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Truth behind Chinese Superstition

Non-linear Effects of Vehicle Traffic on Urban Air Quality in Beijing

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Abstract

Employing hourly data records from 2013 and 2014 in Beijing, we investigate the causal effects of vehicle traffic on air pollution. An arguably exogenous variation in vehicle use that results from the staggered and rotating driving restriction program there, combined with a widespread Chinese superstition about the unlucky number four, allows us to better track causal effects of traffic-induced air pollutants in a generalized 2SLS framework. We find that: (1) Traffic has contributed 47.6% of the deterioration in air quality in Beijing; for the specific pollutants $PM_{2.5}$, PM_{10}, NO2, and CO, 37.2%, 50.0%, 42.3%, and 55.7%, respectively, are estimated to be caused by vehicle traffic. (2) The average marginal effects of traffic on air pollution at night are 2.5 times what they are in daytime. (3) There is a non-linear, U-shaped relationship between the Chinese Traffic Congestion Index (TCI) and concentration of air pollutants, with the inflection point occurring when TCI falls in the range of 5 to 5.5, indicating that damage caused by air pollution escalates disproportionately as traffic jams intensify and increase in frequency. We conclude that urban air pollution abatement strategies could be more effectively targeted if policy makers considered the dynamics documented here of the relationship between traffic congestion and air pollution, as these vary over time and congestion level.

Key Words: air pollution, traffic congestion, non-linear relationship, Beijing

JEL Codes: R40, R41, Q50, Q53

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1. Introduction

Traffic congestion and air pollution are two of the most pressing problems facing developing metropolises. Both are negative externalities arising from the urban economy that in turn induce further negative externalities to human health as well as to the broader set of economic activities that cause them.[1] Transport authorities often assume that alleviating traffic congestion will reduce urban air pollutant levels (Chin 1996). Traffic demand control policies, either through pricing or direct regulation (Mahendra 2008), have therefore become the most widely adopted practices to restrain vehicle use. However, there is currently little empirical basis for accepting or rejecting such practices, especially when a full policy assessment extends beyond traffic congestion alleviation to air pollution mitigation and other economic effects.[2]

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[1]Studies on the externalities of urban development include, for instance, Rothenberg (1970), Nechyba and Walsh (2004), and Arnott (2007). Traffic congestion causes time and commute costs (see Arnott et al. 1993; Arnott and Kraus 1998) and deterioration in social welfare (see Arnott and Small 1994; Parry and Bento 2002) and reduces labor supply (see Gutiérrez-i-Puigarnau and van Ommeren 2010; Viard and Fu 2015). Beyond these economic costs, air pollution has also been linked to infant health problems (see Chay and Greenstone 2003, 2005; Currie and Neidell 2005), morbidity (Ostro 1983, 1987) and mortality (Chen et al. 2013a).

[2]Empirical evidence of the impact of vehicle restrictions on air pollution and economic activities has begun to accumulate. Representative work includes Eskeland and Feyzioglu 1995, Davis 2008, Salas 2010, Lin et al. 2011, Sun et al. 2014, Viard and Fu 2015, Chen et al. 2013b, Liang et al. 2015, Gallego et al. 2013, and Cao et al. 2014. However, the conclusions are mixed, even for the same cities, including Mexico City (Davis 2008; Salas 2010) and Beijing (Sun et al. 2014; Viard and Fu 2015). Gallego et al. (2013) conclude that such policies may appear effective in the short run, but, in the long run, effectiveness can be reduced after households have adjusted their stock of vehicles. Xu et al. (2015) point out differences in findings regarding whether vehicle restrictions have a long-term effect on road congestion and air pollution. As Viard and Fu (2015) point out, such restrictions may be ineffective due to either non-compliance or compensating responses such as inter-temporal driving substitution. At the same time, if effective, they may reduce economic activity by increasing commute costs and reducing workers' willingness to supply labor for any given level of compensation.

More clearly understanding both the dynamics contributing to traffic-induced air pollution and the potential policy interventions could help better design urban transport and environmental policies.

In this paper, we study the causal effects of vehicle traffic on urban air pollution. Establishing causality is a critical first step before more elaborate empirical strategies can be developed to examine how air pollutant concentration will ultimately shift in response to varying traffic conditions. To conduct our research, we used hourly data records of air pollutants, Beijing's traffic congestion index (TCI) and meteorological reports from 2013 and 2014 in Beijing. Beijing can be regarded as an ideal place for this research because traffic is becoming an increasingly dominant source of air pollution in the city. As one of the world's largest developing megacities, Beijing has already had almost all of its polluting industrial plants relocated to other regions (Zhao and Yin 2011; Sun et al. 2004). In addition, the main fuel source for winter heating has gradually become natural gas, regarded as a much cleaner energy source than coal (Liang et al. 2015).

Despite the rich data availability and the clear importance of traffic-induced air pollution in Beijing, we remain mindful of the potential for reverse causality (Neidell 2009; Wang et al. 2014) that could bias our estimates. For example, people might change travel behavior in response to air pollution levels, in turn changing the traffic congestion level. We hope to minimize this issue by using the exogenous variation in daily vehicles that arises due to the widespread Chinese superstition about the number four in connection with Beijing's staggered and rotated one-day-per-week driving restriction.

On October 11, 2009, the one-day-per-week driving restriction policy was introduced in Beijing and has been in effect continually ever since.[3] This measure, enforced from 7 a.m. to 8 p.m., grouped the last digits of license plates into five pairs: one and six, two and seven, three and eight, four and nine, and five and ten. Each pair is assigned to a weekday (from Monday to Friday) on which driving is restricted. The assignment of these pairs to weekdays is rotated every 13 weeks.[4]

[3]We describe the policy background in detail in Section 2.2.

[4]For example, a car with a plate ending with number four might be prohibited from driving on Monday in May but on Tuesday in June. Before 2009, the rotation period was one month.

Vehicle owners can choose a license plate number from a list of randomly generated numbers. Most Chinese people avoid the unlucky number "4," because its pronunciation sounds like "death" in Chinese. This cultural preference induces most Chinese people to avoid the number four as the last digit of their plate number, suggesting more vehicles will be on the road in Beijing on the day when the tail number combination four and nine is restricted from driving (hereafter "four and nine" days). Therefore, the four and nine days act as a quasi-natural experiment that exerts an unintentional shock on local traffic.

The exogenous variation of local traffic introduced by the four and nine days in Beijing allows us to identify the causal effects of traffic-induced air pollutants by the typical instrument variable (IV) estimation. We are trying to examine the specific impact of urban air quality solely through the channel of vehicle traffic, and the "four and nine" day comparison works particularly well for this purpose; it works better than a comparison between holidays and weekdays because, on holidays, air quality is affected through multiple channels, including production schedule changes and increased tourism.

Other advantages of the "four and nine" day comparison include:

1) The fact that the particular numbers restricted on a certain weekday are changed every 13 weeks tends to rule out certain adaptation behaviors, i.e., that some people might intentionally avoid being prohibited from driving on a certain weekday by choosing their last license plate digit accordingly.[5]

2) The system meanwhile also ensures that the four and nine days are evenly distributed across weekdays and seasons, which rules out other potentially seasonal impact channels.

3) As part of Chinese culture, the number four is avoided across most routine aspects of life, including telephone numbers, membership cards, and office floors. Because of the pervasiveness of this preference, the choice of license plate number is unlikely to correlate with other confounding factors that affect both local traffic and air quality.

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[5] Gallego et al. (2013) point out that households can adjust their stock of vehicles in response to the driving restriction policy, which can weaken policy effects in the long run. However, during our 2013-2014 study period, the driving restriction policy in Beijing was accompanied by a lottery policy that controlled the growth of vehicle ownership through a lottery system that randomly allocated the issuance of license plates (regardless of plate number) and, thus, restricted the number of vehicles that could be registered.

We apply a generalized 2SLS framework to test, in the first stage, whether traffic conditions are affected by the exogenous shock of the four and nine days, and then, in the second stage, whether such traffic changes result in corresponding changes in air pollutant levels. Our estimates indicate that traffic has contributed to 47.6% of the deteriorating air quality (measured by the Chinese Air Quality Index) in Beijing. For specific pollutants, vehicle traffic is estimated to account for 37.2% of $PM_{2.5}$, 50.0% of PM_{10}, 42.3% of NO_2 and 55.7% of CO. We then extend our research to examine the hourly relationship between traffic congestion and air pollution and how air pollutants ultimately shift in response to varying traffic levels. We find that the average marginal effects of traffic on air pollution at night are 2.5 times what they are in the daytime and that there is a non-linear, U-shaped relationship between the traffic congestion index (TCI) and air pollutant levels, with the inflection point occurring when TCI measures between 5 and 5.5, indicating damage worsens disproportionately as traffic jams proliferate.

The main advantage of using IV is that it makes explicit the source of traffic variation used to evaluate traffic-induced air pollution. However, a common drawback is that IV estimation is based only on the "compliers" affected by the instrument (Imbens and Angrist 1994). Specifically, IV estimates the effect on air pollution of the subset of extra vehicles that are on the road on four and nine days. If the traffic-induced effect on air pollution is not constant across vehicles with different license plate tail numbers, then we can only interpret the IV estimation as a local effect induced by the four and nine days. The core issue is whether the local effect of the IV estimator is close to the real marginal effect. By comparing simulation results of different traffic policy interventions with representative studies, we show that our IV estimator has superior performance in policy evaluations. In fact, the four and nine days induce a widespread shock on vehicles across all tail numbers due to either non-compliance or compensating responses such as inter-temporal driving substitution (Viard and Fu 2015). We find significant variations in traffic between the four and nine days and other weekdays, even during the non-restricted hours of the day (i.e., before 7 a.m. and after 8 p.m.) when vehicles with any tail numbers are allowed. In the most conservative explanation, the four and nine days increase TCI by 0.54-0.55, which exacerbates air pollution in turn by 10.53%-10.73%, according to our two-stage estimation.

Many studies, spanning several disciplines and employing various methods, have examined the relationship of traffic to air pollution. Studies from the natural sciences, such as atmospheric environmental studies, are the main tool used to evaluate potential effects from urban vehicle emissions.[6] Instead of using a regression framework, atmospheric environmental studies use, for example, rich theoretical models to simulate air pollutants, based on the chemical composition of vehicle emissions.[7] By doing so, these studies track air pollutant sources and analyze them chemically, emphasizing the dynamic formation process of primary and secondary pollutants. Although scientific studies tend to show that transportation acts as a major contributor to air pollution (Huan and Kebin 2012),[8] debate continues, mostly centering on what exactly is the net magnitude of traffic-induced air pollution in urban areas and how precisely traffic damages air quality (for example, Guo et al. 2014 and Li et al. 2015).[9]

The influence of traffic on air pollution has been widely studied across the social sciences. However, the evidence is often inconclusive regarding the causal effects of traffic on air pollution. Following an influential study by Davis (2008) on the impact of a driving restriction program in Mexico, empirical evidence based on rigorous methods began to accumulate. By using both OLS and Regression Discontinuity Design (RDD), Lin et al (2011) tested whether driving restriction policies have mitigated air pollution in multiple Chinese cities, including Beijing. Specifically, for the one-day-per-week driving restriction after the 2008 Olympics, they found no evidence of air pollution mitigation. This conclusion was also supported by Cao et al (2014). By contrast, using the same empirical strategy, while emphasizing spatial variation in air quality changes, Viard and Fu (2015) found significant pollution reduction

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[6]Examples ofatmospheric environmental studies include Sun et al. (2004), Wanget al. (2009a), Wang and Xie (2009), Molina et al. (2010), Cai and Xie (2011), Zhang et al. (2013), Guo et al. (2014), Levy et al. (2014) and Li et al. (2015).

[7]For example, the Operational Street Pollution Model (OSPM) is in essence a parameterized semi-empirical model, which makes *a priori* assumptions about the flow and dispersion conditions of air pollution. For a detailed discussion, please refer to Wang and Xie (2009).

[8]Many scientific studies have confirmed that local vehicle emissions are major contributors to air pollutants, including carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter (PM) and volatile organic compounds (VOC); see, for example, Wang and Xie (2009) and Guo et al. (2014). However, a few studies produced different results. For instance, Zhang et al. (2013) collected monthly data from urban sites in Beijing and found traffic emissions played only a minor role in deteriorating air quality.

[9]We are not aware of any atmospheric study that has tested a simulation model using data different from what was used to calibrate it. Potential weaknesses of simulation models are their complexity, with the large number of parameters (Berkowicz et al. 1996), uncertainty about changing weather conditions (Elminir 2005), few research samples collected (Wang et al. 2009b), and data spanning only a very short period (Chen and Ye 2015). In addition, simulation approaches take vehicle emissions as exogenous: they do not account for adaptive responses by city dwellers and other economic actors.

due to Beijing's driving restrictions, in particular, that air pollution fell 8% under the one-day-per-week driving restriction.[10] In other efforts, Chen et al. (2013b) examined policy effects on air pollution mitigation by comparing Beijing with other non-Olympic cities before, during and after the Olympics in a Difference-in-Difference (DID) specification, and Liang et al. (2015) examined the effects on Beijing air quality of various government-driven interventions, such as steps taken in relation to the Asia-Pacific Economic Cooperation (APEC) conference and other efforts focused on winter heating. Even though significant air pollution mitigation was found in both studies, policy evaluations on air quality impacts suffer from a common weakness: they evaluate a battery of actions simultaneously, and therefore impact analysis cannot disentangle the effects of traffic control from other policy interventions such as plant closures.

Ours is not the first study to use the four and nine days as an exogenous shock. Prior studies include Sun et al. (2014), Zhong (2015) and Yang et al. (2016). We add to the existing literature in three respects. First, we take more care to establish the causal relationship between traffic and air pollutants. Existing literature either does not recognize that traffic and air pollution may be simultaneously determined or fails to solve this identification problem. The work of Sun et al. (2014) and Zhong (2015) used reduced form strategies, which directly examined the impacts of the four and nine days on urban air pollutants and human health (measured by ambulance calls). We make a substantial improvement by emphasizing that our IV meets the exclusion restriction (Imbens and Angrist 1994), i.e., traffic is the only impact channel that links the four and nine days with air pollution.

Second, our data set is richer and more comprehensive than that used in previous studies. Existing literature that has examined the link between traffic and air pollution primarily focuses on Beijing and the data used in these studies are mostly daily records of traffic and air pollution information (for example, Sun et al. 2014 and Yang et al. 2016). By contrast, we have collected richer information on hourly air quality, traffic and meteorological conditions for Beijing during 2013-2014, which allows us to better control for unobserved temporal factors as well as to explore the difference in hourly impacts of traffic on air pollutants.

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[10] An important issue with Regression Discontinuity Design (RDD) in practice is bandwidth selection (Imbens and Lemieux 2008). For example, although Davis (2008) finds no evidence that a driving restriction policy improved air quality in Mexico, Salas (2010) argues that Davis' (2008) results using the RDD are sensitive to assumptions about time window and time trend.

Third, it is extremely difficult to detect non-linear relationships between endogenous traffic congestion and air pollutants.[11] We address this problem by separately looping our 2SLS framework across small sub-samples divided by fixed TCI intervals. Specifically, we use 0.5 as an interval to divide TCI and estimate average marginal contributions to air pollutants so TCI intervals are gradually incremented by the 0.5 level. In this way, we plausibly detect the non-linear relationship between TCI and air pollution, given that valid IVs are limited.

In addition to identifying causal effects and exploring the non-linear relationship of hourly variations in traffic to air pollution in Beijing, we believe our research makes three important contributions. First, our study can be linked to, and adds to, a broader literature on environmental policies. Impact evaluations of improved health and economic consequences linked to air pollution reduction in relation to traffic require a rigorous analysis of the relationship between traffic conditions and air quality. Our study can provide a strong empirical basis for such broader environmental and economic research. Second, studies from the natural sciences that evaluated the contributions of vehicle traffic to air quality in Beijing have not yet reached a consistent conclusion. The debate among academics and policy makers still goes on regarding how much air pollution can be attributed to Beijing's vehicle traffic. Our research and findings, using econometric methods, can make a significant contribution to this interdisciplinary literature. Third, deeper insight into traffic-induced air pollution can provide crucial assistance in making optimal policy recommendations. The non-linear effects of traffic congestion on air quality that are detected in our research clearly demonstrate that efforts to keep the congestion index from rising above the "inflection point" will have disproportionate effects on alleviating pollution in Beijing.

This paper proceeds as follows. In Section 2, we provide an overview of the Beijing driving restriction policy and air pollution situation, and we describe the number preferences of Chinese culture. In Section 3, we describe our hourly records of air pollutants, traffic congestion and weather conditions in Beijing, which are our primary data sources. We also discuss empirical challenges. In Section 4, we present our empirical models and discuss identifying assumptions. In Section 5, we present our main results, including a discussion of statistical inferences in a setting in which the non-linear traffic-related air pollutants and discrepancies in impacts over time are tested. In Section 6, we provide a variety of robustness checks, including discussion of

[11] We discuss this empirical challenge in detail in Section 5.5.

potential data manipulation, alternative traffic measurements and the main drawback of IVs. Finally, in Section 7, we discuss policy implications and conclude.

2. Background

2.1 Vehicle Growth, Congestion and Air Pollution in Beijing

In recent years, Beijing has experienced explosive vehicle growth due to both rapid urban in-migration and income growth. Beijing took seven years to increase its car "population" from one million to two million but only four more years to reach three million, and three more to reach four million. In 2005, Beijing had 2.6 million cars. By 2013, it had 5.4 million vehicles, with an annual growth rate of 9.8%, while the volume of private cars alone reached 4 million (Figure 1 (a)). This dramatic increase in vehicle ownership has naturally led to a significant increase in the share of trips made by private vehicles. The share of all trips made by cars has increased from 5% in 1986 to over 30% in 2014, while the share of bicycle trips has decreased profoundly, from 62.7% in 1986 to 11.3% in 2014 (Figure 1 (b)). Because of the rapid growth of car ownership and resulting greater car use, traffic congestion has become an increasing problem. The Beijing Transportation Annual Report (2001-2013)[12] stated that average speed of vehicles on arterial roads during morning rush hour decreased from 60 km/h in 2001 to 23 km/h in 2013, with even larger drops in vehicle speeds on secondary roads.

Along with vehicle growth and congestion, a severe related environmental problem in Beijing is air pollution. From 2000 to 2014, the average Air Quality Index (AQI)[13] in Beijing was 96.8, where 0 is excellent air quality and over 300 is severe pollution. This means that, on average, the air was rated as "polluted" for nearly 50% of the days of the average year in that 14-year period (Figure 2). Air quality is different during winter heating periods compared with other periods when artificial heating is not widely used: in winter heating periods, the average AQI reached 102.5, about 10% higher than the pollution index in non-heating periods.[14] In 2013, a new standard measurement of air quality incorporating the particularly harmful pollutant known

[12]The Beijing Transportation Annual Report (2001-2013).See http://www.bjtrc.org.cn/JGJS.aspx?id=5.2&Menu=GZCG.

[13]Before 2013, air quality was measured by the Air Pollution Index (API) instead of AQI (see the notes for Figure 2 for details).

[14]In Beijing, the legal heating period lasts from Dec.15 to Mar.15 of the next year; see http://www.tianqi.com/news/108879.html.

as $PM_{2.5}$was introduced. According to this air quality measurement, in 2013, the number of days when air quality in Beijing met an acceptable standard (AQI<100) accounted for only 48% of the year, with the days when the air was "seriously" or "severely" polluted accounting for 16%. The average annual $PM_{2.5}$ concentration was 89.5 μg/m,[15] 2.5 times China's Ambient Air Quality Standard and about nine times the World Health Organization (WHO) standard.

Beijing's growing fleet of cars emits massive amounts of carbon monoxide (CO), nitrous oxide (NO_x), and volatile organic compounds (VOCs); these, along with Particulate Matter (PM)[16], all contribute importantly to Beijing's painfully poor air quality. According to the Beijing Municipal Environmental Protection Bureau (2014),[17] vehicle emissions accounted for nearly 31% of local air pollution. Further analysis suggests that vehicle emissions contribute 6%-22% of suspended particulates, 46% of hydrocarbons, 74% of NO_x, and 23% of PM_{10} (Hao et al. 2005).

2.2 Beijing's Driving Restriction Program

To combat traffic congestion and air pollution, Beijing's city government has implemented multiple policies in recent years, including regulatory measures such as its vehicle registration and driving restriction programs, as well as price-based measures (Qin et al. 2013).[18] Aside from a four-day trial in August 2007, the first application of driving restrictions in Beijing was in July and August 2008, before and during the Summer Olympics. Vehicles were restricted from driving every other day. Vehicles with odd-ending plate numbers were prohibited from driving on odd-numbered days and those ending with even plate numbers were prohibited from driving on even-numbered days. Restrictions were enforced virtually "around the clock" from 6

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[15]Source: Air Quality Conditions of Key Regions and 74 Cities in 2013, released by Ministry of Environmental Protection in 2014;http://www.mep.gov.cn/gkml/hbb/qt/201403/t20140325_269648.htm.

[16]Particulate matter (PM_{10} and $PM_{2.5}$, i.e.,airborne particles smaller than 10 or 2.5 microns) is also known as suspended particulate. $PM_{2.5}$ is especially dangerous to health.

[17]See Beijing Environmental Statement (2014), http://www.bjepb.gov.cn/bjepb/341240/index.html.

[18]Beijing was the first city in China to implement a driving restriction program, although this kind of policy is not new worldwide (Mahendra 2008).Early in the 1970s, Buenos Aires, Argentina, adopted a similar program, banning half of automobiles from entering the city center each day based on the odd or even last digits of their license plates. Another similar restriction program was used in the 1980s in Caracas, Venezuela's capitol and largest city, and in Athens, Greece, from 1985 until 1991 (de Grange and Troncoso 2011). In Mexico City, a one day per week driving restriction was introduced in 1989. Sao Paulo in Brazil, Bogota and Medellin in Colombia, and Santiago in Chile also introduced driving restrictions. More recently, after Beijing, a few more Chinese cities, including Changchun, Lanzhou, Hangzhou, Guiyang, and Chengdu, adopted driving restrictions (Wang et al. 2014).

a.m. through 3 a.m. across all of metropolitan Beijing. Drivers who broke this rule could be fined 100 RMB per day and required to drive back to their place of origin.

The policy proved to be a success in reducing traffic congestion and ambient air pollution during the 2008 Olympics (Chen et al. 2013b). Encouraged by this apparently significant policy effect, the Beijing municipal government decided to continue with a similar but less restrictive program. For most of September 2008, the policy was kept in place, but in a smaller area inside and including the Fifth Ring Road.[19] Starting September 28, 2008, Beijing officials announced a half-year trial of more permissive driving restrictions. This new measure, enforced from 6 a.m. to 9 p.m., divided license plates into five groups based on their last number (one and six, two and seven, three and eight, four and nine, and five and zero) and assigned each pair to be restricted from driving on a specified weekday (Monday through Friday), with these restrictions rotated monthly among weekdays.

When this half-year trial ended, the government started a new round of driving restrictions to last one year, with only minor changes in restriction times and rotation periods. The hours affected by restrictions were shortened to 7 a.m. to 8 p.m. and the rotation period was extended to 13 weeks (four periods a year) rather than monthly. In the following years, the municipal government continued this measure; this one-day-per-week driving restriction continues in Beijing through the present day. One minor modification, which came into force on January 9, 2011, provided for charging an additional 100 RMB penalty for a second violation on the same day, at least three hours after the first.

2.3 Number 4, Chinese Culture and License Plate Number Distribution

As discussed above, the number four is traditionally avoided. License plate number choice is no exception, as reflected in Table 1. If people did not have any particular number preference, each license plate tail number should have a relative equal share, around 10%. However, vehicle license plates ending in four accounted for less than 1.7% of the total in 2013 and this proportion dropped even further, to 1.5%, in 2014, significantly less than the share of license plates ending in each of the other nine digits.

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[19]Beijing is one of very few Chinese cities to possess multiple ring roads (or beltways). It is now served by six circumferential or loop routes (“ring roads”) that encircle the city center. The loop route nearest to the city center is the Second Ring Road, and the ring road farthest from the city center is the Sixth Ring Road.

Because there are very few vehicles with 4 as the last digit of their license plate, fewer vehicles are restricted on the four and nine restriction days (see Table 1). As a result, more vehicles than usual are allowed on the road on whatever weekday the tail numbers four and nine are restricted, compared with other weekdays. This variation in license plate tail numbers creates an exogenous shock that increases local traffic on whichever weekday is the "four and nine day" under the system of banning each pair of numbers on a rotating basis (described above).

3. Data Description and Statistical Challenges

3.1 Data Source and Statistical Description

In this study, we compiled three hourly data sets of Beijing's local traffic congestion index (TCI), air pollutant measures and meteorological conditions. Our hourly data started at 4 p.m. January 18, 2013, and ended at 7 a.m. December 25, 2014. We also constructed a daily record of date-specific characteristics that distinguish holidays and weekends from weekdays during 2013 and 2014. We describe each data source and variable measurement in detail below.

3.1.1 Traffic Congestion Index

The Traffic Congestion Index (TCI) was obtained from the Beijing Transportation Research Center (BTRC).[20] The TCI is an aggregated index measuring traffic conditions in Beijing's central city area. This index is used to evaluate overall performance of the road network and reflects road network congestion intensity under the interaction of road network supply and traffic demand (Wen and Zhang2014). The index is calculated using real-time speeds collected from over 40,000 cars daily in the area enclosed by the Fifth Ring Road, weighted based on traffic volumes on each road (Wen and Zhang 2014).[21] The TCI has a scale of 0 to 10, with 0 meaning no congestion and ten referring to a completely congested road with no movement. According to the Beijing Transportation Research Center, when the TCI is four to six, it means light congestion, in which some of the ring roads or major arteries are jammed, and travelers need 1.5 to 1.8 times the average travel time to complete their trips. When the TCI ranges from six to eight, this is categorized as "moderate" congestion, in which most of the ring roads and major arteries are congested, and travelers have to spend 1.8 to two times the average

[20]For real-time TCI, please see http://www.bjtrc.org.cn/PageLayout/IndexReleased/zhishu.php. For a TCI description, please see http://www.bjtrc.org.cn/PageLayout/IndexReleased/IndexReader.aspx?menuid=li4.

[21]For an extended discussion regarding TCI calculations, see Wen and Zhang (2014).

travel time to get to destinations. When TCI is in the range of eight to ten, most roads in the city are severely congested, and travelers need to spend more than double the normal travel time to complete their trips. The TCI is hourly average time series data.

Table 2 provides TCI statistics from 4 p.m., January 18 2013 through 7 a.m., December 25 2014. Because 1.8% of the original records were missing, we were left with 16,631 hourly TCI observations for the final analysis. The 24-hour TCI is averaged at 2.44. Through the entire 24-hour day, over the two-year period, traffic was congested about 17.39% (2893/16631) of the time, indicating a TCI exceeding four in those time periods. In the daytime (7 a.m. to 8 p.m.), on average, there was congestion 29.77% (2892/9716) of the time. However, traffic congestion gets much worse during peak travel hours: during morning peak hours (7 a.m. to 9 a.m.), traffic is congested 45.15% (935/2071) of the time, while during evening peak hours (5 a.m. to 7 p.m.), there is congestion 50.96% (1063/2086) of the time. Further graphic analysis of hourly TCI distribution follows in a subsequent section.

3.1.2 Air Quality Data

Corresponding with the hourly traffic congestion index, air pollution measures are also hourly, in the form of the Beijing Air Quality Index (AQI) and hourly average concentration data for $PM_{2.5}$, PM_{10}, CO, and NO_2, obtained from the Beijing Environmental Protection Bureau (EPB). This hourly pollution data was collected from eight state-controlled monitoring stations located within Beijing's Fifth Ring Road, including Dongsi and Temple of Heaven in the Dongchen district, Wanshou Nishinomiya and Park Office in the Xichen district, the Agricultural Exhibition Hall and the Olympic Sports Center in the Chaoyang district, Wanliu in the Haidian district, and Gucheng in the Shijingshan district.[22] In addition, we have also collected hourly $PM_{2.5}$ concentrations reported by the US embassy in Beijing,[23] which has monitored $PM_{2.5}$ in Beijing since 2008 to provide such health information to Americans in Beijing; its monitoring station is located at the US embassy (39.9608E, 116.474N), within the Fourth Ring Road in the Chaoyang district. This hourly measure of $PM_{2.5}$ from a different, independent source provides additional robustness in measuring the impact of traffic on pollutant concentration.

[22]For the geographic locations of the eight monitoring stations, please see the map at http://zx.bjmemc.com.cn/. Strictly speaking, the Gucheng monitoring station is located just outside the West Fifth Ring Road. However, we are including it in our sample because we need a station to reflect the pollution concentration level in the western part of Beijing.

The AQI measures six atmospheric pollutants: ground-level ozone (O_3), particle pollutants $PM_{2.5}$ and PM_{10}, carbon dioxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2).[23] The AQI is an index ranging from 0 to 500, with higher values indicating higher pollutant concentrations. Air quality is defined as "excellent" if AQI is between 0 and 50, "good" if it is between 51 and 100, "slightly polluted" if it is between 101 and 200, "moderately polluted" if it is between 201 and 300, and "severely polluted" if higher than 300. A crude categorization refers to a day with AQI at or below 100 as "blue sky." In addition to overall AQI, we are also interested more specifically in the hourly concentrations of four component air pollutants – $PM_{2.5}$, PM_{10}, CO, and NO_2 – for two reasons. First, the official reported maximum value of AQI is 500, but Beijing has individual extremely polluted days when AQI would very likely exceed 500. For instance, Beijing's smog on February 2, 2013 and January 15 and 16, 2014 have been rated by the Ministry of Environmental Protection of China as beyond the index. As a result, during these extremely polluted days when the AQI is officially limited to 500, the concentration of specific air pollutants may better reflect Beijing's air pollution level.[24] Also, scientific studies have found that PM, CO, and NO_x are the primary components of automobile exhaust (Wu et al. 2011) and our research uses econometric methods to investigate the impact of traffic on these specific pollutants.

Table 2 provides descriptive information regarding hourly AQI and concentrations of specific atmospheric pollutants in 2013 and 2014. In our sample, the aggregated AQI ranges from six to 500 and averages 122.4 during this two-year period. Specifically, 49.22% (8165/16587) of hours in our sample are classified as "polluted," and 17.78% (2949/16587) of hours at least moderately polluted. The pollution situation gets worse in winter (December through February), when our sample shows that 25.68% (974/3793) of hours are at least moderately polluted (AQI>=201), with 10.57% of hours classified at the serious pollution level (AQI>=301).

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[23]An individual score (IAQI) is assigned to each pollutant, and the final AQI is the highest of those six scores. The pollutants can be measured quite differently. $PM_{2.5}$ and PM_{10} concentrations are measured as averaged over 24 hours, whereas SO_2, NO_2, O_3, and CO are measured as averages per hour. The final API value is calculated per hour according to a formula published by the Ministry of Environmental Protection. See https://en.wikipedia.org/wiki/Air_quality_index.

[24]For the formula used to convert specific pollutants to AQI, please see http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/jcgfffbz/201203/t20120302_224166.htm.

3.1.3 Meteorological Conditions

Our study also considers a variety of meteorological conditions expected to affect the level of air pollutants. These meteorological data were obtained from the ISD-Lite data set published by the National Oceanic and Atmospheric Administration (NOAA),[25] including hourly average records of air temperature, relative humidity, dew point temperature,[26] sea-level pressure,[27] wind direction, and wind speed.

Beijing's air quality is not only affected by wind speed, but also in significant part determined by wind direction (see, for example, Guo et al. 2014 and Chen and Ye 2015). The benefit of northerly wind is due to a lack of heavily polluting industries in regions north of Beijing. However, easterly and southeasterly winds tend to bring pollutants from coastal and mid-China cities with dense populations and heavy industries that consume enormous amounts of coal and other fossil fuels (Liang et al. 2015). Therefore, we control for wind-specific impacts by including 16 wind directional quadrants and interacting these with 16 wind speed levels.[28]

In addition, we have controlled for other meteorological variables, including air temperature, relative humidity, and dew point temperature, all of which affect air pollutants as well (see, for example, Liu et al. 2010a; Liu et al. 2010b). Indeed, some of these meteorological variables are correlated. For example, decrease in dew point temperature together with increasing sea-level barometric pressure is usually accompanied by northerly wind that brings drier and fresher air to Beijing (Liang et al. 2015). Summary statistics of meteorological variables are presented in Table 2.

3.1.4 Date-Specific Controls

We also constructed date-specific controls for our sampled period in 2013 and 2014, namely the "four and nine" restricted weekdays, official holidays, holiday-makeup days, odd-even days and "day of the week" (one for each of the seven days). The four-and-nine day indicator is a binary variable, reflecting whether the tail numbers four and nine are restricted on

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[25]See https://www.ncdc.noaa.gov/isd/data-access.

[26]For detailed discussion of dew point temperature, please see http://www.weatherquestions.com/What_is_dewpoint_temperature.htm.

[27]All meteorological variables are derived from hourly records, except for sea-level pressure, which is recorded every two hours.

[28]For brevity, we denote wind directions as an index (1 to 16) that is summarized in Table 2.

that weekday; 1 indicates that four and nine are restricted while 0 indicates otherwise. An official holiday (such as National Holiday, Labor Day, Chinese New Year, etc.) is denoted as a dummy variable as well, with 1 indicating an official holiday. For important national holidays, such as Labor Day (May 1) and National Day (October 1), people are allowed an extended holiday period of seven days, which usually include three paid-leave days, two unpaid-leave days, and two weekend days. People need to work on two other weekend days to make up for the two unpaid-leave days; therefore, we name these two days “holiday-makeup” days and use binary variables for them. The dummy variable odd-even day reflects the odd-even traffic restriction policy implemented during the APEC meeting on November 3-12, 2014, with 1 indicating an odd-even restriction was in effect. For brevity, the variable “day of the week” listed in Table 2 is an index representing each day from Monday (=1) through Sunday (=7). However, to control for the daily fixed effects from Monday through Sunday, the “day of the week” index will be transformed into seven dummies in our regression analysis. We control for these date-specific variables for two main reasons. First, these date-specific variables are expected to be highly correlated with the TCI. Second, these date-specific variables might affect concentration of air pollutants in other ways as well. For example, during holidays or APEC meeting times, air quality might be affected by other changes in economic activities, such as reductions in plant production and increases in tourism. Summary statistics for all of these date variables are also reported in Table 2.

3.2 Statistical Challenges

A natural start to exploring the correlation between urban traffic conditions and air quality is by directly plotting hourly variations of TCI and AQI together, as shown in Figure 3. As expected, traffic patterns show clear morning and evening peaks, which start at around 8 a.m. and 6 p.m., respectively. However, we observe an almost opposite diurnal pattern of annual average hourly AQI distribution, which reaches a lower level in the morning followed by another bottom at around noon. Moreover, the highest AQI level appears around midnight, when, at almost the same time, traffic congestion reaches its lowest level. Hourly correlation patterns between TCI and other specific air pollutants, i.e., $PM_{2.5}$, $NO_{2,}$ and CO, show the same change trend as AQI (see Graph A1).

All of these pattern analyses suggest that there is a negative correlation between traffic and air quality by time of day. This contradicts our expectation and indicates that simple OLS might lead to biased estimates, due to either omitted variable bias (OVB) or reverse causality. First, the observed inverted relationship could be driven by other omitted factors; for example, meteorological conditions are known to affect dispersion of air pollutants that significantly affect local air quality. Scientific studies have pointed out that relatively high pollution levels occur at night because of temperature inversion, which occurs at night and traps pollutants near the earth's surface (Meng et al. 2008). Once any of these omitted factors (i.e., other determinants of air pollution, such as meteorological conditions or date-specific characters) are correlated with city dwellers' travel behavior (and therefore TCI), typically OVB occurs. Second, even if we could control for detailed temporal factors and weather variables, reverse causality might be another source of potential identification challenges that threaten our estimation results (Davis 2008; Viard and Fu 2015). For instance, in response to polluted weather, people might avoid taking outdoor trips to reduce their exposure, which would lead to less traffic on those days (Neidell 2009).

4. Identification

4.1 OLS Estimates

The first concern with our empirical work discussed in Section 3.2 is that simple OLS fails to control for confounding factors that 1) are correlated with traffic conditions and 2) exert their own separate effects on air quality, for example, meteorological conditions, holidays, season-specific shocks and pollution levels remaining from previous time periods (lagged pollution levels). If the statistical challenges only come from potential OVB, one common solution is to estimate a multiple linear regression model using OLS, while controlling for other confounding factors that might affect both TCI and the concentration of air pollutants, as described by the following equations:

$$Poll_{ymdh} = \beta_0 + \beta_1 TCI_{ymdh} + W_{ymdh}\theta + Z_{ymd}\gamma + \tau Poll_{ymd,h\text{-}1} + \lambda_y + \mu_m + \eta_h + \varepsilon_{ymdh} \tag{1}$$

$$W_{ymdh}\theta = \theta_1 Tem_{ymdh} + \theta_2 Rhu_{ymdh} + \theta_3 Slp_{ymdh} + \theta_4 Dwp_{ymdh} + \sum_{i=1}^{16} \theta_{5i} Wsp_{ymdh} * Dir_i \tag{2}$$

where subscript sets y, m, d, h denote the year, month, day, and hour, respectively. $Poll_{ymdh}$ denotes hourly AQI as well as hourly concentration of specific air pollutants for AQI, $PM_{2.5}$, PM_{10}, NO_2, and CO. TCI_{ymdh} represents the average hourly Traffic Congestion Index (TCI) in central Beijing. We carefully construct hourly meteorological conditions (see Equation (2)), W_{ymdh}, which include temperature (Tem_{ymdh}), relative humidity (Rhu_{ymdh}), sea-level air pressure (Slp_{ymdh}) and wind velocity. The latter is a vector of interaction variables, created through the interactions of 16 wind direction dummies (Dir_{ymdh}) with wind speed (Wsp_{ymdh}). Z_{ymd} is a vector of variables that control for unobserved temporal factors, including the dummies such as holiday, holiday-makeup, odd-even day and day of the week. Lagged pollution, $Poll_{ymd,h-1}$, is included to allow for persistence of air conditions across hours, and also to capture the initial state of air pollution for the next hour. λ_y, μ_m, and η_h capture fixed effects of year, month, and hour, respectively.

Table 3 presents the estimation results of five OLS regressions with different sets of control variables. The dependent variable is the logarithmic form of hourly AQI averaged across the eight monitoring stations within the Fifth Ring Road. The key explanatory variable is hourly average TCI in the central city area. Starting from a simple OLS in Column 1, we gradually add meteorological conditions (Column 2), date-specific characters (Column 3), time-fixed effects (Column 4) and lagged pollution variables (Column 5). Our benchmark specification with most control variables is listed in Column 5, in which R^2 is even larger than 0.94. However, the results are still similar to our findings in Figure 3 in terms of sign: there is a significantly negative relationship between air quality and traffic congestion even when a set of variables including meteorological conditions is controlled. We suspect reverse causality might be another potential source of endogeneity that will affect our causal effects identification. As mentioned above, travel behavior (either travel choice or travel mode) can also be affected by temporal air pollution level, which in turn changes the TCI level.

4.2 Performance of the Four and Nine Days

In Figure 4, we compare hourly variations of TCI and AQI between “four and nine” days and other weekdays. Figure 4 (a) shows traffic congestion is heavier on the four and nine days compared with other weekdays, indicating Beijing’s traffic conditions are significantly correlated (95% CI is not overlapped) with whether the number four is restricted. In principle, the TCI discrepancy between the four and nine days and other weekdays might only be observable during the hours affected by the driving restriction policy. However, Figure 4(a) clearly shows this discrepancy actually emerged early in the morning (starting at 6 a.m.) and continued late at night (until 10 p.m.), at least three hours longer than the official restricted time. Therefore, although some drivers may try to avoid heavy congestion at peak hours by leaving early and returning late, there should be more of them on dates when numbers four and nine are banned, given that the traffic is much worse on those days. While more vehicles on the road will naturally lead to higher vehicle emissions, the AQI difference might not be noticeable by comparing the four and nine days to other weekdays due to the cumulative and continuous characteristics of air pollutants as well as meteorological variations. Figure 4(b) shows there is no significant difference in hourly AQI variation (some have 95% CI overlapped) between the four and nine days and other weekdays. This is consistent with our general observations, because a four and nine day is only one day in any given week, with another weekday or a weekend before and after. Figure 4(b) further confirms the speculation that we might find an insignificant effect of the driving restriction program on air quality if we only rely on a reduced form that directly establishes the link between the four and nine days and AQI.[29] Therefore, we adopt a different estimation strategy from that used by Sun, Zheng and Wang (2014) and Zhong (2015) in that we use the four and nine days as an instrument for TCI through which to establish the link between TCI and AQI.

To further illustrate the characteristics of the four and nine days, we compare the difference in TCI, bus passenger ridership (BPV), subway passenger ridership (SPR),[30] and AQI between the four and nine days and other restricted (normal weekday) days and non-restricted days in Table 4. The first column indicates that congestion is much heavier on the four and nine days compared to other restriction days, as discussed above. Another finding is that, on the four and nine days, both bus and subway passenger ridership is generally significantly lower than on other restriction days, suggesting that, on the four and nine days, more people shift to private vehicles for public transport (see Columns 2 and 3).[31] Again, we lack any conclusive finding regarding AQI in comparing the four and nine days with other weekdays (see Column 4). This underscores that TCI is the only clear channel that links the four and nine days with AQI.

In sum, the significant difference in number of vehicles between the four and nine days and other weekdays demonstrates the validity of this exogenous variation and enables us to test the impact of traffic congestion on air quality. The variations in TCI on the four and nine days extend from restricted to unrestricted hours, which in turn enlarges the IV's shock to TCI and unintentionally rectifies the distribution of license plate numbers on the four and nine days.

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[29]Other specific air pollutants, i.e. $PM_{2.5}$, NO_2 ,and CO, show the same results as the AQI (see Graph A2).

[30]Summary statistics for daily volume of public transport passengers (both BPV and SPV) are listed in Table A1.

[31]During official holidays, people may make fewer trips, in which case both traffic flow and public transit usage would be reduced. However, on the four and nine days, more vehicles are allowed on the road than on other days, indicating that the public could choose to shift from public transport to private vehicle. Therefore, there might exist substitution effects between public transport commuting and private vehicle use, as described in Table 4.

5. Estimating Traffic-induced Air Pollution

5.1 2SLS Specification

To obtain consistent estimates, we use IV estimation to overcome endogeneity. As discussed previously, we apply a generalized 2SLS framework in the first stage to test whether traffic conditions are affected by the exogenous shock of the four and nine days; in the second stage, we estimate whether the traffic changes result in a greater concentration of air pollutants.

We first run the following first-stage regression, in which TCI is regressed as a function of both the IV and other relevant control variables:

$$TCI_{ymdh} = \alpha_0 + \alpha_1 IV_{ymd} + W_{ymdh}\delta + Z_{ymd}\omega + \tau Poll_{ymd,h\text{-}1} + \lambda_y + \mu_m + \eta_h + \varepsilon_{ymdh} \quad (3)$$

Here, we use the four and nine days (IV_{ymd}) as an instrument for TCI_{ymdh}. Subsequently, the second stage equation estimates the impact of traffic conditions on air quality, which is essentially induced by IV_{ymd}:

$$Poll_{ymdh} = \beta_0 + \beta_1 \widehat{TCI_{ymdh}} + W_{ymdh}\theta + Z_{ymd}\gamma + \tau Poll_{ymd,h\text{-}1} + \lambda_y + \mu_m + \eta_h + \nu_{ymdh} \quad (4)$$

We are mainly interested in the estimated coefficient β_1, which captures the direct effect of traffic conditions on air pollution. Because the variation in TCI_{ymdh} arises from superstitions about the number 4, it is arguably independent of other confounding factors (for example, W_{ymdh}, Z_{ymd}) and other temporal factors in Equation (3) that might affect ε_{ymdh}, which mitigates concerns about reverse causality.

5.2 Estimation Results

We use the generalized 2SLS framework to examine the links between TCI and AQI, with results presented in Table 5. We examined the impact of traffic conditions on air quality, using three different model specifications: a linear-linear model (Columns 1 and 2), log-linear model (Columns 3 and 4), and log-log model (Columns 5 and 6). The first-stage estimates of each specification are listed in Columns 1, 3, and 5; second-stage estimation results are listed in Columns 2, 4, and 6.

In the first stage, we use both TCI (Column 1) and log TCI (Columns 3 and 5) as dependent variables to estimate the influence of the four and nine days on traffic conditions, while controlling for meteorological conditions, temporal factors, and fixed effects using our benchmark specification (Column 5 of Table 3), including holiday dummies, holiday-makeup dummy, odd-even days, yearly fixed effect, monthly fixed effect, day of the week fixed effect, hourly fixed effect, and lagged pollution level. As expected, the coefficients of the four and nine days are all positive and highly significant in the first-stage estimations, suggesting that traffic conditions are much worse on the day when the tail numbers four and nine are restricted. Compared with other days, the traffic congestion index on four and nine days is increased by an average of 0.54-0.55 (Columns 1 and 3), which is 14% higher (Column 4) and significant at the 1% level. In addition, the first stage F statistic is higher than 25, and this high significance suggests the selected IV is a valid and reliable instrument.

In the second stage, we further examine the impact of traffic conditions on air quality induced by the four and nine days factor. In all three model specifications, the results show the estimated coefficients of TCI are positive and significant at the 1% level, suggesting traffic congestion has a significant influence on air quality. Specifically, a one-unit increase in TCI will result on average in an increase of 19 in AQI (Column 2), which is a 19.5% increase in AQI (Column 4). The elasticity estimation from the log-log model specification suggests that a 10% increase in TCI will lead to a 7.5% increase in AQI.

We then use a similar approach to analyze the average concentrations of $PM_{2.5}$, PM_{10}, CO, and NO_2 linked to traffic conditions. Following our approach for AQI, we also conduct the estimations using linear-linear model specification, linear-log model specification, and log-log model specification. The results are presented in Table 6. Note that we have also controlled for all other variables as our benchmark specification (Column 5 of Table 3). In all specifications, the results show that TCI has positive and significant influence on air pollutants. In the semi-log estimation, we find that a one-unit increase in TCI level will result in an average increase in $PM_{2.5}$ of 15.24%, PM_{10} of 20.48%, NO_2 of 17.33%, and 22.81% of CO. For the log-log specification, we find a 10% increase in traffic congestion level will result in an average increase in $PM_{2.5}$ of 5.59%, PM_{10} of 7.19%, NO_2 of 6.7%, and CO of 9.89%. Estimated elasticity between traffic and CO (log-log specification) is close to 1, indicating they have almost perfect elasticity. This is highly in line with the conclusions of previous scientific literature and indicates our model performs well. Scientific studies report that the primary source of CO in developing metropolises is vehicular emissions (Han and Naeher 2006). This is particularly true in Beijing (Wu et al. 2011).

5.3 Traffic-Induced Air Pollution

The direct explanation of the 2SLS estimation results relates to superstition-induced variations in air pollution in Beijing: The four and nine days result in a TCI increase of 0.54-0.55 (see Columns 1 and 3 in Table 5), which worsens AQI by an average of 10.53%-10.73%

according to our second-stage estimation (i.e., semi-elasticity is 19.51% in Column 4 of Table 5). Similarly, for the specific pollutants $PM_{2.5}$, PM_{10}, NO_2 and CO, 8.38%, 11.26%, 9.53%, and 12.54% are estimated to be caused by extra vehicles on the road; the first stage is the same as the AQI and the second stage semi-elasticity estimations are listed in Table 6.

To evaluate traffic-induced air pollution in Beijing, we combine our 2SLS results with observed TCI values (listed in Table 2) for further analysis. Note that the mean value of TCI in our research sample is 2.44 (Table 2). With this information, combined with the semi-elasticity estimates (see log-linear results listed in Table 6), we are able to calculate the contribution of traffic to air pollutants in Beijing by multiplying 2.44 by each of these semi-elasticity estimates The analysis suggests that traffic contributed 47.6% of the deteriorating air quality in Beijing. In particular, for levels of $PM_{2.5}$, PM_{10}, NO_2 and CO, 37.19%, 49.94%, 42.29% and 55.66% are estimated to have been caused by traffic.

5.4 Hourly Marginal Effects

To further detect how hourly air pollution concentration varies with traffic conditions, we apply our 2SLS regression for the 24 hourly sub-samples of TCI, AQI, and other specific air pollutants. For each of these 24 regressions, we use a log-linear model and benchmark specification (removing the hourly fixed effect). Figure 5 shows the relationship between hourly average TCI and its relative marginal contribution to air pollutants, using hour as the horizontal axis (0-23) and marginal TCI contributions at different levels as the left vertical axis. In Figure 5, the bar chart below in yellow is the histogram of the TCI mean value at different times, while the solid line and shaded parts above represent the estimated marginal contribution of hourly sub-samples and their respective 95% confidence intervals.

The results using hourly sub-samples also demonstrated that TCI exerts significant and positive influence over air pollutants across hours, as depicted in Figure 5 (a)-(d). However, the marginal effect of TCI on air pollutants varies substantially across hours, and a diminishing marginal effect was observed: the higher the level of TCI, the lower the marginal impacts on air pollutants.[32] As introduced in Section 3, the TCI measures overall traffic congestion of the network using real-time vehicle speed from floating cars weighted by traffic volume, but mainly based on vehicle speed. When the road is clear – for example, when the TCI is less than 2 – a one-unit TCI increase would allow for a large number of vehicles swarming into the road, resulting in a large concentration of vehicular emissions. However, as traffic congestion spreads and intensifies – for example, when the TCI is larger than 4 – adding only a few vehicles on the road would increase TCI by one unit, though resulting in a small amount of incremental vehicular emissions. In other words, Figure 5 (a)-(d) provides evidence that the level of traffic-induced air pollutants is more directly related to vehicle volume than speed. On average, the marginal effects of traffic on AQI at night (8 p.m. to 8 a.m.) are 2.47 times the marginal effects during the day (8 a.m. to 8 p.m.). For specific pollutants, the nighttime marginal effects for $PM_{2.5}$, PM_{10}, NO_2, and CO are estimated to be 2.86, 2.62, 3.74 and 2.86 times the daytime marginal effects.

5.5 Estimation of Traffic-induced Air Pollution by Congestion Level

Based on the cumulative nature of traffic congestion, estimating marginal effects across either hours or specific congestion levels cannot directly reveal the relationship between traffic congestion and air pollutant concentration. Moreover, the discrepancy of marginal effects between daytime and nighttime reveals evidence of a potentially non-linear relationship between TCI and air pollution. To address this issue, a common practice is to construct a quadratic (or even higher-order) form of TCI to capture the potentially non-linear effects. However, adding a squared TCI to the model would require another instrumental variable because now both TCI and squared TCI are endogenous variables. Unfortunately, we cannot match the number of endogenous variables even by adding another instrument using the squared value of the four and nine days instrument because our IV is a dummy variable. The squared value of a dummy is the same as itself and this would not add to our model.

[32] Because Beijing's driving restriction program is only enforced from 7 a.m. to 8 p.m., a potential argument about our hourly estimation is that the IV (four and nine days) may only affect the TCI that falls in this hourly range. Despite the restricted hours, Figure 5 (a) shows that the TCI discrepancy in traffic congestion between the four and nine days and other weekdays actually emerged as early in the morning as 6 a.m. and continued as late at night as 11 p.m., roughly four hours longer than the effective vehicle restriction time. In fact, the effective shock of hourly TCI induced by the IV has been enlarged, due either to people's non-compliance or compensating responses. Even if our hourly impacts discussion were only based on the effective vehicle restriction time, all of our basic findings discussed in Section 5.3 would still hold.

To address this defect, we take a different approach to evaluate the contributions of vehicle traffic to concentration of specific air pollutants as traffic congestion gradually worsens, as described by the following equations:

$$Poll_{ymdh} = \beta_0 + \beta_1 TCI_{ymdh} + W_{ymdh}\theta + Z_{ymd}\gamma + \tau Poll_{ymd,h\text{-}1} + \lambda_y + \mu_m + \eta_h + \varepsilon_{ymdh}$$
$$\forall TCI_{ymdh} \leq \sum_{i=2}^{19} 0.5 \times i \tag{5}$$

Similarly, we apply the 2SLS regression for each sub-sample of TCI as TCI increases by a level of 0.5. For each estimation, we multiply the estimated coefficient β_1 (marginal effect of TCI on air pollutants) by its relative mean value of TCI to obtain the contributions of vehicle traffic to air pollutants as traffic congestion escalates.[33]

In Figure 6, the solid line above depicts contributions of vehicle traffic to air pollution concentrations as TCI increased by a level of 0.5, and the shaded portions represent 95% confidence intervals. Graphic analysis clearly shows that there is a U-shaped relationship between TCI and its cumulative contribution to air pollution. Specifically, the contributions of vehicle traffic to AQI (Figure 6(a)), $PM_{2.5}$ (Figure 6 (b)) and NO_2 (Figure 6 (c)) stays stable or rises slowly when the TCI is smaller than 5.5. After that, the impacts rise at a substantial growth rate, indicating air pollution damage is becoming more severe at an increasing rate as traffic jams get worse, with the air damage, in other words, worsening faster than the traffic. Taking AQI as an example, vehicle traffic only contributes to 2.18% of the deterioration in air quality when TCI is 5, and 2.67% when TCI is 6; however, this contribution increases to 9.45% and 26.86% when TCI reaches 7 and 8. The contribution of vehicle traffic to CO also exhibits the same rule as other air pollutants (Figure 6 (d)) but the inflection point appears a little bit earlier, approximately when TCI equals 5. In summary, these findings confirm that worsening traffic conditions contribute heavily to air pollution, particularly after a definable inflection point.

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[33]For example, if we start from the subsample in which TCI is less than 2, we estimate the marginal effect of TCI on Log (AQI) using our 2SLS estimation to obtain the estimated coefficient of TCI (=0.0583). We then multiple the estimated coefficient (=0.0583) by the mean value of TCI (=1.2019) to get the contribution (=0.0700 or 7%) of vehicle traffic on Log (AQI) when TCI is less than 2. Next, we continue to evaluate the total traffic-induced air pollution when the TCI is less than 2.5, and then when the TCI is less than 3, continuing this process until the TCI is less than 9.5, which includes all TCI distributions.

The bar chart below, Figure 7, is the density distribution of TCI. As shown in the figure, even if the total congested time (TCI>5)[34]merely accounts for 10.5% of all hours, the increment of air pollution (AQI) generated is at a level estimated at 4.5 times that averaged during the 89.5% of time classified as "not congested" (TCI<=5). Similarly for other pollutants, $PM_{2.5}$, NO2, and CO, increments of traffic-induced air pollutants resulting during congested time average, respectively, 3.77, 6.01, and 5.3 times larger than that resulting during similar periods of non-congested time. The policy implication of this finding supports regional traffic diversion, especially when the TCI is larger than 5.5.

6. Additional Evidence and Further Discussion

6.1 Air Quality Data

Even though Tables 5 and 6 provide causal evidence linking traffic conditions with air quality in Beijing, a potential concern with the results is that officially reported air quality data might be deliberately manipulated, which would introduce non-classic measurement error (Chen et al. 2012; Ghamem and Zhang 2014). Because China defines a day with an AQI (or API before 2013) at or below 100 as a "blue sky" day, local authorities benefit from positive publicity. In the absence of independent verification mechanisms, the discontinuous incentive structure implicitly created might be associated with anomalies in AQI scores near that cut-off point (AQI=100) (Ghamem and Zhang 2014). We speculate that local governments may be less likely to report AQI numbers just above 100 when they are close to achieving "blue sky" days. Discontinuity around the cut-off (API=100) would suggest the count of blue sky days may have been subject to data manipulation (Chen et al. 2012).

A place to start data checking is by duplicating density analysis from existing literature and applying it to the air quality data in this paper. Figure A3 (a) to (h) shows AQI densities from eight state-controlled air quality monitoring stations located within Beijing's Fifth Ring Road, while Figure A3 (i) shows average city-wide AQI density. We highlight the potential cut-off point where AQI equals 100 to check whether a suspicious degree of discontinuity occurs around the cut-off. In contrast with previous studies, we fail to find any significant discontinuity around the cut-off point for any of the density graphs, indicating that the hypothesis about data

[34]Slight congestion is defined as TCI larger than 4. In order to keep in line with the turning point that appears when TCI falls by 5 to 5.5, we calculate the proportion of the time that TCI is larger than 5.

manipulation does not hold for our air quality data. There are two possible explanations for our divergence from some earlier studies. First, our study used AQI data from 2013 and 2014, while both studies by Chen et al (2012) and Ghamem and Zhang (2014) used air pollution index (API) data from before 2010. Since 2013, with the unprecedented attention paid by the central government to air quality, coupled with requirements that air pollutant records be reported on-line in real time, air quality monitoring data may have been significantly improved. Second, prior studies used daily API from local government-controlled monitoring stations, while we collected hourly AQI from state-controlled monitoring stations, which directly report their data to China's Ministry of Environmental Protection and have reported real-time air quality information on-line since 2013. Therefore, the possibility of intentional data manipulation has been limited.

An alternative way to test the credibility of air quality data is to compare the difference between state-controlled monitoring data and US Embassy monitoring station data[35]. We chose three state monitoring stations – the Agricultural Exhibition Hall (39.9716 E, 116.473 N), Dongsi (39.9522 E, 116.434 N) and the Olympic Sports Center (40.0031 E, 116.407 N) – with distances to the US Embassy[36] of 1.5 km, 5.5 km, and 6.6 km, respectively. The relevant $PM_{2.5}$ statistics from these monitoring stations are displayed in Table 7. As shown there, the average $PM_{2.5}$ provided by the US Embassy is higher than that of the national monitoring stations, in the range of 7.43-8.22 (Column 2 in Table 7). However, the difference between the two closer monitoring stations – Agricultural Exhibition Hall and Dongsi – and the US Embassy is not statistically significant once we control for station-level effect. In Column 4 of Table 7, in order to conduct a robustness check, we used our 2SLS method to estimate the links between traffic and air pollution based on the $PM_{2.5}$ concentration provided by individual stations rather than the city average level used previously. The results show the estimated semi-elasticity of traffic-induced $PM_{2.5}$ with AQI is 0.1932 using US Embassy $PM_{2.5}$ data. The estimated coefficients using the $PM_{2.5}$ data from the closer monitoring stations, the Agricultural Exhibition Hall and Dongsi, are 0.2 and 0.1871, respectively. These estimates are quite close, with the difference less than 0.01. However, with increased distance (see the Olympic Sports Center station in Column 4), the estimated difference also increased, in line with our expectation.

[35]See http://www.stateair.net/web/post/1/1.html.

[36]See http://www3.epa.gov/pm/implement.html.

6.2 Alternative Traffic Measurement

Another concern is that our results might be highly dependent on the quality of traffic measurement, given that we rely on the TCI, which is a secondary aggregated index, rather than on directly observable information. Considering this issue, we conducted a further robustness check by collecting daily records of vehicle speed within the Fifth Ring Road during the morning peak (7 a.m. to 9 a.m.) and evening peak (5 p.m. to 7 p.m.) driving times during the study period. Data source and summary statistics are in Table A2.

In Columns (1) to (4) of Table 8, we use TCI and vehicle speed as the traffic measurement to estimate the effect of traffic conditions on AQI during the morning peak period (MP) and evening peak (EP) period. Following the previously discussed 2SLS method, we used daily average records, controlling for district fixed effects in the model specification. The results show that, during the morning peak, estimated semi-elasticity is 0.08 (Column (1)) using TCI measurement while it is -0.04 (Column (2)) using vehicle speed measurement. Similarly, during the evening peak, the estimated semi-elasticity is 0.06 (Column (1)) using TCI measurement, while it is -0.03 (Column (2)) using vehicle speed measurement. Lower vehicle speed indicates a higher level of traffic congestion, leading to a higher TCI value, in line with our expectations. However, it is difficult to compare the magnitude of estimates using the two different measures. The estimated semi-elasticity using TCI is around double that using vehicle speed. These results also hold when we estimate the impact specifically on $PM_{2.5}$ (in Columns (5) to (8) of Table 8), NO2, and CO (Table A3). To better understand the magnitude of these estimates and their implications, we further explore the links between TCI and vehicle speed.

Figure 7 examines the relationship between TCI and vehicle speed during morning and evening peak hours, using local polynomial smooth plots with 95% confidence intervals. The diamond blue line and square red line represent the plot lines derived from the MP and EP, respectively. These two lines, based on different time periods, are highly consistent, reinforcing that we do capture the nature of the relationship between TCI and vehicle speed. The figure shows there is a non-linear relationship between TCI and vehicle speed with two inflection points.[37]The average vehicle speed at MP is 30.95 km/hour and at EP is 26.71 km/hour,

[37]Local polynomial smooth plots cannot directly obtain accurate values of the thresholds because smooth plots depend on the selection of smooth piecewise polynomial functions. However, we can easily detect the credible range of the inflection points: the first occurs when TCI falls in the range of values between 1.5 and 2 (vehicle speed between 34 and 36 km/hour) and the second occurs when TCI falls in the range of values between 8.5 and 9 (vehicle speed between 16 and 18 km/hour).

highlighted by the two dashed lines. We then use the average value of vehicle speed to discuss estimated coefficients in Table 8. For instance, when the MP TCI increases from 3 to 4, the corresponding MP vehicle speed (Figure 7) decreases from 30.82 km/hour to 28.69 km/hour. Together with the estimated marginal effects in Column 2 of Table 8, we estimate that AQI will increase by 8.35% (28.69-30.82)*(-0.0392)), which is quite close to the estimated TCI semi-elasticity (8.01%) in Column 1 of Table 8. We further find that, if we use TCI and vehicle speed to measure traffic conditions, the absolute and relative differences, respectively, in estimated traffic-induced air pollution during the morning peak are only 0.24% and 4.06% (= (8.35-8.01)/8.35*100%). Similarly, when the EP TCI increases from four to five, the corresponding EP vehicle speed (Figure 7) decreases from 27.94 km/hour to 26.01 km/hour. If we use TCI and vehicle speed to measure traffic conditions, the relative difference in estimated traffic-induced air pollution during the morning peak is only 5.94%.[38]

In sum, our estimates are quite robust under different conditions, i.e., when we use alternative air pollution data sources and traffic congestion measurements.

6.3 Local Effects and Marginal Effects

The main advantage of using IV is that it makes explicit the source of TCI variation used to evaluate traffic-induced air pollution. However, a common drawback of IV estimation is that it is only based on "compliers" affected by the instrument (Imbens and Angrist 1994). Specifically, not every vehicle in our sample responds to the instrument, and therefore our IV results are only representative of those extra vehicles driven on roads on the weekday when the tail number four is restricted from driving. One might posit that, if vehicular emissions are not constant between tail number four vehicles and other vehicles, our 2SLS framework would only estimate the local average effects on air quality induced by the sub-sample of vehicles allowed to drive on the four and nine days. If that were the case, estimated impacts of traffic control policies on Beijing's air quality in existing studies might not be as large as our policy evaluations suggest when using our IV estimator. To address this concern empirically, we proceed to compare our assessment of policy interventions with representative economic studies that directly examine total average

[38]The same analysis was conducted using other pollutants: $PM_{2.5}$, NO_2, and CO. The calculated absolute difference in the effect of TCI and vehicle speed on air pollution is very small. The calculated relative difference between these two is also less than 10.86%.

treatment effects of different traffic control policies in Beijing using alternative empirical strategies.

Table 9 presents estimated results of Beijing's traffic control policies in different periods: the odd-even restriction during APEC and the one-day-per-week restriction. Table 9 (Column 1) reports the impact of the odd-even restriction during APEC on TCI: the odd-even restriction reduced TCI remarkably, by 1.1, within the Fifth Ring Road. Using our benchmark estimation with semi-elasticity 0.1951 (Column 4 of Table 5), we then calculated a reduction of AQI of 21.53% (Column 2) due to the APEC conference odd-even restriction. As a comparison, Column 3 of Table 9 presented estimates by Viard and Fu (2015) that used the RDD to explore the impact of the odd-even restriction on Beijing's air quality; they found that AQI was reduced in a range of 19.28% to 21.74%. Similarly, our empirical strategy found that the one-day-per-week restriction reduced TCI by 0.45 and mitigated AQI by 8.87%. This is also highly in line with the finding by Viard and Fu (2015), who estimated the air quality impact between 7.93% and 14.81%.

Our results show that traffic-induced air pollution on the days when the tail number four was restricted increased by 10.61% (Column 2, Table 9). The average TCI increased by 0.54 (the first column of Table 9) on that day because the restriction affected fewer vehicles. However, using a reduced form which directly examined the impacts of the four and nine days on urban air pollutants, neither Sun et al. (2014) nor Zhong (2015) found that the four and nine days exerted any significant influence on AQI in Beijing. For comparison, we followed their empirical strategy and used reduced form to directly explore the impact of the odd-even restriction, one-day-per-week restriction and four and nine days on air quality. We found the directly observed AQI significantly decreased by 54.54% during the period of odd-even restriction; however, no significant effect was detected for either the one-day-per-week restriction or the four and nine days (Column 4 in Table 9). Again, this reflects that, in a typical IV setting, the four and nine days exert indirect influence on AQI only through the channel of traffic conditions.

Despite the superior performance of our IV estimator in policy evaluations, the core issue of IV's drawback is whether local effects of the IV estimator are close to the real marginal effect. Given that the one-day-per-week driving restriction is enforced from 7 a.m. to 8 p.m. on weekdays, the four and nine days could still induce a widespread shock on vehicles across all tail numbers due to non-compliance or compensating responses such as inter-temporal substitution of driving (Viard and Fu 2015). This is particularly true if we detect a significant difference in TCI between the four and nine days and other weekdays even during the unrestricted hours of the day (i.e., before 7 a.m. and after 8 p.m.). However, as revealed by part (a) of Figure 4, the significant difference in TCI between the four and nine days and other weekdays lasts from 6 a.m. to 10 p.m., far beyond officially regulated driving restriction hours. Such non-compliance and compensating responses therefore not only significantly extend the IV's shock on traffic conditions in the first stage, but also, to a certain extent, rectify the distribution of license plate numbers on the four and nine days. This can explain why our policy evaluations are consistent with existing studies enumerated in Table 9.

6.4 Systematic Difference of Vehicles with Plates Ending in Four

The empirical evidence presented so far uses the mechanism of reverse reasoning in which our IV estimator has been *a priori* treated as the real marginal effect for traffic policy evaluation. In other words, the superior performance of the IV estimator in policy evaluations provides empirical support for the "pre-assumption" that our IV estimator is close to the real marginal effect. One potential objection to our analysis of the effect of congestion on pollution when using IV is that cars with license plates ending in four and nine are excluded from the sample, and these may differ in a systematic way from the rest of the sample, biasing the results. We have three responses.

First, we believe that whether one believes in the superstition or not should be more shaped by specific cultural background than by seemingly irrelevant vehicle emissions from one's car. In Chinese culture, people tend to avoid the number four regardless of whether they are poor or rich. This suggests that number four will be avoided as a tail number for all types of vehicles, regardless of whether they are luxury or economy automobiles, high-emission or low-emission vehicles.

Second, even if there are systematic differences between groups of vehicles based on their license numbers, the four and nine exclusion is not total. There are vehicles that violate the rules, and some four and nine cars are on the road during restricted times. Meanwhile, the exclusion is in effect only during certain hours; times before 7 a.m. and after 8 p.m. are unrestricted, and four and nine vehicles may be used.

Finally, but more importantly, there is no basis for assuming any systematic difference in vehicles ending in nine. For vehicles ending in four, we could suspect potential systematic differences – for instance, as their owners are unusual in ignoring a common superstition, they may tend to be "non-conformists" and have systematically different cars as well. However, these vehicles with plates ending in four constitute only 1.5 percent of the total (see Table 1), so their exclusion could not have a major effect on the sample. In fact, for a period, Beijing's municipal government even removed number four from the last digit of randomly generated plate numbers (Sun et al. 2014; Viard and Fu 2015). As a result, the sample distribution of vehicles with other tail numbers will approximate the population distribution of all vehicles if four is not in the last digit list of plate numbers.

In sum, if vehicle emissions are consistent across license plate numbers, the sample results are not changed by the exclusion of “four and nine” cars; even if there are some differences between the set of tail number four vehicles and other vehicles, these are likely to be minor and our IV estimates can capture most of the marginal effect of the vehicles on local air quality.

7. Conclusion

Severe traffic congestion and poor air quality are two of the most pressing problems in developing metropolises from both health and economic perspectives. Traffic-induced air pollution is a crucial economic problem and the effect of potential policy interventions is an important area for economic analysis. In this paper, we used rich hourly data records from 2013-2014 to investigate the effects of traffic on air pollution in Beijing. Our research objective was to answer two questions: First, what exactly is the traffic-induced contribution to air pollution in urban areas? Second, how does air quality vary with the severity of traffic congestion over time?

These questions were examined in relation to Beijing’s one-day-per-week driving restriction. We showed that the widespread Chinese superstition avoiding the unlucky number four unintentionally releases extra vehicles onto the roads on days when vehicles with license tail number four are prohibited from driving. We found that the days when plates ending in four are restricted had 14% more traffic congestion than other weekdays.

Using the variation in traffic conditions induced by “four and nine” days, the 2SLS estimation found that traffic has contributed 47.6% of the deterioration in Beijing’s air quality. For specific pollutants, our estimates are that, for $PM_{2.5}$, PM_{10}, NO_2 and CO, respectively 37.19%, 49.94%, 42.29% and 55.66% of these pollutants are caused by vehicle traffic. Our estimates differ from those of prior studies that used a reduced form to examine the difference in air pollution between the four and nine days and other weekdays. This suggests that focusing on traffic as the only impact channel of IV is important to addressing endogeneity, e.g., the potential of confounding traffic’s contribution to air pollution with contributions from other causes.

By looping our 2SLS framework across sub-samples divided by small fixed TCI intervals, we discovered the non-linear relationship between traffic congestion and air pollution without extra instrumental variables. Our graphic analysis shows a U-shaped relationship between traffic congestion and its cumulative contribution to air pollution. The inflection point of the U-shaped relationship occurs when TCI falls in the range of 5 to 5.5. Worsening traffic conditions after that point appear to disproportionately intensify the contribution of traffic congestion to air pollution. While total hours in a state of traffic congestion account for 10.50% of all hours, incremental air pollution induced by congested hours (TCI>5) is 4.49 times that of the contribution of traffic during the "no congestion" time (TCI<=5). The apparent policy implication favors a regional traffic diversion strategy, at least when the TCI exceeds 5.5.

We separately simulate the total impacts of the odd-even restriction and the one-day-per-week driving restriction on air quality using our estimated coefficients. We show that our policy simulation results are in line with those of earlier studies that assess policy impacts through various empirical strategies. The superior performance of our IV estimator in policy evaluations underscores that our estimated local effects are close to real marginal effects. In fact, our IV induces an arguably widespread shock on vehicles across all tail numbers due to non-compliance or compensating responses such as inter-temporal substitution of driving.

In recent months, Beijing has taken a series of emergency measures, including taking cars off the road to reduce air pollution on days classified as a red alert air pollution level. Meanwhile, the municipal government is considering introduction of a stricter odd-even driving restriction program for the entire winter, when coal-fired heating causes smog that causes severe deterioration in air quality. This research shows that efforts to keep the congestion index from rising above the "inflection point" (of 5 to 5.5) will have disproportionate effects in alleviating pollution. The research demonstrates clearly that congestion above that level has very disproportionate effects in worsening air pollution – after that point, pollution gets worse faster than congestion does – so pollution benefits from relieving congestion above that level will also be disproportionate. Our results can therefore provide a more rigorous basis for policy design of more effectively targeted air pollution abatement strategies, considering the dynamic relationship between traffic congestion and air pollution that varies over time and congestion level.

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Tables and Figures

Table 1. Distribution of Automobile License Plate Numbers

Tail Number	2013 (Percent)	2014 (Percent)	*Definition of* the four and nine days
1	9.93	9.80	
2	9.86	9.84	
3	9.57	9.67	
4	***1.71***	***1.51***	
5	10.74	10.69	
6	12.26	12.37	
7	10.41	10.39	
8	12.76	12.88	
9	12.23	12.34	
0	10.53	10.51	
1 & 6	22.19	22.17	0
2 & 7	20.27	20.23	0
3 & 8	22.33	22.55	0
4 & 9	***13.94***	***13.85***	**1**
5 & 0	21.27	21.20	0

Data source: Beijing Traffic Management Bureau, 2013-2014.

Notes: The driving restriction policy in Beijing applies to all private cars on one weekday per week from 7 a.m. to 8 p.m. The tail numbers of license plates are put into five groups: one and six, two and seven, three and eight, four and nine, and five and zero. Each pair is assigned to a certain weekday (from Monday to Friday) for the driving restriction. The assignment of these number pairs to weekdays has been rotated every 13 weeks since 2010. For example, a car with a plate ending in five might be prohibited from driving on Monday in May but rotated to Tuesday in June.

Table 2. Summary Statistics

Variable	Def. (Unit)	Mean	SD	Min	Max	N
Air Pollutant						
AQI	Hourly Index	122.4	86.95	6	500	16587
$PM_{2.5}$	Hourly record (µg/m3)	89.08	80.13	3	584.2	16584
$PM_{2.5}$ (US Emb.)	Hourly record (µg/m3)	99.73	95.85	2	886	17339
PM_{10}	Hourly record (µg/m3)	123.2	91.77	5	1000	15866
NO_2	Hourly record (µg/m3)	62.19	33.72	3.667	235.8	16498
CO	Hourly record (mg/m^3)	1.432	1.178	0.133	9.213	16413
Traffic Congestion						
TCI	Hourly Index (0-10)	2.442	1.779	0.613	9.444	16631
Meteorological Condition						
Temperature	Hourly average (Celsius)	13.13	11.77	-16	41	17520
Relative humidity	Hourly average (%)	52.84	25.49	3	109.5	17520
Sea-level pressure	Hourly average (hPa)	1016	10.26	991.2	1046	17520
DewPT	Hourly average (Celsius)	1.719	14.25	-40	26.90	17520
Wind speed	Hourly extreme (m/s)	2.817	2.075	0	17.50	17520
Wind direction	Index (1-16)	8.477	4.552	1	16	17520
Date Variable						
The Four and Nine days	Dummy (0, 1)	0.126	0.332	0	1	730
Day of the week	Index (1-7)	3.996	1.999	1	7	730
Holiday	Dummy (0, 1)	0.085	0.279	0	1	730
Holiday-makeup	Dummy (0, 1)	0.023	0.151	0	1	730
Odd-even day	Dummy (0, 1)	0.014	0.116	0	1	730

Data sources: The measurements of air pollutants were obtained from the China National Environmental Monitoring Centre, 2013-2014 (see http://www.cnemc.cn/ and http://106.37.208.233:20035/); hourly meteorological conditions were downloaded from the ISD-Lite data set published by the National Oceanic And Atmospheric Administration (NOAA) (see https://www.ncdc.noaa.gov/isd/data-access).

Notes: Table provides air pollutant records from 4 p.m., January 18, 2013 to 7 a.m., December 25, 2014. In the raw hourly TCI records, 1.8% original records are missing on a random basis. Air pollutants consist of hourly average concentration of AQI, $PM_{2.5}$, PM_{10}, CO, and NO, calculated by the eight national monitoring stations located within the Fifth Ring Road of Beijing. $PM_{2.5}$ (US Emb.) represents the hourly $PM_{2.5}$ record obtained from the US Embassy monitoring station (39.9608E, 116.474N), which is a different source of $PM_{2.5}$ monitoring within the Fourth Ring Road of Beijing. Wind direction is an index denoted by 1 to 16, representing 16 wind directional quadrants. All meteorological variables are derived from hourly records, except for sea-level pressure, which is recorded every two hours. Holiday-makeup represents weekends when people go to work to make up for paid days before or after holidays. Day of the week listed in this table is an index representing Monday (=1) to Sunday (=7). However, both wind direction and the “day of the week” indexes will be transformed into dummies in our further regression analysis.

Table 3. OLS Regression: Biased Estimates Due to Either Omitted Variables or Reverse Causality

	(1) Ln(AQI)	(2) Ln(AQI)	(3) Ln(AQI)	(4) Ln(AQI)	(5) Ln(AQI)
TCI	-0.0254***	-0.0249***	-0.0282***	-0.0187**	-0.0166**
	(-3.48)	(-3.95)	(-3.73)	(-2.61)	(-2.51)
Temperature		-0.0152***	-0.0155***	0.0262***	0.0229***
		(-5.32)	(-5.27)	(7.24)	(6.00)
Sea-level pressure		-0.0149***	-0.0150***	-0.0118***	-0.0109***
		(-23.56)	(-24.40)	(-16.64)	(-14.63)
Relative humidity		0.0041***	0.0041***	0.0064***	0.0057***
		(3.29)	(3.20)	(5.07)	(4.41)
DewPT		-0.0015	-0.0015	0.0198***	0.0183***
		(-0.47)	(-0.48)	(7.78)	(7.97)
Holiday			-0.0259***	-0.0814***	-0.0707***
			(-3.21)	(-8.24)	(-6.94)
Holiday-makeup			0.0394	-0.0015	0.0106
			(1.15)	(-0.05)	(0.37)
Odd-even days			-0.2880***	-0.3429***	-0.3166***
			(-7.34)	(-14.47)	(-11.95)
Lag. Ln(AQI)					0.0847***
					(3.12)
Wind (Spd*16 Dir-dummies)	N	Y	Y	Y	Y
Day of the week *FE*	N	N	Y	Y	Y
Year *FE*	N	N	N	Y	Y
Month *FE*	N	N	N	Y	Y
Hour *FE*	N	N	N	Y	Y
_cons	4.6194***	20.1878***	20.1530***	17.2532***	15.8990***
	(187.77)	(35.08)	(35.98)	(22.03)	(18.04)
N	15706	15706	15706	15706	14929
R^2	0.004	0.223	0.232	0.352	0.947

Notes: We control wind-specific impacts (i.e., Wind (Spd*16 Dir-dummies) in this table) by including 16 wind directional quadrants and interact these with 16 wind speeds. Standard errors are adjusted by clustering by the hour.*t*-statistics in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 4. Characteristics of the Four and Nine Days

Pairwise	(1) TCI-diff.	(2) BPV-diff.	(3) SPV-diff.	(4) AQI-diff.
4&9 days vs odd-even days	1.5128***	-1.5842***	-0.8011***	44.7715***
	(8.25)	(-13.23)	(-7.27)	(4.87)
4&9 days vs 1&6 days	0.5740***	-0.1771***	-0.0574*	-0.6327
	(10.61)	(-5.15)	(-1.82)	(-0.24)
4&9 days vs 2&7 days	0.4271***	-0.2234***	-0.0783**	-6.7598**
	(7.94)	(-6.53)	(-2.49)	(-2.56)
4&9 days vs 3&8 days	0.5260***	-0.1101***	-0.0303	-1.9161
	(9.79)	(-3.23)	(-0.97)	(-0.73)
4&9 days vs 5&0 days	0.5865***	-0.1694***	-0.0453	6.0816**
	(10.89)	(-4.95)	(-1.44)	(2.29)
4&9 days vs Other-restriction days	0.5388***	-0.1845***	-0.0605***	-0.3551
	(11.90)	(-9.08)	(-2.73)	(-0.17)
4&9 days vs Non-restriction days	0.9010***	2.0216***	2.2997***	-0.8822
	(19.96)	(75.72)	(87.48)	(-0.40)

Data sources: The daily volume of public transport passengers is provided by the Beijing Traffic Management Bureau 2013-2014.

Notes: This table compares the differences in Traffic Congestion Index (TCI in Column 1), Bus Passenger Volume (BPV in Column 2), Subway Passenger Volume (SPV in Column 3) and Air Quality Index (AQI in Column 4) between four and nine days and other weekdays. It also compares these differences between the four and nine days and other-restriction days as well as non-restriction days. Summary statistics for the daily volume of public transport passengers (i.e., BPV and SPV) from 2013 and 2014 are listed in Table A1. *t*-statistics in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 5. 2SLS Estimation for AQI: Level, Semi-Elasticities and Elasticities

	(1)	(2)	(3)	(4)	(5)	(6)
	Linear-Linear		Log-Linear		Log-Log	
	1st stage	*2nd stage*	*1st stage*	*2nd stage*	*1st stage*	*2nd stage*
	TCI	AQI	TCI	Ln(AQI)	Ln(TCI)	Ln(AQI)
TCI		18.7829***		0.1951***		
		(3.51)		(3.26)		
Ln(TCI)						0.7512***
						(3.64)
Four and Nine days	0.5437***		0.5457***		0.1406***	
	(5.03)		(5.04)		(5.83)	
Temperature	0.0212***	2.6249***	0.0214***	0.0186***	0.0072***	0.0176***
	(3.64)	(8.34)	(3.64)	(5.32)	(3.92)	(4.77)
Sea-level pressure	0.0068***	-0.7644***	0.0063***	-0.0123***	0.0022***	-0.0128***
	(4.41)	(-8.42)	(4.25)	(-15.96)	(5.05)	(-16.83)
Relative humidity	0.0056***	0.6795***	0.0057***	0.0045***	0.0020***	0.0042***
	(3.28)	(6.00)	(3.25)	(3.57)	(3.89)	(3.12)
DewpT	-0.0137***	1.2884***	-0.0128**	0.0216***	-0.0044***	0.0224***
	(-2.95)	(4.52)	(-2.77)	(7.45)	(-3.28)	(7.01)
Holiday	-0.8251***	5.1639	-0.8226***	0.1166***	-0.3047***	0.1846***
	(-4.02)	(1.52)	(-4.01)	(4.39)	(-4.71)	(3.87)
Holiday-makeup	0.7691**	-20.7937***	0.7737**	-0.1481**	0.1862**	-0.1370
	(2.60)	(-2.98)	(2.61)	(-2.13)	(2.20)	(-1.64)
Odd-even days	-0.9758***	-14.9158***	-0.9800***	-0.1057**	-0.3735***	-0.0180
	(-5.13)	(-4.31)	(-5.09)	(-2.78)	(-7.82)	(-0.32)
Lag. AQI	-0.0005***	0.2595***				
	(-4.40)	(7.00)				
Lag. Ln(AQI)			-0.0793***	0.0922***	-0.0190***	0.0860***
			(-5.20)	(3.33)	(-4.47)	(3.06)
Wind (Spd*Dir)	Y	Y	Y	Y	Y	Y
Year *FE*	Y	Y	Y	Y	Y	Y
Month *FE*	Y	Y	Y	Y	Y	Y
Day of the week *FE*	Y	Y	Y	Y	Y	Y
Hour *FE*	Y	Y	Y	Y	Y	Y
1st stage *F-stat.*	25.40		25.45		34.31	
N	14929	14929	14929	14929	14929	14929
R^2	0.663	0.958	0.664	0.947	0.768	0.947

Notes: Standard errors are adjusted for by clustering by the hour. *t*-statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6. Impacts of TCI on Air Pollutants

	(1)	(2)	(3)	(4)	(5)
Linear-Linear	AQI	$PM_{2.5}$	PM_{10}	NO_2	CO
TCI	18.7829***	14.8172***	28.7321***	9.0022***	0.3746***
	(3.51)	(3.33)	(3.67)	(4.25)	(3.77)
N	14929	14926	14094	14821	14782
Log-Linear	Ln(AQI)	Ln($PM_{2.5}$)	Ln(PM_{10})	Ln(NO_2)	Ln(CO)
TCI	0.1951***	0.1524**	0.2048***	0.1733***	0.2281***
	(3.26)	(2.54)	(2.94)	(3.73)	(4.08)
N	14929	14926	14094	14821	14782
Log-Log	Ln(AQI)	Ln($PM_{2.5}$)	Ln(PM_{10})	Ln(NO_2)	Ln(CO)
Ln(TCI)	0.7512***	0.5587**	0.7190***	0.6704***	0.9890***
	(3.64)	(2.58)	(2.98)	(4.33)	(4.80)
N	14929	14926	14094	14821	14782

Notes: All regressions use the four and nine days to overcome the endogeneity of the TCI variable, while controlling for other temporal factors and removing fixed effects, strictly in line with Table 5. Coefficients of other control variables have expected signs and statistical significance. For brevity, they are not reported here. Standard errors are adjusted for by clustering by the hour. *t*-statistics in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 7. Monitoring Stations near the US Embassy

Monitoring Stations (Location) [Distance to US Embassy]	(1) Mean (STD)	(2) Unconditional Diff.	(3) Conditional Diff.	(4) Traffic-induced $PM_{2.5}$
US Embassy	98.05			0.1932**
(39.9608E, 116.474N)	(92.14)			(2.06)
	[16960]			[15812]
Agricultural Exhibition Hall	89.00	7.7759***	0.0961	0.2000**
(39.9716E, 116.473N)	(84.83)	(30.14)	(0.39)	(2.32)
[1.5 km]	[15757]	[15638]	[15638]	[14027]
Dongsi	89.29	8.2206***	0.0338	0.1871**
(39.9522E, 116.434N)	(84.06)	(30.51)	(0.13)	(2.36)
[5.5 km]	[16073]	[15946]	[15946]	[14140]
Olympic Sports Center	85.44	7.4253***	0.6961***	0.2452***
(40.0031E, 116.407N)	(77.18)	(28.25)	(2.75)	(3.12)
[6.6 km]	[14160]	[14039]	[14039]	[12822]
City average	89.08	8.6872***	0.6212***	0.1524**
	(80.13)	(32.98)	(2.53)	(2.54)
	[16584]	[16048]	[16048]	[14926]

Notes: Column 2 reports raw (unconditional) differences in means of $PM_{2.5}$ relative to the records from the US Embassy station, while Column 3 reports conditional differences after removing meteorological conditions, date characteristics and time-fixed effects. Column 4 reports the 2SLS results, strictly in line with our benchmark framework (Table 5) but using the $PM_{2.5}$ record monitored by specific monitoring stations instead of the city average concentration. For comparison, the last three rows duplicate baseline results at the city level. *t*- statistics are listed in parentheses; square brackets report the sample size. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 8. Daily Records with Regional Fixed Effects

	(1) Ln(AQI)	(2) Ln(AQI)	(3) Ln(AQI)	(4) Ln(AQI)	(5) Ln($PM_{2.5}$)	(6) Ln($PM_{2.5}$)	(7) Ln($PM_{2.5}$)	(8) Ln($PM_{2.5}$)
TCI(MP)	0.0801***				0.0691**			
	(2.86)				(2.14)			
Speed(MP)		-0.0392***				-0.0338**		
		(-2.88)				(-2.14)		
TCI(EP)			0.0595***				0.0512**	
			(2.96)				(2.19)	
Speed(EP)				-0.0291***				-0.0251**
				(-2.98)				(-2.19)
Date Controls	Y	Y	Y	Y	Y	Y	Y	Y
Meteorological Conditions	Y	Y	Y	Y	Y	Y	Y	Y
Year *FE*	Y	Y	Y	Y	Y	Y	Y	Y
Month *FE*	Y	Y	Y	Y	Y	Y	Y	Y
District *FE*	Y	Y	Y	Y	Y	Y	Y	Y
N	4156	4156	4139	4139	4147	4147	4130	4130
R^2	0.522	0.516	0.540	0.544	0.620	0.615	0.628	0.630

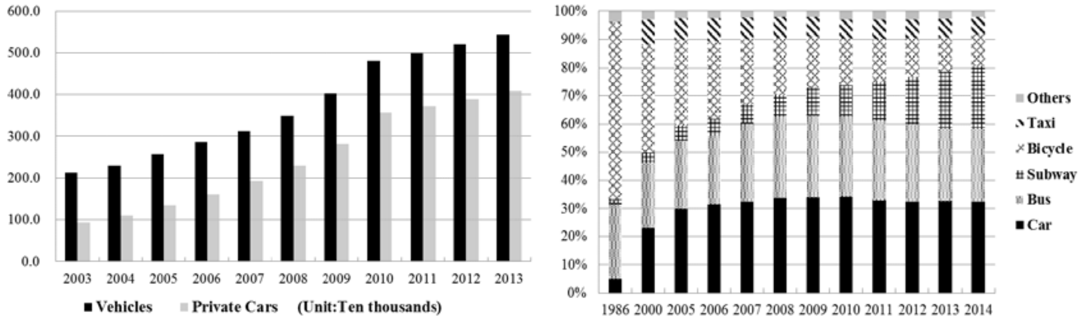
Notes: Meteorological conditions in this table denote all of the meteorological variables in line with our benchmark framework (Table 5) but use daily average values. Coefficients of other control variables have expected signs and statistical significance. For brevity, they are not reported here. Standard errors are robust to heteroscedasticity. *t* statistics in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 9. Results Comparison

Traffic Control Policies	(1) Changes in TCI	(2) Traffic-induced AQI (%)	(3) Economic Study Comparison (%)	(4) Reduced-form Regression
Odd-Even	-1.1034***	-21.53	[-19.28, -21.74]	-0.5454***
	(-9.56)		Viard and Fu (2015)	(-3.41)
One -Day-Per-Week	-0.4501***	-8.78	[-7.93, -14.81]	-0.0526
	(-15.38)		Viard and Fu (2015)	(-0.62)
The Four and Nine Days	0.5437***	10.61	Insig.	0.0473
	(5.03)		Sun et al. (2014); Zhong (2015)	(0.75)

Notes: Column 1 compares the differences in TCI between specific traffic-control days (i.e., odd-even days, one-day-per-week days and the four and nine days) and other days, respectively. Column 2 reflects changes in traffic-induced AQI by multiplying the TCI variation by our IV estimator (i.e., the semi-elasticity 0.1951 in Column 4 of Table 5). Column 4 reports the reduced-form estimates that directly explore the impact on air quality of the odd-even restriction, the one-day-per-week restriction and the four and nine days, respectively. *t*- statistics in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

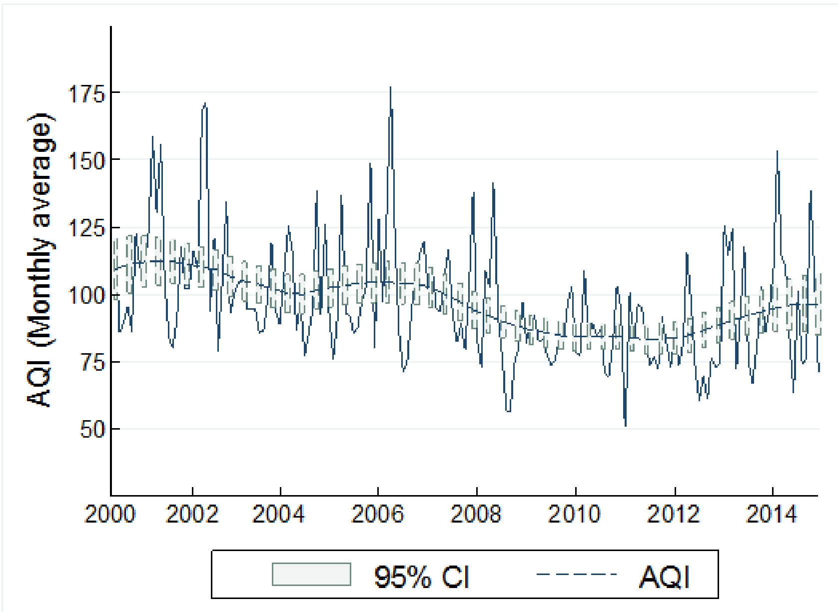
Figure 1. Vehicle Growth and Travel Modes in Beijing



(a) Vehicle growth in Beijing (b) Changes in share of travel modes

Data source: Beijing Traffic Management Bureau

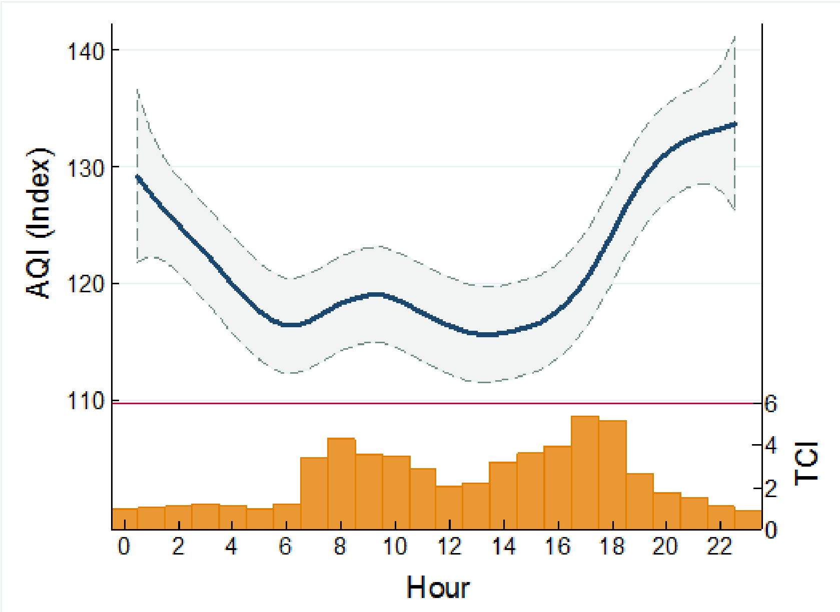
Figure 2. Air Quality in Beijing: 2000-2014



Data source: Ministry of Environmental Protection of China (http://datacenter.mep.gov.cn/)

Notes: The Air Quality Index (AQI), introduced in Beijing in 2013, is an index that consists of six major air pollutants. Before 2013, air quality was measured by the Air Pollution Index (API), which consisted of only three major air pollutants, including SO_2, NO_X, and Total Suspended Particulates (TSP). To examine the uniform time trend of air quality from 2000 to 2014, we specifically changed to the new AQI measure in 2013 and 2014 (for the calculation method, see http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/jcgfffbz/201203/t20120302_224166.htm), but we still denote it as AQI in the graph legends above.

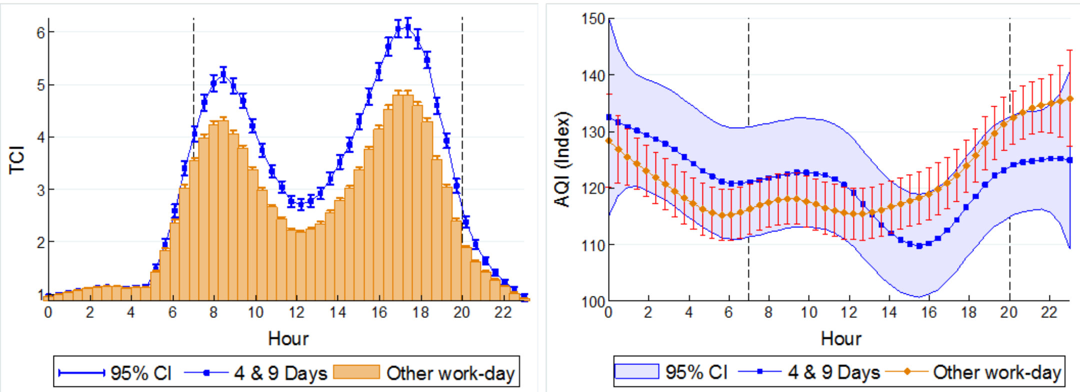
Figure 3. Diurnal Pattern of AQI and TCI in Beijing: Negative Correlation between AQI and TCI



Data source: Hourly records of TCI obtained from Beijing Transportation Research Center. Real-time AQI is reported by the Ministry of Environmental Protection of China (http://datacenter.mep.gov.cn/).

Notes: The graph at the top of the frame displays the hourly AQI trend during our study period (i.e., 2013-2014). The curve with the solid line represents the mean values of AQI within each hour interval, while the 95% confidence band is added as a gray area. The histogram at the bottom of the frame displays hourly average TCI among all observations in our dataset.

Figure 4. The 24-hour Pattern of TCI and AQI on Four and Nine Days and Other Weekdays

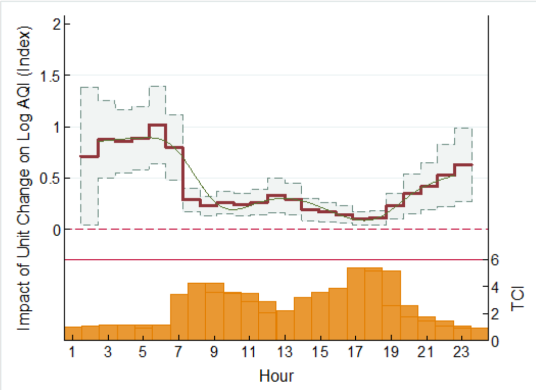


(a) Hourly Distribution of TCI(b) Hourly Distribution of AQI

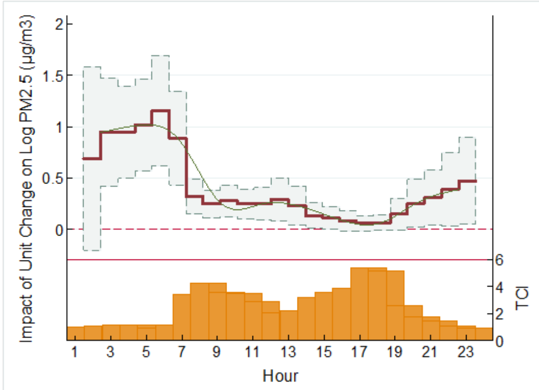
Data source: Hourly records of TCI obtained from the Beijing Transportation Research Center. Real-time AQI is reported by the Ministry of Environmental Protection of China (http://datacenter.mep.gov.cn/).

Notes: Figure compares the hourly variation of TCI and AQI between the four and nine days and other weekdays. The overlapped confidence intervals (CIs) indicate an insignificant difference (at the 95% significance level) in TCI (or AQI) between the four and nine days and other weekdays, while the non-overlapped 95% CIs indicate such difference is statistically significant.

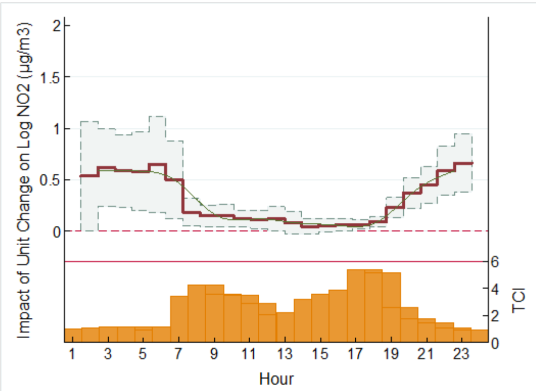
Figure 5. Hourly Regression Results



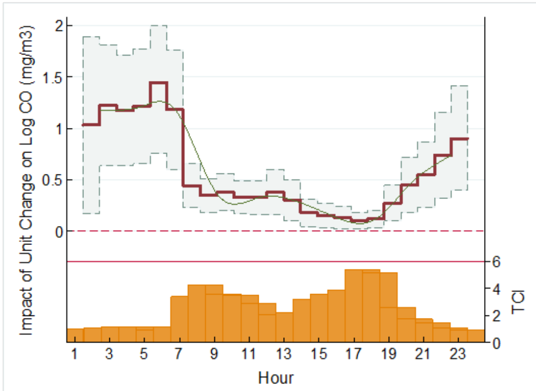
(a) Marginal impacts of hourly TCI on AQI



(b) Marginal impacts of hourly TCI on $PM_{2.5}$



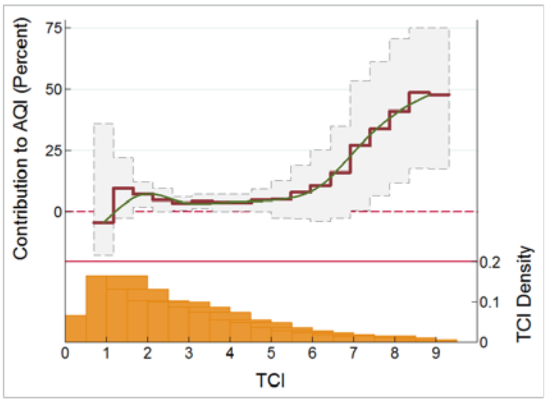
(c) Marginal impacts of hourly TCI on NO_2



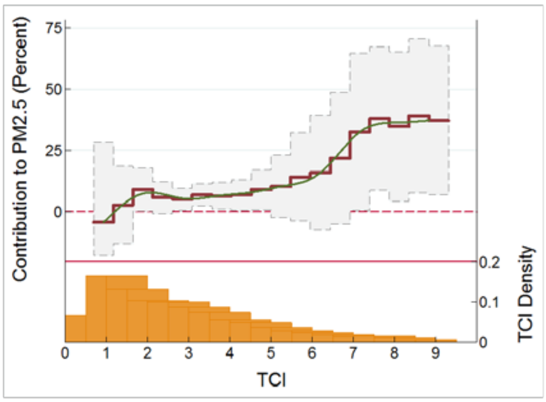
(d) Marginal impacts of hourly TCI on CO

Notes: Figure 5 displays changes in log air pollutants with a one-unit increase in TCI at a particular one-hour interval. The bar chart below is the histogram of hourly TCI mean values at different times. The solid line and shaded parts above represent the estimated marginal contribution (log-linear IV estimator) of hourly subsamples and their relative 95% confidence intervals (CIs). Once the CIs (shaded parts) go across the dash line (Y-axis equals zero), the changes in log air pollutants will no longer be significantly different from zero at the 95% significance level.

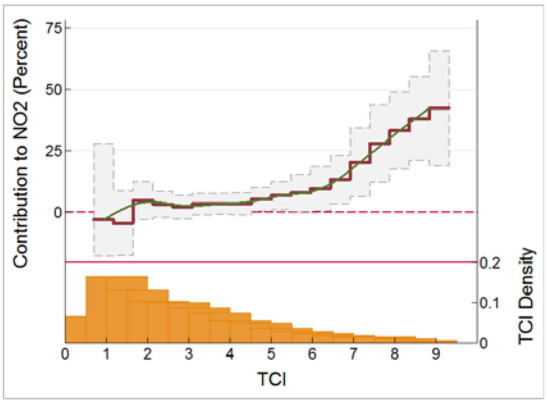
Figure 6. Non-linear Relationship between TCI and Air Pollutants



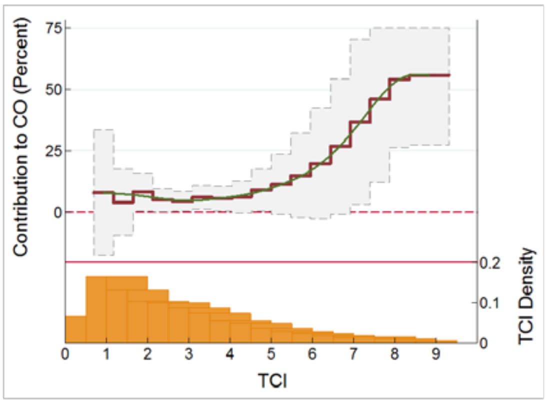
(a) Relationship between TCI and AQI



(b) Relationship between TCI and $PM_{2.5}$



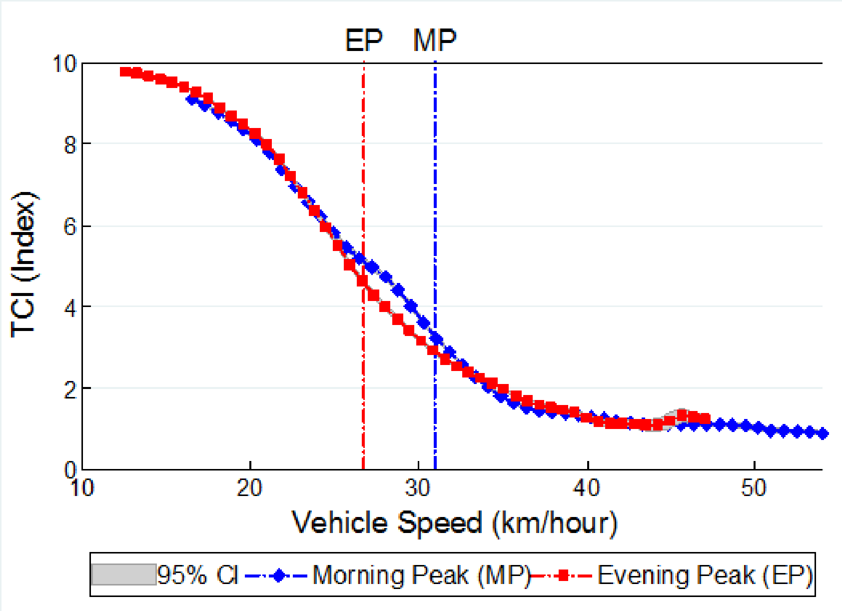
(c) Relationship between TCI and NO_2



(d) Relationship between TCI and CO

Notes: The bar chart below is the TCI density distribution of TCI, while the solid line above displays contributions of vehicle traffic to air pollution concentrations as TCI increases, with the shaded portions representing 95% confidence intervals (CIs). Once the CIs (shaded parts) go across the dash line (Y-axis equals zero), the changes in log air pollutants will no longer be significantly different from zero at the 95% significance level.

Figure 7. Relationship between TCI and Vehicle Speed



Notes: Figure 7 displays the relationship between TCI and vehicle speed during morning peak (MP) and evening peak (EP) hours, using local polynomial smooth plots with 95% confidence intervals (CIs). Narrow CIs indicate good performance in fitting the relationship between TCI and vehicle speed. The blue and red lines represent the plot line derived from the MP and EP, respectively. The dashed lines separately highlight the mean values at MP and EP.

Appendix

Table A1. Summary Statistics for Daily Volume of Public Transport Passengers in Beijing, 2013-2014

Variable	Def. (Unit)	Mean	SD	Min	Max	N
BPV	Bus passenger volume (million)	13.019	1.494	5.810	15.482	730
SPV	Subway passenger volume (million)	9.029	1.538	1.825	11.559	730

Data sources: Beijing Traffic Management Bureau 2013-2014.

Notes: We also collected daily records of bus and subway passenger ridership in 2013 and 2014 for the analysis. The daily passenger ridership of bus and subway data was from the Beijing Daily Transport Operation Monitoring, released by the Transport Operation Control Center of Beijing.

Table A2. Summary Statistics for Daily Records in Six Districts of Beijing

Variable	Def. (Unit)	Mean	SD	Min	Max	N
AQI	Daily Index	123.2	76.86	4	440.7	4210
$PM_{2.5}$	Daily record (μg/m3)	89.63	70.25	3	417.4	4201
PM_{10}	Daily record (μg/m3)	125.7	78.70	6	567	4189
NO_2	Daily record (μg/m3)	62.80	28.36	3.304	202.4	4035
CO	Daily record (mg/m^3)	1.439	1.046	0.179	8.142	4189
TCI (MP)	Morning Peak Index (0-10)	4.023	2.550	0.600	9.400	4326
TCI (EP)	Evening Peak Index (0-10)	5.123	2.636	0.700	9.800	4308
Speed (MP)	Morning Peak Speed (km/hour)	30.95	7.750	16.50	54	4326
Speed (EP)	Morning Peak Speed (km/hour)	26.71	6.150	12.50	47	4308
Temperature	Daily average (Celsius)	13.52	11.08	-9.700	31.80	4380
Relative humidity	Daily average (%)	5.345	1.940	0.900	9.700	4380
Sea-level pressure	Daily average (hPa)	1012	9.903	990	1039	4380
Solar-radiation	Daily total (hours)	6.459	4.126	0	14.10	4380
Wind speed	Daily extreme (m/s)	7.947	3.254	3	20.8	4380
Wind direction	Index (1-16)	8.477	4.553	1	16	4380

Data sources: The measurements of air pollutants were obtained from China National Environmental Monitoring Center, 2013-2014 (See http://www.cnemc.cn/ and http://106.37.208.233:20035/). Daily meteorological conditions were downloaded from the China Meteorological Data Sharing Service System (see http://cdc.nmic.cn/home.do) and the daily TCI at both morning peak and evening peak are provided by the Beijing Traffic Management Bureau for 2013-2014.

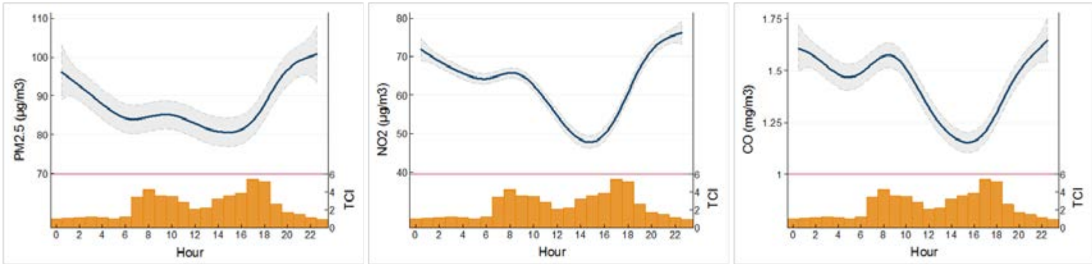
Notes: Table provides air pollutant records from 1/18/2013 to 12/31/2014. Observations consist of daily records at six districts of Beijing.

Table A3. Daily Records with Regional Fixed Effects

	(1) Ln(NO_2)	(2) Ln(NO_2)	(3) Ln(NO_2)	(4) Ln(NO_2)	(5) Ln(CO)	(6) Ln(CO)	(7) Ln(CO)	(8) Ln(CO)
TCI(MP)	0.1054***				0.1099***			
	(2.82)				(4.08)			
Speed(MP)		-0.0510***				-0.0537***		
		(-2.82)				(-4.08)		
TCI(EP)			0.0796***				0.0816***	
			(2.89)				(4.22)	
Speed(EP)				-0.0386***				-0.0400***
				(-2.88)				(-4.23)
Date Controls	Y	Y	Y	Y	Y	Y	Y	Y
Meteorological conditions	Y	Y	Y	Y	Y	Y	Y	Y
Year *FE*	Y	Y	Y	Y	Y	Y	Y	Y
Month *FE*	Y	Y	Y	Y	Y	Y	Y	Y
District *FE*	Y	Y	Y	Y	Y	Y	Y	Y
N	4032	4032	4016	4016	4137	4137	4120	4120
R^2	0.671	0.663	0.678	0.679	0.624	0.612	0.645	0.653

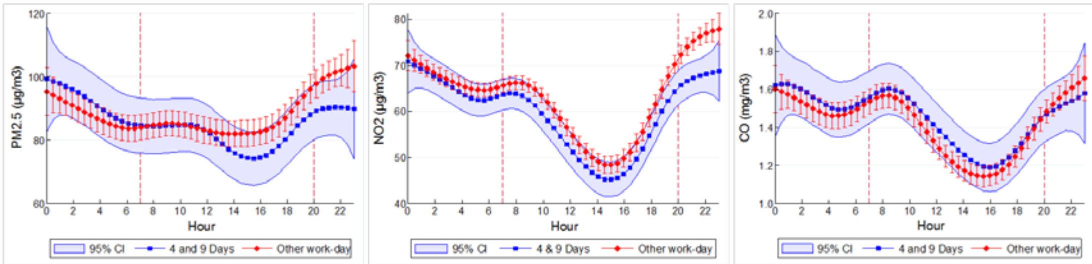
Notes: See Table 8. Standard errors are robust to heteroscedasticity. *t* statistics in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Figure A1. Hourly Pattern of Air Pollutants and TCI in Beijing



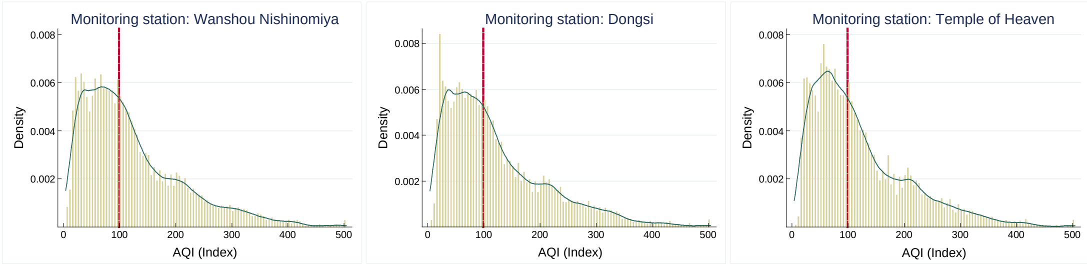
Data Source and *Notes* see Figure 3.

Figure A2. Hourly Distribution of Air Pollutants

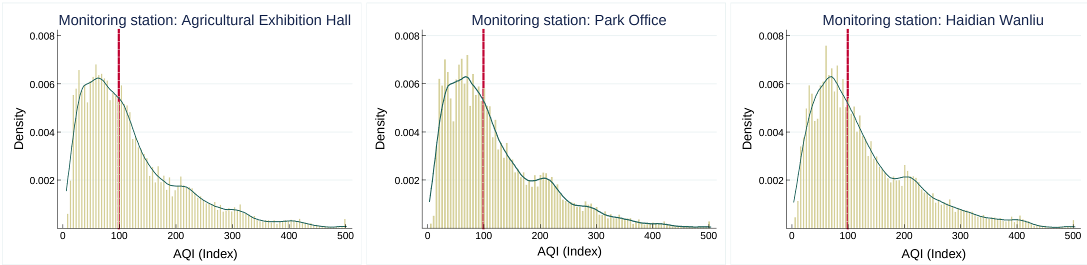


Data Source and *Notes:* see Figure 4.

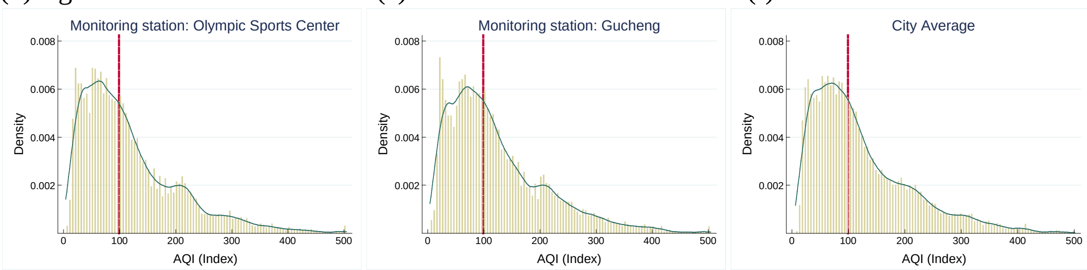
Figure A3. AQI Density



(a) Wamshou Nishinomiya (b) Dongsi (c) Temple of Heaven



(d) Agricultural Exhibition Hall (e) Park Office (f) Haidian Wanliu



(g) Olympic Sports Center (h) Gucheng (i) City Average

Notes: Figure displays the density analysis using air quality data applied in this paper. Figures (a) to (h) depict the AQI density for eight individual state-controlled air quality monitoring stations located within the Fifth Ring Road in Beijing, while Figure (i) shows the AQI density pattern at a citywide average level. Dashed lines highlight the potential cut-off point where AQI equals 100.