Traffic Congestion, Ambient Air Pollution, and Health: Evidence from Driving Restrictions in Beijing

Nan Zhong, Jing Cao, Yuzhu Wang

Abstract: Vehicles have recently overtaken coal to become the largest source of air pollution in urban China. Research on mobile sources of pollution has foundered due both to inaccessibility of Chinese data on health outcomes and strong identifying assumptions. To address these, we collect daily ambulance call data from the Beijing Emergency Medical Center and combine them with an idiosyncratic feature of a driving restriction policy in Beijing that references the last digit of vehicles' license plate numbers. Because the number 4 is considered unlucky by many in China, it tends to be avoided on license plates. As a result, days on which the policy restricts license plates ending in 4 unintentionally allow more vehicles in Beijing. Leveraging this variation, we find that traffic congestion is indeed 22% higher on days banning 4 and that 24-hour average concentration of NO_2 is 12% higher. Correspondingly, these short-term increases in pollution increase ambulance calls by 12% and 3% for fever and heart-related symptoms, while no effects are found for injuries. These findings suggest that traffic congestion has substantial health externalities in China but that they are also responsive to policy.

JEL Codes: I18, Q52, R41

Keywords: Air pollution, Driving restrictions, Health

AIR POLLUTION is a major environmental threat to people in both developing and developed countries. According to the 2014 United Nations Environment Programme (UNEP) Year Book, air pollution has become the leading cause of environmentally related deaths. An estimated 7 million premature deaths were connected to

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air pollution globally in 2012, among which 3.7 million were caused by outdoor air pollution. Pollution from the transport sector is responsible for a large portion of the health effects. Road transport accounted for 50% of the health cost in OECD countries in 2010 (UNEP 2014). With its rapid economic development and less stringent environmental standards, China is experiencing deteriorating air quality. Moreover, because of the fast-growing transport sector, vehicle emission has become one of the major sources of air pollution in urban China, which could lead to significant social costs. While it is important to quantify the negative externalities of air pollution, surprisingly little literature has documented the relationship between air pollution and health in China, especially the contribution of road transport to the total health impact of air pollution. Even less is known about Chinese policies that might affect air pollution and health.

In this paper, we use a driving restriction policy introduced in Beijing as a natural experiment to study the health effects of mobile sources of air pollution. The policy was introduced in 2008 to alleviate traffic congestion and reduce vehicle emissions in Beijing. Under the policy, vehicles are restricted from the road each workday based on the last digit of the vehicle's license plate number. Because the number 4 is considered unlucky in Chinese culture, it tends to be avoided on license plates, resulting in fewer vehicles with plate numbers ending in 4 compared with other numbers.[1] Hence, this driving restriction unintentionally allows more vehicles on the road in Beijing on days in which the number 4 is restricted. We compiled a novel data set of traffic congestion, ambient air pollution, and records of ambulance calls, exploiting time series variations in the number of vehicles allowed on the road attributable to the idiosyncratic feature of the driving restriction, and exploring the relationship between traffic condition, ambient air pollution, and health. The driving restriction provides a compelling setting for estimating the effects of air pollution on health. First, the variation in air

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1. The number 4 is considered to be unlucky in Chinese culture because it sounds like "death" in Chinese. Due to this reason, people try to avoid using the number 4 in places like phone numbers and plate numbers. Since there are few people willing to choose a vehicle license plate with 4 in it, the Beijing Traffic Management Bureau even stopped issuing plate number with 4. Other papers that investigate the impact of Chinese superstitious beliefs have focused on the willingness to pay for special license plates in Hong Kong (e.g., Woo et al. 2008; Ng, Chong, and Du 2010; Fortin, Hill, and Huang 2014).

pollution induced by days with different restricted numbers is unlikely to correlate with other confounding factors; therefore, this treatment can be considered to be "as good as random." Second, it helps address potential measurement error in the reported ambient pollution levels (Angrist and Krueger 2001).

This paper shows that this exogenous variation in the number of vehicles allowed on the road is a significant predictor of traffic condition, ambient air pollution, and health in Beijing. Specifically, on days when vehicles with license plates ending in the number 4 are restricted (hereafter referred to as the "number 4 day"), the traffic congestion index increases by 22%. The number 4 day also has a significant impact on ambient air pollution. The 24-hour average concentration of nitrogen dioxide (NO_2), which is a major vehicular pollutant, is 12% higher over the period from noon on the number 4 day to noon the next day compared to other days. The concentration of particulate matter smaller than 10 micrometers (PM10) and sulfur dioxide (SO_2) also show similar patterns, though not statistically significant. Given that a significant portion of PM10 and SO_2 comes from sources other than vehicular emission, this indicates that the effect of the number 4 day may also affect pollutants other than vehicular emissions that vehicle trips enable. Correspondingly, the short-term increase in the pollution level increases ambulance calls. On days after the number 4 day, the emergency ambulance call rates related to heart disease and fever are higher by 3% and 12%, respectively, while no effects are found for injuries as a control group. Looking at subpopulation groups, we find that the point estimates for the population aged 65 and above are larger than those of younger population groups. However, comparing the mean ambulance call rates of each subpopulation, the population aged 15 and 64 has the largest percentage change. With a distributed lag model, there is no significant temporal displacement effect or lag effect on ambulance call rates. These findings suggest that traffic congestion has substantial health externalities in China but that they are also responsive to policy.

The findings in this paper contribute to the literature on air pollution and health in developing countries. Although associations between air pollution and health have been well documented, most of them are based on developed countries where air pollution levels are relatively lower. These estimates cannot be extrapolated to developing countries where air pollution levels are much higher if a nonlinear health effect of pollution exists. Furthermore, while most of the existing literature on this topic in China focuses on particulate matter (PM) or total suspended particulate (TSP), the findings of this study shed some light on the health impact of more traffic-related pollutants such as NO_2. With the rapid growth in road transportation and an increasing share of air pollution from traffic sources in developing countries, it is crucial for policy makers to understand the negative social externalities.

This study also has important policy implications for transportation policies. Traffic congestion is a problem of urban areas worldwide, but the social benefits of reducing traffic congestion have not been fully understood. Knittel, Miller, and Sanders (2011) examined the relationship between traffic, ambient air pollution, and infant health. The traffic shocks they used were from non-policy-related sources such as accidents or road closures. In contrast, the present study is based on an actual policy aiming to reduce traffic congestion. This study suggests that implementing this driving restriction policy can result in significant co-benefits on air quality and health. Since this study is based on a natural experiment at high baseline pollution levels, the results may be more generalizable to other factors affecting traffic congestion in polluted cities.

In addition, this study is relevant to the driving restriction policy and its effects. Driving restrictions have been introduced in many cities worldwide before Beijing, but their effectiveness is debatable. Davis (2008) examined the driving restriction introduced in Mexico City in 1989 and found it ineffective, since people were purchasing secondhand cars to avoid this inconvenience. On the other hand, Viard and Fu (2015) employed regression discontinuity design and difference-in-difference approach to evaluate the environmental and economic effects of Beijing's driving restriction, and found significant improvement in air quality and increases in television viewers during the restriction hours for workers with discretionary work time. Anderson et al. (2015) exploited a variation in daily congestion in Beijing induced by the driving restriction and people's superstitions toward the number 4 and found a strong effect of traffic congestion on self-reported happiness. Results of the present study suggest that the driving restriction in Beijing is effective in reducing traffic congestion and air pollution. In addition, it is also effective in improving health outcomes. The difference in effectiveness implies that people responded to similar policies differently in the two cases. Possible reasons for the effectiveness of the driving restriction in Beijing might be related to the policy limiting vehicle sales and the upgrading of the subway system. In December 2010, Beijing introduced a policy that limits the issuance of vehicle license plates to 20,000 per month, which prevents people from purchasing additional vehicles to circumvent the driving restriction. Meanwhile, the large-scale opening of new subway lines provides extra public transit alternatives for people when their vehicles are restricted. Now that many other cities in China have replicated or are about to replicate this driving restriction, it is important to understand the conditions for this policy to be effective.

The rest of this paper is organized as follows. Section 1 provides a background of Beijing's transportation and air pollution situation, as well as its driving restriction policy. Section 2 describes the data. Section 3 presents the empirical strategy and results. Section 4 concludes.

1. BACKGROUND

1.1. Air Pollution and Health

Literature on the relationship between air pollution and health includes both epidemiological and economic studies. Most of the epidemiological studies in this field were conducted in the United States and OECD countries (e.g., Dockery et al. 1993; Pope et al. 1995; Pope et al. 2002; Cohen et al. 2004; Cohen et al. 2005), with a focus on PM and mortality. The levels of PM in these studies are much lower than the levels in

China. Some epidemiological studies conducted in the 1950s might be more relevant to developing countries, considering the high pollution level back then (Logan and Glasg 1953; Greenburg et al. 1962). Some epidemiological studies have been conducted in China as well. Most of them focused on the impact of pollution from coal burning, such as TSP and sulfur dioxide (SO_2), on mortality (e.g., Gao et al. 1993; Xu et al. 1994; Dong et al. 1995; Xu et al. 1996; Chang et al. 2003; Kan and Chen 2003; Aunan and Pan 2004). However, few, if any, studies focused on the impact of pollution from the transport sector. With the fast-growing transport sector in urban China and more stringent industrial emission control policies, there is a decreasing trend in TSP and SO_2 emission from industrial sources and an increasing trend of pollution from traffic sources in urban China. As major pollutants from traffic sources, nitrogen oxides (NO_x) are considered to have increasing potential with the rapid motorization in China (Hao and Wang 2005; Hilboll, Richter, and Burrows 2013). Hence, it is important to understand the relationship between human health and traffic-emitted pollutants such as NO_x in China.

One problem when estimating the effect of air pollution on health is that air pollution is not randomly assigned to individuals, and it is difficult to measure the effects when other unobserved determinants of health correlate with air pollution. For example, health-conscious people may live in neighborhoods with better air quality or avoid exposure to high pollution. Another problem that may complicate the estimation is measurement error when using the ambient air pollution level as a measure of individual exposure (Zivin and Neidell 2013). To avoid these problems, some economic studies use econometric tools such as fixed effects and instrumental variables to estimate the effects. For example, Currie, Neidell, and Schmieder (2009) explored the effects of air pollution on infant health, using maternal fixed effects to control for unobserved characteristics of mothers. Currie and Neidell (2005) examined the impact of air pollution on infant death, using within zip code–month variation in pollution levels to control for unobserved seasonal and area factors. Chay and Greenstone (2003) examined the impact of reduced TSPs induced by the 1981–82 recession to examine the impact on infant mortality rates. Chen et al. (2013a) explored the impact of different TSPs due to the different winter heating policies in northern and southern China on life expectancy and mortality. Studies have used variations of pollution caused by port activity, airport runway congestion, and road traffic congestion to explore the health impact of air pollution from traffic sources (Currie and Walker 2011; Knittel et al. 2011; Moretti and Neidell 2011; Schlenker and Walker 2016). However, no studies have employed these econometric tools to estimate the effects of air pollution from traffic sources on health in China.

1.2. Transportation Problem and Air Pollution in Beijing

With its high population density and extensive economic activities, Beijing is facing transportation problems, as are other mega-cities around the world. During the past couple of decades, Beijing has experienced rapid change in the transportation sector along with economic growth. According to the annual report of the Beijing Transportation Research Center (2013), transportation needs in Beijing have been increasing steadily in the past decades, reaching 30.3 million trips per day in 2012.[2] The mix of transportation modes is also changing. The most distinct change is the share of trips by private vehicles, which increased from 5% in 1986 to 34% in 2010. The stock of motor vehicles in Beijing has been increasing dramatically, reaching 5.2 million in 2012. Much of the increase has been driven by private vehicles, which accounted for 80% of the total vehicle stock in 2012. Because of the rapid growth of ownership and usage of private vehicles, the traffic congestion problem is becoming more serious. In 2012, the average road speed during peak hours on workdays was around 25 kilometers per hour (km/h), and the average hours of congestion was over 4 hours per day.[3]

Air pollution is another serious problem in Beijing. According to the Beijing Environmental Statement, in 2012, the annual average concentration of SO_2, NO_2, PM10, and carbon monoxide (CO) in Beijing was 28 micrograms per cubic meter ($\mu g/m^3$), 52 $\mu g/m^3$, 109 $\mu g/m^3$, and 1.4 mg/m^3, respectively. The annual average concentration of NO_2 and PM10 exceeds the level specified in the World Health Organization's (WHO) annual mean air quality guidelines by one-fourth and over five times, respectively. The level of SO_2 also exceeds WHO's 24-hour mean guidelines on nearly half of the days in 2012.[4] With the Ambient Air Quality Standard of China, which is much looser than the WHO standard, NO_2 and SO_2 meet the second-class air quality standard (the standard applied to residential areas) and PM10 exceeds the second-class air quality by 9%.[5] Many studies have confirmed that mobile sources have replaced coal burning and become the most important contributor to Beijing's air pollution. Vehicle emissions are identified as major contributors to pollutants including, CO, NO_x, PM, and volatile organic compounds (VOCs) (Hao et al. 2000, 2001; Hao, Hu, and Fu 2006; Walsh 2007; Westerdahl et al. 2009). According to a report by the Beijing Municipal Environmental Protection Bureau (EPB) in 2012, vehicle-emitted NO_x , CO, and PM smaller than 2.5 micrometers in diameter (PM2.5) accounted for 56.9%, 85.9%, and 22.2%, respectively, of the total emission from all sources in Beijing.[6]

Although several scientific studies have linked exposure to air pollutants with adverse health effects, the mechanism of how air pollution affects health remains unclear.

2. Trips counted here include those within the Sixth Ring Road and exclude trips by foot.

3. Here congestion is defined as when travel time is 50% longer than running with the speed limit.

4. Details of the WHO air quality guidelines can be found on WHO's website: http://whqlibdoc.who.int/hq/2006/WHO_SDE_PHE_OEH_06.02_eng.pdf?ua=1.

5. According to Ambient Air Quality Standard (GB3095-2012), the first-class standard applies to nature reserve areas, and the second-class standard applies to residential, business, and industrial areas. Details of the Ambient Air Quality Standard of China can be found on the website of China National Environmental Monitoring Center: http://www.cnemc.cn/publish/106/news/news_25941.html.

6. Here the vehicle emitted PM2.5 includes both primary and secondary emission but excludes vehicle-induced road dust. http://www.bjepb.gov.cn/bjepb/323474/331443/331937/331945/449229/index.html.

According to the United States Environmental Protection Agency, short-term exposure to PM, NO_x, and sulfur oxides (SO_x) has negative effects on health. For PM, small particles such as PM10 and PM2.5 are considered to pose the most severe problems because they can penetrate into the lungs and even the bloodstream. NO_x and SO_x can react with other compounds to form small particles. These particles can penetrate into sensitive parts of lungs and cause or worsen respiratory disease, as well as aggravate existing heart disease. In the presence of sunlight, NO_x is a precursor of ozone. Exposure to ozone can also trigger a variety of health problems, including respiratory system diseases and heart problems. Exposure to CO can cause negative effects on health by reducing the oxygen-carrying capacity of the blood. At high levels, CO can cause heart and respiratory problems, and extremely high levels of CO can lead to death.[7]

1.3. Driving Restriction in Beijing

Beijing is not the first city to introduce a driving restriction policy. Similar restrictions were implemented in Santiago, Chile, in 1986 and in the Mexico City metropolitan area in 1989. Several Latin American cities followed suit, including São Paulo, Brazil, and Bogotá, Colombia. During the 2008 Olympic Games, Beijing implemented a short-term driving restriction referred to as the "Odd-even driving restriction" in which vehicles with odd plate numbers were restricted on odd days and those with even plate numbers were restricted on even days. This policy was proved to be a success in reducing traffic congestion and ambient air pollution. Seeing the significant effects, the government decided to continue with a less stringent version of the policy. On October 11, 2008, the Beijing government announced the implementation of a half-year trial of the driving restriction until April 10, 2009. The driving restriction was based on the last digit of the vehicle's license plate number. From Monday to Friday, vehicles with license plate numbers ending in 1 or 6, 2 or 7, 3 or 8, 4 or 9, and 5 or 0, respectively, were banned from the roads. The restricted day of the week for different numbers rotated every 4 weeks. Service vehicles such as police cars, fire engines, ambulances, postal vehicles, taxis, and public buses were exempt. The driving restriction was in force within (and including) the Fifth Ring Road,[8] from 6:00 in the morning to 21:00 in the afternoon. When this half-year trial ended, the government started a new round of the driving restriction lasting 1 year. This time, the restricted day of the week changed every 13 weeks, and the restriction area and hours were narrowed to inside (and excluding) the Fifth Ring Road and from 7:00 to 20:00. The third round of the driving restriction began immediately after the previous round on April 11, 2010. Since then, there have been no changes in the policy, and the restriction remains in force. Also, the penalty for violating the regulation has

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7. http://www3.epa.gov/airquality/carbonmonoxide/health.html.

8. The distance from the city center to the Fifth Ring Road is between 10 and 15 km, depending on which part of the road is in question. The area within the Fifth Ring Road largely coincides with the urban area of Beijing.

changed over time. Initially, drivers who violated the restriction were stopped and fined 100 yuan (around $16.3) for the day. Since there would be no extra penalty if the violator was caught more than once in a day, some people were willing to risk being caught and pay for the daily fine. To improve enforcement, since 2011, the government has changed this daily penalty to 100 yuan every 3 hours.

With the gradual changes in policy, it is reasonable to expect people's behavior and response toward the restriction to change over time. Wang, Xu, and Qin (2014), using a 2010 household travel survey in Beijing, found that the driving restriction did not significantly influence individuals' choice to drive. They found that a large percentage of drivers left home before 7:00 to circumvent the driving restriction and that violations of the driving restriction were common. After 2011, with the improvement of the transport surveillance system and the stricter penalty for violating the restriction, the Beijing Traffic Management Bureau claimed that compliance with the driving restriction had improved. The opening of new subway lines linking the central city area with the rural area[9] and the increase of parking fees[10] since 2011 have also helped provide people with alternative means of transportation other than private vehicles.

With people's gradually changing behavior and different policy packages, the effects of driving restrictions could be very different. For example, Davis (2008) measured the effect of Mexico City's driving restriction on air quality using a regression discontinuity design, based on hourly pollution measures from monitoring stations. The results showed no evidence that the restrictions had improved air quality. In addition, evidence from additional sources indicates that the restriction led to an increase in the total number of vehicles in circulation as well as a change in composition toward high-emissions vehicles like used vehicles. However, Salas (2010) argued that changes in methodology can alter its conclusions. Specifically, Salas (2010) showed that there are different effects within different time windows, which is consistent with the hypothesis that people gradually adapt to the policy.

A few studies have focused on the effect of Beijing's driving restriction, but no consensus has been reached yet. The mixed results are partly due to the different identification methods employed and likely related to the studies' different time windows. Chen et al. (2013b) examined policies implemented during and after the 2008 Olympic Games in Beijing by using a differences-in-differences approach. Their results suggest that the odd-even driving restriction during the Olympic Games was effective in improving air quality, while the one-day-off-the-road driving restriction implemented

9. Five subway lines were opened on December 30, 2010 (lines Daxing, Yizhuang, Fangshan, Changping, and the western part of line 15), extending the subway service area to suburb areas. And on December 31, 2011, three new lines were opened (lines 8, 9, and the eastern part of line 15), which further improved the linkage between the city center and Beijing's suburb areas.

10. The parking fee for nonresidential areas in central Beijing was increased on April 1, 2011. Compared to old parking fee standards, the new standards are higher by around five times.

after the Games was less effective. Lin, Zhang, and Umanskaya (2011) employed a regression discontinuity approach to study the effects of driving restriction in Beijing and found similar results. However, by using a similar regression discontinuity approach, Viard and Fu (2015) found that Beijing's air pollution index reduced 21% during the one-day-off-the-road driving restrictions. The difference between Lin et al. (2011) and Viard and Fu (2015) may be due to different length of time windows used and the inclusion of different time trends.

In our study, the daily variation in number of vehicles allowed on the road induced by the number 4 days provides a compelling setting for studying the driving restriction. Two recent studies employed a similar identification strategy to study Beijing's driving restriction. Sun, Zheng, and Wang (2014) find that restricting more vehicles had a positive impact on traffic speed but little effect on the concentration of particulate matter. Anderson et al. (2015) find a strong effect of daily congestion on self-reported happiness. However, my study found a significant effect on air pollution while they did not. The difference between our findings and theirs may be due to the different pollutants, time windows, and definitions of 24-hour average concentration used. First of all, their analysis is mainly based on air pollution index data, while we looked at more traffic related pollutant NO_2. Second, another possible reason is the different time windows we looked at. The time window they focused on is the first two years of the policy, when the enforcement was not very stringent. And the time period we focused on is 2012, when the enforcement was stricter and people were getting used to the driving restriction, and potentially had found alternatives that they are comfortable with during days when their vehicles are restricted. Finally, they looked at the number 4 day's effect on the current day's pollution level, while we looked at the number 4 day's effect on the pollution level over the period from noon on the number 4 day to noon the next day. Due to meteorological conditions, air pollution in Beijing is more likely to diffuse during the daytime and to accumulate from late afternoon till the next morning. Hence, the 24-hour period from noon to noon is more appropriate to reflect emissions during the day. A more detailed discussion regarding this is provided in section 2.2.

2. DATA

In this study, we combined three major data sets for the year 2012: measures of traffic congestion, ambient air pollution, and health outcomes. The details of each set of data are as follows.

2.1. Measure of Traffic Congestion

As a measure of traffic congestion, we collected a traffic congestion index.[11] This index is calculated based on the real-time speed of vehicles on the road collected from taxis

11. The traffic congestion index is maintained by the Beijing Transportation Research Center (http://www.bjtrc.org.cn/).

and street monitors in the area within the Fifth Ring Road of Beijing. It is weighted by the traffic volume on each road. The index describes the relationship between travel time according to real-time speeds on the road and travel time in obedience to the road's speed limit. It is on a scale from zero, which represents no congestion at all, to 10, which represents a very congested road. The explanation of its values is shown in table 1, presented as the amount of time needed compared to driving at the speed limit.

The traffic congestion index we obtained is 15-minute average time series data. The data show that on a typical workday, the morning peak starts at around 7:00 and ends at 9:00, and that the evening peak is from around 17:00 to 19:00. The maximum congestion index during peak hours could reach a value of six and above, which is two to three times higher than during nonpeak hours. With the 15-minute average traffic congestion index, we explored how traffic conditions vary within a day. We divided the 24 hours within a day into three periods: peak hours, nonpeak hours, and nonrestricted hours. Peak hours include morning peak hours from 7:00 to 9:00 and evening peak hours from 17:00 to 19:00. Nonpeak hours include the hours between 7:00 and 20:00 when the driving restriction is in force but exclude peak hours. Nonrestricted hours, which include the hours before 7:00 and after 20:00, are the hours when the driving restriction is not in force. Rows 2–5 in panel A of table 2 show that the values of the congestion index are very different in the three time spans, with the largest value during peak hour hours, and the smallest value during nonrestricted hours.

2.2. Measure of Air Quality

As a measure of air quality, we obtained two sets of data. One was measured and recorded by the Beijing Environmental Protection Bureau (EPB), and the other one was from the US embassy in Beijing.

Table 1. Traffic Congestion Index and the Corresponding Traffic Condition

Values	Congestion Level	Extra Time Spend on Road
0–2	No congestion	Running with the speed limit, do not need extra time.
2–4	Almost no congestion	20%–50% times longer than running with the speed limit.
4–6	Slightly congested	50%–80% times longer than running with the speed limit.
6–8	Moderately congested	80%–110% times longer than running with the speed limit.
8–10	Heavily congested	110% times longer or more than running with the speed limit.

Note. The table lists values of the traffic congestion index with the corresponding congestion level and extra time needed.

Table 2. Summary Statistics for Measure of Traffic Congestion, Air Quality, and Health

	Obs.	Mean	SD	Min	Max
	A. Measure of Traffic Congestion				
All hours	28,071	2.28	1.83	.30	9.70
Morning peak hours	2,359	3.48	2.23	.49	8.79
Evening peak hours	2,396	5.15	2.14	.91	9.70
Nonpeak hours	10,655	2.91	1.37	.49	9.52
Nonrestricted hours	12,661	.99	.48	.30	8.61
	B. Measure of Air Quality				
All stations:					
NO_2 (μg/m3)	8,841	50.24	27.35	0	204.8
PM10 (μg/m3)	9,672	106.67	74.94	4	600
SO_2 (μg/m3)	9,026	28.65	28.85	4	195.5
PM2.5 (μg/m3)	8,295	90.52	81.72	0	994
Urban stations:					
NO_2 (μg/m3)	3,938	57.81	24.89	1.6	204.8
PM10 (μg/m3)	4,305	116.22	76.16	5	600
SO_2 (μg/m3)	4,053	29.44	29.88	4	195.5
Rural stations:					
NO_2 (μg/m3)	4,903	44.17	25.92	0	171.2
PM10 (μg/m3)	5,367	99.00	73.05	4	600
SO_2 (μg/m3)	4,973	28.01	27.97	4	195.5
	C. Measure of Health				
All heart	2,196	5.102	2.614	0	16.522
Coronary	2,196	.416	.619	0	4.695
Fever	2,196	1.651	1.323	0	9.392
Injury	2,196	8.542	3.323	0	25.332

Note. The table lists summary statistics for measure of traffic congestion, air quality, and health in the main study period 2012. The measure of traffic congestion is the 15-minute average traffic congestion the index for the area within the Fifth Ring Road. Measures of air quality include station-level 24-hour average NO_2, PM10, and SO_2 concentrations over the period from noon the current day to noon the next day from 27 EPB stations, and hourly PM2.5 concentration from the US embassy in Beijing. Measures of health are district-level daily emergency ambulance call rates (number of ambulance calls per million people) related to all heart diseases, coronary heart disease, and fever.

Air quality in Beijing is measured and recorded by a network of air quality monitoring stations operated by the EPB. As of 2012, this network consisted of 27 stations distributed uniformly in both urban and rural areas of Beijing. The stations measure and record concentrations of three major air pollutants: NO_2, PM10, and SO_2. The first set of data used here is the station-level 24-hour average concentration of NO_2, PM10, and SO_2 in 2012. These data are converted from the 24-hour average pollutant-specific air pollution index (API) reported by the EPB. The pollutant-specific API is an index scaled from 0 to 500, calculated by a function based on the pollutant's concentration. One thing to note here is that the 24-hour period refers to the period from 12:00 midday on the previous day to 12:00 on the current day.

Another set of data is the hourly PM2.5 concentration measured and reported by the US embassy in Beijing. Concerned about Beijing's air quality and its potential health impacts, the US embassy in Beijing started to monitor PM2.5 in 2008 and to provide this information as a resource for the health of the American community. The monitor is located at the site of the embassy, which is within the Fourth Ring Road. With this hourly measure of PM2.5, we were able to further explore the temporal feature of driving restriction's effects on air pollution and health. Summary statistics of air quality data are presented in panel B of table 2.

There have been concerns about data quality in China for a long time, and the discrepancy between the air quality index reported by the US embassy in Beijing and the API reported by the EPB is always debatable. Possible reasons behind this might be due to different pollutants being measured (PM2.5 for the US embassy, and PM10 for the EPB before 2013) and different locations of monitoring stations (a single station at the US embassy versus the city average for the EPB). Starting in 2013, the EPB began to measure and record levels of PM2.5 as well. In response to the data quality issue, we chose the EPB monitoring station closest to the US embassy (within a distance of 1.6 km) and compared the PM2.5 measurements from the two stations. Figure 1 presents the 24-hour average measures of PM2.5 from these two stations in 2013. The two measures covariated very well, with a correlation coefficient of 0.92. The mean value of PM2.5 from the US embassy was slightly higher (by 9%) than the one from the EPB, but the difference is not unreasonable considering the different monitoring locations.

Among the three pollutants monitored by EPB, NO_2 is considered to have the closest connection with road transportation, PM10 is also considered to be a major pollutant from traffic, while SO_2 mainly comes from coal burning (Hao et al. 2001; Hao and Wang 2005; Westerdahl et al. 2009; Li et al. 2015).[12] Though most NO_2 emissions come from traffic, the hourly variation of NO_2 in Beijing does not match traffic patterns exactly. As suggested by environmental science studies, the concentration of NO_2 in Beijing reaches the lowest level around noon and early afternoon. Then, it starts to increase and remains at high levels from the evening until the next morning (Chen, Tang, and Zhao 2015). This diurnal pattern can be explained by the chemical

12. According to the SO_2 emission inventory by Li et al. (2015), industrial and power-generating emissions accounted for around 62% of total SO_2 emissions in Beijing; residential emissions and transportation emissions accounted for 34% and 4% of the total emissions, respectively.

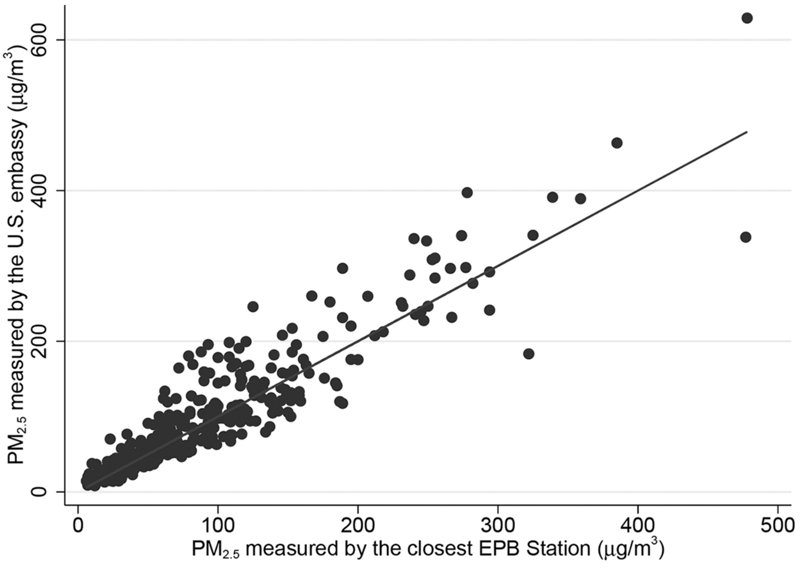

Figure 1. Association of PM2.5 concentrations measured in the Nongzhanguan station and the US embassy. The figure plots the 24-hour average concentrations of PM2.5 measured by the Nongzhanguan station operated by EPB and the US embassy of Beijing in 2013. Nongzhanguan is the EPB station that is located closest to the US embassy, as it is located within 1.6 km to the US embassy.

reaction with other gaseous pollutants and by meteorological conditions. First of all, most NO_2 is not directly emitted from vehicles but is converted from the vehicular emissions of NO, which is part of the reason why the level of NO_2 does not respond to commuting peaks immediately. Second, the chemical reaction between NO, NO_2, and O_3 in the presence of sunlight results in a low concentration of NO_2 during the daytime (Chen et al. 2009). Another reason for the relatively high level of pollution during the nighttime is the temperature inversion that occurs at night, which traps pollutants near the surface. For particulate matter, as suggested by figure 2, the hourly US embassy PM2.5 data show similar diurnal patterns: the concentration reaches its bottom at around 13:00, and the daily maximum appears in the evening hours, starting from 20:00. This diurnal pattern has also been recorded by related studies and is considered to be influenced by temperature inversion and boundary layer development patterns (Zhao et al. 2009). Since the level of pollution in Beijing does not respond to traffic conditions as they occur but only starts to show an effect in the early evening, we matched the 24-hour average air pollution level, from 12:00 on the current day to 12:00 on the next day, with the traffic conditions on the current day. More details will be discussed in section 3.

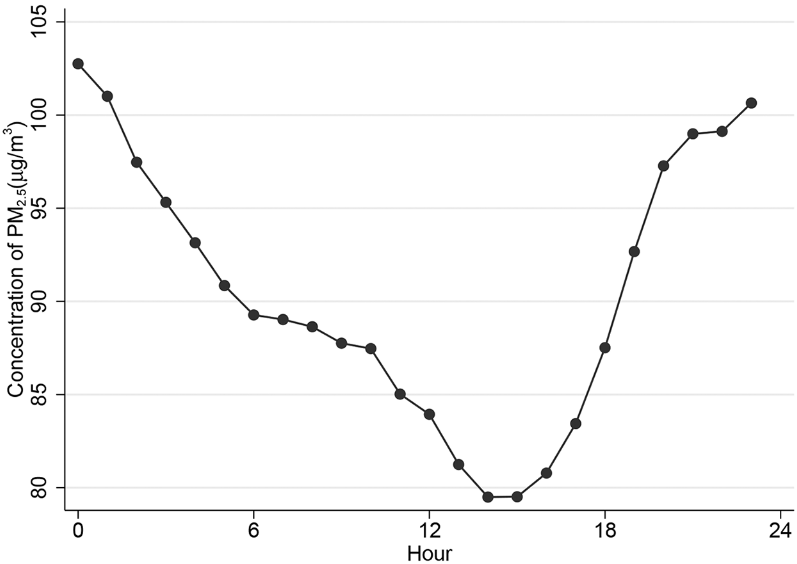

Figure 2. Diurnal pattern of PM2.5 concentration in Beijing. The figure plots the annual average hourly variation of PM2.5 concentration, based on hourly measurement of PM2.5 concentration by the US embassy in Beijing in 2012.

2.3. Measure of Health

While previous research has focused primarily on the effects on mortality, we focus on air pollution's effects on morbidity in this paper. The usual measure of morbidity comes from hospital inpatient and emergency room admission data. However, in Beijing's case, inpatient admission data might not be a good measure of contemporaneous health conditions of local people. Given the unequal distribution of health resources in China, Beijing's high-quality medical resources draw a significant number of patients from outside of Beijing. A large portion of inpatient cases in Beijing are not local residents. On the other hand, with limited medical resources and a large number of patients from both inside and outside of Beijing, a patient who seeks an inpatient slot may not be able to get registered at once. Another possible source of morbidity is emergency room visit data; however, the health department in Beijing does not provide this data set.

Here we collected the number of emergency ambulance calls in Beijing in 2012 as a measure of health outcomes. The data were recorded by Beijing Emergency Medical Center (EMC), which takes charge of emergency medical calls and provides emergency medical services within the urban area of Beijing. When an urgent medical condition occurs, the client is supposed to dial in and report the patient's symptoms, situation, age, gender, and location. Then, the EMC will send doctors and an ambulance to the scene immediately, where the doctor will make an preliminary diagnosis to confirm the patient's self-reported symptoms.[13] With this detailed set of records, the EMC helps to provide a daily district-level data set on the number of ambulance calls by patients' self-reported symptoms and the preliminary diagnosis, as well as the numbers of calls by different gender and age categories. The data cover all six districts in the urban area of Beijing.

The data set used in this study includes three types of self-reported symptoms, which are symptoms related to heart disease, fever, and injury. Respiratory illnesses are not included here because there are very few respiratory cases, possibly due to the fact that most respiratory disease patients are not in such a critical condition that they need an ambulance. On the contrary, heart-related disease was more common in the data set and is considered to be correlated with air pollution.[14] Within the group of heart disease, we included a category for coronary heart disease. This is one of the most common heart diseases, and its symptoms are relatively easier for patients to confirm. Another symptom included in the data set was fever, which can be caused by inflammation and is also a common respiratory symptom. Fever has been used in other studies as a measure for respiratory morbidity (Peters et al. 1997). Finally, we included injury as a control group.[15]

District-level total population and population by age and gender categories were also collected for the calculation of emergency call rates. The permanent population in the six districts of the urban area is over 12 million and accounts for around 60% of the total permanent population in Beijing. Summary statistics for the daily district-level emergency ambulance call rates data can be referred to in panel C of table 2.

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13. From an interview with an EMC employee, it was learned that average response time (time start from calling the EMC until the arrival of the ambulance) is within 15 minutes. Patients in critical condition prefer EMC ambulance service than other alternatives such as driving or taking a taxi.

14. Injury, cerebrovascular disease, and cardiovascular disease are the top three disease types of emergency ambulance calls.

15. We counted the following self-reported and preliminary diagnosed symptoms as heart-related problems: arrhythmia, heart attack, heart failure, angina or any description of precordial distress. If the self-reported symptom was clearly stated as coronary diseases, we counted it as both heart-related disease and coronary disease. Fever includes those who reported fever as their main symptom. The category injury included damages to the body by external forces but did not include those caused by car accidents. In 2012, the EMC received 164,074 emergency medical calls from the urban area of Beijing. The number of calls for these three diseases type accounts for around 40% of the total. On average, the daily number of patients with a final diagnosis of heart-related disease upon admission to the hospital is 56, and the number for injury is 103 (Beijing Municipal Health Bureau 2013). The patients' counts based on self-reported symptoms in our data set account for roughly 95% of the counts based on final diagnosis upon admission to the hospital.

3. EMPIRICAL STRATEGY AND RESULTS

Since there are fewer vehicles with license plate numbers ending in the number 4, the driving restriction in Beijing unintentionally allows more vehicles on the road during days on which plate numbers ending in 4 are restricted. This quirk of the driving restriction provides an exogenous shock to the air pollution level that is unlikely to correlate with other short-term determinants of health. To examine the distribution of number of vehicles with license plate ended in different numbers, we sampled passing vehicles on a street segment within the Fifth Ring Road on a Saturday and a Sunday (March 5 and October 15, 2016) and obtained 2,533 observations. Because the driving restriction is not in force during weekends, the sample on weekends should in general reflect the distribution of number of vehicles across different last digit plate numbers. The top figure in figure 3 plots the distribution. As expected, the 4 and 9 group contains the least number of vehicles, which is only around 60% of the number of other groups. Table 3 compares the mean values of weather variables and air pollution levels on the number 4 days and other days. As expected, while the mean value of air pollution is higher on the number 4 day, no statistically significant difference is observed between the two groups for weather conditions. The number 4 day is also expected to be distributed evenly among the days of the week because the policy rotates the assignment of restricted numbers to weekdays every 3 months.[16] In the following section, we use this exogenous variation of the number of vehicles allowed on the road induced by the driving restriction to explore the relationship between traffic condition, air pollution, and health.

3.1. Effects of the Number 4 Day on Traffic Congestion

We first tested whether the larger number of vehicles on the road during the number 4 days has any impact on the traffic conditions. The measure for traffic congestion condition is the congestion index. We expected a higher congestion level during the number 4 days. The bottom figure in figure 3 plots the average traffic congestion index by days with different restricted numbers with 95% confidence intervals. The number 4 days have a significantly higher value of traffic congestion index compared with days with other restricted numbers.

16. During the 1-year period of 2012, there were in total four rounds of rotation of restricted numbers on different weekdays. Hence, the number 4 day distributed evenly through Mondays to Thursdays, but much less on Fridays. To ensure the robustness of results, we tried enlarging our sample of air pollution to include an extra 3 months in 2013 to balance the day of the week when the number 4 is restricted. Results are largely unchanged with this enlarged sample. However, restricted by the heath data, we keep our main study period to be the year 2012.

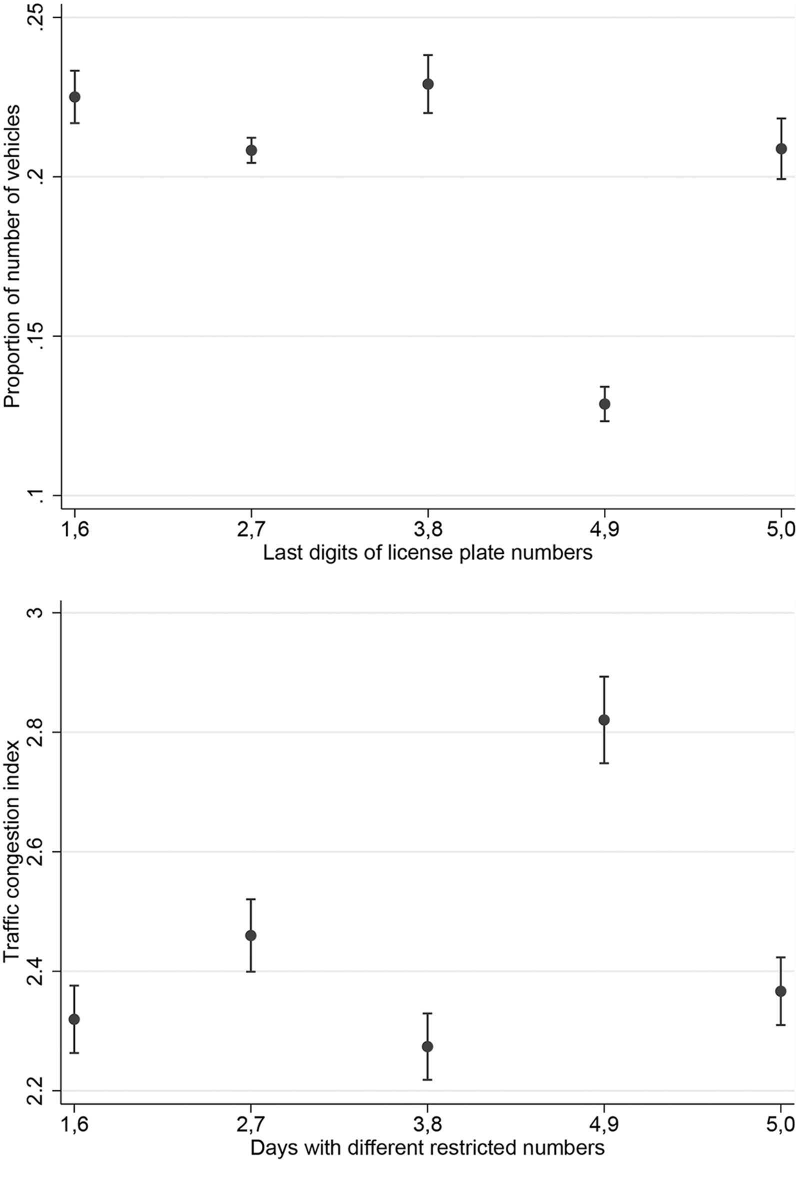

Figure 3. Distribution of number of vehicles by different last digits of license plate numbers and traffic congestion index by days with different restricted numbers. The top figure plots the proportion of the number of vehicles by different last digits of license plate numbers in Beijing, with 95% confidence intervals. Data for the figure were obtained by counting the passing vehicles on street segments within the Fifth Ring Road on a Saturday and a Sunday (March 5 and October 15, 2016), which includes 2,533 observations. The bottom figure plots the average traffic congestion index by days with different restricted numbers, with 95% confidence intervals.

Table 3. Comparison of the 24-Hour Average Weather and Air Quality Measures over the Period from Noon the Current Day to Noon the Next Day between the Number 4 Days and Other Days

	Number 4 Days		Other Days			
	Mean	SD	Mean	SD	*p*-Value	*t*-Statistic
Weather variables:						
Min temp (°C)	6.763	11.837	6.594	12.202	.929	.090
Max temp (°C)	17.619	12.901	17.576	12.181	.982	.022
Dew point (°C)	2.898	12.983	1.479	14.832	.531	.627
Air pressure (hPa)	1015.440	10.262	1016.150	10.166	.654	−.449
Precipitation (mm)	.123	.455	.212	1.071	.569	−.571
Wind speed (m/s)	2.598	1.418	2.829	1.265	.246	−1.162
Sky condition	.288	.195	.282	.208	.854	.184
Air quality:						
NO_2 (μg/m3)	59.224	31.896	48.893	25.140	.000***	12.537
PM10 (μg/m3)	120.420	72.835	104.540	75.092	.000***	7.020
SO_2 (μg/m3)	35.325	36.852	27.201	27.170	.000***	8.901

Note. The table lists mean value and standard deviation for 24-hour average weather and air quality measures over the period from noon the current day to noon the next day for the number 4 days and other days. *p*-values and *t*-values are presented based on mean value *t*-test between the two groups.

We use the following equation to estimate the effect of the number 4 day on traffic congestion:

$$\begin{aligned}\text{Congestion}_{ti} = {} & \alpha_0 + \alpha_1 \mathbf{1}\{DR\_4_t\} + \text{holiday}_t + \text{weather}_t \\ & + \text{month}_t + \text{dow}_t + \text{hour}_i + \epsilon_{ti},\end{aligned} \tag{1}$$

where Congestion_{ti} is the 15-minute average congestion index on date t and time i, and $\mathbf{1}\{DR\_4_t\}$ is the dummy variable indicating the date on which plate numbers ending with 4 are restricted. We included a dummy for holidays to reflect the possible different traffic conditions during holidays. We also included daily average weather variables, including linear and quadratic terms in air temperature, dew point temperature, sea level pressure, wind direction, wind speed, precipitation, sky condition (fraction of the total celestial dome covered by clouds or other obscuring phenomena), and dummies for eight wind directions, to account for effects of weather on traffic conditions. Finally, we included the month of the year, day of the week, and hour of the day fixed effects to account for unobserved factors correlated to the traffic condition in a given month, weekday, and hour.

The coefficient of interest is α_1, which represents the number 4 day's effects on the value of the congestion index. Table 4 presents the estimated results. Panel A of table 4 presents the estimates based on the full sample. Considering that people may exhibit different travel behaviors during weekends and holidays, and fixed effects might not

Table 4. Effects of the Number 4 Day on the Traffic Congestion Index

	All Hours (1)	Peak Hours (2)	Morning Peak (3)	Evening Peak (4)	Nonpeak Hours (5)	Nonrestricted Hours (6)
A. Full sample	.528***	1.117***	.845***	1.375***	.810***	.062**
	[.056]	[.106]	[.101]	[.171]	[.090]	[.030]
Obs.	28,071	4,755	2,359	2,396	10,655	12,661
B. Excludes weekends and holidays	.508***	1.036***	.769***	1.290***	.792***	.066**
	[.052]	[.094]	[.090]	[.155]	[.081]	[.030]
Obs.	19,275	3,267	1,623	1,644	7,287	8,721
Weather	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Hour FE	Y	Y	Y	Y	Y	Y

Note. The table regresses the 15-minute average traffic congestion index of the urban area of Beijing on the dummy of number 4 days for different time periods. Regressions include weather controls (linear and quadratic terms of minimum and maximum temperature, dew point, air pressure, precipitation, sky condition, wind speed, and dummies for eight wind directions), holiday, day of week, month, and hour fixed effects (FE). Robust standard errors (in brackets) are clustered by date. Panel A presents estimates based on the full sample. Panel B presents estimates based on the sample excluding weekends and holidays. Compared to the mean value of the traffic congestion index reported in table 2, the number 4 day is associated with an average of a 22% increase in the traffic congestion index for all hours.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

be able to perfectly control for this, we narrowed down the sample to include only weekdays (excluding weekends and holidays) in panel B. Column 1 in table 4 shows that the number 4 day corresponds to an average increase of 0.508–0.528 in the congestion index. To determine whether there are different effects on different times of the day, we restricted the sample to peak hours, nonpeak hours, and nonrestricted hours. Peak hours include morning peak hours from 7:00 to 9:00 and evening peak hours from 17:00 to 19:00. Nonpeak hours include all hours from 7:00 to 20:00 when the driving restriction is in force but exclude peak hours. Nonrestricted hours include the hours before 7:00 and after 20:00, when the driving restriction is not in force. When the sample is limited to peak hours, the magnitude of the effect increases to 0.769–0.845 for morning peak hours, and 1.290–1.375 for evening peak hours. For nonpeak hours, the effect is at 0.792–0.810. And for nonrestricted hours, the effect is only 0.062–0.066. All estimates during the period when the driving restriction is in force are significant at the 1% level, while the estimate for the nonrestricted hours is significant only at the 10% level. Compared with the mean value of the traffic congestion index, during number 4 days, the congestion index is higher by around 22% on average. The effect is larger during the evening peak hours at around 26%. Although the significance level is lower, there is also a small effect during the nonrestricted hours. This is reasonable, because if people cannot use their vehicles to get to work during the day when restrictions are in place, they cannot make the return trip when the restriction is not in place. The coefficients in panel A and panel B are largely the same. Since the driving restriction is only in force on workdays, it makes more sense to compare the number 4 days only with other weekdays as in panel B. In following sections, we mainly report estimations based on the weekdays sample.

These results confirm that the number 4 day has a significant effect on traffic congestion. It has a positive impact on the level of congestion during all periods of the day. The impact is largest during evening peak hours, followed by morning peak hours and nonpeak hours. The impact is marginal during the nonrestricted hours.

As suggested in the top figure of figure 3, the number of vehicles ending with the numbers 4 and 9 is around 60% of the number ending with any other number combination. Based on this distribution of number of vehicles by the last digit of the license plate numbers, and assuming that the enforcement of the driving restriction is close to 100%, there will be around 10% more vehicles on the road on the number 4 days. Based on empirical evidence from the bulk of studies in the field of transport engineering, the relationship between traffic speed and traffic flow is in general considered to be a nonlinear relationship. While the traffic flow is small compared to the road capacity, speed remains nearly constant. As the flow approaches the capacity, the speed starts to decrease in an accelerating rate. Hence, an around 10% change in the number of unrestricted vehicles with an around 20% higher congestion index is possible. According to the annual report of the Beijing Transportation Research Center, from 2011 to 2012, the number of trips made by private vehicles per day increased by 4.4%, while the daily average traffic congestion index increased by 8.3%, which is a relationship comparable to what we found in our study.

3.2. Effects of the Number 4 Day on Ambient Air Pollution

We then estimated the number 4 day's effect on ambient air pollution by running the following regression.

$$\begin{aligned}\text{Pollution}_{mt} = {} & \alpha_0 + \alpha_1 \mathbf{1}\{DR\_4_t\} + \text{holiday}_t + \text{weather}_t \\ & + \text{month}_t + \text{dow}_t + \text{station}_m + \epsilon_{mt},\end{aligned} \tag{2}$$

where Pollution_{mt} is the 24-hour average measure of pollutant concentration of NO_2, PM10, or SO_2 measured by the EPB monitoring station m on date t. As discussed in section 2, the level of certain pollutants such as PM and NO_2 in Beijing tends to be lower during the daytime and higher during the night due to meteorological conditions (Chen et al. 2009; Zhao et al. 2009). Hence, traffic emissions during morning peak hours might not accumulate as readily due to the meteorological conditions in favor of dilution of pollutants. In contrast, emissions during the evening peak hours accumulate relatively more easily starting from the evening until the next morning. Based on the hypothesis that the traffic conditions today have an impact on air quality during the time period from noon of the current day to noon the next day, we used the 24-hour average concentration for pollutants during this period as the dependent variable. As before, we included weather variables, including linear and quadratic terms in air temperature, dew point temperature, sea level pressure, wind speed, precipitation, sky condition (fraction of the total celestial dome covered by clouds or other obscuring phenomena), and dummies for eight wind directions as controls. We have also run regressions with only linear weather variables as controls; the results are largely the same. Please refer to the online appendix for the results. To match with the 24-hour average air pollution measure, the weather variables used here are averaged values over the same period from noon to noon as well. The day of the week fixed effect, month fixed effect, and monitoring station fixed effect were also included to control for possible unobserved temporal and spatial factors. Considering the potential serial correlation within a station over time and spatial correlation among stations within a day, we tried clustering the standard errors at the station level, date level, and a two-way clustering at both station and date level. We reported the largest error among the three, which is the error clustered at the date level, to show the most conservative significance level.

The coefficient of interest is α_1, which represents the number 4 day's effects on the air pollution level. Since there are more vehicles on the road on the number 4 days, we expected α_1 to be positive. Table 5 presents estimated results using equation (2). Columns 1–3 show the effects on NO_2, PM10, and SO_2, respectively. Among the three pollutants, NO_2 is considered the most closely related to road traffic. Column 1 suggests that the number 4 day is associated with an increase of 5.76 $\mu g/m^3$ in 24-hour

Table 5. Effects of the Number 4 Day on Air Pollution

	NO_2 (1)	PM10 (2)	SO_2 (3)	NO_2 (4)	PM10 (5)	SO_2 (6)	CO (7)	NO_2 (8)
All stations	5.76**	8.39	2.73	5.17**	8.26	2.60	.35**	7.00***
	[2.310]	[7.689]	[2.300]	[1.997]	[7.074]	[2.124]	[.151]	[2.430]
Obs.	5,938	6,416	5,839	5,590	6,278	5,538	2,590	2,471
Urban stations	6.82**	11.03	3.6	5.82**	10.65	3.63	.40**	8.02***
	[2.680]	[8.841]	[2.568]	[2.301]	[8.196]	[2.364]	[.171]	[2.942]
Obs.	2,647	2,854	2,602	2,483	2,793	2,471	1,703	1,596
Rural stations	4.88**	6.29	2.03	4.68**	6.36	1.81	.27**	5.25**
	[2.101]	[6.980]	[2.160]	[1.875]	[6.384]	[2.022]	[.130]	[2.028]
Obs.	3,291	3,562	3,237	3,107	3,485	3,067	887	875
Weather	Y	Y	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Station FE	Y	Y	Y	Y	Y	Y	Y	Y
Lag pollution				Y	Y	Y		

Note. We regress station-level 24-hour average pollution concentration (μg/m3) over the periods from noon the current day to noon the next day on the dummy of number 4 days. The table presents estimates based on the sample excluding weekends and holidays. Regressions include weather controls (linear and quadratic terms of minimum and maximum temperature, dew point, air pressure, precipitation, sky condition, wind speed, and dummies for eight wind directions), day of week, month, and monitoring station fixed effects (FE). Columns 1–3 present the effects on NO_2, PM10, and SO_2 in the year 2012. Columns 4–6 add controls for one lag term of air pollution. Columns 7 and 8 present the effects on CO and NO_2 in the year 2013. Compared to the mean value of each pollutant, the results suggest that the number 4 day is associated with a 12%–13% increase in NO_2 and a 23% increase in CO. Robust standard errors (in brackets) are clustered on date level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

average NO_2 concentrations from noon of the current day to noon the next day, which is an approximately 12% increase compared to its mean value. Since the driving restriction is only in force within the Fifth Ring Road, we are interested in the heterogeneity in the effects on pollution for urban areas and rural areas. When we limited the sample to urban stations, the effects on NO_2 increased to 6.82 $\mu g/m^3$. For rural stations, the effects were smaller at around 4.88 $\mu g/m^3$, but still statistically significant. It is not surprising to see positive and significant effects in rural areas where the driving restriction is not in force, because a large proportion of people who reside in the rural areas of Beijing commute to the urban center for work on a daily basis.[17] Columns 2 and 3 show

17. According to the Beijing Municipal Bureau of Statistics, people who reside in areas outside the Fifth Ring Road account for 51% of the total population by the end of 2014. In some typical residence communities outside the Fifth Ring Road, around 80% of the residences work within the Fifth Ring Road (Zheng et al. 2014).

the effects on PM10 and SO_2, pollutants that are less closely related to traffic than NO_2. While the sign of coefficients is correct, the significance level is much lower. Columns 4–6 present similar results from regressions with a lag term of the pollution level as an additional control to account for the potential influence of the pollution level from the previous day. Figure 4 plots residuals from estimating equation (2) without the number 4 day dummy by days with different restricted numbers. It shows consistent results as the estimates reported in table 5.

Another pollutant that is closely related to vehicle emissions is carbon monoxide (CO). However, the concentration of CO was not monitored during our main study period. Instead, we collected the same 24-hour average concentration of CO in the year 2013, when EPB first started to monitor the pollutant, for 12 monitoring stations in Beijing. Columns 7 and 8 of table 5 present the effects on CO and NO_2 in the year 2013, respectively. The results suggest that the number 4 day is associated with a

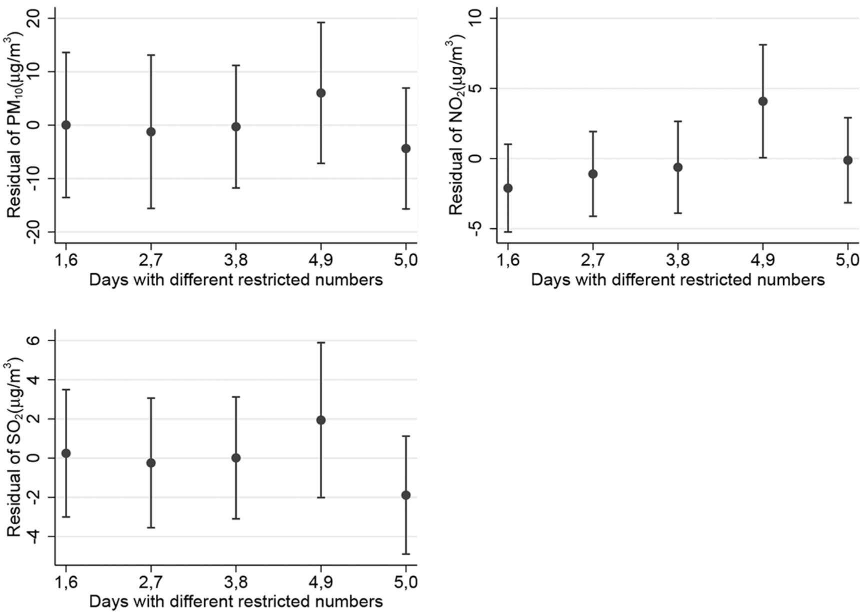

Figure 4. Variation of pollution by days with different restricted numbers. The figure plots residuals from estimating equation (2) without the number 4 day dummy by days with different restricted numbers. Specifically, we regresses station-level 24-hour average pollution concentration (μg/m3) for the periods from noon the current day to noon the next day on weather controls (linear and quadratic terms of minimum and maximum temperature, dew point, air pressure, precipitation, sky condition, wind speed, and dummies for eight wind directions), day of week, month, and monitoring station fixed effects. This figure plots the residuals by days with different restricted numbers with 95% confidence interval.

0.35 $\mu g/m^3$ and 7.00 $\mu g/m^3$ increase in 24-hour average CO and NO_2 concentration from noon of the current day to noon the next day, which is an approximately 23% and 13% increase compared to their mean values.

To further explore the temporal feature of how number 4 days affect ambient air pollution, we ran more tests based on the hourly PM2.5 data measured by the US embassy in Beijing. We divided each 24-hour period into eight 3-hour periods and ran regressions for each of the periods during the number 4 day and the subsequent day. For this set of regressions, we used the 3-hour average concentration of PM2.5 as the dependent variable and the number 4 day as the independent variable. Weather, day of the week, holiday, and month fixed effects are controlled.[18] Coefficients for the 16 periods are plotted in figure 5. Although the significance level is not high, the coefficients show the expected temporal pattern. As shown in figure 5, the effects start to appear at around 21:00 on the number 4 days and gradually disappear at around 12:00 the next day. The magnitude of effects is comparable to the effects of PM10. This provides some evidence of the lagged effects of traffic conditions on the air pollution level in Beijing.

To check how plausible it is to find a 12% increase in the 24-hour average NO_2 associated with the number 4 days, we conducted a back-of-the-envelope calculation of the emissions inventory. Suppose that in the best case scenario, the enforcement of the restriction is close to 100%, and vehicles that are not restricted on a day are not in greater demand to compensate for restricted vehicles. As suggested in figure 3, we assume that the number of vehicles ending with the numbers 4 and 9 is around 60% of the number ending with any other number combination. Based on these assumptions, on the non–number 4 days, around 78% of the vehicles are allowed on the road, while on the number 4 days, 87% of all vehicles are allowed on the road.

Besides number of vehicles, the number 4 days also affect driving speed. Vehicle emissions highly depend on the driving speed. Most estimations of vehicle fleet emission inventories are based on average travel speed, and there is a negative relationship between the emissions factor and the traveling speed in an urban setting such as Beijing. According to the annual report of the Beijing Transportation Research Center, in 2012, the average road speed during peak hours is around 25 km/h. Based on the linear relationship between the traffic congestion index and road speed, the daily average road speed should be around 30 km/h. Based on our estimated results, there is a 22% increase in the traffic congestion index on the number 4 days. It corresponds to a drop of daily average road speed from 30 km/h to 23 km/h on the number 4 days. We then refer to the emissions factor table published by the California Air Resources Board (2010) for speed-based emissions factors. The corresponding increase in the emissions factor of NO_x and CO on the number 4 days is around 14% and 15%, respectively.

18. Weather variables were 3-hour average values matched with each 3-hour period.

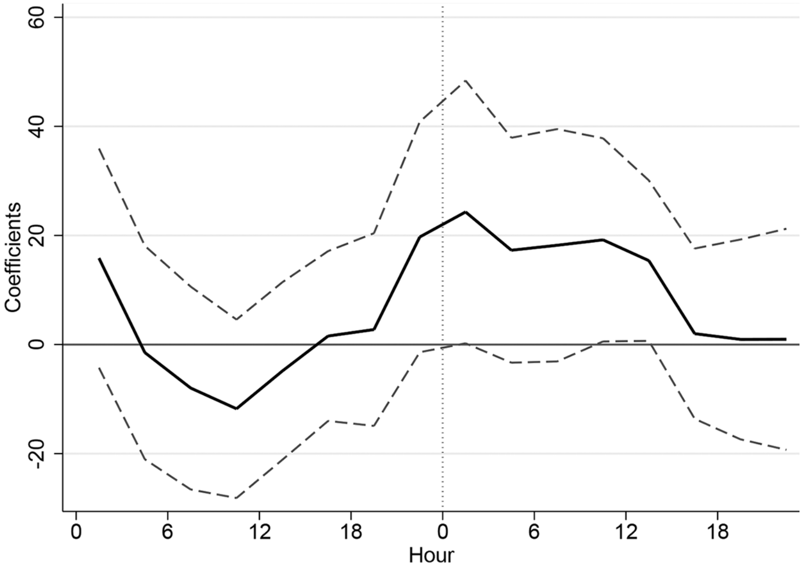

Figure 5. Effects of the number 4 day on PM2.5. The 3-hour average PM2.5 concentration (μg/m3) monitored by the US embassy in 2012 is regressed on the dummy of number 4 days for the 16 3-hour periods of the number 4 day and the subsequent day. Regressions include weather controls (linear and quadratic terms of minimum and maximum temperature, dew point, air pressure, precipitation, sky condition, wind speed, and dummies for eight wind directions), holiday, day of week, and month fixed effects. Coefficients for the 16 periods are plotted in the figure, with 90% confidence interval.

Here we assume that the relationship between emissions factors and driving speed in China is similar to the one in the United States.

Putting together the change in the number of vehicles on the road and the change in emissions factors, the increase in total traffic-emitted NO_x and CO on the number 4 days is around 27% and 28%, respectively. Considering that vehicle-emitted NO_x and CO account for 57% and 86% of the total emission, and that NO_x and CO emitted by heavy-duty diesel trucks that are not affected by the driving restrictions account for around 10% and 2% of the vehicular emission (Huo et al. 2011), the number 4 day is estimated to increase the concentration of NO_x and CO by around 14% and 24%. This back-of-the-envelope estimation is in general consistent with our estimates.

On one hand, the increase in ambient air pollution associated with the number 4 days can be directly caused by the increase in the number of vehicles on the road and the higher vehicular emissions. But on the other hand, Viard and Fu (2015) found that the driving restriction in Beijing resulted in an increase in television viewership, suggesting that the higher commute costs created by the restrictions make people spend more time at home. Hence, the inconvenience in traveling caused by driving restrictions may result in a reduction in labor supply or a negative impact on economic activities due to fewer number of trips, which may lead to reduction in emissions beyond the transportation sector.

3.3. The Number 4 Day, Ambient Air Pollution, and Health

3.3.1. Effects of the Number 4 Day on Ambulance Call Rate

We began with the following regression to explore the effect of the driving restrictions on health, particularly how the number 4 day affects local health outcomes. As mentioned in the previous section, the day's traffic conditions mainly affect pollution levels from early evening until the next morning. Hence, the number 4 day is expected to have major effects on health outcomes on the next day. In equation (3), we used a district-level measure of health outcomes on the next day as the dependent variable; $\mathbf{1}\{DR\_4_t\}$ on the right-hand side is the number 4 day dummy that equals one if the number 4 is restricted on date *t*. Day of the week, month, and district fixed effects were included to account for possible unobserved temporal and spatial factors. Weather variables, including linear and quadratic terms in air temperature, dew point temperature, sea level pressure, wind speed, precipitation, sky condition, and dummies for eight wind directions were also included to account for effects of weather on health.

$$\begin{aligned}\text{Health}_{dt} = \; & \alpha_0 + \alpha_1 \mathbf{1}\{DR\_4_t\} + \text{holiday}_t + \text{weather}_t \\ & + \text{month}_t + \text{dow}_t + \text{district}_d + \epsilon_{dt}\end{aligned} \tag{3}$$

Table 6 presents the results from equation (3). The measure of health outcome is the district-level daily emergency ambulance call rates (number of emergency ambulance calls per million people) by self-reported and preliminary diagnosed symptom. Regressions were weighted by district-level population size. Symptom types that are expected to be affected by pollution include heart-related symptoms and fever. Injury was included to provide a falsification test. Standard errors were clustered on date level. Estimates reported in the table were based on the sample that includes only weekdays.

Panel A in table 6 presents the effects for the overall population. The number 4 day has significant positive effects on both coronary heart disease and fever, but no impact on the control group injury. The point estimates in panel A show that the number 4 day is associated with an increase of 0.168, 0.081, and 0.193 in ambulance call rates related to all heart symptoms, coronary heart problems, and fever, respectively. Panels B and C report coefficients for male and female populations. There is no significant difference between the two subpopulations for fever. However, for coronary heart disease, the coefficient for females is insignificant at 0.034, much smaller than that of males at 0.112. Panels D–F report coefficients for different age categories. For fever, the point estimate for the population aged 65 and older is the largest at 1,321,

Table 6. Effects of the Number 4 Day on Ambulance Call Rate

	All Heart (1)	Coronary (2)	Fever (3)	Injury (4)
A. Full population	.168	.081***	.193***	−.091
	[.116]	[.031]	[.060]	[.136]
B. Males	.232*	.112***	.202**	−.119
	[.132]	[.035]	[.078]	[.176]
C. Females	.141	.034	.211***	.003
	[.147]	[.043]	[.078]	[.142]
D. 65 and older	.594	.156	1.321***	−.799
	[.743]	[.233]	[.440]	[.590]
E. 15–64	.153	.081***	.074**	.002
	[.102]	[.021]	[.030]	[.131]
F. Younger than 15	. . .	. . .	.179	−.093
	. . .	. . .	[.292]	[.251]
Obs.	1,458	1,458	1,458	1,458
Weather	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
District FE	Y	Y	Y	Y

Note. We regress district-level daily ambulance call rate (number of calls per million people) of the next day on the dummy of number 4 days. The table presents estimates based on the sample excluding weekends and holidays. Regressions include weather controls (linear and quadratic terms of minimum and maximum temperature, dew point, air pressure, precipitation, sky condition, wind speed, and dummies for eight wind directions), day of week, month, and district fixed effects (FE). Robust standard errors (in brackets) are clustered on date level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

compared to 0.074 for the population aged 15–64, and 0.179 for the population below 15 years old.

Multiplying coefficients estimated in table 6 with population size, panel A of table 7 reports the predicted increase in the number of emergency ambulance calls on number 4 days for the urban area of Beijing. With a population size of 12.28 million, the urban area of Beijing is estimated to have 2.063 and 2.37 more emergency ambulance calls related to heart diseases and fever during number 4 days. Although table 6 shows that the subpopulation aged 65 and older has the largest point estimates, a significant portion of the increase in emergency ambulance calls occurs in the subpopulation aged 15–64 given its large population size. Panel B of table 7 reports the percentage change of ambulance call rates by dividing the coefficients in table 6 by the mean values of ambulance call rates. The percentage increase in ambulance call rates associated with number

Table 7. Effects of the Number 4 Day on Ambulance Calls: Changes in Number and Percentage Change

	All Heart (1)	Coronary (2)	Fever (3)
A. Changes in number of calls:			
Full population	2.063	.995	2.370
	[1.424]	[.381]	[.737]
Males	1.457	.703	1.269
	[.829]	[.220]	[.490]
Females	.846	.204	1.266
	[.882]	[.204]	[.468]
65 or older	.713	.187	1.585
	[.892]	[.280]	[.528]
15–64	1.525	.808	.738
	[1.017]	[.209]	[.299]
Younger than 15	. . .	. . .	.199
	. . .	. . .	[.324]
B. Percentage change:			
Full population	3.30%	19.50%	11.70%
	[.023]	[.075]	[.036]
Males	5.40%	29.60%	11.80%
	[.031]	[.092]	[.045]
Females	2.50%	8.00%	15.00%
	[.027]	[.101]	[.055]
65 or older	2.50%	6.90%	13.40%
	[.032]	[.103]	[.045]
15–64	5.20%	42.20%	20.80%
	[.035]	[.109]	[.085]
Younger than 15	. . .	. . .	6.20%
	. . .	. . .	[.101]

Note. Panel A of the table lists changes in the number of emergency ambulance calls in the urban area of Beijing by multiplying coefficients estimated in table 6 by population size. Panel B lists the percentage change of ambulance call rates, which is calculated by dividing the coefficients in table 6 by the mean value of ambulance call rates. Standard errors in brackets.

4 days is 3.3%, 19.5%, and 11.7% for all heart-related symptoms, coronary heart problems, and fever, respectively. Breaking into subpopulations, rows 2–3 of panel B show a difference in percentage changes of ambulance call rates for coronary heart problems between male and female groups. The percentage increase for the male group is around 30%, while the increase in the female group is only 8%. Rows 4–6 show the percentage changes for different age groups. While the point estimates for the population aged 65 and older shown in table 7 are larger than those of other age groups, the

percentage increase presented in row 4 of panel B is much smaller compared to that of the population aged 15–64.

3.3.2. Relationship between Ambient Air Pollution and Health

To further explore the linkage between ambient air pollution and health outcomes, we use the following instrumental variable approach to regress ambulance call rates by symptom on instrumented air pollution concentration.

$$\begin{aligned} \text{Pollution}_{dt} &= \alpha_0 + \alpha_1 \mathbf{1}\{DR\_4_t\} + \text{holiday}_t + \text{weather}_t \\ &\quad + \text{month}_t + \text{dow}_t + \text{district}_d + \epsilon_{dt} \end{aligned} \tag{4}$$

$$\begin{aligned} \text{Health}_{dt} &= \beta_0 + \beta_1 \widehat{\text{Pollution}}_{dt} + \text{holiday}_t + \text{weather}_t \\ &\quad + \text{month}_t + \text{dow}_t + \text{district}_d + \eta_{dt}. \end{aligned} \tag{5}$$

In equation (4), the district-level 24-hour average air pollution concentration for the period from noon of the current day to noon the next day is the dependent variable.[19] As shown in the previous section, since the driving restriction only has a significant impact on the level of NO_2, we used the concentration of NO_2 as the measure of air pollution. In the second-stage equation (5), the health outcome for the next day is regressed on the estimated NO_2 level from noon of the current day to noon the next day from equation (4). Other control variables include weather variables, day of the week, month of the year, and district fixed effects. Estimates were weighted by district-level population size, and standard errors were clustered by date.

Table 8 presents the effects of instrumented NO_2 on ambulance call rates. Panel A shows the effects for the overall population. There are significant effects on the ambulance call rates for coronary heart problems and fever but no effects on injury. Based on estimates from the instrumental variables (IV) regression, a one standard deviation increase in NO_2 is associated with a 7.8%, 41.9%, and 34.7% increase in ambulance call rates of heart-related symptoms, coronary heart problems, and fever, respectively. This relationship between NO_2 and health should be explained with caution. As mentioned earlier, the traffic condition is related to a series of pollutants, such as NO_2, PM10, PM2.5, CO, and O_3. With these possible sources of endogeneity but only one instrument variable, the model is underidentified. The estimates presented here can be viewed as a relationship between heath and air pollution from traffic sources, using NO_2 as an indicator of traffic-related air pollution. The magnitude of health effect is relatively larger compared to the association between general hospital admissions

19. To match the air pollution level with health data, the station-level air pollution data were averaged into district level. For each district, the daily average pollution level would be the average daily pollution level from all monitoring stations within it.

Table 8. Effects of Instrumented NO_2 Concentration on Ambulance Call Rate

	All Heart (1)	Coronary (2)	Fever (3)	Injury (4)
A. Full population	.016	.007**	.023**	−.004
	[.013]	[.003]	[.009]	[.848]
B. Males	.029*	.012***	.018*	−.002
	[.016]	[.004]	[.010]	[.696]
C. Females	.007	.001	.030***	.005
	[.016]	[.004]	[.011]	[.638]
D. 65 and older	.032	−.002	.160**	−.084
	[.078]	[.024]	[.065]	[.792]
E. 15–64	.017	.008***	.008*	.005
	[.012]	[.003]	[.004]	[.674]
F. Younger than 15	. . .	. . .	.023	−.008
	. . .	. . .	[.031]	[.552]
Obs.	1,377	1,377	1,377	1,377
Weather	Y	Y	Y	Y
Day of week	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
District FE	Y	Y	Y	Y

Note. We regress district level daily ambulance call rate (number of calls per million people) on district-level instrumented 24-hour average NO_2 concentration over the periods from noon the previous day to noon the current day (μg/m3). The table presents estimates based on the sample excluding weekends and holidays. Regressions include weather controls (linear and quadratic terms of minimum and maximum temperature, dew point, air pressure, precipitation, sky condition, wind speed, and dummies for eight wind directions), day of week, month, and district fixed effects (FE). Robust standard errors (in brackets) are clustered on date level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

and air pollution recorded in previous literature (Pope, Bates, and Raizenne 1995) but comparable to the findings that focused on emergency room visits (Guo et al. 2010; Schlenker and Walker 2016).

3.3.3. *Displacement and Lag Effects*

The baseline regressions in the previous sections only examine the effect of the number 4 day on contemporaneous health outcomes. However, if air pollution has lagged effects on health, the contemporaneous estimation will underestimate the total health effects. On the other hand, if there is a temporal displacement of health effects, which makes already vulnerable people call the ambulance earlier, then the regression will overestimate the effects.

To further explore the temporal dynamics of the number 4 day's impacts on health, we estimated a distributed lag regression that included three lag terms of the number 4 day dummy and one lead term as a falsification test. If the number 4 day has lagged effects on health, then the coefficients for lag terms should be positive. Conversely, if there is a temporal displacement of health effects, then a decrease in ambulance call rates should be observed in subsequent periods; hence, the coefficients for lag terms should be negative. Table 9 and figure 6 report the results for the distributed lag model. As expected, the coefficient of lead term does not show any statistically significant health effect. The largest effects emerge for the current term. For lag terms, there is no statistically significant effect. Results show no sign of any temporal displacement effect for heart diseases or fever.

Aside from traffic pollution, some medical studies have suggested that exposure to heavy traffic itself can be associated with mental stress and onset of cardiovascular diseases (Wener et al. 2003; Peters et al. 2004). Based on findings of these studies, a higher

Table 9. Effects of the Number 4 Day on Ambulance Call Rate: Distributed Lag Model

	All Heart (1)	Coronary (2)	Fever (3)
DR_4_{t+1}	.082	.025	−.009
	[.107]	[.033]	[.056]
DR_4	.213*	.099***	.225***
	[.123]	[.036]	[.065]
DR_4_{t-1}	.098	.058	.075
	[.128]	[.037]	[.070]
DR_4_{t-2}	.144	.024	.085
	[.116]	[.037]	[.064]
DR_4_{t-3}	−.022	−.027	−.017
	[.104]	[.037]	[.060]
Obs.	2,172	2,172	2,172
Weather	Y	Y	Y
Day of week	Y	Y	Y
Month FE	Y	Y	Y
District FE	Y	Y	Y

Note. The table regresses a distributed lag model, using district-level daily ambulance call rate (number of calls per million people) on the next day as dependent variable, the number 4 day dummy and its one lead and three lag terms as independent variables. Regressions include weather controls (linear and quadratic terms of minimum and maximum temperature, dew point, air pressure, precipitation, sky condition, wind speed, and dummies for eight wind directions), day of week, month, and district fixed effects (FE). Robust standard errors (in brackets) are clustered on date level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

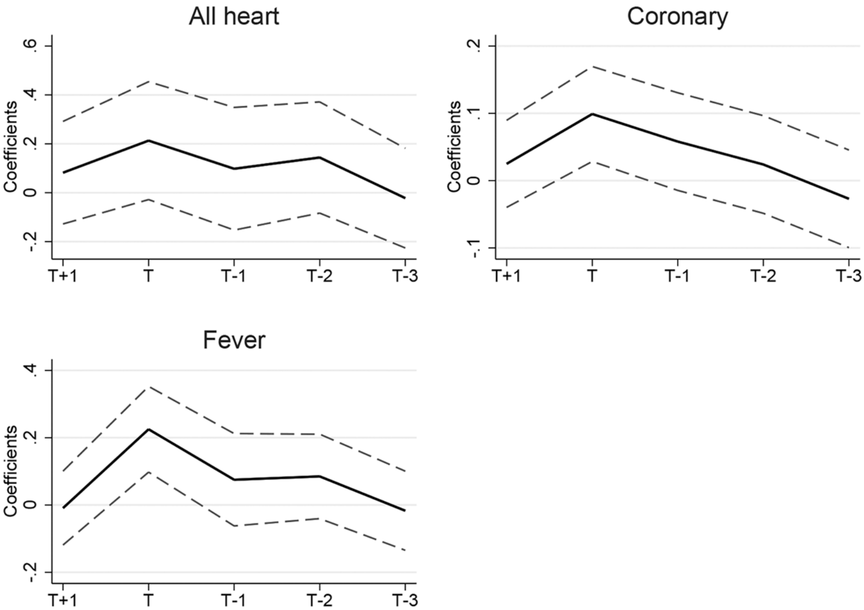

Figure 6. Effects of the number 4 day on ambulance call rate—distributed lag model. Daily ambulance call rate (number of ambulance calls per million people) related to heart diseases, coronary heart disease, or fever on the next day is regressed on the number 4 day dummy, and its one lead and three lag terms. Regressions include weather controls, day of week, month, and district fixed effects.

level of stress or a higher probability of cardiovascular diseases is associated with exposure to heavy traffic within a relatively short period of time, for example, just after the completion of the trip or within 1 hour of the exposure. Based on the results reported in table 9, the lack of effect on the number 4 day and the increase in number of patients on the day after the number 4 day suggests that the health effect is unlikely to be caused by exposure to the congestion and should be mainly caused by the increase in air pollution level over the period from noon on the number 4 day until noon the next day. However, without health data on an hourly level, we are not able to rule out the possibility that there may be a health effect resulting from direct exposure to heavy traffic within a short period of time.

4. CONCLUSION

This study exploits a unique feature of the driving restriction policy and the superstitious resentment of the number 4 in Beijing to examine the relationship between traffic congestion, ambient air pollution, and health. Based on the license plate number's last digit, the driving restriction policy in Beijing unintentionally allows more vehicles on the road during days when the number 4 is restricted. This provides an exogenous shock of air pollution for estimating the effects on health. We found that the number 4 day is a strong predictor of traffic conditions, ambient air pollution, and local health outcomes. The traffic congestion level is 22% higher on days restricting the number 4, and the 24-hour average concentration of NO_2 from noon of the number 4 day to noon the next day is 12% higher. Besides the vehicular emission NO_2, the concentration of PM10 and SO_2 also shows a similar pattern, though not statistically significant. It indicates that the effect of the number 4 day may affect also other pollutants other than vehicular emissions that vehicle trips enable. These short-term increases in air pollution increase ambulance calls by 3.3%, 19.5%, and 11.7% for heart-related symptoms, coronary heart disease, and fever, respectively, while no effects are found for injuries. While the point estimates of changes in ambulance call rates for the population aged 65 and older are larger, the percentage increase for the population aged 15–64 is higher. Given the large size of the population aged 15–64, a significant proportion of the increase in ambulance calls is attributed to this group. With a distributed lag model, we found no significant forward displacement or lagged effects of traffic congestion–induced pollution on health.

The results suggest the significant health impacts of air pollution from the road transportation sector and the substantial negative health externalities of traffic congestion in China. With rapid urbanization and motorization, traffic congestion and air pollution have become serious problems in large Chinese cities. It is therefore crucial to quantify the negative externalities coming from the transport sector. Evidence from this study can help to inform policy decisions. Although various transport policies have been implemented in different Chinese cities over the past few years, little evidence has been provided on the effects of these policies. While the effects of the driving restriction policy remain debatable, many densely populated Chinese cities (e.g., Nanchang, Changchun, Lanzhou, Guiyang, Hangzhou, and Chengdu) have replicated or are about to replicate this policy. This study helps provide evidence on the potential social benefits of reducing traffic congestion through policies like the driving restriction policy. Results suggest that a driving restriction policy could be effective in reducing traffic congestion and air pollution and improving local health outcomes in certain contexts.

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