Superstitious Driving Restriction: Traffic Congestion, Ambient Air Pollution, and Health in Beijing

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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, I 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, I find that traffic congestion is indeed 20% 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 estimates are largely unchanged when day of the week fixed effect, weather, and lagged pollution are included. These findings suggest that traffic congestion has substantial health externalities in China but that they are also responsive to policy.

*Columbia University, School of International and Public Affairs. I would like to especially thank Douglas Almond, Geoffrey Heal, and Wolfram Schlenker for their invaluable advice, help and support. I also grateful to Xiaojia Bao, Suresh Naidu, Matthew Neidell, Nicole Ngo, Cristian Pop-Eleches, Eric Verhoogen, and seminar participants at Columbia University for helpful comments and discussion. All errors are my own.

1 Introduction

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. As estimated 7 million premature deaths were connected to 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. Thus, this study aims to explore the effects of the driving restriction policy and air pollution from traffic sources on health in China.

In this paper, I 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. I collected data on traffic congestion, ambient air pollution, and 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

[1] The number four is considered to be unlucky in Chinese culture because it sounds like death in Chinese. Due to this reason, people tries to avoid to use the number four in places like phone numbers and plate numbers. Since there are few people willing to choose a vehicle license plate with four in it, the Beijing Traffic Management Bureau even stopped issuing plate number with four. 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., Fortin, Hill, and Huang 2014; Ng, Chonga, and Du 2010; Woo et al. 2008).

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 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 "number 4 day"), the traffic congestion index increases by 20%. The number 4 day also has an significant impact on ambient air pollution. The 24-hour average concentration of nitrogen dioxide (NO_2) from noon on the number 4 day to noon the next day is 12% higher. 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 2.9% and 11.5%, respectively, while no effects are found for injuries as a control group. Looking at subpopulation groups, I 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 estimates are largely unchanged when controlling for weather, lagged pollution, and day of the week fixed effect. 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 are an important contribution 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 urban planning and transportation policies. Traffic congestion is a problem of urban areas worldwide, and policy makers must understand the social benefits of reducing traffic congestion. Knittel et al. (2011) examined the relationship between traffic, ambient air pollution, and infant health, but 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 policy can result in significant social 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 enforcement of driving restrictions. 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. Results of the present study, on the other hand, suggest that the driving restriction in Beijing is effective in reducing traffic congestion and air pollution, and 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 2,000 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 2 provides a background of Beijing's transportation and air pollution situation, as well as its driving restriction policy. Section 3 describes the data. Section 4 presents the empirical strategy and results. Section 5 discusses the economic valuation. Section 6 concludes.

2 Background

2.1 Air Pollution and Health

Literature on the 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. 2002; Cohen et al. 2004), 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 2004; 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; Hillbol et al. 2013). Hence, it is important to understand the relationship between human health and traffic-emitted pollutants like 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. To avoid these problems, some economic studies use econometric tools such as fixed effects and instrumental variables to estimate the effects. For example, Currie et al. (2009) explored the effects of air pollution on infant health, using maternal fixed effects to control for unobserved characteristics of mothers. Chay and Greenstone (2003) examined the impact of reduced TSPs induced by the 1981-1982 recession to examine the impact on infant mortality rates.

Chen et al. (2013) 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; Knittle et al. 2011; Moretti and Neidell 2011; Schlenker and Walker 2011). However, no studies have employed these econometric tools to estimate the effects of air pollution from traffic sources on health in China.

2.2 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, 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 exponentially, 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 25km/h, and the average hours of congestion was over 4 hours per day.[3]

Air pollution is another serious problem in Beijing. In 2012, the annual average concentration of SO_2, NO_2, particulate matter smaller than $10\mu g$ (PM_{10}), and carbon monoxide (CO) in Beijing was $28\mu g/m^3$, $52\mu g/m^3$, $109\mu g/m^3$, and $1.4mg/m^3$, respectively (EPB 2012). The annual average concentration of NO_2 and PM_{10} 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,

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

[3]Here congestion is defined as when it takes 50% more travel times than running with the speed limit.

[4]Details of the WHO air quality guidelines are presented in Table 1. `http://whqlibdoc.who.int/hq/2006/WHO_SDE_PHE_OEH_06.02_eng.pdf?ua=1`

NO_2 and SO_2 meets the second-class air quality standard (the standard applied to residential areas) and PM_{10} 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 carbon monoxide (CO), NO_x, PM, and volatile organic compounds (VOCs)(Hao et al. 2000; Hao et al. 2001; Fu et al. 2001; Walsh 2007; Westerdahl et al. 2009; Wang et al. 2010). According to a report by the Beijing Municipal Environmental Protection Bureau (EPB) in 2012, vehicle-emitted NO_x , CO, and PM smaller than $2.5\mu g$ $PM_{2.5}$ 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. Short-term exposure to PM, NO_x, and sulfur oxides (SO_x) all have negative effects on health. For PM, small particles such as PM_{10} and $PM_{2.5}$ are considered to pose the greatest 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.

2.3 Driving Restriction in Beijing

Beijing is not the first 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 Sao Paulo, Brazil and Bogota, Columbia. 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

[5] According to Ambient Air Quality Standard(GB3095-2012), first class standard applies for nature reserve areas, second class standard applies for residential, business, and industrial areas. Details of second class standard are presented in Table 1.

[6] Here the vehicle emitted $PM_{2.5}$ 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`

those with even plate numbers were restricted on even days. This policy 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 four weeks. The driving restriction was in force within (and including) the Fifth Ring Road, 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 one year. This time, the restricted day of the week changed every 13 weeks, and the restriction area was 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 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 a 100 yuan every three 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 et al. (2013), 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 violations of 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 subway lines linking the central city area with the rural area [7] and the increase of

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

parking fees [8] since 2011 have also helped encourage people to switch from private vehicles to the public transportation system.

Hence, 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 (Chen et al. 2011; Viard and Fu 2011; Sun et al. 2014). The mixed results are partly due to the different identification methods employed and likely related to the studies' different time windows.

3 Data

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

3.1 Measure of Traffic Congestion

As a measure of traffic congestion, I collected a traffic congestion index maintained by the Beijing Transportation Research Center [9]. This index is calculated based on the real-time speed of vehicles on the road collected from taxis 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

[8] Parking fee for non-residential areas in central Beijing was increased on Apr.1st 2011. Compared to old parking fee standards, the new standards are higher by around five times.

[9] Data were obtained from Beijing Transportation Research Center: http://www.bjtrc.org.cn/

road's speed limit. It is on a scale from zero, which represents no congestion at all, to ten, which represents a very congested road. The explanation of its values is shown in Table 3, presented as the amount of time needed compared to driving at the speed limit.

The traffic congestion index I obtained is a 15-minutes average time series data. Figure 2 presents the 15-minute variation of the traffic congestion index in 2012. It shows 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 value of six or above, which is two to three times higher than during non-peak hours. With the 15-minute average traffic congestion index, I explored how traffic conditions varies within a day. First, I divided the 24 hours within a day into three periods: peak hours, non-peak hours, and non-restricted hours. Peak hours include morning peak hours from 7:00 to 9:00, and evening peak hours from 17:00 to 19:00. Non-peak hours include the hours between 7:00 and 20:00 when the driving restriction is in force, but exclude peak hours. Non-restricted 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 to 5 in Panel A of Table 4 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 non-restricted hours.

Besides the value of the congestion index, I also generated a data set covering the duration of peak hours each day. Following the description of the traffic congestion index in Table 3, I defined morning peak hours as the period of time before 13:00 during which all 15-minute average congestion indices reached four or above. I used the same definition for evening peak hours, which were after 13:00. Based on this definition of morning and evening peak hours, I determined the duration, starting time, and ending time of morning and evening peak hours on a daily basis. Summary statistics for these variables are also listed in Panel A of Table 4.

3.2 Measure of Air Quality

As a measure of air quality, I 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.

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 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, PM_{10}, and SO_2. The first set of data used here is the station-level 24-hour average concentration of NO_2, PM_{10}, and SO_2 in 2012. This data is 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. Table 2 shows the pollutant's concentration and its corresponding API range. With the value of API, air quality is classified into five categories based on health concerns. Air quality is defined to be "excellent" if API is below 50, "good" if it is between 50 and 100, "slightly polluted" if it is between 100 and 200, "moderately polluted" if it is between 200 and 300, and "heavily polluted" if it is above 300 (see Table 2). One thing to note here is that the 24-hour period refers to the period from 12:00 on the previous day to 12:00 on the current day.

Another set of data is the hourly $PM_{2.5}$ 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 $PM_{2.5}$ 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 $PM_{2.5}$, I was 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 4.

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 always debatable. Possible reasons behind this might be due to difference in the pollutants being measured ($PM_{2.5}$ for the US embassy, and PM_{10} 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 $PM_{2.5}$ as well. In response to the data quality issue, I chose the EPB monitoring station closest to the US embassy (within a distance of 1.6 kilometers), and compared the $PM_{2.5}$ measurements from the two stations. Figure 4 presents the daily measures of $PM_{2.5}$ from these two stations in 2013. The two measures covariated very well, with a correlation coefficient of 0.92. The mean value of $PM_{2.5}$ 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 location.

Among the three pollutants monitored by EPB, NO_2 is considered to have the closest connection with road transportation, PM_{10} is also considered to be a major pollutant from traffic, while SO_2 mainly comes from coal burning(Hao et al. 2001; Westerdahl et al. 2009; Hao et al. 2005). Though most NO_2 emissions come from traffic, the hourly variation of NO_2 in Beijing doesn't match traffic patterns exactly. The concentration of NO_2 doesn't have a clear morning peak, and it reaches the lowest level around noon. Then, it starts to increase and remains at high levels from the evening until the next morning. This diurnal pattern can be explained by the chemical 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 level of NO_2 doesn't respond to commuting peaks immediately. Second, the chemical reaction between NO, NO_2, and O_3 in the presence of sun light 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 matters, the hourly US embassy $PM_{2.5}$ data shows 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 (see Figure 5). 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 doesn't respond to traffic conditions as they occurred but only starts to show their effects in the early evening, I 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 4.

3.3 Measure of Health

While previous research has focused primarily on the effects on mortality, I 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.[10] Another possible source of morbidity is emergency room visit data; however, the health department in Beijing doesn't provide this dataset.

Here I collected the number of emergent ambulance calls in Beijing in 2012 as a measure of health outcomes. The data was 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 symptom, situation, age, gender and location. Then, the EMC will send doctors and an ambulance to the scene immediately. With this detailed set of records, EMC helps to provide a district-level data set on the number of ambulance calls by patients' self-reported symptoms, as well as the numbers of calls by different gender and age categories. The data covers all six districts in the urban area of Beijing.

The data set 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 (Peters et al. 2001). Within the field of heart disease, I 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). Lastly, I included injury as a control group.

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 eight million, and accounts for around 65 percent of the total permanent population in Beijing. Summary statistics for this data set can be referred to in Table 5.

[10] http://www.people.com.cn/GB/paper503/2137/341362.html

3.4 Weather Data

Weather data in Beijing was obtained from the ISD-Lite data set published by National Oceanic and Atmospheric Administration (NOAA).[11] The data set contains hourly records of air temperature, dew point temperature, sealevel pressure, wind direction, wind speed, sky conditions (the fraction of the total celestial dome covered by clouds or other obscuring phenomena), and precipitation. To match weather data with the 24-hour average air pollution measure, I averaged the weather indicators based on the same 24-hour period from 12:00 to 12:00. The 24-hour wind direction is the vector average of hourly reported wind directions.[12]

4 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. Table 6 compares the mean values of weather variables, visibility, 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 and visibility. 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 three months.[13] In the following section, I 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.

[11] Data was obtained here: http://cdo.ncdc.noaa.gov/pls/plclimprod/poemain.accessrouter?datasetabbv=DS3505

[12] http://www.ndbc.noaa.gov/wndav.shtml

[13] During the one year period of 2012, there was in total four rounds of rotation of restricted numbers on different weekdays. Hence, the number four day distributed evenly through Mondays to Thursdays, but much less on Fridays. To ensure the robustness of results, I enlarge my sample for air pollution to include and extra three month in 2013 to balance the day of week when the number four is restricted. Results are largely unchanged with this enlarged sample. However, restricted by the heath data, my main study period is the year of 2012.

4.1 Effects of the Number 4 Day on Traffic Congestion

I first tested whether the higher number of vehicles on the road during the number 4 days has any impact on the traffic condition. The measure for traffic congestion includes both the value of the congestion index and the duration of congestion. I expected a higher congestion level and more congested hours during the number 4 days.

The effect of the number 4 day on traffic congestion is estimated by the following equation:

$$\begin{aligned} Congestion_t &= \alpha_0 + \alpha_1 \mathbb{1}\{DR\_4_t\} + holiday_t + weather_t \\ &+ month_t + dow_t + hour_t + \epsilon_t \end{aligned} \tag{1}$$

where $Congestion_t$ is the 15-minutes average congestion index on date t, and $\mathbb{1}\{DR\_4_t\}$ is the dummy variable indicating the date on which plate numbers ending with 4 are restricted. I included a dummy for holidays to reflect the possible different traffic conditions during holidays. I also included daily average weather variables, including linear and quadratic terms in air temperature, dew point temperature, sealevel 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 the traffic condition. Finally, I included the month of the year, day of the week, and hour of the day fixed effect 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 congestion index. Column 1 in Table 7 shows that the number 4 day corresponds to an average increase of 0.52 in the congestion index. To determine whether there are different effects on different times of the day, I restricted the sample to peak hours, non-peak hours, and non-restricted hours. Peak hours include morning peak hours from 7:00 to 9:00 and evening peak hours from 17:00 to 19:00. Non-peak hours include all hours from 7:00 to 20:00 when the driving restriction is in force but exclude peak hours. Non-restricted 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 0.85 for morning peak hours, and 1.37 for evening peak hours. For non-peak hours, the effect is slightly lower at 0.78. And for non-restricted hours, the effect is only 0.063. All estimates during the period when the driving restriction is in force are significant at the 1% confidence level, while the estimate for the non-restricted hours is significant only at the 10% confidence level. Compared with the mean value of the traffic congestion index, during number 4 days, the congestion index is higher by around 23%. The largest effect is during the evening peak hours, when the congestion index is higher by 30%. Although the significance level is lower, there is also a small effect during the non-restricted 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. Finally, as a sensitivity check, I narrowed down the sample to include only weekdays (excluding weekends and holidays). Since people may exhibit different travel behavior during weekends and holidays, and fixed effects might be unable to perfectly control for this, I only compared traffic conditions on number 4 days with other weekdays using the narrowed down sample. The magnitude of the effects is stable across the two specifications.

To further explore the effects of number 4 days on the congestion pattern and to determine whether people adjust their travel behavior during the number 4 days, I tested the effects on the duration of congestion, and the starting and ending times of the morning and evening peaks with the same method. As described earlier, I defined a 15-minute period as "congested" if the congestion index during that period reached 4 or above, and calculated the duration of congestion by counting the number of "congested" 15-minute periods. Column 1 of Table 8 shows the effects of number 4 days on the number of congested hours for the whole day. The effect is estimated to be 2.47 at the 1% confidence level, which means congested hours increase by 2.47 hours on number 4 days. Columns 2 and 3 show that the effect is 1.18 for morning peak hours and 1.25 for evening peak hours. Compared with the mean value, the number 4 day is associated with a 50% increase in daily congested hours. In Table 9, the starting and ending time of the morning and evening peak hours are the dependent variables. For morning peak hours, the estimated coefficients are -0.13 and 1.05 for starting and ending time, respectively, which means morning congestion periods tend to start around 8 minutes earlier and end around 1 hour later during the number 4 days. For evening peak hours, the coefficients are estimated at -0.86 and 0.39, which means evening congestion periods start around 50 minutes earlier and end about 23 minutes later.

These results confirm that the number 4 day has a significant effect on traffic congestion. On the one hand, it has a positive impacts on the level of congestion during all periods of the day. The impact is largest during evening peak hours and morning peak hours, followed by non-peak hours. The impact is marginal during the non-restricted hours. On the other hand, the number 4 day causes an increase in congestion hours. The results show that traffic is heavier during number 4 days, and there is no sign of people redirecting travels toward non-restricted hours to circumvent the restriction.

4.2 Effects of the Number 4 Day on Ambient Air Pollution

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

$$\begin{aligned} Pollution_{mt} &= \alpha_0 + \alpha_1 \mathbb{1}\{DR\_4_t\} + holiday_t + weather_t \\ &+ month_t + dow_t + station_m + \epsilon_{mt} \end{aligned} \tag{2}$$

where $Pollution_{mt}$ is the daily measure of pollutants concentration of NO_2, PM_{10}, or SO_2 measured by the EPB monitoring station m on date t. As discussed in Section 3, the level of certain pollutants such as PM and NO_2 in Beijing tends to be lower during daytime and higher during the night due to meteorological conditions (Chen et al. 2009; Zhao et al. 2009). Hence, traffic emission during morning peak hours might be hard to accumulate due to the meteorological conditions in favor of dilution of pollutants. In contrast, emission during the evening peak hours is relatively easier to accumulate starting from the evening until the next morning. Based on the hypothesis that the traffic condition today has an impact on air quality during the time period from noon of the current day to noon the next day, I used the 24-hour average concentration for pollutants during this period as the dependent variable. As before, I included weather variables including linear and quadratic terms in air temperature, dew point temperature, sealevel 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. 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 holiday fixed effect, month fixed effect, day of the week fixed effect, and monitoring station fixed effect were also included to control for possible unobserved temporal and spatial factors. Standard errors were two-way clustered at the station and date level to account for both serial correlation within a station over time and spatial correlation among stations within a day. Since Beijing has only 27 stations and too few cluster may yield over-rejection of the no-effect null hypothesis (Bertrand et al. 2004; Cameron et al. 2008), here I used the wild cluster bootstrap approach described in Cameron, Gelbach, and Miller (2008) to calculate the p-values.[14]

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, I expected α_1 to be positive. Table 10 presents estimate results using equation(2). Columns 1 to 3 show the effects on NO_2, PM_{10}, 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 5.76-6.03$\mu g/m^3$ increase in 24-hour average NO_2 concentration 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, I expect heterogeneity in the effects on pollution for urban areas and rural areas. When I limited the sample to urban stations, the effects on NO_2 increased to 6.82-6.92$\mu g/m^3$. For rural stations, the effects were smaller at around 4.88-5.29$\mu g/m^3$, 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. Columns 2 and 3 show the effects on PM_{10} 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 to 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. To check for robustness, I also ran regressions without controls for weather and day of the week fixed effect. The results (available upon request) were largely unchanged.

To further explore the temporal feature of how number 4 days affect ambient air pollution, I ran more tests based on the hourly measure of $PM_{2.5}$ data measured by the US embassy in

[14]Bertrand et al. (2004) and Cameron, Gelbach, and Miller (2008) have shown that clustering can over-reject when the number of clusters are small. Here I use the STATA command cgmwildboot by Judson Caskey to carry out the wild cluster bootstrap approach and calculate the p-values for coefficients.

Beijing. I 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, I used the 3-hour average concentration of $PM_{2.5}$ as the dependent variable and controlled for holiday, weather, month of year, and day of the week fixed effects as before. Weather variables were 3-hour average values matched with each 3-hour period. Coefficients for the 16 periods are presented in Table 11 and Figure 6. Although the significance level is not high, the coefficients show the expected temporal pattern. As shown in Figure 6, 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 PM_{10}. This provides some evidence of the lagged effects of the traffic condition on the air pollution level in Beijing.

A review of the air quality standard regulated by the MEP of China (Table 1) can enhance understanding of the magnitude of effects. The standard for 24-hour mean NO_2 concentration is 80 $\mu g/m^3$. The mean value of 24-hour average NO_2 concentration in Beijing is 50.24 $\mu g/m^3$ (see Panel B of Table 4). On number 4 days, the pollution level is estimated to be higher by 6.03 $\mu g/m^3$. Even after adding the 6.03 $\mu g/m^3$ effect to the 50.24 $\mu g/m^3$ mean, the concentration is still below the air quality standard for residential area set by MEP.

4.3 The Number 4 Day, Ambient Air Pollution, and Health

4.3.1 Effects of the Number 4 Day on Ambulance Call Rate

I began with the following regression to explore the effect of the driving restriction on health, particularly how the number 4 day affects local health outcomes. As mentioned in the previous section, the day's traffic condition mainly affects 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), I used a district-level measure of health outcomes on the next day as the dependent variable, $\mathbb{1}\{DR\_4_t\}$ on the right hand side is the number 4 day dummy that equals to one if number 4 is restricted on date t. Holiday, month of the year, day of the week, 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, sealevel pressure, wind speed, precipitation, sky condition, and dummies for eight wind directions were also included to account for effects of weather on health.

$$
\begin{aligned}
Health_{dt} &= \alpha_0 + \alpha_1 \mathbb{1}\{DR\_4_t\} + holiday_t + weather_t \\
&+ month_t + dow_t + district_d + \epsilon_{dt}
\end{aligned} \tag{3}
$$

Table 12 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 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 both district and date level, and p-value was calculated using the wild cluster bootstrap approach. Each coefficients in the table is from a different regression. The first column of each panel is from regressions using the full sample, while the second column of each panel is from regressions using the sample excluding weekends and holidays.

Panel A in Table 12 presents the effects for the overall population. The number 4 day has significant positive effects on both heart-related symptoms and fever, but no significant impact on the control group “injury”. The point estimates in Panel A show that the number 4 day leads to an increase of 0.155, 0.081, and 0.190 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 0.027, much smaller than that of males at 0.118. Panels D to F report coefficients for different age categories. For fever, the point estimate for the population aged 65 and older is the largest at 1.253, compared to 0.068 for the population aged 15 to 64, and 0.274 for the population below 15 years old.

Multiplying coefficients estimated in Table 12 with population size, Panel A of Table 13 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 1.9 and 2.33 more emergency ambulance calls related to heart diseases and fever during number 4 days. Although Table 12 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 to 64 given its large population size. Panel B of Table 13 reports the percentage change of ambulance call rates by dividing the coefficients in Table 12 by the mean values of ambulance call rates. The percentage increase in ambulance call rates associated with number 4 days is 3%, 19%, and 12% for all heart-related symptoms, coronary heart problems, and fever, respectively. Breaking into subpopulations, rows 2 to 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 to 6 show the percentage changes for different age groups. While the point estimates for the population aged 65 and older shown in Table 13 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 to 64.

4.3.2 Relationship between Ambient Air Pollution and Health

To further explore the linkage between ambient air pollution and health outcomes, I first ran a set of tests using traditional OLS regressions. To match the air pollution level with health data, the station-level air pollution data were averaged into district level. In this set of regressions, I used district-level ambulance call rates by symptom as the dependent variable, and pollution concentration as the independent variable. As before, weather condition, holiday, month of the year, day of the week, and district fixed effects were included as controls. Estimates were weighted by district-level population size, and standard errors were two-way clustered by district and date. Table 14 reports the OLS estimates. Although the significance level is low, the positive coefficients suggest a positive relationship between the ambient air pollution level and ambulance call rates related to heart problems and fever.

However, estimates from traditional OLS regressions may suffer from biases introduced by measurement error or any unobserved determinants of both pollution and health. In this study, I assigned the ambient pollution level from monitoring stations to the people residing in the district. This might not precisely reflect individuals' exposure to air pollution, since there might be spatial variation in the pollution level within a district and people might commute between districts. Time-varying unobserved factors that affect both pollution and health, such as weather, can also generate bias in estimates. To prevent this problem, I examined the effects of ambient air pollution on health, using the following instrumental variable approach to regress ambulance call rates by symptom on instrumented air pollution concentration.

$$\begin{aligned} Pollution_{dt} &= \alpha_0 + \alpha_1 \hat{Congestion}_t + holiday_t + weather_t \qquad (4) \\ &+ month_t + dow_t + district_d + \epsilon_{dt} \\ Health_{dt} &= \beta_0 + \beta_1 \hat{Pollution}_{dt} + holiday_t + weather_t \qquad (5) \\ &+ month_t + dow_t + district_d + \eta_{dt} \end{aligned}$$

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. On the right-hand side, $\hat{Congestion}_t$ is the daily traffic congestion index instrumented by the number 4 day. As shown in the previous section, since the driving restriction only has a significant impact on the level of NO_2, I 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 in equation (4). Other control variables include weather variables, holiday, month of the year, day of the week, and district fixed effects. Estimates were weighted by district-level population size, and standard errors were two-way clustered by both district and date.

Table 15 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 heart-related symptoms and fever but no effects on injury. Based on estimates from the IV regression, a one standard deviation increase in NO_2 is associated with a 6%, 35%, and 27% 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, PM_{10}, $PM_{2.5}$, CO, and O_3. With these possible sources of endogeneity but only one instrument variable, the model is under identified. 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.

4.3.3 Displacement and Lag Effects

The baseline regressions in the previous sections only examine the effect of the traffic condition and air pollution 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 air pollution's impacts on health, I estimated a distributed lag regression that included three lag terms of instrumented NO_2 concentration and one lead term as a falsification test. If the instrumented NO_2 concentration 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 16 reports the results for the distributed lag model. As expected, the lead term does not have a statistically significant health effect. The largest effects emerge for the current term. For lag terms, the previous day's NO_2 concentration has a positive effect on the current day's coronary heart disease ambulance call rate. Results show no sign of any temporal displacement effect for heart disease or fever.

5 Economic Cost of the Number 4 Day

Findings of this study show that the number 4 day has a significant impact on traffic condition, ambient air pollution, and ambulance call rates. To evaluate the economic cost of the number 4 day, or the economic cost of a weaker driving restriction, I first examined the economic costs of a higher level of traffic congestion. Results in Section 4.1 show that during the number 4 days, the average increase of the traffic congestion index is 0.52. Based on the traffic congestion index and the corresponding extra time spent on the road presented in Table 3, this can be translated into an average increase of 7% in travel time. According to the 2012 Beijing Transport Annual Report, the average travel time of private vehicles is 42.5 minutes; thus, the number 4 day is associated with a 3-minute increase in average travel time for private vehicles. The number of passenger trips by private vehicles in 2012 was 9.9 million per day. Multiplied by the 3-minute increase in average travel time, this amounts to 0.5 million extra hours per day. To express it in economic values, I multiplied the extra hours by the average wage in Beijing in 2012, and obtained a daily cost of $ 0.59 million.

The health effects found in this study are only a portion of the total health effects. The ambulance call data used in the study only counts sick people with an acute condition who have to call an ambulance; it does not count those who feel sick but just stay home or go to the hospital by themselves. In addition, I only estimated the contemporaneous health effects by focusing on the daily variation of air pollution; I did not account for any long-term health effects of air pollution. Finally, the data focused on those living in the urban areas of Beijing. I was unable to estimate the potential effects of people living in the rural areas of Beijing, where air pollution is also affected by the driving restriction.

To monetize morbidity, one common approach is to estimate by people's willingness to pay (WTP) to avoid illness. The WTP approach should capture the value of the suffering avoided, the time lost, and the medical treatment costs of illness. However, to my knowledge, no contingent valuation studies for morbidity have been conducted in China. Thus, I used the value of statistical life (VSL) multiplied with the estimated number of deaths from increased ambulance calls to valuate the health cost. The VSL used here is $0.76 million, which is based on the estimated VSL in Krupnick et al. (2006) and adjusted for income difference. The estimated number of deaths was calculated by multiplying the number of increased ambulance calls on the number 4 day by emergency patients' mortality rate. As shown in Table 15, the number 4 day increases the number of ambulance calls related to heart diseases and fever by 4.2 cases in the urban areas of Beijing. Based on the number of emergency call patients and the number of deaths presented in Wan et al. (2008), the mortality rate of emergency call patients in Beijing is estimated at 4.2%. Multiplying the two numbers, I estimated the increase in deaths of emergency patients at 0.18. The health cost is therefore estimated to be $0.14 million per day.

6 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. I 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 20% 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. These short-term increases in air pollution increase ambulance calls by 3%, 19%, and 12% 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 to 64 is higher. Given the large size of the population aged 15 to 64, a significant proportion of the increase in ambulance calls is attributed to this group. With a distributed lag model, I 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 a 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 a certain context.

7 Reference

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8 Figures

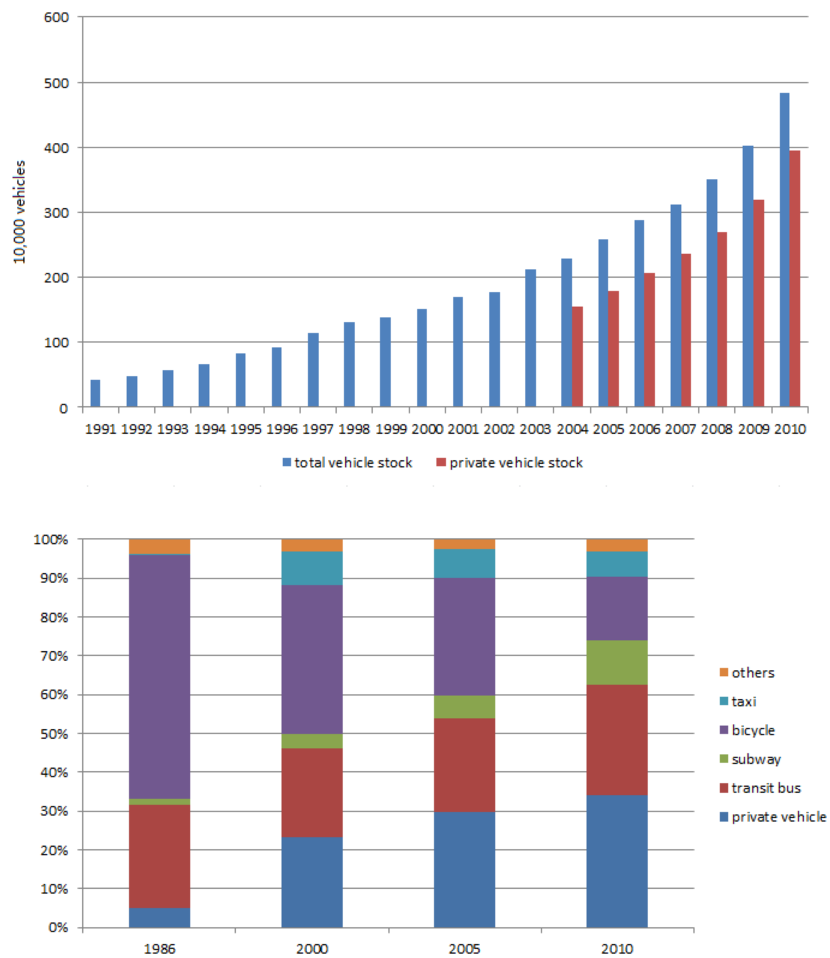

Figure 1: Vehicle Stock and Mode of Transportation in Beijing

Notes: Figure at the top plots the trends of total vehicle stock and private vehicle stock in Beijing. The bottom figure shows changes in mode of transportation in Beijing. Data for the figure come from Beijing Transport Annual Report.

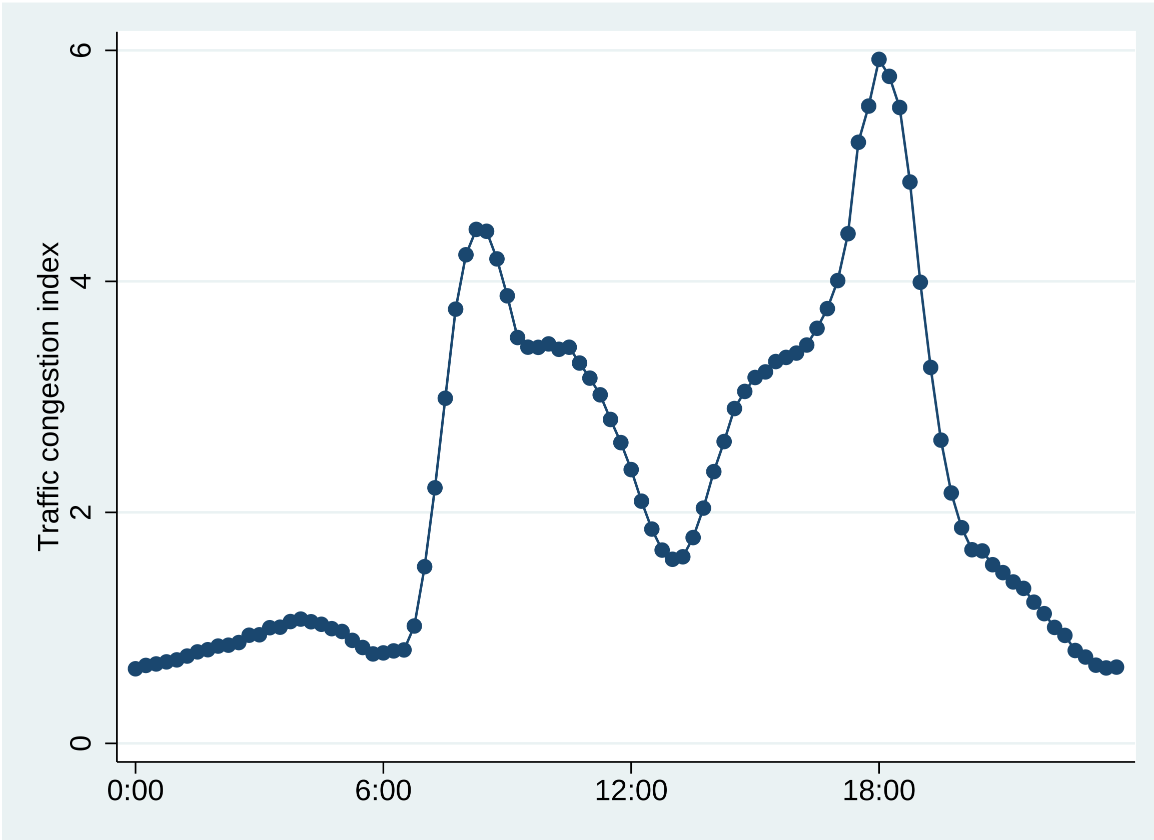

Figure 2: Average 15-minutes Traffic Congestion Index in 2012

Notes: This graph plots the average 15-minutes traffic congestion index in the year of 2012, based on the 15-minutes traffic congestion index for urban area of Beijing reported by Beijing Transport Research Center.

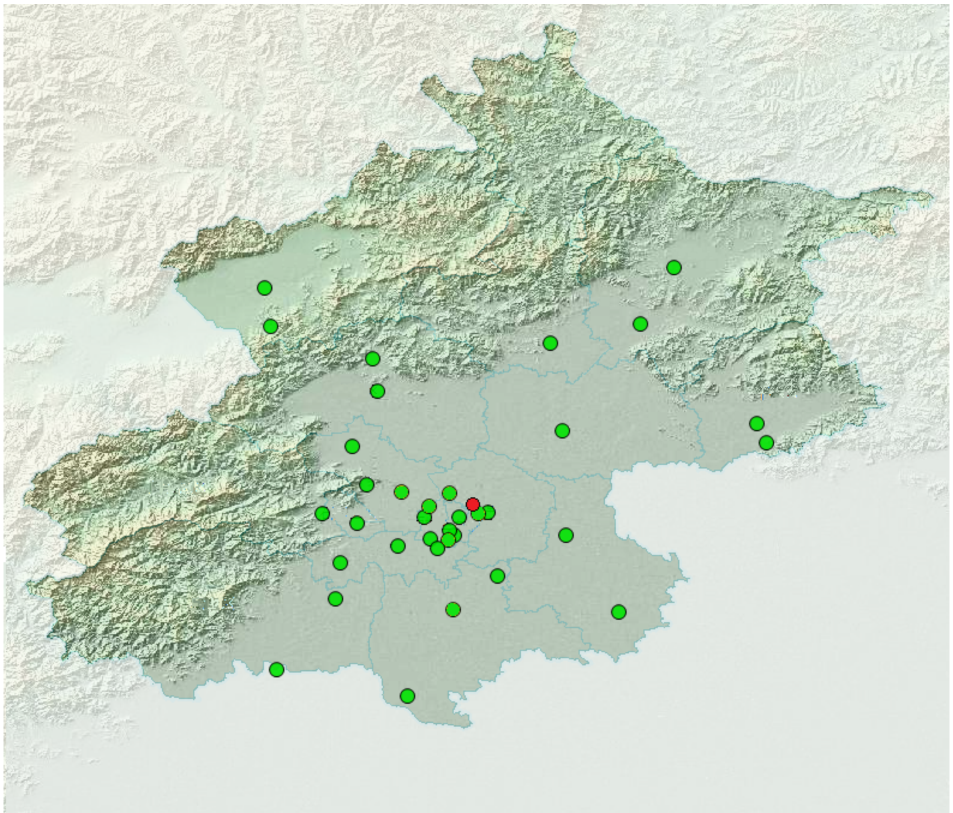

Figure 3: Location of Air Quality Monitoring Stations

Notes: Air quality in Beijing was monitored by a network of 27 monitoring stations in 2012. Green dots in the graph show the locations of the 27 monitoring stations operated by Beijing Environmental Protection Bureau. Red dot in the graph shows the location of US Embassy of Beijing, which started to provide $PM_{2.5}$ measurement from 2008.

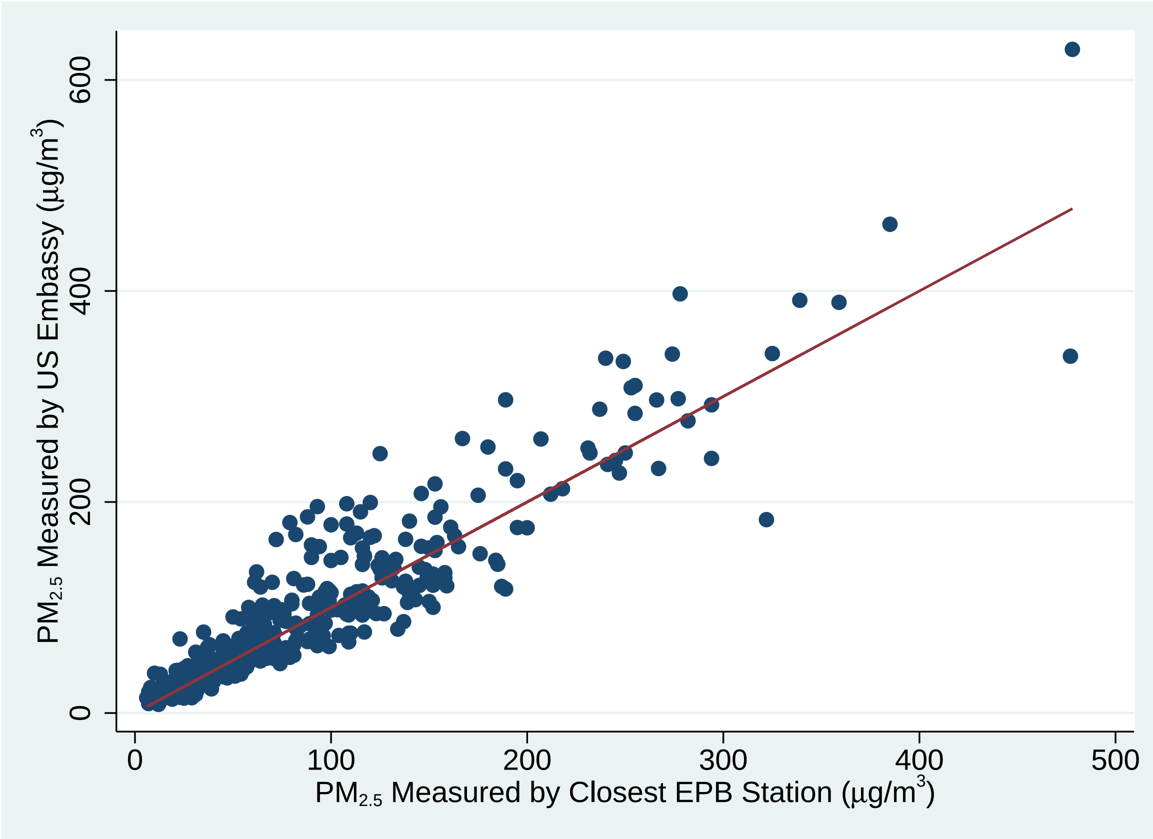

Figure 4: Association of $PM_{2.5}$ Concentrations Measured in Nongzhanguan Station and US Embassy

Notes: The graph plots the 24-hour average concentrations of $PM_{2.5}$ measured by Nongzhanguan station operated by EPB and the US embassy of Beijing in 2013. Nongzhanguan is the EPB station that locates closest to US embassy, which locates within 1.6 kilometers to the US Embassy.

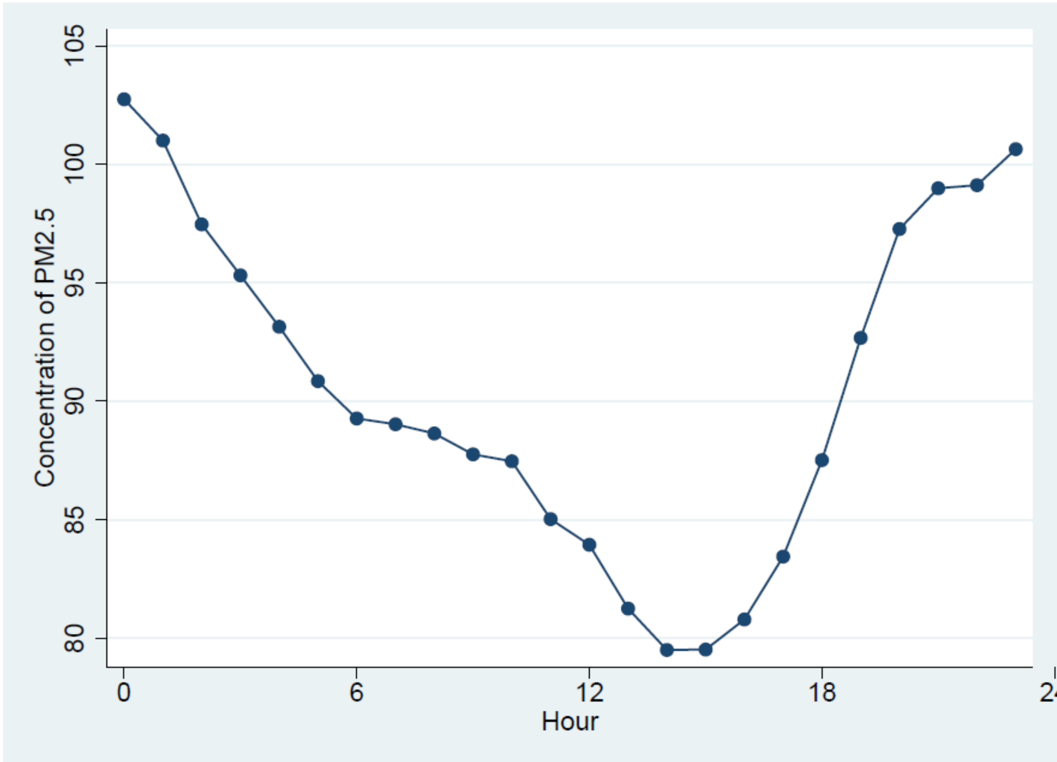

Figure 5: Diurnal Pattern of $PM_{2.5}$ Concentration in Beijing

Notes: The graph plots the annual average hourly variation of $PM_{2.5}$ concentration, based on measurement from US Embassy in the year of 2012.

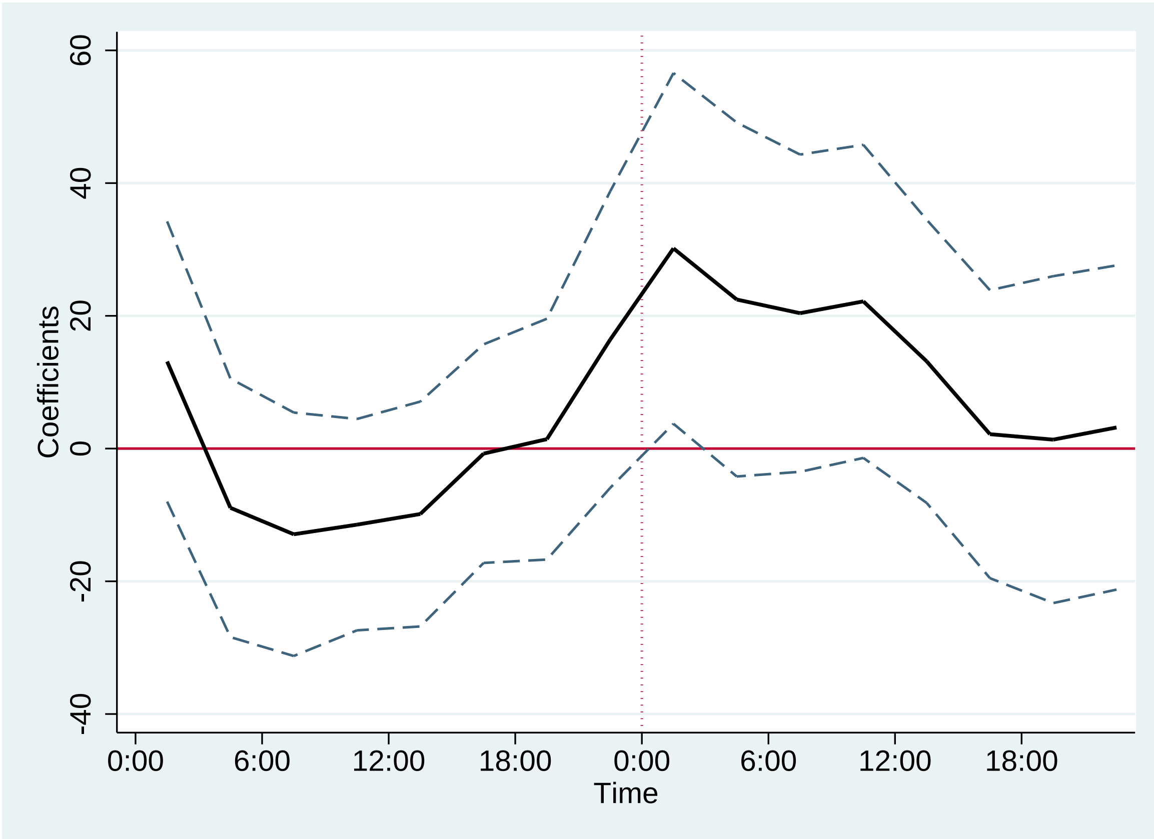

Figure 6: Effects of the Number 4 Day on $PM_{2.5}$

Notes: The 3-hour average $PM_{2.5}$ concentration is regressed on the dummy of number 4 days for the sixteen 3-hour periods of the number four 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, month, and day of week fixed effects. Coefficients for the 16 periods are plotted in the figure, with 10% confidence interval. Coefficients are also presented in Table 11.

9 Tables

Table 1: Air Quality Standard by MEP and WHO

	Annual Mean($\mu g/m^3$)	24-hour Mean($\mu g/m^3$)
	MEP Second Class Air Quality Standard	
PM_{10}	70	150
$PM_{2.5}$	35	75
SO_2	60	150
NO_2	40	80
	WHO Air Qulity Guideline	
PM_{10}	20	50
$PM_{2.5}$	10	25
SO_2	-	20
NO_2	40	-

Note: Table lists second class air quality standards set by Ministry of Environmental Protection of China (air quality standards that applied to residence, business, and industrial area, according to Ambient Air Quality Standard (GB3095-2012)) and air quality guidelines set by WHO (http://whqlibdoc.who.int/hq/2006/WHO_SDE_PHE_OEH_06.02_eng.pdf?ua=1).

Table 2: Pollution Concentration and Corresponding Air Pollution Index

PM_{10}	NO_2	SO_2	API	Air quality level	Air quality condition	Notes of health effects
24-hour average ($\mu g/m^3$)						
50	80	50	50	I	Excellent	Daily activity will not be affected.
150	120	150	100	II	Good	Daily activity will not be affected.
350	280	800	200	III	Slightly polluted	The symptom of the susceptible is slightly aggravated, while the healthy people will have stimulated symptoms.
420	565	1600	300	IV	Moderate polluted	The symptoms of the patients with cardiac and lung diseases will be aggravated remarkably. Healthy people will experience a drop in endurance and increased symptoms.
500	750	2100	400	V	Heavy polluted	Exercise endurance of the healthy people drops down, some will have strong symptoms. Some diseases will appear.
600	940	2620	500			

Note: Table lists pollution concentration and the corresponding range of air pollution index (API) for PM_{10}, NO_2, and SO_2. The corresponding air quality condition and health concerns for five categories of API are also listed in the table.

Table 3: 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, don't 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: Table lists values of traffic congestion index with the corresponding congestion level and extra time needed.

Table 4: Summary Statistics for Measure of Traffic Congestion and Air Quality

	Obs.	Mean	Std.Dev.	Min.	Max.
Panel A: Measure of Traffic Congestion					
15-minutes Average Traffic Congestion Index					
All hours	28071	2.28	1.83	0.30	9.70
Morning peak hours	2359	3.48	2.23	0.49	8.79
Evening peak hours	2396	5.15	2.14	0.91	9.70
Non-peak hours	10655	2.91	1.37	0.49	9.52
Non-restricted hours	12661	0.99	0.48	0.30	8.61
Hours of Congestion					
All day	231	4.17	2.27	0.25	12.25
Morning peak	231	2.17	1.08	0.25	5.25
Evening peak	251	2.62	1.58	0.25	7.50
Starting and Ending Times of Peak Hours					
Morning Peak					
Starting time	231	8.09	1.02	7.25	12.00
Ending time	231	10.03	1.18	8.00	13.00
Evening Peak					
Starting time	253	16.44	1.31	13.00	18.50
Ending time	253	18.85	0.74	14.50	21.50
Panel B: Measure of Air Quality					
All Stations					
NO_2	8841	50.24	27.35	0	204.8
PM_{10}	9672	106.67	74.94	4	600
SO_2	9026	28.65	28.85	4	195.5
$PM_{2.5}$	8295	90.52	81.72	0	994
Urban Stations					
NO_2	3938	57.81	24.89	1.6	204.8
PM_{10}	4305	116.22	76.16	5	600
SO_2	4053	29.44	29.88	4	195.5
Rural Stations					
NO_2	4903	44.17	25.92	0	171.2
PM_{10}	5367	99	73.05	4	600
SO_2	4973	28.01	27.97	4	195.5

Note: Table lists summary statistics for measure of traffic congestion and air quality in 2012. Measures of traffic congestion include 15-minutes average traffic congestion index, duration of congested hours, and starting and ending times of morning and evening peaks. Measures of air quality include 24-hour average NO_2, PM_{10}, and SO_2 concentrations from EPB stations, and hourly $PM_{2.5}$ concentration from US Embassy in Beijing.

Table 5: Summary Statistics for Measure of Health

	Obs.	Mean	Std.Dev.	Min.	Max.
Overall Population					
All heart	2196	5.102	2.614	0	16.52
Coronary	2196	0.416	0.619	0	4.695
Fever	2196	1.651	1.323	0	9.39
Injury	2196	8.542	3.323	0	25.33
Male					
All heart	2196	4.293	2.964	0	18.349
Coronary	2196	0.379	0.789	0	6.116
Fever	2196	1.718	1.758	0	11.236
Injury	2196	8.048	4.109	0	26.966
Female					
All heart	2196	5.531	3.477	0	22.436
Coronary	2196	0.424	0.884	0	9.615
Fever	2196	1.409	1.692	0	16.026
Injury	2196	6.131	3.488	0	25.918
Age 65 or Older					
All heart	2196	23.569	14.128	0	93.75
Coronary	2196	2.266	3.994	0	31.25
Fever	2196	9.857	9.414	0	78.125
Injury	2196	19.632	12.675	0	93.75
Age 15 to 64					
All heart	2196	2.923	1.879	0	13.947
Coronary	2196	0.192	0.467	0	4.024
Fever	2196	0.355	0.577	0	4.184
Injury	2196	4.475	2.448	0	19.526
Age under 15					
All heart	2196	0.097	0.911	0	17.241
Coronary	2196	0	0	0	0
Fever	2196	2.879	5.33	0	34.483
Injury	2196	2.45	4.752	0	40.541

Note: Table lists summary statistics for emergency ambulance call rates (number of ambulance calls per million people) by disease type and subpopulation groups.

Table 6: Comparison of Weather and Air Quality between the Number 4 Days and Other Days

	Number 4 Days		Other Days		P-Value	T-Value
	Mean	Std.Dev.	Mean	Std.Dev.		
			Weather Variables			
Min Temp (°C)	6.763	11.837	6.594	12.202	0.929	0.090
Max Temp (°C)	17.619	12.901	17.576	12.181	0.982	0.022
Dew Point (°C)	2.898	12.983	1.479	14.832	0.531	0.627
Air Pressure (hPa)	1015.44	10.262	1016.15	10.166	0.654	-0.449
Precipitation (mm)	0.123	0.455	0.212	1.071	0.569	-0.571
Wind Speed (m/s)	2.598	1.418	2.829	1.265	0.246	-1.162
Sky Condition	0.288	0.195	0.282	0.208	0.854	0.184
Visibility	5.917	4.217	6.347	4.868	0.564	-0.577
			Air Quality			
$NO_2(\mu g/m^3)$	59.224	31.896	48.893	25.140	0.000***	12.537
$PM_{10}(\mu g/m^3)$	120.420	72.835	104.540	75.092	0.000***	7.020
$SO_2(\mu g/m^3)$	35.325	36.852	27.201	27.170	0.000***	8.901

Note: Table lists mean value and standard deviation for weather and air quality variables 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.

Table 7: Effects of the Number 4 Day on Traffic Congestion Index

	1	2	3	4	5	6
	All hours	**Peak Hours**	**Morning Peak**	**Evening Peak**	**Non-peak Hours**	**Non-restricted Hours**
				Panel A: Full sample		
	0.52***	1.12***	0.85***	1.37***	0.78***	0.063*
	[0.060]	[0.11]	[0.098]	[0.18]	[0.094]	[0.033]
Obs.	28,071	4,755	2,359	2,396	10,655	12,661
				Panel B: Excludes weekends and holidays		
	0.50***	1.09***	0.76***	1.31***	0.72***	0.064*
	[0.060]	[0.12]	[0.095]	[0.18]	[0.088]	[0.034]
Obs.	19,275	4,092	1,623	1,469	6,462	8,721
Weather	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Day of Week RE	Y	Y	Y	Y	Y	Y
Hour FE	Y	Y	Y	Y	Y	Y

Note: Table regresses traffic congestion index on 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, month, day of week, and hour fixed effects. Robust standard errors in brackets. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 8: Effects of the Number 4 Day on Duration of Congestion Periods

	1	2	3
	Peak Hours	**Morning Peak**	**Evening Peak**
	Panel A: Full sample		
	2.47***	1.18***	1.25***
	[0.33]	[0.14]	[0.24]
Obs.	231	231	251
	Panel B: Excludes weekends and holidays		
	2.45***	1.19***	1.22***
	[0.32]	[0.14]	[0.23]
Obs.	191	197	202
Weather	Y	Y	Y
Month FE	Y	Y	Y
Day of week	Y	Y	Y

Note: Table regresses duration of congestion periods on dummy of number 4 days. 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, month, and day of week fixed effects. Robust standard errors in brackets. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 9: Effects of the Number 4 Day on Starting and Ending Time of Peak Hours

	1	2	3	4
	Morning Peak		**Evening Peak**	
	Starting Time	**Ending Time**	**Starting Time**	**Ending Time**
	Panel A: Full sample			
	-0.13***	1.05***	-0.86***	0.39***
	[0.034]	[0.12]	[0.19]	[0.089]
Obs.	231	231	251	251
	Panel B: Excludes weekends and holidays			
	-0.14***	1.05***	-0.85***	0.37***
	[0.029]	[0.12]	[0.18]	[0.086]
Obs.	197	197	202	202
Weather	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Day of Week	Y	Y	Y	Y

Note: Table regresses starting and ending time of morning and evening peak hours on dummy of number 4 days. 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, month, and day of week fixed effects. Robust standard errors in brackets. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 10: Effects of the Number 4 Day on Air Pollution

	1	2	3	4	5	6
	NO_2	PM_{10}	SO_2	NO_2	PM_{10}	SO_2
	Panel B: Full sample					
All stations	6.03**	11.53**	3.56*	5.41***	11.10	3.44**
	[0.016]	[0.048]	[0.094]	[0.006]	[0.118]	[0.44]
Obs.	8841	9649	8777	8376	9493	8366
Urban stations	6.92***	14.39	4.49	5.98***	13.76	4.66*
	[0.002]	[0.128]	[0.13]	[0.000]	[0.304]	[0.07]
Obs.	3938	4293	3910	3727	4229	3738
Rural stations	5.29**	9.25*	2.79	4.99**	8.98	2.47
	[0.02]	[0.044]	[0.17]	[0.01]	[0.122]	[0.178]
Obs.	4903	5356	4867	4649	5264	4628
	Panel B: Excludes weekends and holidays					
All stations	5.76***	8.39	2.73**	5.17***	8.26	2.60*
	[0.008]	[0.138]	[0.034]	[0.000]	[0.204]	[0.082]
Obs.	5938	6416	5839	5590	6278	5538
Urban stations	6.82***	11.03	3.6	5.82***	10.65	3.63*
	[0.000]	[0.194]	[0.14]	[0.000]	[0.356]	[0.06]
Obs.	2647	2854	2602	2483	2793	2471
Rural stations	4.88***	6.29	2.03	4.67**	6.35	1.81
	[0.000]	[0.16]	[0.134]	[0.012]	[0.168]	[0.218]
Obs.	3291	3562	3237	3107	3485	3067
Weather	Y	Y	Y	Y	Y	Y
Day of Week	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Lag Pollution				Y	Y	Y

Note: Table regresses 24-hour average pollution concentration for the periods from noon the current day to noon the next day on the dummy of number 4 days. 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, month, day of week, and monitoring station fixed effects. Column 4-6 also controls for lag term of air pollution. Robust standard errors are two-way clustered on both station and date level. Considering clustering with small number of stations might yield over-rejection of null hypothesis, P-values in brackets are calculated with wild cluster bootstrap approach. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 11: Effects of the Number 4 Day on $PM_{2.5}$ for Different Time Periods

	1	2	3	4
	Number 4 Day		**Day after Number 4 Day**	
	Full sample	**Weekdays**	**Full Sample**	**Weekdays**
0am-3am	15.8	11.5	29.1*	24.5
	[12.2]	[12.1]	[16.0]	[16.1]
Obs.	348	230	347	235
3am-6am	-1.47	-9.71	24.5	20.8
	[11.9]	[12.1]	[16.3]	[16.2]
Obs.	348	230	347	235
6am-9am	-7.97	-13.5	21.2	17.9
	[11.3]	[11.3]	[14.8]	[14.6]
Obs.	346	229	345	234
9am-12pm	-11.8	-13.3	24.0*	20.9
	[9.95]	[9.84]	[14.3]	[14.2]
Obs.	346	230	345	232
12pm-15pm	-4.86	-10.2	15.5	12.3
	[9.89]	[10.3]	[12.8]	[12.9]
Obs.	350	235	349	235
15pm-18pm	1.56	-0.32	8.84	5.08
	[9.46]	[9.82]	[13.5]	[13.6]
Obs.	351	236	351	237
18pm-21pm	2.74	2.5	4.72	0.5
	[10.7]	[10.9]	[14.2]	[14.3]
Obs.	348	235	348	234
21pm-24pm	19.7	18	6.52	2.64
	[12.8]	[13.5]	[14.5]	[14.8]
Obs.	347	235	347	234
Weather	Y	Y	Y	Y
Day of Week	Y	Y	Y	Y
Month FE	Y	Y	Y	Y

Note: Table regresses 3-hour average $PM_{2.5}$ concentration on the dummy of number 4 days for the sixteen 3-hour periods of the number four 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, month, and day of week fixed effects. Robust standard errors in brackets. Significance levels are indicated by *** 1%, ** 5%, * 10%. Coefficients presented here are plotted in Figure 6.

Table 12: Effects of the Number 4 Day on Ambulance Call Rate

	1 **All Heart**	2 **Coronary**	3 **Fever**	4 **Injure**
		Panal A: Full Population		
Full Sample	0.155***	0.081***	0.190***	-0.055
	[0.000]	[0.000]	[0.000]	[0.624]
Weekdays	0.168***	0.081***	0.193***	-0.091
	[0.000]	[0.000]	[0.000]	[0.492]
		Panel B: Males		
Full Sample	0.176*	0.118**	0.205***	-0.069
	[0.096]	[0.012]	[0.000]	[0.408]
Weekdays	0.232***	0.112*	0.202***	-0.119
	[0.000]	[0.066]	[0.000]	[0.120]
		Panel C: Females		
Full Sample	0.171	0.027	0.203***	0.002
	[0.218]	[0.240]	[0.000]	[0.944]
Weekdays	0.141	0.034	0.211***	0.003
	[0.378]	[0.370]	[0.000]	[0.892]
		Panel D: Ages 65 and older		
Full Sample	0.253	0.188	1.253***	-0.917
	[0.626]	[0.396]	[0.000]	[0.464]
Weekdays	0.594	0.156	1.321***	-0.799
	[0.198]	[0.456]	[0.000]	[0.588]
		Panel E: Ages 15 to 64		
Full Sample	0.156	0.073	0.068***	-0.005
	[0.100]	[0.164]	[0.000]	[0.910]
Weekdays	0.153*	0.081*	0.074***	0.002
	[0.078]	[0.070]	[0.000]	[0.968]
		Panel F: Ages below 15		
Full Sample	-	-	0.274	-0.053
	-	-	[0.448]	[0.716]
Weekdays	-	-	0.179	-0.093
	-	-	[0.724]	[0.562]
Full Sample Obs.	2190	2190	2190	2190
Weekdays Obs.	1458	1458	1458	1458
Weather	Y	Y	Y	Y
Day of Week	Y	Y	Y	Y
Month FE	Y	Y	Y	Y

Note: Table regresses daily ambulance call rate for the next day on the dummy of number 4 days. 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, month, day of week, and district fixed effects. Robust standard errors are two-way clustered on both district and date level. Considering clustering with small number of district might yield over-rejection of null hypothesis, P-values in brackets are calculated with wild cluster bootstrap approach. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 13: Effects of the Number 4 Day on Ambulance Calls - Changes in Number and Percentage Change

	1 All Heart	2 Coronary	3 Fever
Panel A: Changes in Number of Ambulance Calls			
Full Population	1.9	1	2.33
Males	1.1	0.74	1.29
Females	1.03	0.16	1.22
65 or older	0.3	0.22	1.5
15 to 64	1.55	0.73	0.68
Younger than 15	-	-	0.3
Panel B: Percentage Change of Ambulance Call Rates			
Full Population	3.29%	19.47%	11.69%
Males	5.40%	29.55%	11.76%
Females	2.55%	8.02%	14.98%
65 or Older	2.52%	6.88%	13.40%
Age 15 to 64	5.23%	42.19%	20.85%
Younger than 15	-	-	6.22%

Note: Panel A of the table lists changes in number of emergency ambulance calls in urban area of Beijing by multiplying coefficients estimated in Table 12 by population size. Panel B lists the percentage change of ambulance call rates, which is calculated by dividing the coefficients in Table 12 by the mean value of ambulance call rates.

Table 14: Ambulance Call Rates Regressed on Pollution

	1	2	3	4
	All Heart	**Coronary**	**Fever**	**Injure**
	Panal A: Ambulance Call Rates Regressed on NO_2			
Full Sample	0.0007	0.0014**	0.0005	-0.0029
	[0.802]	[0.022]	[0.620]	[0.120]
Weekdays	0.0006	0.0018*	0.0009	-0.0072***
	[0.752]	[0.052]	[0.612]	[0.002]
	Panel B: Ambulance Call Rates Regressed on PM_{10}			
Full Sample	0.0001	0.0004*	0.0002	-0.0001
	[0.890]	[0.096]	[0.374]	[0.862]
Weekdays	0.0003	0.0005***	0.0005	-0.0013*
	[0.638]	[0.000]	[0.322]	[0.082]
	Panel C: Ambulance Call Rates Regressed on SO_2			
Full Sample	0.0021	0.0015**	0.0028***	-0.0037
	[0.236]	[0.042]	[0.000]	[0.338]
Weekdays	0.0013	0.0016	0.0037***	-0.0068*
	[0.468]	[0.164]	[0.000]	[0.064]
Full Sample Obs.	2048	2048	2048	2048
Weekdays Obs.	1377	1377	1377	1377
Weather	Y	Y	Y	Y
Day of Week	Y	Y	Y	Y
Month FE	Y	Y	Y	Y

Note: Table regresses district level daily ambulance call rate on 24-hour average pollution concentration from noon the day before to noon the current 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, month, day of week, and district fixed effects. Robust standard errors are two-way clustered on both district and date level. Considering clustering with small number of district might yield over-rejection of null hypothesis, P-values in brackets are calculated with wild cluster bootstrap approach. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 15: Effects of Instrumented NO_2 Concentration on Ambulance Call Rate

	1	2	3	4
	All Heart	**Coronary**	**Fever**	**Injure**
	Panal A: Full Population			
Full Sample	0.012**	0.006***	0.018***	-0.004
	[0.022]	[0.000]	[0.000]	[0.720]
Weekdays	0.016***	0.007***	0.022***	-0.003
	[0.000]	[0.000]	[0.000]	[0.882]
	Panel B: Males			
Full Sample	0.017**	0.010***	0.018***	-0.006
	[0.036]	[0.000]	[0.000]	[0.404]
Weekdays	0.023***	0.011*	0.020***	0.002
	[0.000]	[0.068]	[0.000]	[0.918]
	Panel C: Females			
Full Sample	0.012	0.001	0.021**	0.001
	[0.370]	[0.660]	[0.034]	[0.826]
Weekdays	0.015	0.001	0.026***	0.000
	[0.312]	[0.720]	[0.000]	[0.936]
	Panel D: Ages 65 and older			
Full Sample	0.016	0.009	0.123***	-0.091
	[0.870]	[0.596]	[0.000]	[0.606]
Weekdays	0.022	0.007	0.142***	-0.110
	[0.764]	[0.702]	[0.000]	[0.570]
	Panel E: Ages 15 to 64			
Full Sample	0.013	0.007	0.006***	0.001
	[0.126]	[0.188]	[0.000]	[0.902]
Weekdays	0.017***	0.007	0.007***	0.008
	[0.000]	[0.144]	[0.000]	[0.654]
	Panel F: Ages below 15			
Full Sample	-	-	0.028	-0.003
	-	-	[0.410]	[0.816]
Weekdays	-	-	0.034	-0.005
	-	-	[0.346]	[0.772]
Full Sample Obs.	2190	2190	2190	2190
Weekdays Obs.	1458	1458	1458	1458
Weather	Y	Y	Y	Y
Day of Week	Y	Y	Y	Y
Month FE	Y	Y	Y	Y

Note: Table regresses district level daily ambulance call rate on instrumented 24-hour average NO_2 concentration for the periods from noon the previous day to noon the current 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, month, day of week, and district fixed effects. Robust standard errors are two-way clustered on both district and date level. Considering clustering with small number of district might yield over-rejection of null hypothesis, P-values in brackets are calculated with wild cluster bootstrap approach. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 16: Effects of Instrumented NO_2 on Ambulance Call Rate - Distributed Lag Model

	1 **All Heart**	2 **Coronary**	3 **Fever**
		Panal A: Full Sample	
$\hat{NO_2}$ in T+1	0.000015	-0.000015	-0.000021
	[0.692]	[0.248]	[0.366]
$\hat{NO_2}$ in T	0.000122**	0.000054***	0.000194***
	[0.04]	[0]	[0]
$\hat{NO_2}$ in T-1	0.000037	0.000041***	-0.000016
	[0.448]	[0]	[0.738]
$\hat{NO_2}$ in T-2	0.000022	-0.000017*	0.000044*
	[0.328]	[0.07]	[0.064]
$\hat{NO_2}$ in T-3	-0.000029	0.000005	-0.000033
	[0.296]	[0.616]	[0.278]
		Panal B: Excludes Weekends and Holidays	
$\hat{NO_2}$ in T+1	0.000022	-0.00001	-0.000014
	[0.586]	[0.23]	[0.464]
$\hat{NO_2}$ in T	0.000173***	0.000062***	0.000231***
	[0]	[0]	[0]
$\hat{NO_2}$ in T-1	0.000053	0.000024***	0.000003
	[0.182]	[0]	[0.954]
$\hat{NO_2}$ in T-2	0.00004	-0.000017	0.000031*
	[0.442]	[0.302]	[0.056]
$\hat{NO_2}$ in T-3	-0.000042	0.000003	-0.000034
	[0.204]	[0.834]	[0.26]
Full Sample Obs.	2166	2166	2166
Weekdays Obs.	1446	1446	1446
Weather	Y	Y	Y
Day of Week	Y	Y	Y
Month FE	Y	Y	Y

Note: Table regresses a distributed lag model, using district level daily ambulance call rate as dependent variable, instrumented NO_2 concentration 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), holiday, month, day of week, and district fixed effects. Robust standard errors are two-way clustered on both district and date level. Considering clustering with small number of district might yield over-rejection of null hypothesis, P-values in brackets are calculated with wild cluster bootstrap approach. Significance levels are indicated by *** 1%, ** 5%, * 10%.