et al. (2017) modeled the effects of license plate–based driving restrictions on air pollution and found that the policy would actually increase pollution (e.g., NO_2, NO_x, O_3) as a result of substitution, the use of alternative modes of transportation, and the purchase of a second car.

The abovementioned studies suggest ways to mitigate urban traffic congestion from different perspectives and provide useful references for government transportation and environmental protection departments. However, two questions require further investigation:

Question 1: While the driving-restriction policy is effective in the short term, is it still valid in the long term?

Question 2: Will the driving-restriction policy have negative effects in the long term?

Adopting a system dynamics approach, this study established a driving-restriction model and used dynamic simulation to investigate paradoxical effects hidden in the system. It was found that the policy will increase the demand for car purchases in the long term, which will increase the total number of vehicles and further aggravate parking-space demand. In particular, searching for parking will increase mileage, which will aggravate traffic congestion and generate more pollutants. The results also showed that over time, the driving-restriction policy will have a “fading” effect, followed by a “rebound” effect. These findings can provide a theoretical reference for policy improvement and optimization.

2. Methods

2.1 System dynamics

First proposed by Forrester in 1956, system dynamics (SD) is designed to analyze complex dynamic feedback systems (Liu et al. 2015). It has been widely applied in many areas, such as green growth strategies (Guo et al. 2018), construction waste reduction (Ding et al. 2018; Yuan and Wang 2014), water security (Sahin et al., 2015), energy management (Zapata et al. 2019; Hsiao et al. 2018), and transport emissions (Liu et al. 2019; Shi et al. 2017). Hence, this method can be applied to analysis and simulation to provide useful references for decision-makers. Dace et al. (2015), for example, established an agricultural greenhouse gas (GHG) emissions model using SD (which supports assessing the effects of decisions and measures) and found there were very limited options for GHG mitigation in the agricultural sector. Wang et al. (2018) used an SD model to forecast changes in China's coal-production capacity under different scenarios (baseline, policy-regulation, and strengthened-policy scenarios) and found that coal overcapacity would continue and face serious challenges in the future.

2.2 SD structure analysis

A causal loop diagram is a graphic model used to qualitatively describe causal relationships between variables—that is, it shows interactions between variables in the form of graph. The advantage of this method is that it can express the relationships between variables in a complex system and help determine the boundaries of the studied system. Fig. 1 shows the causal loop diagram established for this study; it includes the driving-restriction policy, air pollution charging fee (APCF), and penalties.

Typical loops for traffic congestion mitigation are as follows:

Loop 1: Degree of traffic congestion$\xrightarrow{+}$Driving restriction$\xrightarrow{-}$Number of private car trips (short term)$\xrightarrow{+}$Number of private car trips$\xrightarrow{+}$Number of vehicle trips$\xrightarrow{-}$Per vehicle area of roads$\xrightarrow{+}$Road bearing capacity$\xrightarrow{-}$Degree of traffic congestion

Loop 2: Degree of traffic congestion$\xrightarrow{+}$Driving restriction$\xrightarrow{+}$New requirement for car purchase$\xrightarrow{+}$Number of private cars from side effect$\xrightarrow{+}$Number of private car trips from side effect$\xrightarrow{+}$Number of private car trips$\xrightarrow{+}$Number of vehicle trips$\xrightarrow{-}$Per vehicle area of roads$\xrightarrow{+}$Road bearing capacity$\xrightarrow{-}$Degree of traffic congestion

Loop 3: Degree of traffic congestion$\xrightarrow{+}$Pressure from ground transportation$\xrightarrow{+}$Probability of receiving a penalty$\xrightarrow{+}$Cost of violation of regulations$\xrightarrow{-}$Number of illegal trips$\xrightarrow{-}$Per vehicle area of roads$\xrightarrow{+}$Road bearing capacity$\xrightarrow{-}$Degree of traffic congestion

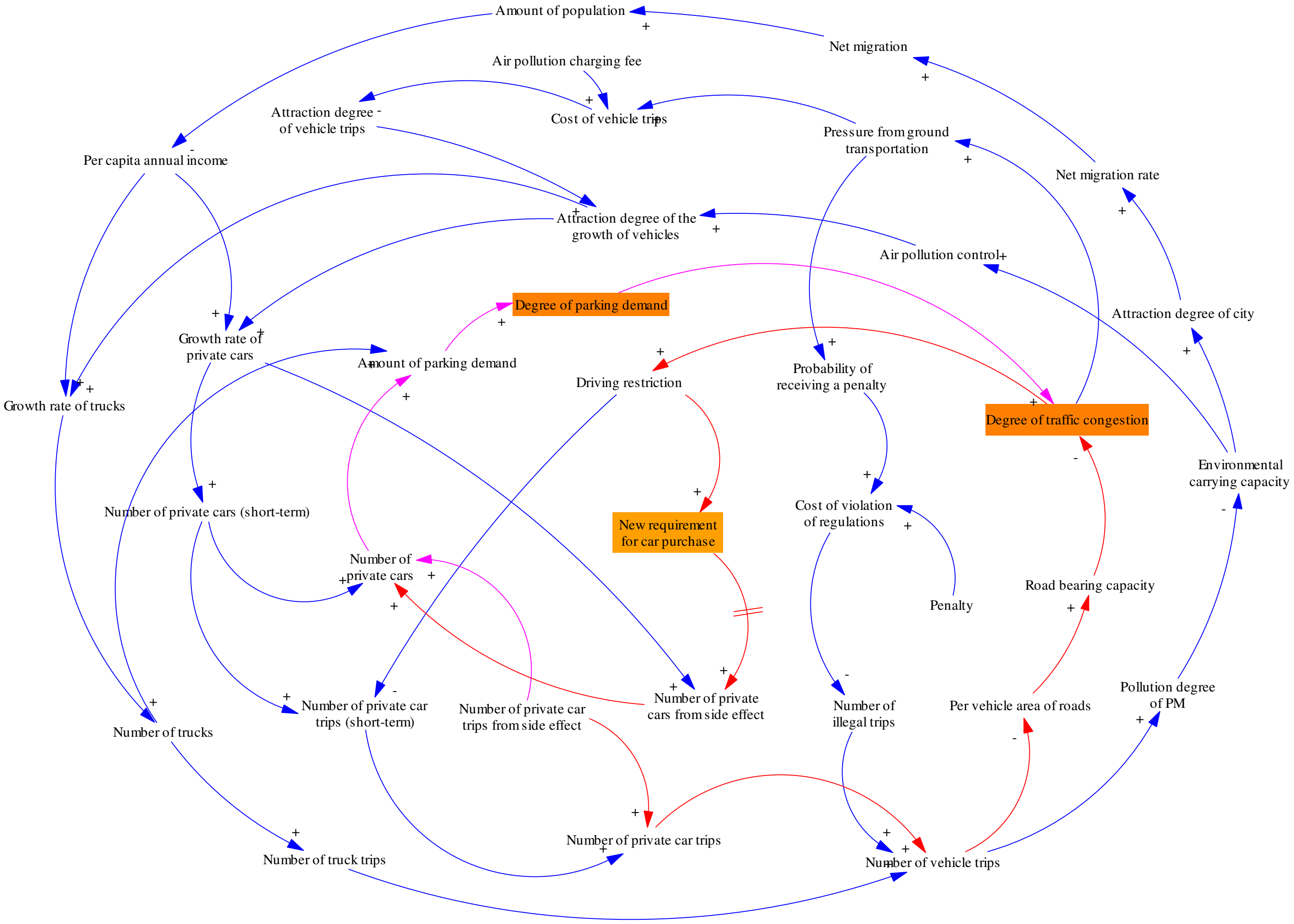


Fig. 1 Causal loop diagram of the driving-restriction model.

Loop 4: Degree of traffic congestion$\xrightarrow{+}$Pressure from ground transportation$\xrightarrow{+}$Cost of vehicle trips$\xrightarrow{-}$Attraction degree of vehicle trips$\xrightarrow{+}$Attraction degree of the growth of vehicles$\xrightarrow{+}$Growth rate of private cars$\xrightarrow{+}$Number of private cars (short term)$\xrightarrow{+}$Number of private car trips (short term)$\xrightarrow{+}$Number of private car trips$\xrightarrow{+}$Number of vehicle trips$\xrightarrow{-}$Per vehicle area of roads$\xrightarrow{+}$Road bearing capacity$\xrightarrow{-}$Degree of traffic congestion

Loop 5: Degree of traffic congestion$\xrightarrow{+}$Pressure of ground transportation$\xrightarrow{+}$Cost of vehicle trips$\xrightarrow{-}$Attraction degree of vehicle trips$\xrightarrow{+}$Attraction degree of the growth of vehicles$\xrightarrow{+}$Growth rate of trucks$\xrightarrow{+}$Number of trucks$\xrightarrow{+}$Number of truck trips$\xrightarrow{+}$Number of vehicle trips$\xrightarrow{-}$Per vehicle area of roads$\xrightarrow{+}$Road bearing capacity$\xrightarrow{-}$Degree of traffic congestion

In Loop 1, the continuous increase in traffic congestion will prompt local governments to adopt the driving-restriction policy, and the number of private car trips (short term) is reduced in the short term; thus the growth rate of the number of private car trips and number of vehicle trips is reduced. The per vehicle area of roads is also improved, which will increase road bearing capacity and reduce traffic congestion. It is a negative feedback loop; after a series of actions in the loop, the growth of traffic congestion is effectively suppressed.

In Loop 2, increasing traffic congestion will intensify the enforcement of the driving-restriction policy, which will lead to a new requirement for car purchases, resulting in certain side effects. Here, the number of private cars will continue to increase as a result of the side effect, increasing the number of private car trips. This will decrease the per vehicle area of roads, reduce road bearing capacity, and aggravate traffic congestion. This is a positive feedback loop; the implementation of the driving-restriction policy creates a new car-purchase demand, which further intensifies traffic congestion in the long term.

Loop 3 is a negative-feedback loop. It increases the cost of violation through a penalty policy, which then reduces the number of illegal trips. Finally, the per vehicle area of roads and road bearing capacity are improved, and traffic congestion is reduced.

Loops 4 and 5 are negative-feedback loops. They increase the cost of vehicle trips through the APCF policy and then reduce the number of private car trips (see Loop 4) and truck trips (see Loop 5) to achieve the purpose of reducing congestion.

In terms of relieving tension related to parking spaces, the following loops are typical:

Loop 6: Degree of parking demand$\xrightarrow{+}$Degree of traffic congestion$\xrightarrow{+}$Driving restriction$\xrightarrow{+}$New requirement for car purchase$\xrightarrow{+}$Number of private cars from side effect$\xrightarrow{+}$Number of private cars$\xrightarrow{+}$Amount of parking demand$\xrightarrow{+}$Degree of parking demand

Loop 7: Degree of parking demand$\xrightarrow{+}$Degree of traffic congestion$\xrightarrow{+}$Pressure from ground transportation$\xrightarrow{+}$Cost of vehicle trips$\xrightarrow{-}$Attraction degree of vehicle trips$\xrightarrow{+}$Attraction degree of the growth of vehicles$\xrightarrow{+}$Growth rate of private cars$\xrightarrow{+}$Number of private cars (short term)$\xrightarrow{+}$Number of private cars$\xrightarrow{+}$Amount of parking demand$\xrightarrow{+}$Degree of parking demand

Loop 8: Degree of parking demand$\xrightarrow{+}$Degree of traffic congestion$\xrightarrow{+}$Pressure from ground transportation$\xrightarrow{+}$Cost of vehicle trips$\xrightarrow{-}$Attraction degree of vehicle trips$\xrightarrow{+}$Attraction degree of the growth of vehicles$\xrightarrow{+}$Growth rate of trucks$\xrightarrow{+}$Number of trucks$\xrightarrow{+}$Amount of parking demand$\xrightarrow{+}$Degree of parking demand

Loop 6 is a positive-feedback loop. Here, an increase in the degree of parking demand will increase the degree of traffic congestion. Some governments will therefore implement a stricter driving-restriction policy, which will lead to a “new requirement” for car purchases. With this side effect, the number of private cars will increase, which will further increase the amount of parking demand and eventually aggravate the degree of parking demand. After a series of functions in this loop, the increase in the degree of parking demand will eventually further exacerbate its growth.

Loops 7 and 8 are negative-feedback loops. They increase the cost of vehicle trips through APCF to constrain the rapid growth of the number of private cars (see Loop 7) and trucks (see Loop 8). Finally, the amount of parking demand is reduced, and the degree of parking demand is alleviated.

In summary, implementing the driving-restriction policy will have immediate effects in the short term (see Loop 1). In the long term, however, it will lead to a new car-purchase demand, which will further aggravate parking demand (see Loop 6), traffic congestion, and air pollution. To this end, this study adopted APCF (see Loops 4, 5, 7, and 8) to reduce vehicle trips, congestion, and air pollution by increasing the cost of vehicle trips. Introducing APCF policy also reduces the degree of vehicle growth to a certain extent, which also inhibits the growth of parking demand. Meanwhile, APCF reduces the attraction degree of the growth of vehicles to some extent, thus inhibiting parking demand growth. In addition, this study adopted the penalty policy (see Loop 3) to reduce the number of illegal trips. Although the penalty policy’s effect on reducing the degree of parking demand is weak, it helps reduce the number of motor vehicle trips. These measures can help overcome the limitations of the driving-restriction policy and further improve it.

2.3 Stock-flow diagram

A stock-flow diagram of the driving-restriction model was constructed based on the analysis in section 2.2 (Fig. 2). The major parameters and equations were obtained based on the *Beijing Statistical Yearbook*, *China Statistical Yearbook*, and existing literature (MEP, 2015–2020). Tables 1-2 show the details. The simulation period was 2011–2025, and the time step was 1.

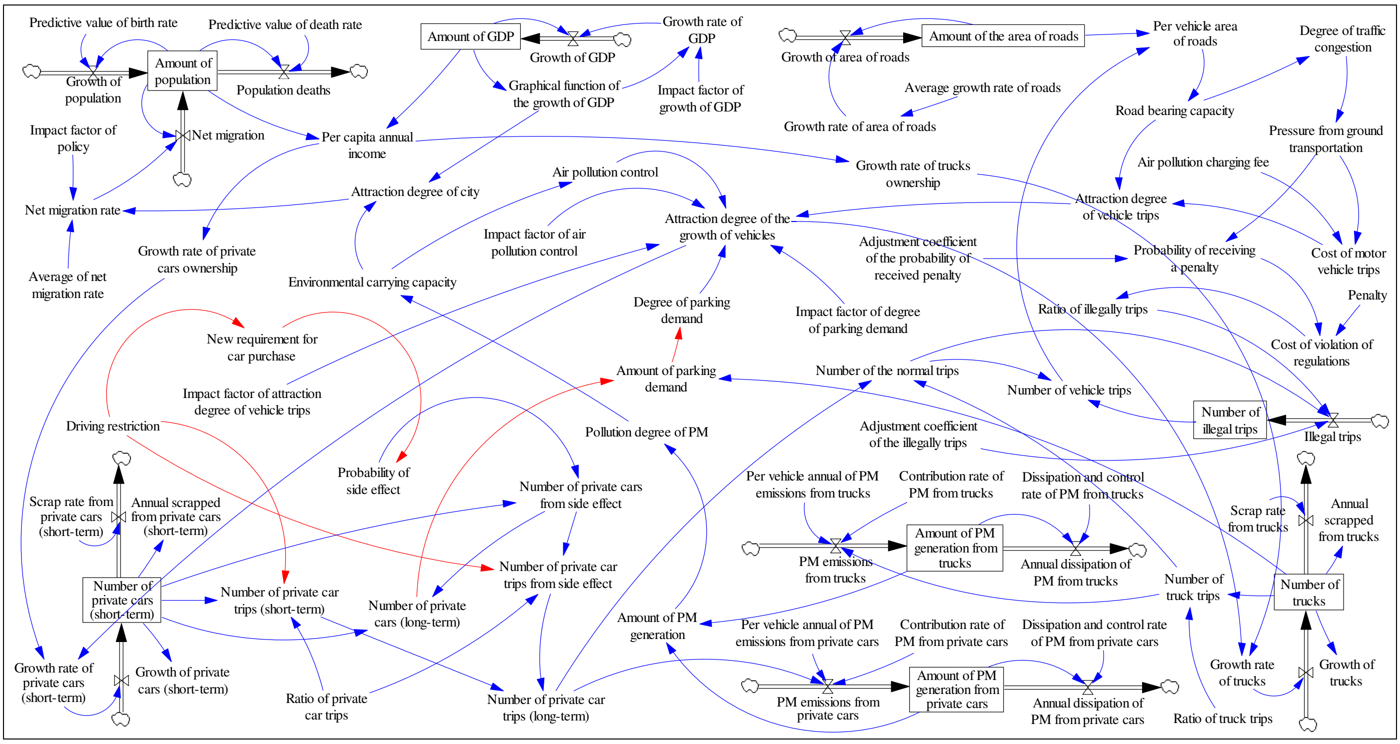


Fig. 2 Stock-flow diagram of the driving-restriction model.

Table 1 Descriptions of the major parameters and equations in the model

Variable name	**Unit**	**Parameter or equation**
Attraction degree of city	Dmnl	0.35*graphical function of the growth of GDP + 0.65*environmental carrying capacity
Attraction degree of the growth of vehicles	%	(1-air pollution control)*impact factor of air pollution control + attraction degree of vehicle trips*impact factor of attraction degree of vehicle trips + (1-degree of parking demand)*impact factor of degree of parking demand
Average of net migration rate	1/year	0.00366
Contribution rate of PM from private cars	%	0.205
Contribution rate of PM from trucks	%	0.795
Degree of parking demand	Dmnl	WITH LOOKUP (amount of parking demand, ([(2e+006, 0) - (1.1e+007, 1)], (2.664e+006, 0.3), (3.186e+006, 0.35), (3.938e+006, 0.4), (4.112e+006, 0.45), (4.312e+006, 0.5), (4.522e+006, 0.55), (4.661e+006, 0.6), (4.709e+006, 0.65), (4.858e+006, 0.7), (5.039e+006, 0.75), (5.19e+006, 0.8), (6e+006, 0.85), (8e+006, 0.9), (1e+007, 0.95)))

Driving restriction		0.2/0/0.5
Net migration rate	1/year	average of net migration rate*attraction degree of city^(impact factor of policy)
New requirement for car purchase	Dmnl	WITH LOOKUP (driving restriction, ([(0, 0) - (1, 1)], (0, 0), (0.1, 0.3), (0.2, 0.6), (0.3, 0.7), (0.4, 0.8), (0.5, 0.9)))
Number of illegal trips	vehicle	INTEG (illegal trips, 0)
Number of private cars from side effect	vehicle	number of private cars (short-term)*probability of side effect
Number of private cars (long-term)	vehicle	number of private cars from side effect + number of private cars (short-term)
Number of private cars (short-term)	vehicle	INTEG (growth of private cars (short-term) - annual scrapped from private cars (short-term), 3.897e+006)

Table 2 Descriptions of the major parameters and equations in the model (continued).

Variable name	**Unit**	**Parameter or equation**
Number of private car trips (long-term)	vehicle	number of private car trips (short-term) + number of private car trips from side effect
Number of private car trips (short-term)	vehicle	(1-driving restriction)*number of private cars (short-term)*ratio of private car trips
Amount of parking demand	vehicle	number of private cars (long-term) + number of trucks
Amount of PM generation from private cars	t	INTEG (PM emissions from private cars - annual dissipation of PM from private cars, 2727.9)
Amount of PM generation from trucks	t	INTEG (PM emissions from trucks - annual dissipation of PM from trucks, 3848.5)
Number of trucks	vehicle	INTEG (growth of trucks - annual scrapped from trucks, 215000)
Number of truck trips	vehicle	number of trucks*ratio of truck trips
Per vehicle annual of PM emissions from private cars	t/(year*vehicle)	0.0007
Per vehicle annual of PM emissions from trucks	t/(year*vehicle)	0.0179
Pollution degree of PM	Dmnl	WITH LOOKUP (amount of PM generation, ([(3000, 0) - (20000, 1)], (3500, 0.1), (4978, 0.2), (5377.8, 0.3), (6093.4, 0.4), (6576.4, 0.5), (7094.8, 0.55), (7585.8, 0.65), (8233.5, 0.75), (8559.5, 0.8), (9076.6, 0.85), (9839.7, 0.9), (10513, 0.95), (13000, 0.98)))
Probability of side effect	Dmnl	LN(new requirement for car purchase+1)
Road bearing capacity	Dmnl	WITH LOOKUP (per vehicle area of roads, ([(10, 0) - (120, 1)], (30, 0.05), (36.1815, 0.1), (37.3342, 0.15), (38.4558, 0.2), (38.6434, 0.25),

	(38.7228, 0.3), (38.9442, 0.35), (39.0162, 0.4), (40.52, 0.45), (43.3769, 0.5), (52.3826, 0.55), (61.0156, 0.6), (80, 0.75), (100, 0.9)))

3. Results

The following policy scenarios were designed to explore the driving-restriction policy’s effect on traffic congestion, emission reduction, parking demand, number of illegal trips, and number of vehicle trips before and after implementation: **Scenario 1**: no policy; **Scenario 2**: single driving-restriction policy; **Scenario 3**: “odd-even” driving restriction; **Scenario 4**: driving restriction + APCF; **Scenario 5**: driving restriction + penalty; and **Scenario 6**: driving restriction + APCF + penalty. Among them, in Scenario 2, 20% of vehicles (except for new-energy vehicles) are restricted from traveling in downtown areas in during traffic-restriction periods; in Scenario 3, 50% of vehicles are restricted.

3.1 Model validation

Definition 1 (Liu 2017): Assume the zero starting point images have two behavioral sequences:

$$X_i=(x_i(1),x_i(2),\cdots,x_i(n))\,,\,X_j=(x_j(1),x_j(2),\cdots,x_j(n))\,,$$

and these two sequences have the same length:

$$X_i^0=(x_i^0(1),x_i^0(2),\cdots,x_i^0(n))\,,\,X_j^0=(x_j^0(1),x_j^0(2),\cdots,x_j^0(n))\,.$$

Then we have

$$\varepsilon_{ij}=\frac{1+|s_i|+|s_j|}{1+|s_i|+|s_j|+|s_i-s_j|} \tag{1}$$

which is known as the grey absolute degree of incidence (GADI) of X_i and X_j, where

$$s_i=\int_1^n (X_i-x_i(1))dt, s_j=\int_1^n (X_j-x_j(1))dt, s_i-s_j=\int_1^n (X_i^0-X_j^0)dt \tag{2}$$

$$x_i^0(k)=x_i(k)-x_i(1)\,,\;\; x_j^0(k)=x_j(k)-x_j(1)\,,k=1,2,\cdots,n. \tag{3}$$

Assume X_i and X_j are two sequences of the same length with nonzero initial values, X_i' and X_j' are the initial images of X_i and X_j, and the zero starting point images of the two behavioral sequences X_i',X_j' are $X_i^{'0}$ and $X_j^{'0}$. The GADI of is $X_i^{'}$ and $X_j^{'}$ is called the grey relative degree of incidence (GRDI) of X_i and X_j. Denote

$$r_{ij}=\frac{1+|s_i^{'}|+|s_j^{'}|}{1+|s_i^{'}|+|s_j^{'}|+|s_i^{'}-s_j^{'}|}. \tag{4}$$

Then,

$$\rho_{ij} = \theta \cdot \varepsilon_{ij} + (1-\theta) \cdot r_{ij} \tag{5}$$

is called the grey synthetic degree of incidence (GSDI) of X_i and X_j, where $\theta \in [0,1]$.

GSDI reflects the degree of similarity or proximity between two sequences. It is a quantitative indicator that comprehensively characterizes whether the sequences are closely related. Therefore, if these two sequences represent the actual value sequence and simulation value sequence, respectively, GSDI can describe the closeness of the two sequences as a whole. In general, the larger the value of the degree of grey incidence, the stronger the degree of compactness, and the smaller the simulation error. See Table 3 for the accuracy test grade.

Table 3 Reference list of the accuracy test grade (Liu 2017).

Accuracy grade	Grade 1	Grade 2	Grade 3	Grade 4
Degree of grey incidence	0.90	0.80	0.70	0.60

Here, the amount of the area of roads is taken as an example. Its historical value and the simulation value sequence are recorded as X_1 and X_2, respectively. Then,

$$X_1 = (91640000,\ 92360000,\ 96110000,\ 100020000,\ 100290000,\ 102750000,\ 103470000,\ 103280000),$$

$$X_2 = (91640000,\ 94397300,\ 97237600,\ 100163000,\ 103177000,\ 106282000,\ 109480000,\ 112774000).$$

According to Definition 1, it can be calculated as

$$|s_1| = 50980000, |s_2| = 71463900, |s_1 - s_2| = 20483900.$$

So,

$$\varepsilon_{12} = \frac{1+|s_1|+|s_2|}{1+|s_1|+|s_2|+|s_1-s_2|} = \frac{1+50980000+71463900}{1+50980000+71463900+20483900} \approx 0.86.$$

Similarly, the following can be calculated:

$$r_{12} = \frac{1+|s'_1|+|s'_2|}{1+|s'_1|+|s'_2|+|s'_1-s'_2|} = \frac{1+0.555+0.775}{1+0.555+0.775+0.22} \approx 0.91.$$

Let $\theta = 0.5$; then,

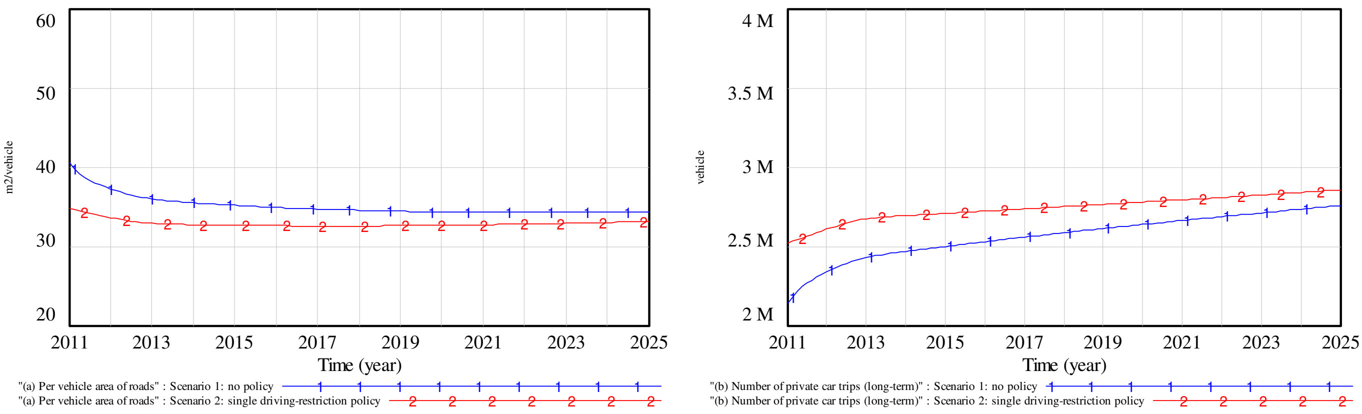
$$\rho_{12} = \theta\varepsilon_{12} + (1-\theta)r_{12} \approx 0.89.$$

The value of GSDI is approximately equal to 0.9. Hence, according to Definition 1 and Table 3, the accuracy test grade is close to “first-class” precision.

3.2 Paradoxical effects of driving-restriction policy

As shown in Fig. 3a and Table 4, compared to curve 1, curve 2 decreases by about 3.58% (in 2025). In the same way, the number of private car trips (long term) increases by about 3.57% (in Fig. 3b). These results show that the driving-restriction policy has not achieved the purpose of alleviating traffic congestion. Fig. 3c shows a slow decline trend in the early stage (2011–2015) and a gradual weakening in the medium term (2015–2022), indicating that the emission-reduction effect gradually fades (i.e., the "fading" effect). In the later stage (after 2022), the effect is close to zero, and there are some signs of rebound (~4.23%). In Fig. 3d, curve 1 shows a rising trend, indicating that with ongoing urbanization, the number of motor vehicles shows a rapid growth trend, leading to an upward trend in parking demand. In particular, curve 2 always remains at a high level, indicating that the policy has further exacerbated parking-space tension (~7.76%).

(a) Per vehicle area of roads　　(b) Number of private car trips (long-term)



(c) Amount of PM generation from private cars　　(d) Degree of parking demand

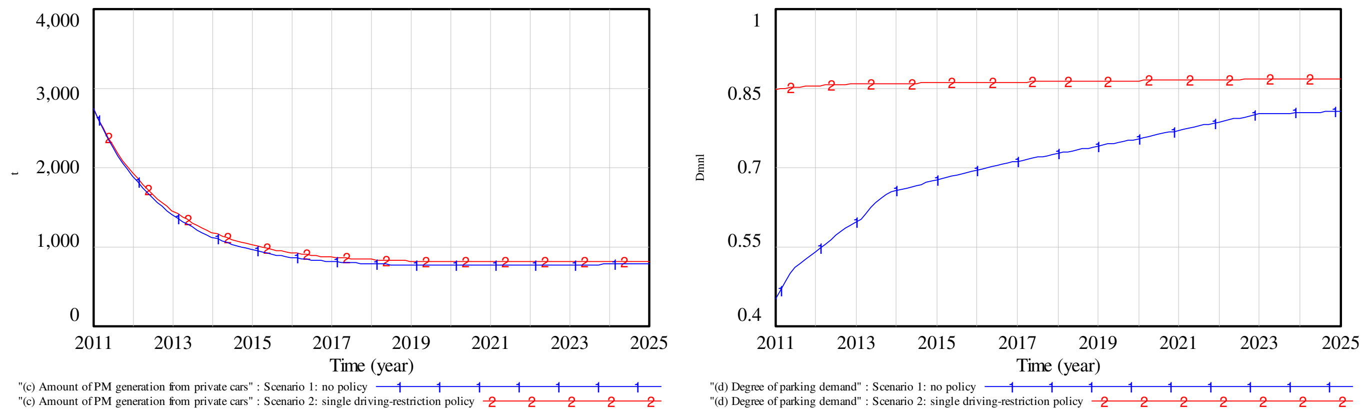


Fig. 3 Effects of driving-restriction policy: (a) per vehicle area of roads, (b) number of private car trips (long term), (c) amount of PM generation from private cars, and (d) degree of parking demand.

Table 4 Paradoxical effects of the driving-restriction policy (in 2025).

Variable	Scenario 1	Scenario 2	Variation (%)
Per vehicle area of roads	34.3594 m^2/vehicle	33.1291 m^2/vehicle	-3.58
Number of private car trips (long-term)	2.75722e+006 vehicle	2.85553e+006 vehicle	3.57
Amount of PM generation from private cars	779.039 t	811.963 t	4.23
Degree of parking demand	0.805674	0.868163	7.76

In summary, implementing the driving-restriction policy will cause various “paradox” effects in the long term, such as further aggravating parking-space tension and showing a “rebound” effect regarding emissions and congestion. The reason for such effects could be that the policy stimulates a new demand for purchasing vehicles. In addition, preferential policies for new-energy vehicles (e.g., unlimited in number) also cause the total number of motor vehicles to increase.

3.3 Scenario optimization and multiple performances

Figs. 4a–d (between curves 1 and 2) show that APCF policy had a more significant effect than the penalty policy while Fig. 4e (between curves 1 and 2) shows that the penalty policy is more effective than APCF. Thus, a combination of APCF and penalty policies is not always optimal (variables 2–4 in Table 5). Fig. 4 (between curves 1 and 3) and Table 5 indicate that introducing the penalty policy had significant effects on the per vehicle area of roads and the number of vehicle trips, changing by 20.13% and 16.76%, respectively; the number of illegal trips changed most significantly (~49.52%). Figs. 4b–d (between curves 1 and 3) were almost unchanged. These results indicate that the penalty policy had the most obvious effect on reducing the number of illegal trips and had a certain positive effect on improving the per vehicle area of roads and reducing the number of vehicle trips. However, the effects on emission reduction, the number of private car trips, and the degree of parking demand were very limited.

Table 5 Influence of the major variables under different scenarios (in 2025).

Variable	**Scenario 4**	**Scenario 6**	**Variation**	**Scenario 5**	**Variation**
Per vehicle area of roads (m^2/vehicle)	61.056	73.3489	20.13%	37.3382	96.44%
Number of private car trips (long-term) (vehicle)	1.37689e+006	1.40721e+006	2.20%	3.08308e+006	-54.36%
Amount of PM generation from private cars (t)	432.265	439.347	1.64%	858.043	-48.80%
Degree of parking demand	0.353816	0.358565	1.34%	0.881563	-59.33%
Number of illegal trips (vehicle)	833373	420720	-49.52%	493237	-14.70%
Number of vehicle trips (vehicle)	2.27301e+006	1.89207e+006	-16.76%	3.71686e+006	-49.09%

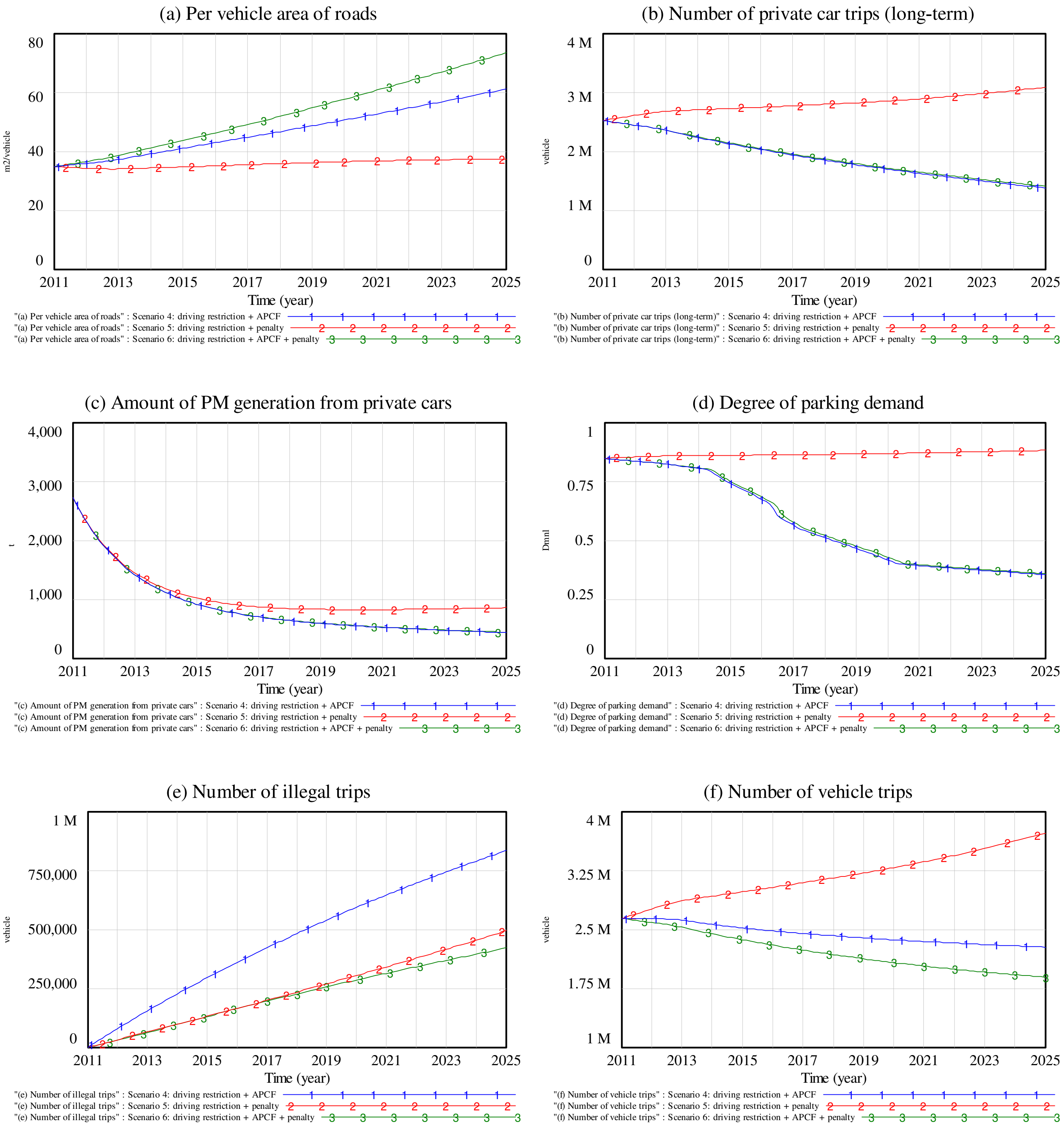


Fig. 4 Influence of the major variables under different scenarios: (a) per vehicle area of roads, (b) number of private car trips (long term), (c) amount of PM generation from private cars, (d) degree of parking demand, (e) number of illegal trips, and (f) number of vehicle trips.

Fig. 4 (between curves 2 and 3) and Table 5 show that after introducing APCF policy, the per vehicle area of roads (Fig. 4a), number of private car trips (long term) (Fig. 4b), amount of PM generation from private cars (Fig. 4c), degree of parking demand (Fig. 4d), and number of vehicle trips (Fig. 4f) changed significantly, decreasing (or increasing) by 96.44%, 54.36%, 48.80%, 59.33%, and 49.09%, respectively. The number of illegal trips (Fig. 4e) was reduced by about 14.70%.

These results indicate that a combined strategy (Scenario 6) can absorb the advantages of the two policies and have multiple performances. It can not only achieve the dual goal of traffic-congestion mitigation (Figs. 4a–b, Fig. 4f) and emission reduction (Fig. 4c) but also reduce parking demand (Fig. 4d) and the number of illegal trips (Fig. 4e). In addition, Fig. 4a and Figs. 4e–f show that combining APCF and penalties has the best effect in terms of alleviating and reducing illegal vehicle travel.

4. Discussion

As urbanization advances and living standards continue to improve, the number of motor vehicles also increases. While some cities in China have implemented driving-restriction policies, these have triggered a new demand for car purchases and have increased, rather than decreased, travel distances. In addition, various preferential policies for new-energy vehicles have further aggravated the demand for parking spaces, thus leading to a series of paradox effects.

4.1 Peer effect and fading effect

Beijing first implemented an “odd-even” driving restriction (in 2008) to alleviate traffic congestion. Other cities soon followed, such as Zhengzhou, Tianjin, and Jinan. However, those cities did not fully account for the comprehensive benefits and negative effects of the policy. Therefore, this type of follow-up behavior by governments (see Loop 1) did not improve the driving-restriction policy based on local conditions, thus producing various negative effects (see Loops 2 and 6). Meanwhile, from a long-term perspective, the policy shown a fading effect (see Fig. 3c and Table 4), and its emission-reduction effect will therefore be gradually weakened.

4.2 Calendar effect and rebound effect

The driving-restriction policy also has a calendar effect (i.e., seasonal effect). In winter and spring, heating causes coal and energy consumption to increase. In addition, meteorological factors in autumn and winter are not conducive to the diffusion of pollutants. Finally, the superposition of various factors leads to the aggravation of air pollution. In addition, in the deep winter season, some cities implement more stringent restrictions (e.g., “odd-even” driving restrictions), which exacerbate traffic congestion to some extent. This further stimulates the new demand for cars.

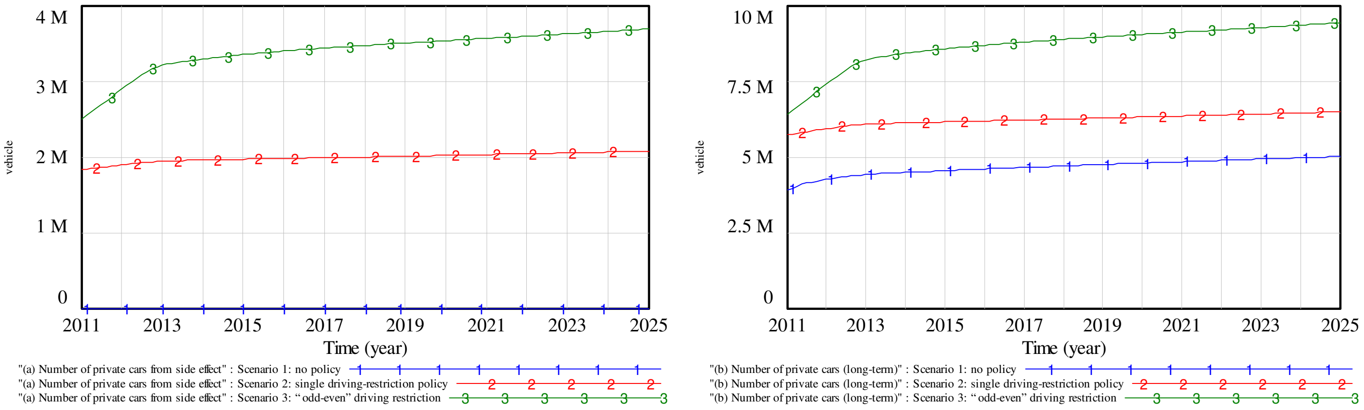
Horizontal analysis showed that the policy has a rebound effect (see Fig. 3c). Loop 6 also shows that the driving-restriction policy will increase parking demand in the long run, and traffic congestion and air pollution will be more severe, showing a rebound trend.

4.3 Paradoxical effects of emission reduction and traffic-congestion relief

Fig. 5a and Table 6 show that with a higher number limit, the number of private cars increases rather than decreases as a result of the side effect. From a long-term perspective (from Scenario 1 to Scenario 3), the number of private cars, caused by the side effect, will increase (from 0 to 3.68644e+006 vehicles). Similarly, in Fig. 5b, from Scenario 1 to Scenario 3, the number of private cars (long term) will rise to 9.42986e+006 in 2025. These results indicate that the driving-restriction policy has induced some side effects in the long-term that will not only increase the total number of private cars but also aggravate parking-space tension.

(a) Number of private cars from side effect

(b) Number of private cars (long-term)



(c) Number of private car trips from side effect

(d) Number of private car trips (short-term)

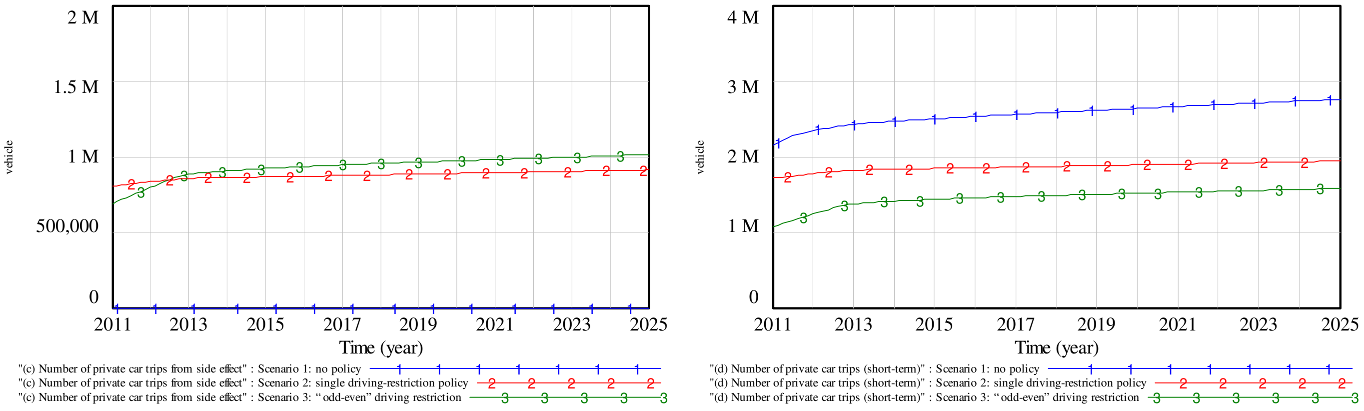


Fig. 5 Paradoxical effects of the major variables under driving-restriction policies: (a) number of private cars from side effect, (b) number of private cars (long-term), (c) number of private car trips from side effect, and (d) number of private car trips (long-term).

The change in Fig. 5c shows that the number of private car trips, caused by side effects, is also increasing; it will gradually increase to 1.01377e+006 vehicles (from Scenario 1 to Scenario 3). Fig. 5d shows that in the short term, the more stringent the traffic restrictions, the lower the number of private car trips, thus having a positive effect on relieving traffic congestion. However, from a long-term perspective, the greater the number of restrictions, the higher the number of private cars and trips (see Figs. 5a–c); that is, pollution and congestion are not controlled, and the number of private cars sharply increases.

Table 6 Side effects of the driving-restriction policy (in 2025). Unit: vehicle.

Variable	Scenario 1	Scenario 2	Scenario 3
Number of private cars from side effect	0	2.07499e+006	3.68644e+006
Number of private cars (long-term)	5.01312e+006	6.48984e+006	9.42986e+006
Number of private car trips from side effect	0	9.12997e+005	1.01377e+006
Number of private car trips (long-term)	2.75722e+006	1.94253e+006	1.57944e+006

4.4 Multiple performances of the combined strategy

Compared to Scenario 6 (see Table 5) and Scenario 2 (see Table 4), the per vehicle area of roads increased by about 121.40%, and the number of private car trips (long term), amount of PM generation from private cars, and degree of parking demand decreased by approximately 50.72%, 45.89%, and 58.70%, respectively. This indicates that the combined strategy has multiple performances: namely, it reduces congestion, emissions, and parking demand.

The combined strategy also has a positive effect on the number of illegal trips and number of vehicle trips (Table 5). However, the penalty policy mainly serves to reduce the number of illegal trips and has little effect on parking demand (see Fig. 4d and Table 5).

5. Conclusions and policy recommendations

5.1 Main conclusions

This study established a driving-restriction policy model to explore the effect of China’s driving-restriction policy on traffic congestion, vehicle emissions, parking demand, and the number of vehicle trips. Based on medium- and long-term simulation results and comparative analysis, the following main conclusions were obtained:

(1) From a short-term perspective, the implementation of the driving-restriction policy can reduce the number of

private car trips (short term) and ease traffic congestion. Over time, however, the effect is gradually weakened, resulting in a fading effect.

(2) From a long-term perspective, the policy fails to effectively reduce traffic congestion. In particular, the policy has stimulated a new car-purchase demand and intensified the growth of private car ownership. At the same time, its side effects are constantly accumulating, which will lead to paradox effects in the long run, such as further aggravating parking-space tension and having rebound effects on emission reduction and traffic congestion.

(3) To overcome the limitations of the policy, this study introduced a combined APCF policy and penalty policy. The simulation results indicated that the combined policy can not only achieve the dual goal of reducing traffic congestion and emissions but also improve parking demand, thus having a positive effect on restraining the number of illegal trips and overall vehicle trips.

5.2 Policy recommendations

Based on the above conclusions, the following policy recommendations can be made.

First, given the peer effect of the driving-restriction policy, it is suggested that the relevant government departments should formulate policies and measures suitable for local conditions based on the characteristics of different regions. In view of the fading effect in the middle and late stages of policy implementation, it is suggested that timely adjustments should be made in the process of policy implementation. Other policies should be introduced to overcome limitations, and supervision should be strengthened to play a guiding role in the policy. Considering the calendar effect, there should be an increase in publicity efforts to better achieve the effect of “off-peak travel.” Given the rebound effect and the paradoxical effects on reducing emissions and congestion, local governments should conduct comprehensive evaluations before policy implementation and formulate an optimized scheme from a long-term perspective to reduce the negative effects.

Second, the combination of administrative means (e.g., driving-restriction policy) and economic means (e.g., APCF and penalties) can bring the collaborative innovation benefits of the combined strategy into full play. The combined strategy can overcome the limitations of a single policy, fully absorb the advantages of each policy, and give full play to multiple performances.

Third, in view of the “new demand” among vehicle owners, publicity regarding the relevant aspects (e.g., traffic congestion, the causes of air pollution) should be strengthened to improve citizens’ awareness. Scientific publicity should also be conducted regarding the harm caused by air pollution, highlighting the role of citizens. The purpose of the policy, implementation details, and other aspects should be publicized to optimize the implementation effect of the policy.

Finally, policies are often not omnipotent. The driving-restriction, APCF, and penalty policies may lead to a decline in the level of public transport supply. Therefore, in the future, remedial measures should be considered, such as subsidy policies, so that a portion of subsidies and APCF can be used to improve public transport infrastructure and reduce the possible negative effects in the process of policy implementation.

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Data availability All the data generated or analyzed during this study are included in this published article.

Declarations

Conflict of interest The author has no conflicts of interest to declare.

Ethical Approval This article does not involve the ethical problem.

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Supplementary Files

- GraphicalAbstract.pdf