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Externalities from restrictions: Examining the short-run effects of urban core-focused driving restriction policies on air quality

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ABSTRACT

To combat urban challenges such as air pollution stemming from excessive vehicle use, policy makers have adopted various driving restriction policies (DRPs) worldwide. Although previous studies have extensively justified the effects of *citywide* DRPs on air quality, little attention has been paid to *urban core-focused* license-plate-based DRPs (UCLDRPs), which have gained increasing popularity among major cities. To bridge this gap, we carried out an empirical evaluation of the short-run effectiveness of Shanghai's UCLDRPs in improving air quality using difference-in-differences (DID) modeling approaches on high-frequency air quality data. The results show that UCLDRPs did not lead to any reduction of air pollutants including NO_2, $PM_{2.5}$, and PM_{10} during peak hours (the restricted time window) in the inner ring area (the restricted area), while contributing to a 14% increase in the concentration of CO. Moreover, the air quality of surrounding zones (the 5 km buffer area) got worse as the concentration of CO and PM_{10} raised by 16% and 8% respectively. Results also justified the temporal-spatial spillover effects in the dynamics: the concentrations of CO and PM_{10} got increased by 10%-20% in the 5 km buffer area within time periods right before or after the restricted time windows.

1. Introduction

The increased transportation demand in many cities around the world has led to a range of urban problems including air pollution and traffic congestion (Sun et al., 2014; Yang et al., 2023; Lei et al., 2023). To combat these challenges, cities have adopted various traffic demand management (TDM) policies. For example, London, Singapore and Stockholm have enforced congestion charges (Lehe, 2019), while Milan, Paris, and Berlin have developed low emission zones (LEZs) (Holman et al., 2015). Driving restriction policies (DRPs) are another alternative for alleviating air pollution and traffic congestion and have been implemented widely in the world because of their low cost and high socio-political acceptability. In the early 1990s, DRPs were adopted in Mexico City and Santiago, and have become increasingly popular in developing countries, such as India, Ecuador, and China (Cantillo and De Dios Ortúzar, 2014; Carrillo et al., 2016; de Buen Kalman, 2021; Kathuria, 2002; Mohan et al., 2017; Pu et al., 2015). Within this category of TDM measures, a unique *urban core-focused* license-plate-based DRP (UCLDRP) has been implemented in the central areas of Shanghai, the

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largest city in China. Under this policy, vehicles with nonlocal license plates are prohibited from entering urban cores (the inner ring area) during the designated time of the day.

Whether DRPs can effectively contribute to reducing air pollution in urban areas is still under debate despite many empirical studies. Quite a few existing studies examined the effects of *citywide* license-plate-based DRPs (CWLDRPs) in cities such as Mexico City and Beijing (Chen et al., 2020; Davis, 2008; Gallego et al., 2013; Salas, 2010; Sun et al., 2014; Zhong et al., 2017). On the other hand, researchers have also evaluated the options of congestion pricing and Low Emission Zones in terms of their performance in cutting down vehicular emissions (Atkinson et al., 2009; Green et al., 2020; Percoco, 2015; Sarmiento et al., 2021; Wolff, 2014; Ye et al., 2021). UCLDRPs, however, have received limited attention, although they have gained increasing popularity among cities. DRPs focusing on urban cores would cause less inconvenience to citizens than citywide policies, and less doubt over social inequity than charging congestion fees or emission fines. It is also assumed that the spatial scope of driving restrictions matters in mitigating air pollution (Bernardo et al., 2021). Therefore, it is necessary to empirically explore the question of how UCLDRPs contribute to air pollution relief, so as to filter out the policy option with the best performance in effectiveness, efficiency, and political practicality.

Evaluating the impacts of UCLDRPs on air quality is nonetheless rather challenging given the complexity of the pollutant dispersion process and human behaviors. Due to the driving behavioral adaptation and the geographical dispersion of air pollutants, driving restriction policies' impacts on pollution levels may not be easily observed and measured (Gu et al., 2017; Guerra and Reyes, 2022; Han et al., 2020; Jia et al., 2017; Lin et al., 2011; Ma and He, 2016; Sarmiento et al., 2021). Previous studies mainly utilize statistical approaches to model before-after comparisons and investigate DRPs' impacts on air quality (Lee et al., 2005; Ma and He, 2016; Mishra et al., 2019). However, air quality is usually subject to many observed and unobserved factors with evident seasonal changes, which may confound the impacts of the policies. Simple before-after comparisons would fail to differentiate the policy impacts from such confounding changes and thus may lead to biased and inconsistent results (Lee et al., 2005; Li and Jones, 2015).

To bridge these gaps, based on high-frequency air quality data, we carried out an empirical evaluation of the short-run effectiveness of Shanghai's UCLDRPs in improving air quality. For accurate identification, we adopt difference-in-differences (DID), a well-recognized causal-inference-based modeling approach, as our empirical strategy. In DID models, samples are divided into the treatment and control groups to mimic an experimental research design. To be specific, we regard the restricted area (the inner ring area) as the treatment group to estimate the effects of the UCLDRP on targeted areas. Simultaneously, we treat the 5 km buffer outside the restricted area as the sub-treatment group to further examine whether the air quality of neighboring areas is affected by the UCLDRP. The remaining area in which vehicles with nonlocal license plates are not restricted is adopted as the control group to mimic what would have happened in treatment and sub-treatment groups in the absence of the UCLDRP. Besides, we apply DID models on samples of unrestricted hours to test whether the policy generates a temporal-spillover effect.

2. Literature review

2.1. Effects of DRPs on air quality

Starting from Santiago, Chile in 1986, DRPs have been widely implemented in cities across the world. Since then, a number of scholars have begun to explore the environmental effects, particularly the performance in air quality improvement, of driving restrictions. A typical example was the license-plate-based DRPs in Mexico City called *Hoy No Circula* (HNC), which banned most drivers from using their vehicles one weekday per week in the entire Mexico City metropolitan area. Davis (2008) and Salas (2010) both employed the regression discontinuity (RD) approach to examine the effects of the policies on air quality, but got contradictory results. The former found no evidence of air quality improvement, while the latter identified positive results. Different from these works, Gallego et al. (2013) used the difference-in-difference (DID) model to test the short-run and long-run effects of the HNC on air quality and proved that the HNC was effective in reducing congestion and pollution in the short run, but increased CO in the long run.

Beijing's license-plate-based DRPs have also attracted much academic attention. In contrast with DRPs in Mexico City, Beijing set the restrictions within the 5th Ring Road, which covered about 660 km^2. Relevant research works presented mixed results as well. On the one hand, some studies showed positive results in improving air quality (Chen et al., 2013; Guerra et al., 2021; Li and Jones, 2015). Viard and Fu (2015) extended related studies by considering the temporal-spatial effect of DRPs on air quality. The results justified the pollution reduction both inter-temporally and spatially and strongly supported Beijing's DRPs were effective in alleviating air pollution. On the other hand, some researchers found limited, or even negative impacts (Lin et al., 2011; Sun et al., 2014; Zhong et al., 2017). Studies on the DRPs in Tianjin and Lanzhou also rejected positive hypotheses (Huang et al., 2017; Ye, 2017; Zhang et al., 2020). Among them, Ye (2017) found that the level of air pollutants surged right after the end of the driving restrictions and it also increased more in areas outside of the restricted zone, suggesting that people may choose to circumvent driving restrictions by evading the restricted hours, acquiring alternative vehicle services, or detouring around the restricted area.

2.2. Effects of urban core TDM policies on air quality

Regarding the size of restricted areas, UCLDRPs are similar to some urban core TDM policies, such as London's congestion charging and Berlin's LEZs (Bernardo et al., 2021; Holman et al., 2015). Considering the possible temporal-spatial substitution effects of travel behaviors under such policies, scholars pay more attention to how the policy contributed to the spillover of vehicle movements and emissions. The literature revealed that, under London's congestion charging, although the air pollutant in central London was relieved, there was a notable increase in certain air pollutant emissions in the surrounding area outside the charging zone (Atkinson et al., 2009; Green et al., 2020; Percoco, 2015). For Berlin's LEZ policy, Sarmiento et al. (2021) found its effects on air pollution were only

Table 1
Summary of research progress on TDM policies on air quality.

Category	References	Context	Scheme of TDM policy	Restricted area/roads	Spatial-temporal resolution	Air quality impacts
DRPs	This paper	Shanghai-China	Nonlocal-license-plate-based DRP	Urban core surface roads	Hourly; 5 stations for restricted area, 8 stations for 5 km buffer area and 14 stations outside the buffer area.	① PM_{10}, $PM_{2.5}$, NO_2, and AQI did not significantly change in restricted area and hours, but CO significantly increased. ② CO and PM_{10} significantly increased in 5 km outside the restricted area for both restricted and unrestricted hours. ③ NO_2 and PM_{10} significantly increased in restricted area for unrestricted hours. ④ There was strong evidence on the temporal-spillover effects.
	Lu et al. (2022)	Shanghai-China	Nonlocal-license-plate-based DRP	Elevated highways	Hourly; 3 stations monitored restricted elevated highways and only 1 station for unrestricted elevated highways.	CO, PM_{10}, and AQI did not significantly change in both restricted road and hours, and unrestricted roads and hours.
	Troncoso et al. (2012)	Santiago-Chile	License-plate-number-based DRP	Metropolitan region	Daily; All stations mixed	CO, $PM_{2.5}$, and PM_{10} significantly decreased.
	Viard and Fu (2015)	Beijing-China	License-plate-number-based DRP	Within 5th Ring Road	Daily; All stations mixed	PM_{10} and AQI significantly decreased.
	Zhang et al. (2020)	Tianjin-China	License-plate-number-based DRP	Within the Outer Ring Road	Daily; All stations mixed	CO and AQI significantly decreased, but $PM_{2.5}$, PM_{10}, and NO_2 did not significantly change.
	Gallego et al. (2013)	Mexico city-Mexico	License-plate-number-based DRP	Entire metropolitan area	Hourly; All stations mixed	CO significantly decreased in the short term, but increased in the long term.
	Zhang et al. (2017)	Bogotá-Colombia	License-plate-number-based DRP	The whole city	Hourly; All stations mixed	CO and PM_{10} were not significantly changed in both restricted and unrestricted hours, but NO_2 significantly increased.
	Ye (2017)	Lanzhou-China	License-plate-number-based DRP	Majority of the downtown areas	Hourly; Stations were grouped by inside and outside the restricted area.	AQI, $PM_{2.5}$, PM_{10}, and CO significantly increased in both restricted and unrestricted hours and worsen outside the restricted area.
Urban core TDM policies	Percoco (2015)	London- UK	Congestion charging	City center	Daily; Stations were grouped by charged area and surrounding area.	$PM_{2.5}$, PM_{10}, and NO_2 significantly decreased in the restricted area, but increased in surrounding areas.
	Wolff (2014)	Berlin-German	LEZs	City center	Daily; Stations were grouped by inside and outside the LEZ.	PM_{10} significantly decreased inside and outside the LEZ.
	Salas et al. (2021)	Madrid-Spain	LEZs	City center	Daily; Stations were grouped by inside and outside the LEZ.	NO_2 significantly decreased inside and outside the LEZ.
	Ye et al. (2021)	Nanchang-China	LEZs	City center	Hourly; Stations were grouped by inside and outside the LEZ.	$PM_{2.5}$, PM_{10}, and AQI significantly decreased not only within the restricted hours and zones, but also unrestricted hours and zones.

significant within the LEZs. And Wolff (2014) provided similar results. However, as for LEZs in central Nanchang, China, Ye et al. (2021) found that the air pollutant reduction caused by LEZs was not only remarkable within the restricted hours and zones, but also extended to unrestricted hours and zones. Salas et al. (2021) also proved the positive impact on reducing NO_2 emissions inside and outside the LEZs in Madrid Central.

2.3. Research gaps

As shown in Table 1, there are essential variations in the policy design, urban context, policy scheme, spatial scope, and spatial–temporal resolution of data, all of which may contribute to the differences in empirical results. For the category of DRPs, the majority of the literature has focused on those implemented in a large portion of cities or even the entire cities. Little research has been conducted on the DRPs implemented in the urban cores with a more refined spatial scale. In addition, most existing studies did not test the spatial–temporal spillover effects and thus failed to answer how drivers' responses and reactions to the policies can contribute to overall effects. In those studies considering spatial or temporal spillover effects, less refined temporal or spatial resolution in research design and data could lead to different outcomes.

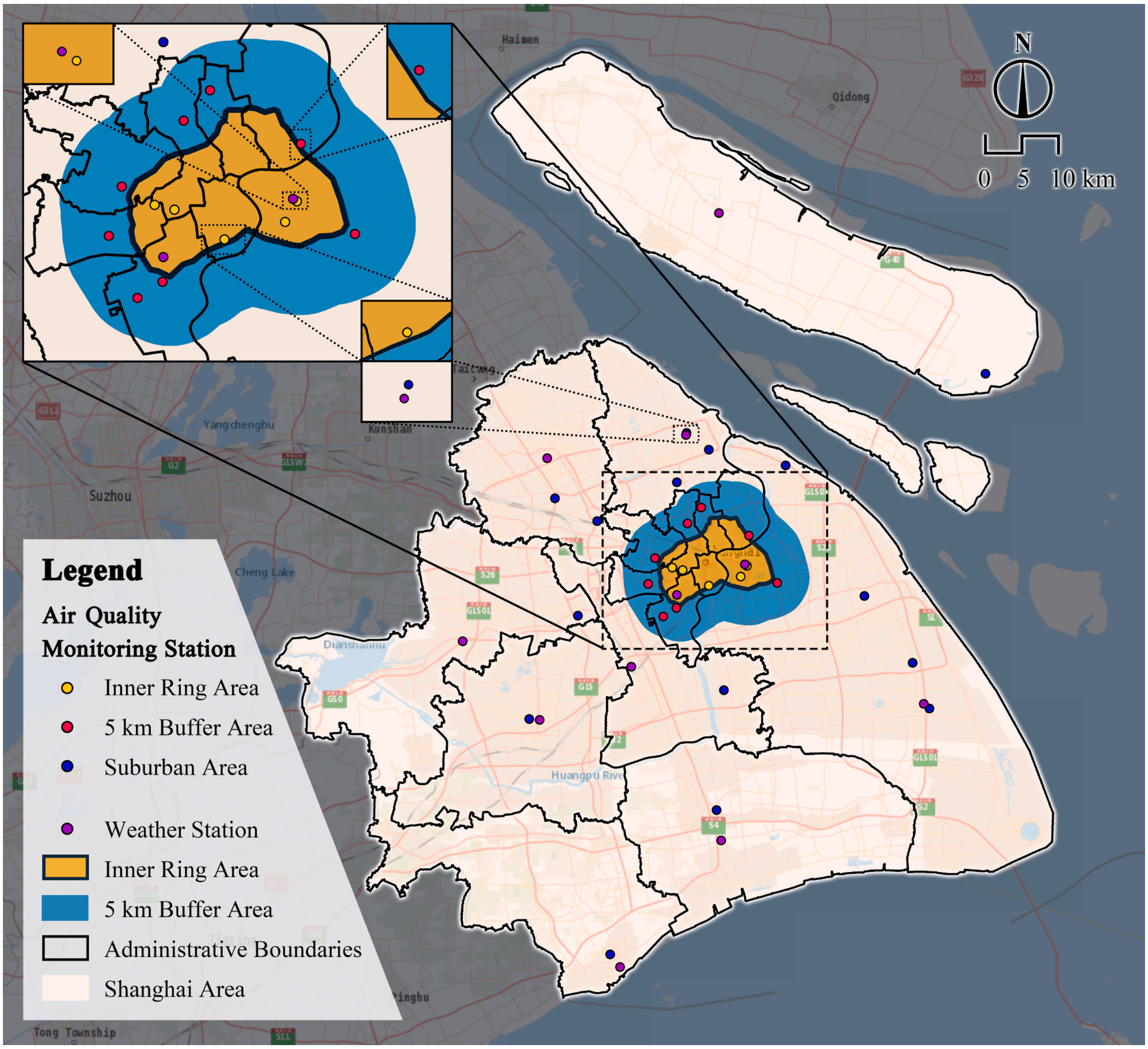

Fig. 1. The inner ring area and environmental monitoring and weather stations in Shanghai.

For the category of urban core TDM policies, existing literature indicated the significant reduction in air pollution in the restricted area and mixed results outside of the restricted area under the implementation of congestion charging and LEZs. However, there are differences between UCLDRPs and these two TDM policies in management approaches and restriction schemes on vehicles. Specifically, LEZs mainly aim at heavy-duty vehicles, while UCLDRPs could be imposed on a wide range of passenger vehicles. Congestion charging is a pricing-based strategy collecting surcharges for vehicles crossing the cordon, while UCLDRPs belong to the regulation-based option that prohibits the driving of vehicles with certain license plates (Lu et al., 2022). Compared with pricing-based strategies, drivers' responses to regulation-based policies might be more radical and rapid (Eliasson and Mattsson, 2006; Linn et al., 2016). For instance, regulation-based policies could lead to second car purchases to avoid driving restrictions, thus undermining the effectiveness of the policies (Guerra and Millard-Ball, 2017; Ramos et al., 2017). Multifold factors could contribute to the divergence in the effects of reducing air pollution among these three categories of TDM policies. More research is needed to empirically identify such differences and evaluate the advantages of implementing UCLDRPs.

3. Background on the UCLDRP in Shanghai

Shanghai, a global megacity and the economic center of China, has a population of about 24.8 million in 2019. The number of daily average passenger trips reached up to 57.1 million in the same year. Among them, trips made by public transport, taxis, non-motorized traffic (including walking, bicycles, and electric bicycles), and private vehicles account for 22.9%, 4.6%, 52.4%, and 20.1%, respectively. Particularly, nearly one-third of private vehicles often appearing in Shanghai are with nonlocal license plates (SCCTPI, 2020). On the one hand, Shanghai has established a unique local license plate auction system, making local license plates expensive

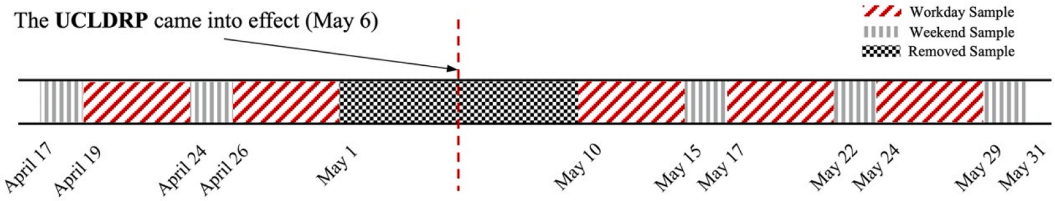

Fig. 2. The timeframe of the data set.

Table 2
The descriptive statistics of the samples of workday peak hours.

	Unit	N	Avg	St. D	Min	25%	50%	75%	Max
All samples									
AQI	–	2711	54.52	23.722	15	38	50	65	169
CO	mg/m^3	2747	0.65	0.227	0.1	0.5	0.6	0.8	1.7
NO_2	μg/m^3	2733	43.77	20.815	9	30	40	53	154
$PM_{2.5}$	μg/m^3	2718	32.16	20.141	1	18	27	40	128
PM_{10}	μg/m^3	2618	47.44	27.350	0	28	42	60	168
Inner ring area samples									
AQI	–	495	53.99	23.427	16	38	50	65	156
CO	mg/m^3	498	0.67	0.236	0.2	0.5	0.6	0.8	1.6
NO_2	μg/m^3	497	44.70	14.677	13	35	42	52	112
$PM_{2.5}$	μg/m^3	495	33.28	19.686	2	19	28	42	119
PM_{10}	μg/m^3	395	48.46	25.094	4	30	45	61	146
5 km buffer area samples									
AQI	–	753	58.64	23.535	19	43	54	70	169
CO	mg/m^3	761	0.69	0.226	0.1	0.5	0.7	0.8	1.6
NO_2	μg/m^3	761	50.83	20.033	18	37	46	62	128
$PM_{2.5}$	μg/m^3	755	34.13	20.770	4	19	29	42	128
PM_{10}	μg/m^3	754	54.61	27.634	8	35	50	69	153
Suburban area samples									
AQI	–	1463	52.59	23.668	15	36	46	63	166
CO	mg/m^3	1488	0.62	0.221	0.1	0.5	0.6	0.7	1.7
NO_2	μg/m^3	1475	39.81	21.954	9	25	35	48	154
$PM_{2.5}$	μg/m^3	1468	30.78	19.869	1	17	25	38	126
PM_{10}	μg/m^3	1469	43.48	27.026	0	24	37	54	168

and challenging to be obtained since the 1990s. In this situation, those residents who are unwilling to pay extra money for local license plates choose to buy vehicles with nonlocal license plates, leading to a lot of nonlocal vehicles running within the boundary of Shanghai (Deng et al., 2023). On the other hand, the strong travel demand from peripheral cities in the Yangtze River Delta region further increased the number of nonlocal vehicles on the road. To mitigate the adverse effects, Shanghai has implemented the nonlocal vehicle driving restriction policy that prohibited nonlocal vehicles from entering designated roads and zones since 2002. But prior to May 6, 2021, Shanghai's nonlocal vehicle DRPs targeted only at elevated highways during daytime (from 07:00 to 20:00). Until recently, the restricted zones of nonlocal vehicle DRPs have been extended to the surface roads in the inner ring area, thus creating the UCLDRP mentioned above (as shown in Fig. 1).

The inner ring area is the economic, political, cultural, and commercial urban core of Shanghai, covering 114 km^2 (about 2% of the total area of Shanghai). Despite only accounting for a small portion of Shanghai, the inner ring area is quite densely populated with 3.27 million residents and the population density of around 30,000 people/km^2. In addition, the inner ring area with fully-fledged transportation infrastructures has a road density of more than 8 km/km^2. However, the infrastructure is still overwhelmed by the ever-growing traffic demand, so the city has witnessed rampant traffic congestion during morning and evening peak hours. Meanwhile, people are concerned over vehicle emissions in the dense urban area as well (Chen et al., 2021; Davis, 2017; Guerra and Reyes, 2022; Lu et al., 2022). In order to relieve congestion and vehicle-related air pollution in the inner ring area, the government announced to the public in October 2020 that a new round of nonlocal vehicle DRPs targeting at the inner ring area (the UCLDRP) would be implemented after May 6, 2021. Nonlocal license plate vehicles will be restricted from driving on surface roads in the inner ring area during weekday morning and evening peak hours (7:00–9:00 and 17:00–19:00). Transportation authorities are highly curious about the actual performance of the policies in combating air pollution, but no empirical research has been conducted.

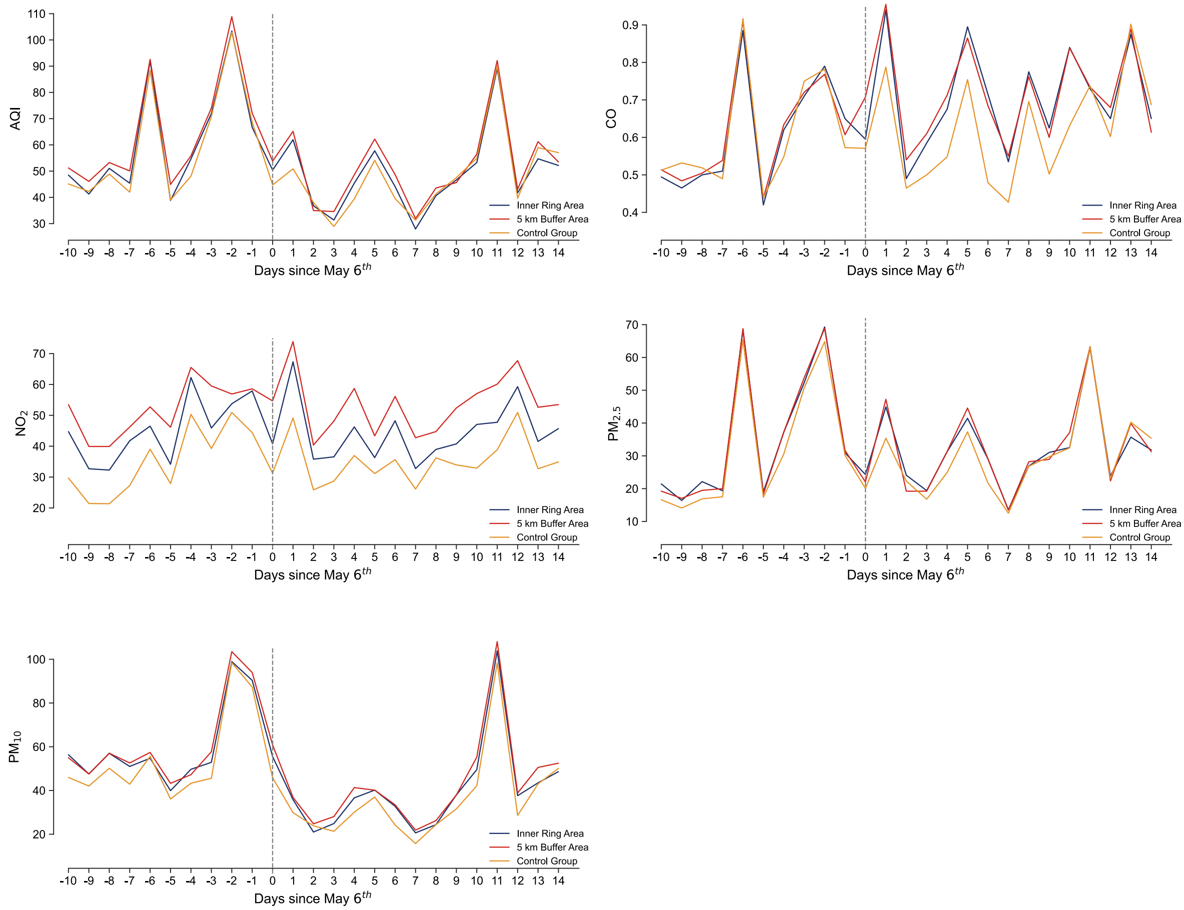

Fig. 3. The temporal variations of the mean values of peak hour AQI and concentrations of air pollutants.

4. Research design

4.1. Data

To assess the impact of the UCLDRPs on air quality, we obtained a comprehensive and high-frequency data set of the air quality index (AQI) and concentrations of four types of air pollutants from the China National Environmental Monitoring Center (CNEMC) and the Shanghai Environmental Monitoring Center (SEMC). The two centers are official institutions responsible for collecting, assuring, preserving, and integrating data on air quality. Specifically, the data set consists of hourly readings of the AQI and air pollutant concentrations of CO, NO_2, $PM_{2.5}$, and PM_{10}, collected from 28 environmental monitoring stations dispersed in the whole of Shanghai[1] (as shown in Fig. 1). These monitoring stations are planned by the center above to cover the entire city territory and avoid the spatial discontinuity of the station readings. Five of them are located in the inner ring area (represented by yellow dots), eight are within the 5 km buffer of the inner ring area (represented by red dots), and the rest is in the suburban area (represented by blue dots). Original data records from the monitoring stations have been cleaned, verified, and reformatted jointly by the authors and staff in the SEMC to ensure the quality of the data used in the analysis.

Due to the data privacy policy, we only have access to the data from April 17, 2021, to May 30, 2021. Given that May 1, 2021, to May 5, 2021, is the official national holiday in China (Labor Day), during this period, social and economic activities were highly different from regular days. Besides, in the following days after the long holiday, the activities and behaviors of urban residents would not go back to normal immediately. Furthermore, travelers may not be aware of the implementation of the UCLDRPs right away. The genuine effects of the policies might be underestimated if we use the full sample that covers the very early days following the implementation of the UCLDRP. Removing the samples near May 6, 2021, would help identify the policy effects more precisely. Thus, we exclude the observations from May 1, 2021, to May 9, 2021, to rule out the potential confounding impact of the holidays and

[1] As a reference, part of hourly readings are provided by the SEMC each day on an open-access website https://link.sthj.sh.gov.cn/aqi/indexMix.jsp.

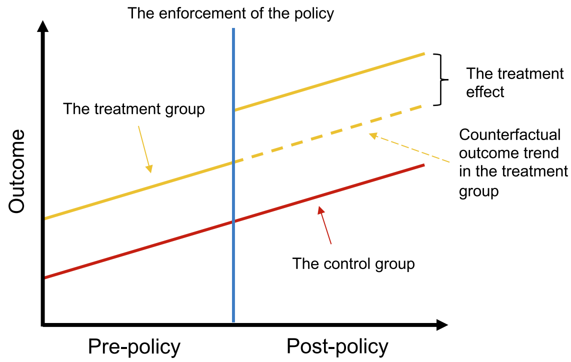

Fig. 4. The graphical explanation of the DID framework.

drivers' reaction lags. The timeframe of the samples used for the subsequent statistical analysis is shown in Fig. 2.

Table 2 offers the descriptive statistics of the samples of workday peak hours (07:00–09:00 and 17:00–19:00), which are the primary interest of this study. The temporal variations of the mean values of peak hour AQI and concentrations of air pollutants are graphically shown in Fig. 3.

Additionally, we acquired hourly weather information recorded by ground-level weather stations in Shanghai (as shown in Fig. 1) to construct control variables, given that weather conditions are important determinants of air pollutants (Tai et al., 2010). To be specific, we match air quality readings of each air quality monitoring station with weather variables from the nearest weather station, including temperature, precipitation, relative humidity, wind speed, barometric pressure, and wind direction. The descriptive statistics of these weather variables are shown in Table A1.

4.2. Methodologies

In this study, we examine the causal effects of UCLDRPs on air quality by employing the difference-in-difference model, a well-acknowledged econometric modeling approach for policy evaluation. The central idea of the DID framework is graphically explained in Fig. 4. We can see that, in DID models, samples are divided into the treatment and control groups. The treatment group consists of samples directly affected by the policy. By contrast, samples in the control group are supposed to be not interfered by the policy. The DID model focuses on the changes in outcomes between the treatment and control groups before and after the enforcement of the policy, instead of directly comparing the difference between the treatment and control groups. The control group serves as the counterfactual to mimic what would have happened in the treatment group in the absence of the policy (Angrist and Pischke, 2008). The treatment effect of the policy can be obtained by taking the differences between the changes in the treatment and control groups before and after the enforcement of the policy.

The standard DID model can be written as follows:

$$lnY_{it} = \beta_0 + \beta_1 TREAT_i \times POST_t + \beta_2 TREAT_i + \beta_3 POST_t + \varepsilon_{it} \tag{1}$$

where lnY_{it} is the natural logarithm of the dependent variable[2] (i.e., the value of AQI or the concentration of various air pollutants); β_0 is the intercept term; $TREAT_i$ is a dummy variable that takes the value of one if the i-th sample is directly affected by the policy (e.g., the UCLDRP) and takes the value of zero otherwise (an indicator of the treatment group); $POST_t$ is also a dummy variable that takes the value of one if day t is after the enforcement of the policy and takes the value of zero otherwise (an indicator of the period after enforcing the policy); β_1 is the coefficient of interest, representing the impact of the policy on the dependent variable; ε_{it} is the error term.

Based on **Eq. (1)**, we utilize an enhanced DID model with fixed effects as follows:

$$\begin{aligned} lnY_{it} = {} & \beta_0 + \beta_1 INNER\_RING_i \times POST_t + \beta_2 5\_KM\_BUFFER_i \times POST_t \\ & + f(weather_t) + \delta_i + \gamma_t + \mu_t + \theta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where $INNER\_RING_i$ and $5\_KM\_BUFFER_i$ are two dummy variables that take the value of one if the i-th station is within the inner ring area or the 5 km buffer area and take the value of zero otherwise. Given the average radius (the average distance from boundaries to the geometric centroid) of the inner ring area is about 5 km, we adopt this distance to create the buffer area with comparable size. Moreover, if those restricted drivers choose to avoid the UCLDRP by adjusting routes, they are likely to drive around the inner ring area while not being too far away from it to minimize detours. For example, Gibson and Carnovale (2015) indicated such spatial substitution mostly exists on roads located 2 km outside the road pricing area. Hence, we believe that it is reasonable to create a 5 km buffer area where the majority of detours are included and considered.

[2] For the dependent variable with zero observations (e.g., PM_{10} in this study), it takes $\ln(Y_{it}+1)$.

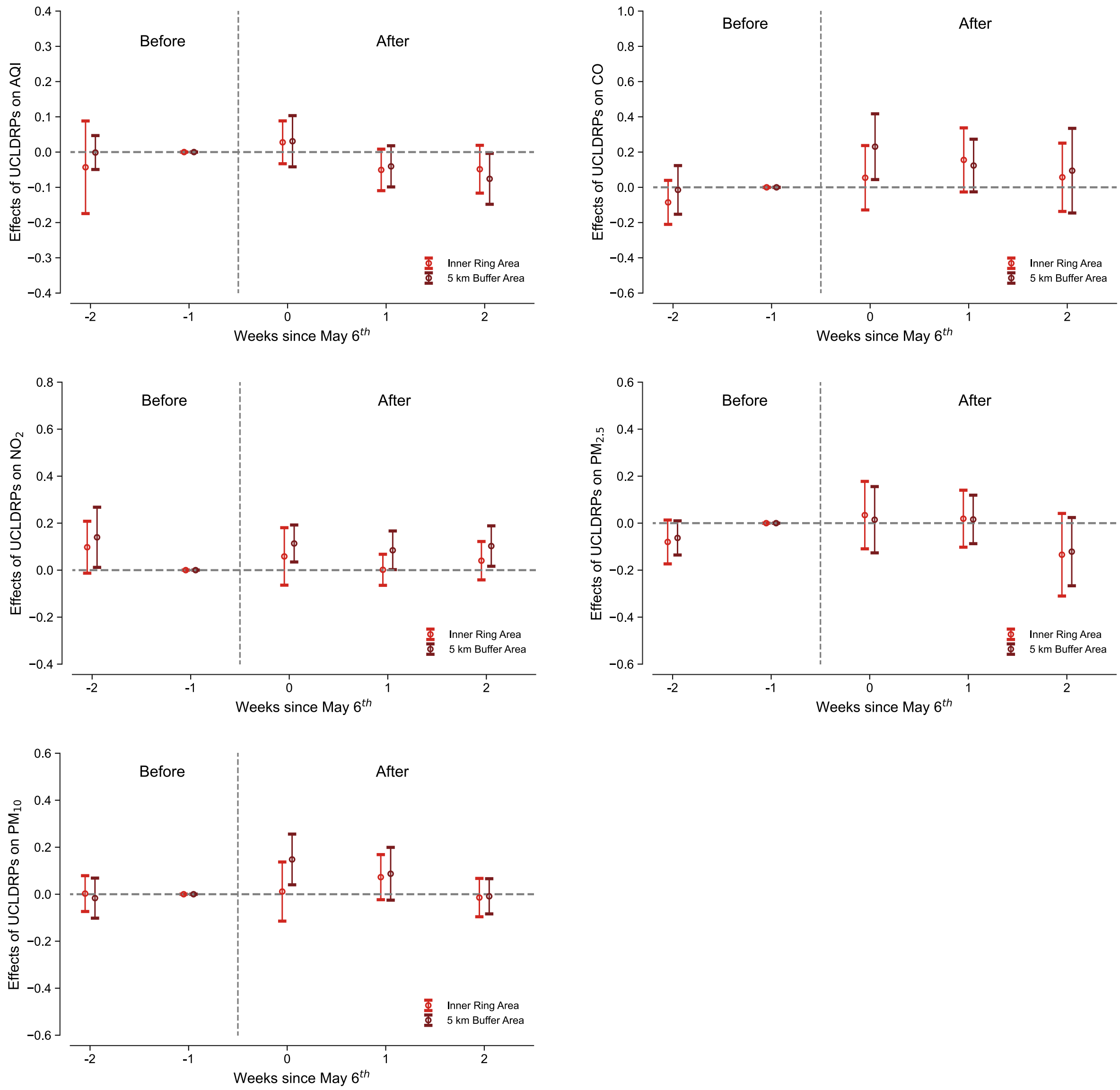

Fig. 5. Results of the common trend assumption test.

$f(weather_t)$ is a bunch of weather control variables, including temperature, precipitation, relative humidity, wind speed, barometric pressure and their squares, as well as a set of dummies denoting 45-degree wind direction bins. δ_i is a set of dummies representing the fixed effects of monitoring stations, which helps absorb the time-invariant attributes of each monitoring station, such as population density, land use, as well as surrounding factories. It also contributes to controlling for the geographical differences among zones. γ_t, μ_t, and θ_t are three sets of dummies representing the fixed effects of hour of the day, day of the week, and week of the year, respectively. They are conducive to netting out the seasonal trends of air pollutants. Other terms are the same as in **Eq. (1)**.

Besides, the time frame of this study is relatively short (two weeks before and three weeks after the policy). The narrow time window can alleviate the interference of other unobserved factors. We also double-checked that there were no other policies that may affect air quality being implemented during this period. Considering that the pollution levels are serially correlated, we cluster the standard error at the monitoring-station level, as informed by Bertrand et al. (2004), to account for potential inner-group error correlations.

It is important to note that the DID model is based on a crucial assumption, namely the common trend assumption. That is, the difference between the outcome of the treatment group and that of the control group is constant over time in the absence of the policy. Otherwise, the control group cannot provide a reliable counterfactual (Angrist and Pischke, 2008). To formally test the common trend assumption, we examine the following DID model:

Table 3
Baseline results (The peak hour model results using workday samples).

	ln(AQI)	ln(CO)	ln(NO_2)	ln($PM_{2.5}$)	ln(PM_{10})
	(1)	(2)	(3)	(4)	(5)
INNER_RING × POST	−0.003	0.131*	−0.015	0.012	0.021
	(0.041)	(0.072)	(0.032)	(0.050)	(0.038)
5_KM_BUFFER × POST	−0.031	0.154**	0.030	−0.003	0.079**
	(0.027)	(0.070)	(0.035)	(0.045)	(0.037)
Weather controls	Y	Y	Y	Y	Y
Hour FE	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y
Week-of-year FE	Y	Y	Y	Y	Y
Monitoring station FE	Y	Y	Y	Y	Y
No. of observations	2,711	2,747	2,733	2,718	2,618
Adj. R-squared	0.492	0.379	0.584	0.431	0.674

*Significant at 10%, **Significant at 5%, ***Significant at 1%.
Robust standard errors clustered at the monitoring-station level in parentheses.

$$lnY_{it} = \beta_0 + \sum_{n=\underline{n},n\neq-1}^{\overline{n}} \beta_{1n} INNER\_RING_i \times Week_{nt} + \sum_{n=\underline{n},n\neq-1}^{\overline{n}} \beta_{2n} 5\_KM\_BUFFER_i \times Week_{nt} + f(weather_t) + \delta_i + \gamma_t + \mu_t + \theta_t + \varepsilon_{it} \tag{3}$$

where $Week_{nt}$ equals one if the n-th week before or after the implementation of UCLDRPs covers day t and equals zero otherwise; $[\underline{n}, \overline{n}]$ takes the value of [-2,2], representing the time range of this study; the week before the implementation of the UCLDRP is omitted as the reference ($n \neq -1$); other terms are the same as in the above. We expected β_{1n} and β_{2n} to be insignificant when it represents the weeks before the implementation of the UCLDRP. Such results mean the common trend assumption is supported.

5. Results

We present our empirical findings in four steps. First, we show the estimated coefficients of interest obtained by examining **Eq. (3)** on workday peak hour samples. This will illustrate whether the common trend assumption of the DID model is valid. Second, we identify the effects of the UCLDRP on the AQI and concentrations of four types of air pollutants, which is the primary interest of this study (the baseline results), by running **Eq. (2)** on the same samples as above. Third, we conduct a placebo test by examining the effects of a falsification UCLDRP using weekend samples to verify the robustness of our baseline results. Finally, we report the sub-model results for separate hours of the day to investigate the spatial–temporal spillover effects, which is so-called the inter-spatial–temporal substitution, of the UCLDRP.

5.1. Common trend assumption test results

Fig. 5 displays the coefficients of interest for common trend assumption tests. We observe that almost all of the coefficients before the enforcement of the UCLDRP (the grey vertical dashed line) are insignificant (confidence intervals straddle zero), both for the inner ring area and the 5 km buffer area. This indicates that the trends of the treatment and control groups are parallel before the implementation of the UCLDRP and thus the utilization of DID models is justified.

5.2. Baseline results

Table 3 shows our baseline results. First, the implementation of the UCLDRP had no significant impact on the AQI and concentrations of NO_2, $PM_{2.5}$, and PM_{10} in the inner ring area (the restricted area), which is in line with the results reported in the literature (Lu et al., 2022; Sarmiento et al., 2021). However, the concentration of CO increased by 14.0%[3]. Second and interestingly, air quality in the 5 km buffer area significantly deteriorated after the implementation of the UCLDRP. Specifically, there was a 16.6% rise in the concentration of CO. Meanwhile, PM_{10} concentrations increased by 8.2%. This implies those restricted drivers may change their routes from the restriction area to the buffer area to avoid driving restrictions, which is the so-called spillover effect (inter-spatial substitution) (Gu et al., 2017; Lu et al., 2022; Ye, 2017).

[3] The percentage point effects of UCLDRP equal to $e^{\beta} - 1$.

Table 4
Placebo test results (The peak hour model results using weekend samples).

	ln(AQI)	ln(CO)	ln(NO_2)	ln($PM_{2.5}$)	ln(PM_{10})
	(1)	(2)	(3)	(4)	(5)
INNER_RING × POST	−0.019	0.072	0.040	−0.104	−0.020
	(0.074)	(0.083)	(0.065)	(0.101)	(0.085)
5_KM_BUFFER × POST	−0.047	(0.016	−0.006	−0.071	0.095
	(0.052)	(0.086)	(0.062)	(0.093)	(0.068)
Weather controls	Y	Y	Y	Y	Y
Hour FE	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y
Week-of-year FE	Y	Y	Y	Y	Y
Monitoring station FE	Y	Y	Y	Y	Y
No. of observations	1,078	1,097	1,100	1,086	1,040
Adj. R-squared	0.757	0.509	0.548	0.642	0.684

*Significant at 10%, **Significant at 5%, ***Significant at 1%.
Robust standard errors clustered at the monitoring-station level in parentheses.

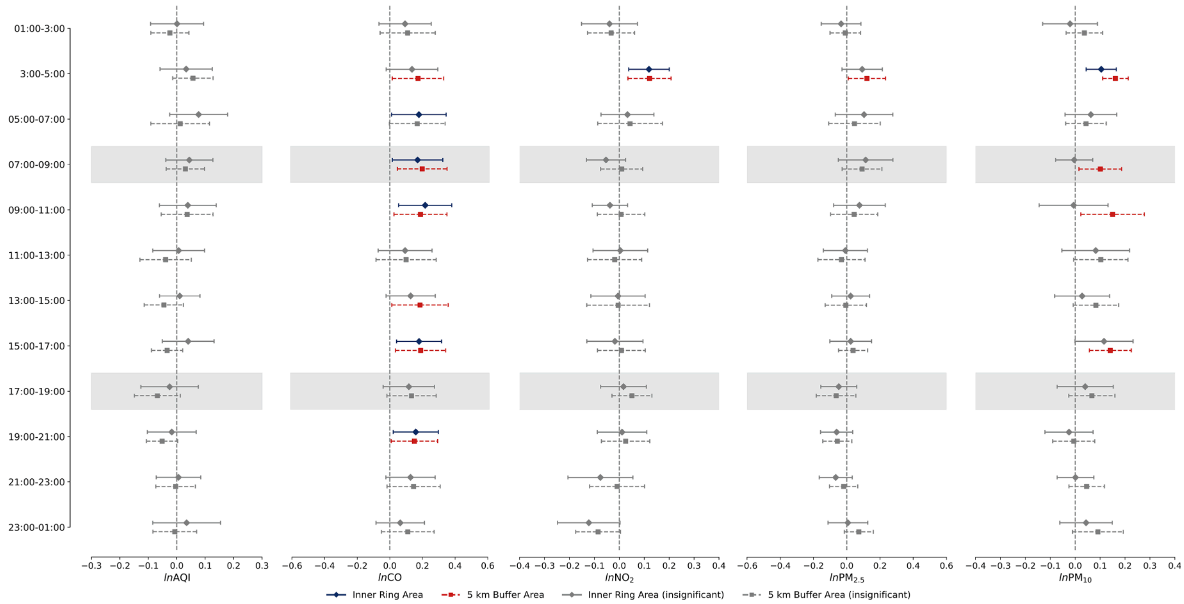

Fig. 6. Spatial-temporal spillover effects of the UCLDRP.

5.3. Placebo tests

One major concern on the validity of our baseline results is that there might be periodic changes (also called seasonality) in the air quality over the treatment and control groups, especially driven by the long national holiday (e.g., before/after the long national holiday, the central and suburban area may have different socio-economic activity patterns, or other endogenous patterns). Accordingly, we conduct a placebo test to rule out this possibility. As mentioned before, the UCLDRP is only in place on workday peak hours. Those non-local vehicles are still free to drive during weekends. Given this, we can apply the same DID model as in Table 3 on weekend samples to test the impact of the “non-existent” UCLDRP on air quality. We expect the estimated coefficients to be insignificant, indicating the changes in air quality during our research period are not driven by seasonal unobserved factors. Table 4 offers the model results. We find that all the treatment effects are insignificant, verifying the robustness of our baseline results.

5.4. Spatial-temporal spillover effects

Fig. 6 graphically displays the coefficients of interest in sub-models for separate hours of the day. We first find strong evidence on the temporal spillover effects of the UCLDRP during daytime off-peak hours. The concentration of CO got increased by 15%-20% in the inner ring area during 5:00–7:00, 9:00–11:00, 13:00–17:00 and 19:00–21:00. Those were time periods right before and after the restricted peak hours. These patterns might be largely attributed to the temporal adjustments made by nonlocal vehicles whose schedules are not fully fixed. More discussion on such adjustments will follow in the next section.

In addition to the temporal spillover effects, the spatial–temporal spillover effects can be seen in more time periods and regarding more air pollutants. In the 5 km buffer area, the concentration of CO increased significantly in all nonpeak hours between 3:00–21:00 except for 11:00–13:00. Similar increases were also shown regarding the concentration of PM_{10} in 09:00–11:00 and 15:00–17:00. When the UCLDRP restricted the driving of nonlocal vehicles in peak hours in the inner ring area, some of the drivers may not only switch to earlier or later departure times, but also use the road network in surrounding areas (the 5 km buffer areas for instance) instead. The combination of these two alternative driving behaviors could lead to more emissions out of the restricted hours and out of restricted areas, as shown above.

Finally, from 03:00 to 05:00, the concentrations of CO, NO_2, $PM_{2.5}$ and PM_{10} were all significantly higher than before in either the inner ring or 5 km buffer area. One possible explanation is that the UCLDRP made nonlocal goods movement vehicles adjust their departure time from morning peak hours to early morning hours to avoid restrictions, given that trucks are one of the major emission sources of NO_2 and PM_{10}, particularly during nights when goods transshipping is common (Yuan, 2018; Yang et al., 2022).

6. Discussions

In general, the UCLDRP did not achieve *short-term* goals of effectively reducing air pollution in the inner ring area, while causing negative impacts on the concentration of certain air pollutants in certain time periods and zones. It is however not totally unexpected, given the nature of the policy—restricting driving in a framework of designated spatial dimension and time windows. The combination of the restrictions, people's responses of travel behaviors, and the spatial dynamics of air pollution may jointly lead to the negative impacts we observe.

The spatial–temporal spillover effects identified through modeling changes in each two-hour period explicitly demonstrate the details of those negative impacts. Most of "worsened air pollution" periods are located right before or after the restricted time windows, suggesting the high possibility of temporal emission spillovers. In this sense, as the UCLDRP only came into effect during morning and evening peak hours, some of the restricted drivers could adjust their schedule to depart in advance or later, which can lead to the worsening of air quality during unrestricted hours (Gibson and Carnovale, 2015; Wang et al., 2014; Yang et al., 2018; Ye, 2017). When those drivers shift their departure times, roads would get more packed during adjacent time periods, simultaneously contributing to the density of emitting vehicles and emission factors (Green et al., 2020; Guerra and Millard-Ball, 2017; Lin et al., 2011; Ye, 2017).

In terms of space, the UCLDRP, as the "pilot program" of citywide DRPs, only targeted at the inner ring area that accounts for 17% of the central city area. This means restricted drivers would have adequate route choices outside but in close vicinity of the inner ring area to avoid the restriction. As a result, such detours could increase traffic volumes in the surrounding area and thus worsen air quality (Lee et al., 2005; Percoco, 2015; Salas et al., 2021; Sarmiento et al., 2021; Ye, 2017). The spatial spillover of vehicles would thus largely undermine the effects of restriction policy, if we take the entire region, or even a slightly larger scale than the restricted area, e.g. the 5 km buffer area, as a whole.

In addition, given the nature of air pollution dispersion, the air quality of the surrounding area would have non-negligible impacts on the air quality of the inner ring area. It is likely in the inner ring area the UCLDRP temporarily contributed to the drop of traffic volume and thus the reduction of emissions. However, such positive effects might be offset by the spread of air pollution in the surrounding area due to the spillover of vehicles. After all, air pollution is a regional issue rather than a local one; while the UCLDRP restricted nonlocal vehicle use in the inner ring area, it might not resolve air pollution problem in a larger spatial scale.

In fact, it is indeed very difficult for policy makers to rule out the above spatial or temporal spillover effects. For instance, an expansion of spatial scope may help improve the air quality in immediately adjacent areas but there will always be spatial limits of the effects. Extending the hours of restrictions also may cause temporal spillover effects before and after restriction time windows. After all, adjusting driving schedule and route is not highly difficult in response to driving restrictions (Guerra et al., 2021). Hence, policies that make the travelling of nonlocal vehicles more costly during unrestricted hours, such as reducing parking supply for nonlocal vehicles in the surrounding area of the city center, would help complement the UCLDRP. In addition, policy makers can enhance the use of alternative modes by increasing the service level and attractiveness of public transportation. Switching drivers of nonlocal vehicles from private to public transport is supposed to be a favorable side product of the UCLDRP.

7. Conclusions

In this study, we investigate the short-run impact of DRPs targeted at the city's central area and nonlocal vehicles on air quality, using Shanghai's UCLDRP as a case study. Specifically, we first compile a high-frequency air quality data set that consists of hourly readings of the AQI and four types of air pollutants collected from 28 environmental monitoring stations in Shanghai. Then, we examine the short-run causal impact of the UCLDRP on the air quality of urban cores (the inner ring area) and surrounding zones (the 5 km buffer area). A batch of DID model results shows that the UCLDRP did not significantly improve the air quality of the inner ring area, while worsening the air quality of the 5 km buffer area. Moreover, after the implementation of the UCLDRP, the air quality of the inner ring and 5 km buffer areas also decreased during unrestricted hours.

We find the implementation of the UCLDRP had no discernable impact on the AQI and concentrations of NO_2, $PM_{2.5}$, and PM_{10} in the restricted area, while the concentrations of CO increased by 14.0%. In the 5 km buffer area, the concentration of CO increased by 16.6% and PM_{10} concentration increased by 8.2%. Results also justified the temporal-spatial spillover effects in the dynamics: the concentrations of CO and PM_{10} got increased by 10%-20% in 5 km buffer areas in time periods right before or after the restricted time windows. In a nutshell, Shanghai's UCLDRP was not only ineffective in improving the air quality of the targeted area during targeted time windows, but also had led to worsened air quality in nearby areas and during non-peak hours.

Admittedly, this study is subject to a few limitations that deserve further attention. It focuses predominantly on the short-term impacts of the UCLDRP on air quality. However, it remains unclear whether such short-term impacts will persist or decline in the long run. In light of this, we call for more research efforts to investigate the policy's long-term impact for a better understanding of its externalities. Moreover, although the changes in air quality could be attributed to those in traffic flows after leveraging DID approaches to control for potential confounding factors, using independent information (e.g., traffic data) to support our hypotheses and conclusions will make the study stronger. Additionally, independent information can help examine whether and to what extent the reduction in air quality after the enforcement of the UCLDRP comes from the induced demand of local vehicles.

CRediT authorship contribution statement

Zhengtao Qin: Investigation, Formal analysis, Writing – original draft. **Yuan Liang:** Conceptualization, Investigation, Data curation, Visualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Chao Yang:** Writing – review & editing. **Qingyan Fu:** Data curation. **Yuan Chao:** Data curation. **Ziang Liu:** Visualization. **Quan Yuan:** Conceptualization, Investigation, Project administration, Funding acquisition, Formal analysis, Supervision, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Appendix

Table A1
The descriptive statistics of weather variables.

	Unit	N	Avg	St. D	Min	25%	50%	75%	Max
Temperature	°C	2752	21.42	3.114	14.40	19.30	20.80	23.30	31.30
Precipitation	mm	2752	0.16	0.627	0	0	0	0	7.70
Relative humidity	%	2752	73.84	18.660	30	60	74	91	100
Wind speed	m/s	2752	1.52	1.228	0	0.4	1.3	2.3	5.7
Barometric pressure	hPa	2752	1010.76	4.678	999.5	1007.1	1010.6	1013.8	1020.0
Wind direction	[0°,45°)	2752	0.24	–	0	–	–	–	1
	[45°,90°)	2752	0.14	–	0	–	–	–	1
	[90°,135°)	2752	0.23	–	0	–	–	–	1
	[135°,180°)	2752	0.11	–	0	–	–	–	1
	[180°,225°)	2752	0.07	–	0	–	–	–	1
	[225°,270°)	2752	0.07	–	0	–	–	–	1
	[270°,315°)	2752	0.07	–	0	–	–	–	1
	[315°,360°)	2752	0.07	–	0	–	–	–	1

Notes. The wind direction is reported in degrees. The north, east, south, and west are set as 0°, 90°, 180°, and 270°, respectively.

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