Investigating the influence of the new ride-hailing policy on air quality using regression discontinuity design

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Abstract

With the increase of the number of ride-hailing, the traffic congestion and environmental

pollution has exacerbated. A new ride-hailing policy was formed as a means of administrative control to improve the negative externality. However, the improvement of air quality caused by the new ride-hailing policy has not been effectively verified. This study employed regression discontinuity design (RDD) to explore the causal relationship between the air quality in Beijing and the new ride-hailing policy to reduce the endogeneity problems. The main results show that the implementation of the new policy reduces air quality index (AQI), particulate matter 10(PM_{10}), and ozone(O_3) by 14%, 12%, and 16%, respectively in the OLS regression analysis. After applying the RDD, this study found that the implementation of the new policy reduced AQI, PM_{10} , and O_3 by 43%, 30%, and 42%. The regression value of regression discontinuity was higher than that of OLS. Additionally, the robustness test reveals that RDD is reasonable. The findings suggest that the implementation of the new ride-hailing policy exerts an improvement effect on air quality. Policy implications to further promote the new ride-hailing policy are hence discussed.

1 Introduction

The sharing economy mode emerged from the rapid development of mobile Internet, cloud computing, Internet of Things, and big data technology (Parente et al., 2018; Geissinger et al., 2017; Huang et al., 2017). In recent years, relying on mobile Internet technology, the sharing economy has rapidly penetrated the field of transportation (Ma et al., 2017) and integrated and matched the supply and demand information among travelers, drivers and vehicles, and finally provide the network service platform for worldwide promotion. The sharing economy for mobility services has begun to grow rapidly in developing economies such as China (Barnes et al., 2020). In 2012, DiDi was officially launched in Beijing. In 2015, Uber entered the Chinese market. Uber achieved \$11.3 billion in revenue in 2018, operates in more than 600 cities in 65 countries, and completes 14 million trips per day (Iqbal, 2019). Didi Chuxing makes 30 million large-scale trips in 400 cities every day, earning \$20 billion in booking revenue (Smith, 2019). The pioneering enterprises of the sharing economy, namely, Dribbling and Uber, accounted for more than 90% of the market share of the online platform market for a long time (Dudley et al., 2017; Young and farber, 2019).

Compared with traditional taxis, the ride hailing can quickly and accurately match the dispersed user demand with the idle vehicle supply, while traveling at a low price. On the one hand, the efficient matching and low-cost mode of travel has increased the demand of passengers for new travel. On the other hand, some consumers have replaced the public transportation via an online car (Zhen, 2017; Rodier, 2018). The rapid spread of ride-hailing services such as Uber and Didi Chuxing may have a major impact on cities where these services are introduced, including the number of trips, alternatives to sustainable transportation, and pollution. Due to an increase in trip generation, changes in travel patterns, and a substitution of sustainable modes of transportation, the introduction of ride-hailing may lead to an overall increase in air pollution (Barnes et al., 2020). Research found that the number of trips brought about by car trips will increase overall trips by 8% to 22%, depending on the characteristics of the city and its population (Alemi et al., 2019). The increase in the number of trips may be due to the increase in vehicle usage by drivers who cannot drive due to disability, lack of a driving license, old age, drinking or under age legal restrictions (Schoettle and Sivak, 2014). Additionally,

Guo et al. (2018) found that after the introduction of Didi Chuxing, car sales to Didi drivers increased significantly. The introduction of Didi Chuxing in Chinese cities is most related to the purchase of fuel-efficient and low-polluting economic vehicles, such as Toyota Camry, Geely Dihao and Geely Vision. In recent years, with the increase in motor vehicle ownership, exhaust has become an important source of urban air pollution (Davis et al., 2017; Xiao et al., 2019; Guerra and Millard-Ball, 2017). Environmental negative externalities require government regulation to eliminate them. A new ride-hailing policy was formed as a means of administrative control to reduce the effect of this negative externality.

Relevant scholars have studied the impact of emission control policies based on the control-command mechanism on emission reduction. Theoretically, the roles and effects of these environmental regulations are evident and can improve air quality significantly. However, their actual effects are ambiguous. Hossein et al. (2017) investigated the effectiveness of traffic restriction enforcement policy on air quality, and found that the maximum reduction in CO, a primary pollutant, was approximately 20%. Invernizzi et al. (2011) failed to measure reductions of PM mass pollution within the areas subject to traffic restriction. Huang et al. (2017) proposed an empirical strategy to estimate the effects of driving restrictions on air quality, the results indicating that the driving restrictions are effective for short-run period, but are ineffective for long-run time period, and heterogeneity in short-run effect for different cut-points was also observed. Ma and He (2016) used the daily PM₁₀ pollution data of Beijing to investigate the short-run and long-run effects of the 20% driving restrictions in Beijing and the key factors shaping the effects. The results showed that in the short run, 20% driving restriction could effectively reduce ambient PM₁₀ levels, while fading away within a year due to long-term behavioral responses of residents.

Relevant studies about the ride-hailing mainly concentrated on the impact of ride hailing on transportation efficiency (Henao and Marshall, 2019), public transportation (Lim et al., 2018; Nelson and Sadowsky, 2019), equality and wellbeing in the sharing economy (Liu and Wayne Xu, 2017; Agussurja et al., 2019), as well as the supply curve of ride-hailing systems (Xu et al., 2019). However, there are few studies about the impact of the ride-hailing policy on air quality. Local policy experiments have been widely used when conducting reform in China since the 1980s, experience in the pilot areas can help adjust or further implement policies on a larger scale (Pan et al., 2019). According to the experimental method of econometrics, the policy which is regarded as a natural experiment is an effective tool to weaken the threat of endogeneity (Li et al., 2017; Pan et al., 2014; Pan et al., 2019). In the existing literature, three methods have been applied to empirically test the effects of restriction policies, including OLS method, Difference-in-Difference (DID) method and RDD. The OLS regression is too simple, not only cannot distinguish the effects of the new ride-hailing policy from other policies in Beijing, nor can it strip away the inherent trend of changes in the urban air quality. Although the DID method can partially control the trend of air quality changes in different regions, it is too difficult to find a city with very similar factors except for the new ride-hailing policy. In addition, DID method cannot distinguish the impact of the new policy from other policies on air quality.

RDD is a quasi-experimental method used when there is no random assignment to the treatment and control groups (Al-Awlaqi et al., 2018; Davezies and Barbanchon, 2017; Mitchell et al., 2017). RDD measures any discontinuous change in the probability of the outcome at the same cut-off. The magnitude of this discontinuity is used to estimate the causal effect of the policy change (Smith et al., 2017). RDD has the characteristics of random experiments, which can estimate the effect of policy shocks more accurately, which

is important to estimate the impact of the new policy on air quality (Lee, 2018). The estimated bias caused by endogenous problems can be controlled. Since the implementation of the new ride-hailing policy has a clear time cut-off point, it can be seen as a factor in the mutation, which can distinguish the new ride-hailing policy from other factors that are continuously changing, thus identifying the impact of the policy. In the new ride-hailing policy, if a mutation in air quality are observed before and after policy implementation and other influencing factors can be identified as continuous changes, then it can consider that the sudden change in air quality is caused by the new policy, that is, the new policy is effective. If no sudden change in air quality is observed, then the policy can be considered ineffective. Hence, this study aims to set up a time series model with the example of new ride-hailing policy in Beijing and used the RD model to explore the impact of the new policy on the air quality in Beijing.

The rest of this study is arranged as follows. Section 2 introduces the context of the riding-hailing policy. The datasets, methods, the model setting are laid out in Section 3. Section 4 discusses the empirical results and discussions. Section 5 puts forward the conclusions and policy implications.

2 Policy Background

Since the mid-1980s, China's government has implemented a variety of regulations to resolve environmental issues. Rapid economic development not only increased the emission of pollutants, it also changed the composition of air pollution in the past decades (Pan et al., 2019). Among major air pollutants, typical pollutants from internal combustion engines of vehicles are nitrogen oxides, volatile organic compounds, carbon dioxide, carbon monoxide, particulate matter, and sulfur dioxide. Among them, incompletely burned particulate matter become the main source of haze (Wu et al., 2016). With the increasing number of motor vehicles in China, the impact of vehicle exhaust pollution on air pollution is increasing (Nagy, 2014). Davis (2008) also found that the concentration of various pollutants in one day's fluctuations is highly correlated with traffic flow. China has spared no efforts to solve air pollution. China has adjusted the standards of vehicle exhaust emission five times, adopted driving restrictions to improve air quality during the Olympics, and revised the price of refined oil to reduce vehicle exhaust pollution. The existing administrative control measures play a limited role in reduction of vehicle emissions. Compared with the driving restrictions, the ride-hailing policy can be seen a quantity control measure aimed at reducing the supply of online cars to alleviate traffic congestion and pollution.

The difficulty of traditional taxi in meeting consumers' travel needs is the main reason for online ride-hailing services. The low access standards for the ride-hailing market not only cannot solve the travel requirements of passengers, but also cause social problems such as empty vehicles, air pollution, and traffic congestion. To this end, the Ministry of Transport issued the "Administrative Measures on Taxi Interim Service for Online Appointment Services" in July 2016, it was implemented on December 21, 2016, this guiding general rule reflects the basic idea of giving priority to the development of urban public transport. The logic of this choice lies in that public transport remarkably reduces negative externalities compared with other modes of transport, and it can help reduce road congestion and pollution. The local government of Beijing clearly stipulated the relevant requirements for the type of driver and vehicle in the regulations on the new policy. The new policy imposes more detailed constraints on a vehicle's wheelbase, displacement, and equipment and the car driver's household registration, physical condition, driving experience, and offending records. Compared with the

relaxed restrictions in the initial period, several existing vehicles in the market withdraw from the platform, leading to a sharp decline in the supply of vehicles (Zhen, 2017). Taking Beijing as an example, there were about 200,000 drivers in the network before the implementation of the ride-hailing policy. Since only 20,000 people had household registration in Beijing, the restriction on household registration reduced the supply of online vehicles by at least 90% (Zhen, 2017).

3 Data And Methods

3.1 Methods

A further distinction between sharp and fuzzy RDDs is necessary. In a sharp RDD, the assignment of the treatment is deterministic, indicating that with the crossing of the threshold, the probability of receiving the treatment jumps from 0 to 1. The processing state of fuzzy RDD is no longer a deterministic function of variables, but a probability function. Fuzzy RDD actually provides an instrumental variable estimation strategy (Hohmann, 2017). Since the implementation of the new ride-hailing policy has a clear time cut-off point, it can be seen as a factor in the mutation, this study used a sharp RDD. Considering only one policy breakpoint, with reference to the variable time trend method mentioned in Angrist and Pischke (2008), the estimated equation of the local average treatment effect (LATE) β at the breakpoint is:

$$y_t = \mu_0 + \beta D_t + \sum_{i=1}^k \alpha_{0i} t^i + D_t \sum_{i=1}^k \gamma_i t^i + u_t$$

1

Where y_t represents the air quality observed on day t , measured with AQI and daily concentrations of PM_{10} , O_3 , and SO_2 . This study defined a dummy variable D_t to control the new policy. When t occurs before the time point (December 21, 2016), D_t is 0; otherwise, it is 1. This study performed polynomial order optimization on the polynomial of time t according to the AIC criterion. It is found that in the majority of regressions, the AIC values are the smallest with eight times. The AIC values of adjacent orders are also small. In addition, other control variables (X_t), such as holiday (dummy variables), maximum and minimum temperatures, wind speed, absence/presence of snow and rain (dummy variables), and the logarithm of the monthly increase of three polluting industries, were included in this work. The regression discontinuity model is mainly concerned with regression coefficient β . The coefficient β measures the impact of the new policy on the air quality. If β is significantly negative, it proves that the new ride-hailing policy can improve air quality.

The implementation of the RD method requires certain conditions for the natural "experiment environment" (Calonico et al., 2019). First, because the polynomial is a continuous variable of time t , other influencing factors change continuously over time except for the new policy. Although Beijing tried several policies before and after the launch of the new policy, these policies progress gradually and have no clear timeline similar to the new policy. Additionally, it is hoped that the policy itself will have an immediate impact on air quality when we estimate the experimental effect at the breakpoint. Therefore, air quality should be sensitive to changes in pollutant emissions, that is, changes caused by the new policy will rapidly affect air quality. In this regard, the concentration of pollutants can be changed within a short period with variations in traffic flow. Davis (2008) used time-sharing data to demonstrate that the concentration of various pollutants in one day's fluctuations is

highly correlated with traffic flow, which provides evidence that Mexico City's air quality is sensitive to traffic flow. For ozone, it reaches its maximum value at the evening peak time and reaches its minimum value before the morning peak, showing obvious intraday fluctuation characteristics. For particulate matter, although the pattern is not so obvious, it also presents a similar fluctuation law. These fluctuation laws help explain that changes in traffic flow can bring about changes in air quality in a relatively short period of time.

3.2 Data

This study used the daily concentration data of AQI, PM_{10} , O_3 , and SO_2 provided by Beijing Environmental Protection Public Network. The time span was from January 1, 2014 to December 31, 2017. AQI is a dimensionless index that quantitatively describes air quality. The larger the value, the more serious the air pollution situation. Given that motor vehicle exhaust does not emit SO_2 , this indicator was used for comparison with other indicators as a counterfactual test variable. The meteorological data were mainly from the Beijing observatory data provided by the Freemeteo website. The monthly increases in the three major polluting industries (non-metallic mineral products; ferrous metal smelting and rolling processing; and electricity, heat production, and supply) were compiled from data published on the website of the Beijing Bureau of Statistics. The monthly increase was in a natural logarithmic form in order to reduce data variance. The statutory holiday dummy variable was determined according to the holiday arrangement notice issued by the State Council yearly. The descriptive statistics of the main variables are shown in Table 1.

Table 1
Statistical characteristics of major variables

Variable name	Unit	Observation	Mean	Standard deviation	Minimum	Maximum
Explained variable						
AQI	Index	1459	115.51	73.36	21	500
PM ₁₀	ug/m3	1420	103.81	76.82	7	820
O ₃	ug/m3	1458	73.95	66.00	5	477
SO ₂	ug/m3	1459	12.84	49.45	2	138
Explanatory variables						
Holiday	Dummy variable	1461	0.32	0.47	0	1
Ht	Celsius	1459	19.35	11.46	-11	42
Lt	Celsius	1459	9.4	10.93	-16	32
Wind	Dummy variable	1459	0.36	0.48	0	1
Snow	Dummy variable	1459	0.02	0.15	0	1
Rain	Dummy variable	1459	0.21	0.41	0	1
Non-metallic mineral	10,000 yuan (constant price)	48	11.05	0.50	9.87	12.14
Ferrous metal	10,000 yuan (constant price)	48	8.73	0.39	9.47	7.87
Electric and heat	10,000 yuan (constant price)	48	9.57	0.64	10.36	6.52

3.3 Statistical analysis

Table 2 shows the mean differences of the relevant variables in the two periods before and after the implementation of the new policy. As can be seen from the table, AQI, PM₁₀, and O₃ considerably decreased before and after the implementation of the new ride-hailing policy, which means that the implementation of the new policy may improve air quality.

Table 2
Mean difference in main variables before and after the implementation of the new policy

Mean variables	Before the implementation	After the implementation	Difference
AQI	119.59 (4.143)	103.68 (3.519)	-15.92*** (5.457)
PM ₁₀	106.94 (4.334)	92.23 (3.957)	-14.71*** (5.930)
O ₃	78.95 (3.808)	59.5 (2.985)	-19.45*** (4.746)
SO ₂	8.00 (0.441)	11.00 (0.560)	3.00** (0.610)
Non-metallic mineral	7.55 (0.040)	7.47 (0.039)	-0.09** (0.052)
Ferrous metal	5.13 (0.036)	5.18 (0.037)	0.05 (0.050)
Electric and heat	9.57 (0.030)	9.67 (0.030)	0.09** (0.045)
Wind	0.46 (0.026)	0.38 (0.025)	-0.08*** (0.034)
Rain	0.15 (0.019)	0.21 (0.021)	0.06** (0.026)
Ht	17.65 (0.609)	20.25 (0.635)	2.60*** (0.291)
Lt	7.63 (0.584)	10.63 (0.602)	3.01*** (0.234)
Note: The brackets are the standard deviation, column (4) is the differential t test, and the parentheses are the standard deviations of the differential t test. The original hypothesis is that the values of the variables in columns (2) and (3) are equal, ***, **, * indicates significant at the level of 1%, 5%, and 10%.			

This study provides monthly averaged and seasonally adjusted data and plots air quality over time. The monthly average was used to eliminate the impact of short-term fluctuations in air quality as much as possible and clearly demonstrate the long-term effects of the new policy (Lee and Lemieux, 2010). Seasonally adjustments are made due to evidence of seasonal characteristics of air quality, which can better show the

true impact of the new ride-hailing policy. Figures 1-4 show the changes in AQI, PM₁₀, SO₂, and O₃ before and after the implementation of the new policy. The three vertical dashed lines in the figure indicate the implementation time of the new policy (December 21, 2016). Specifically, AQI has remarkably improved since the implementation of the new policy. The concentration profile of PM₁₀ over time coincides with that of AQI, indicating that the main pollutant is PM₁₀. The concentration of O₃ also shows a notable downward trend due to the implementation of the new policy. No evident change was found for SO₂ before and after the implementation of the new policy.

Since Beijing has begun to implement a series of measures to improve air quality during the implementation of the new ride-hailing policy, we have reason to believe that the graphic features described in the figure are caused by other factors. Therefore, this study plotted the monthly industrial production growth of the three major polluting industries over time, as shown in Figures 5-7. As shown in the figures, except for the non-metallic mineral products industry, which demonstrated a reduction in production before and after the implementation of the new policy, the two other industries did not considerably change. It is obvious that the improvement in air quality before and after the implementation of the new policy cannot be ruled out by the other factors.

4 Results And Discussions

4.1 OLS regression results

Before designing the regression discontinuity model, we used the single difference method to analyze the effect of the new ride-hailing policy and examined the results. The purpose is to compare the effect and conclusion of regression discontinuity regression to strengthen the persuasiveness of the conclusion. First, we used the single difference method to analyze the impact of the new ride-hailing policy, with particular attention to the new policy dummy variable and the coefficients of the three added variables of the pollution industry. This study simultaneously controlled weather and statutory holiday variables. The results are shown in Table 3. From model (2) to model (7), the legal holidays, meteorological conditions and the monthly increase value of the pollution industry are added. The ordinary least-squares (OLS) regression results indicated that the coefficient of the new policy dummy variable is significantly negative. When all variables were controlled, the implementation of the new policy made AQI, PM₁₀, and O₃ reduce by 14%, 12%, and 16%, respectively, and the decrease was equivalent to their respective full-sample averages of 12%, 12%, and 22%, respectively.

Table 3
Impact of the new policy on air quality based on OLS regression

	AQI				PM ₁₀	O ₃	SO ₂
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Policy	-14.929 ^{***} (4.413)	-14.846 ^{***} (4.377)	-14.651 ^{***} (4.369)	-14.297 ^{***} (4.418)	-11.759 ^{**} (4.648)	-16.025 ^{***} (3.961)	-6.999 ^{***} (0.925)
Non-metallic mineral				4.664 (3.962)	8.338 ^{***} (4.169)	-2.224 (3.553)	-8.857 ^{***} (0.830)
Ferrous metal				-8.617 [*] (4.892)	4.290 (5.148)	8.563 [*] (4.386)	4.761 (1.025)
Electric and heat				-2.291 (5.566)	-18.833 ^{***} (5.857)	-11.037 ^{***} (4.991)	2.715 (1.166)
Seasonal and date adjustments	N	Y	Y	Y	Y	Y	Y
Weather	N	N	Y	Y	Y	Y	Y
Observation	1419	1419	1419	1419	1419	1419	1419
Note: The standard deviations in parentheses are robust standard deviations. ***, **, * indicate significant levels at 1%, 5%, and 10%, respectively.							

However, the result of OLS regression is not necessarily reliable. The effects of other policies cannot be directly observed because Beijing implemented a series of environmental policies before and after the implementation of the new policy. This situation introduces the endogenous problem of neglected variables. Several abnormal findings can also be observed from the OLS regression results. For example, the increase in the monthly production value of non-metallic minerals reduces the concentration of SO₂; the increase in the monthly output value of the electric heating and ferrous metals industries reduces the concentration of PM₁₀ and AQI, respectively. These findings indicate that applying the regression discontinuity model is necessary to eliminate endogenous problems.

4.2 RDD results

Before RD regression, the breakpoints caused by the implementation of the new ride-hailing policy can be observed. In Figures 8-11, the vertical line represents the implementation date of the new policy (December 21, 2016). The daily concentrations of AQI, PM₁₀, and O₃ at the breakpoints decreased remarkably, which means that the implementation of the new policy has a local treatment effect, implying the existence of a causal relationship. This relationship was explored through further empirical analysis.

When the single-difference method could not effectively evaluate the new policy, this study used the RDD to estimate the coefficient of the model. Different from least-squares estimation, the RDD has no strict

requirements on the endogeneity of the variable itself. The only requirement is to assume that the individual cannot accurately manipulate the assignment of variables. Moreover, the research design of the RDD is close to that of random experiments (Bertanha and Imbens, 2019). Therefore, the estimation results are reliable. Table 4 lists the regression results of RDD when the 8-order polynomial is used to fit the time trend.

Table 4
Impact of new riding-hailing policy on air quality based on RD Regression

	AQI				PM ₁₀	O ₃	SO ₂
	(1)	(2)	(3)	(4)	(5)	(7)	(8)
Policy	-79.863*** (6.679)	-77.031** (9.761)	-66.537** (8.393)	-42.708** (11.872)	-29.541** (9.046)	-40.556** (12.314)	8.963 (5.829)
Pollution industry	N	N	N	Y	Y	Y	Y
Seasonal and date adjustments	N	Y	Y	Y	Y	Y	Y
Weather	N	N	Y	Y	Y	Y	Y
Polynomial order	8	8	8	8	8	8	8
Observation	1421	1421	1421	1421	1421	1421	1421
Note: The standard deviations in parentheses are robust standard deviations. ***, **, * indicate significant levels at 1%, 5%, and 10%, respectively.							

As can be seen from the Table 4, the regression coefficients of AQI, PM₁₀, and O₃ were still significantly negative after controlling all variables, and the regression coefficient of the counterfactual testing variable SO₂ was no longer significantly negative. The overall consistency between the OLS estimates and the RDD estimates strengthens our conclusions. The implementation of the new policy reduced AQI, PM₁₀, and O₃ by 43%, 30%, and 42%, respectively, and had no significant effect on SO₂. The RD regression value was much higher than the OLS regression value. The OLS regression underestimated the impact of the new policy on air quality.

4.3 Robustness test

4.3.1 Manipulation of driving variables

The effectiveness of RDD depends on two assumptions. First, the driving variable itself is not subject to human control (Aktaruzzaman and Farooq, 2017; Liu et al., 2017). The forcing variable involved in this research is time. McCrary (2008) develops a formal approach to testing whether the forcing variable is manipulated. The method of McCrary (2008) was used to test whether the density function of the grouping variable is discontinuous at the breakpoint. As shown in Figure 12, the confidence intervals of the density function estimated on both sides of the breakpoint werelargely overlapped. Therefore, no significant difference

exists in the density function on both sides of the breakpoint, and the driving variable obeys the random distribution requirement. That is, the forcing variable meets the requirement that it is not considered to be manipulated, and this test supports the validity of the RDD estimation.

4.3.2 Continuity test of covariates

The other assumption of RD is that the distribution of other covariates near the breakpoint is continuous, except for the investigation variable, and the "jump " phenomenon does not occur when the bandwidth is sufficiently small (Liu et al., 2017). If the control variable "jumps" at the breakpoint, then the influence of the explanatory variable on the interpreted variable will be disturbed by the control variable. Therefore, this study examined the continuity of the covariates at the breakpoint, and the test results are shown in Table 5. The conditional density functions of other covariates are continuous at the breakpoint, thus satisfying the smoothness requirement.

Table 5
Covariance regression estimates

	AQI	PM ₁₀	O ₃	SO ₂
Holiday	-0.134 (0.342)	-0.134 (0.342)	-0.136 (0.339)	-0.117 (0.358)
Ht	-3.513 (3.478)	-3.513 (3.377)	-3.475 (3.449)	-3.499 (3.708)
Lt	-1.239 (1.220)	-1.239 (1.221)	-1.268 (1.233)	-1.193 (1.144)
Wind	0.27 (0.261)	0.268 (0.261)	0.27 (0.257)	0.285 (0.293)
Rain	0.155 (0.351)	0.154 (0.353)	0.146 (0.378)	0.143 (0.369)
Snow	-0.003 (0.003)	-0.001 (0.001)	-0.002 (0.002)	-0.003 (0.009)
Non-metallic mineral	0.400 (0.414)	0.400 (0.414)	0.434 (0.410)	0.176 (0.430)
Ferrous metal	0.226 (0.406)	0.226 (0.406)	0.237 (0.402)	0.150 (0.428)
Power heating	0.190 (0.411)	0.190 (0.411)	0.196 (0.408)	0.145 (0.432)
Note: The standard deviations in parentheses are robust standard deviations. ***, **, * indicate significant levels at 1%, 5%, and 10%, respectively.				

4.3.3 Placebo test

In order to avoid mechanical correlations, the estimation results are also significant at a number of assumed critical points. This study randomly selected the following dates as hypothetical breakpoints before and after the implementation date of the new policy (December 21, 2016): July 1, 2014; June 1, 2015; and March 1, 2017. This study examined the presence of a similar 'jump' phenomenon in air quality before and after the breakpoint. The results of regression are shown in Table 6. The results indicate that the estimated value of the local effect at these breakpoints is not significant, which further illustrates the stability and effectiveness of the RDD regression results.

Table 6
Regression results based on hypothetical breakpoints

Dependent variable	Breakpoint	July 1, 2014	June 1, 2015	March 1, 2017
AQI	Covariate	53.894 (40.851)	-48.797 (29.693)	-32.669 (34.910)
	No covariate	-4.036 (2.880)	-66.562** (26.051)	8.308 (34.122)
PM ₁₀	Covariate	-42.169 (30.179)	20.599 (22.985)	-49.790 (40.062)
	No covariate	-28.470 (40.111)	-66.561** (26.051)	-2.552 (30.911)
O ₃	Covariate	54.746 (51.123)	-7.242 (23.146)	-23.708 (31.978)
	No covariate	26.218 (37.087)	-29.098 (20.846)	8.398 (35.486)
SO ₂	Covariate	-1.849 (1.418)	-2.567 (4.898)	-5.607 (4.455)
	No covariate	-7.130 (5.189)	-0.762** (4.004)	-9.442** (2.844)
Note: The standard deviations in parentheses are robust standard deviations. ***, **, * indicate significant levels at 1%, 5%, and 10%, respectively.				

5 Conclusions And Policy Implications

The new ride-hailing policy is a quantitative control measure that aims to limit the number of vehicles on the internet to improve external issues, such as traffic congestion and air quality. Since the introduction of the new policy, compliant vehicles and drivers have been rapidly reduced due to strict restrictions on the type of vehicle operators and vehicle types. However, the improvement of air quality caused by the new policy has not been effectively verified. This study fills the gap by employing RDD to explore the causal relationship between the air quality and the new ride-hailing policy to weaken the endogeneity problems. The findings suggest that the implementation of the new ride-hailing policy still exerted an improvement effect on air quality, which reduced AQI, PM₁₀, and O₃ by 43%, 30%, and 42%, respectively. The RDD regression value was higher than the OLS regression value, indicating that the OLS estimate was endogenous and underestimated. This study contributes both to the understanding of the effects of the ride-hailing policy, and more specifically to the nascent literature examining the impact of ride-hailing services in developing countries.

This study proposes the following policy implications based on the findings. First, from the perspective of the short-term effects of the new ride-hailing policy, the implementation of the new ride-hailing policy helps improve the air quality in Beijing. Urban traffic congestion and air pollution are complex public goods and externalities issues. Administrative control measures can effectively improve air quality in a short period of time, so they are often favored by emerging countries. It is necessary to designate a passenger car reform plan based on the actual conditions of different cities, and to promote the new policy of nationwide. Second, the implementation of the new policy has contributed to the drastic decline of the vehicles on the platform in a relatively short period. For a time, an imbalance existed between supply and demand, and the traditional cruising car and public transport modes gradually recovered. As the world's most densely populated city, the Tokyo did not cause serious congestion problems like Beijing. The key is that Tokyo has solved the problem of traffic congestion in big cities by building urban rail transit. At present, the total length of rail transit lines in Tokyo ranks first in the world. The rail transit network has a high coverage rate, and urban rail transit accounts for 86% of Tokyo's total travel volume (Lin and Du, 2017). Therefore, government should Improve the quality of public transport such as buses and subways, encourage healthy lifestyles (such as inspiring walking and cycling), ensuring that sustainable alternatives are timely and affordable can safeguard that these trips are not cannibalized by ride-hailing services. For an example, the government can strengthen the construction of transportation infrastructure through measures such as increasing transportation routes, constructing rail transit, and improving bicycle parking facilities to promote the development of new riding policies.

This study has a number of limitations. First, RDD is a quasi-experimental method used when there is no random assignment to the treatment and control groups. Since RDD can distinguish the effects of new policy and other policies on air quality, the empirical analysis herein presents strong evidence that the new ride-hailing policy exerts an improvement effect on air quality. However, there are limitations inherent in the RDD that the generalized degree of the results is tightly constrained. Since the RDD estimation uses the local average treatment effect, the sample of the empirical research mainly focuses on the air quality of the years before and after the implementation of the new policy. The study includes only a short time frame of 4 years, and the sample estimate is different from the full sample estimate. Therefore, this study cannot assume that the results can be extrapolated to other points in time. Second, we collected data from Chinese cities, and this study is limited to a Chinese context where the vehicle fleet emission can be different from others. The introduction of new policies for ride-hailing in other developing economies requires further study, such research may provide different results.

Declarations

Conflicts of interest/Competing interests

(All authors declare no conflict of interest)

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Figures

Figure 1

AQI (ug/m3)

Figure 2

PM₁₀ (ug/m3)

Figure 3

SO₂ (ug/m³)

Figure 4

O₃ (ug/m³)

Figure 5

Non-metallic mineral products industry

Figure 6

Ferrous metal smelting and rolling processing industry

Figure 7

Electricity, heat production, and supply industry

Figure 8

AQI breakpoint

Figure 9

PM_{10} breakpoint

Figure 10

O₃ breakpoint

Figure 11

SO₂ breakpoint

Figure 12

Probability density distribution of grouping variables on both sides of the breakpoint