Highway toll and air pollution: evidence from Chinese cities

Fu, Shihe and Gu, Yizhen

Southwestern University of Finance and Economics, University of California, Berkley

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Shihe Fu
Research Institute of Economics and Management
Southwestern University of Finance and Economics
e-mail: fush@swufe.edu.cn

Yizhen Gu
Department of City and Regional Planning
University of California, Berkley
e-mail: yizhengu@berkeley.edu

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Abstract: Most highways in urban China are tolled to finance their construction. During the eight-day National Day holiday in 2012, highway tolls are waived nationwide for passenger vehicles. We use this to test highway tolls' effect on air pollution. Using daily pollution and weather data for 98 Chinese cities in 2011 and 2012 and employing both a regression discontinuity design and differences-in-differences method with 2011 National Day holiday as a control, we find that eliminating tolls increases pollution by 20% and decreases visibility by one kilometer. We also estimate that the toll elasticity of air pollution is 0.16. These findings complement the scant literature on the environmental impact of road pricing.

JEL Code: H23; Q53; R41; R48

Key words: highway toll; air pollution; visibility; regression discontinuity design; differences-in-differences.

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1 Introduction

Vehicles generate a few types of negative externalities, such as traffic congestion, air pollution, and traffic accidents (Parry, *et al*., 2007), but much attention has focused on congestion externalities. To reduce traffic congestion to the socially-optimal level, a toll equal to congestion externalities should be charged (Walters, 1961). This congestion pricing theory has been modeled in various ways but few models consider pollution externalities resulting from vehicle emissions. [1] Congestion pricing has been practiced in some cities (for example, London and Stockholm), but empirical evidence on its effect on air pollution is scant. This study uses data from the removing of highway tolls in urban China and demonstrates that tolls can substantially decrease air pollution.

China's highway network has grown rapidly: expressway mileage grows from 522 kilometers in 1990 to 41,005 in 2005, and is expected to reach 85,000 by 2020 (Yang and Lee, 2008, P.1).[2] On most expressways a toll is charged to finance the capacity costs. Toll rates are regulated by provincial governments and vary by vehicle type, expressway, and province. [3] A Ministry of Transportation survey estimates that in 2010 a sample of twelve provinces collect RMB 100 billion toll revenue.[4] Whether tolls are below or above the socially optimal level is unclear; however, eliminating tolls will certainly lead to excess vehicles on the road. One example is Shanghai Hujia Expressway. Built in 1988 and already at capacity, traffic flow increases by 20% the day after its toll is abolished on January 1, 2012. [5]

Urban air pollution is a serious issue in China. According to a World Bank survey of 186 countries, the mean annual level of PM_{10}, the concentration of particulate matter with diameter of 10 micrometers (μm) or less measured in microgram (ug) per cubic meter (m^3), in urban China is 82 in 2011, making it the 22th most polluted. [6] In 2003, total health costs due to air pollution are estimated to be 1.2 to 3.8% of China's GDP (The World Bank, 2007). In 2005, the economic costs of suspended particulates and ozone in China are estimated to be $112 billion (in 1997 US dollar) (Matus, *et al*., 2012).

Vehicles are the major contributor to urban air pollution in China (Cai and Xie, 2007). A large proportion of vehicles travel on highways and most of these are passenger vehicles. In Beijing, passenger vehicles represent 82% of highways traffic, compared to 55% on arterials and 70% on residential roadways (Liu, *et al*., 2005). Removing highway tolls will lead to socially-excessive passenger vehicle travel due to more congestion and more emissions.

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[1] For example, Arnott, *et al*. (1993) study the peak-period congestion pricing; Arnott (2007) studies congestion pricing when agglomeration economies are present.
[2] In this paper we use highway and expressway interchangeably.
[3] For a discussion of toll policy in Chinese provinces, see Yang and Lee (2008).
[4] Data source (in Chinese): http://finance.sina.com.cn/roll/20111017/150210634992.shtml.
[5] Source (in Chinese): http://www.chinanews.com/gn/2012/01-02/3577503.shtml.
6 Source: http://wdi.worldbank.org/table/3.13#.

Empirical studies on congestion pricing's effect on air pollution are scarce. Daniel and Bekka (2000) adapt TRANPLAN, a widely used highway modeling program, to simulate the effect of congestion pricing on vehicle emissions using data from New Castle County, Delaware. They find that congestion pricing can reduce emissions from 5% to 15% on the major highways in different scenarios. Mitchell, *et al*. (2005) simulate the impact of different road pricing schemes on air quality using data from Leeds, UK. Anas and Lindsey (2011) review a few simulation and estimation studies in London, Stockholm, and Milan. These studies show that tolls can reduce vehicle emissions by 8.5% to 19% depending on the city, toll rate, and pollutant type. No similar studies have been conducted in China.

This paper uses a quasi-natural experiment in China to study the effect of removing highway tolls on urban air pollution. This complements the empirical evidence on congestion pricing's effect on air pollution. On July 24, 2012, the China State Council announces that highway tolls will be waived for passenger vehicles with fewer than eight seats during the four official holidays: Spring Festival, Tomb-Sweeping Day, Labor Day (May 1), and National Day (October 1), beginning with National Day 2012.[7] There are eight days during the 2012 National Day holiday (September 30 to October 7, 2012), when highway tolls are first waived. We use the seven-day National Day holiday in 2011 (October 1 to October 7, 2011) as the comparison. Since highways connect cities where trips start and end, a change in traffic flow on highways due to a change in tolls is highly correlated with a change in traffic flow in cities that highways connect. Therefore, this exogenous change in highway tolls enables us to test the effect of highway toll on urban air pollution.

We use the daily air pollution and weather data for 98 major cities in China for 2011 and 2012 and employ both a panel regression discontinuity design method and a differences-in-differences method to test the effect of removing highway tolls on urban air pollution. The toll rate ranges from RMB 0.26 to 0.9 per passenger vehicle per kilometer depending on the city and highway. Removing the highway toll during the 2012 National Day holiday period increases urban air pollution (measured by air pollution index) by 20% compared with the National Day holiday period in 2011. We provide further evidence to show that this is not due to trip demand shifting from before or after the holiday to the holiday period. In addition, PM_{10} increases by 27% and visibility decreases by one kilometer. We also estimate the toll elasticity of pollution to be 0.16. These results imply increased congestion, pollution, and traffic accidents. Since toll revenues are a redistribution of wealth, our findings suggest that removing highway tolls lowers social welfare. A back-of-envelop calculation shows that during the eight days without tolls, the health costs incurred due to the increase in PM_{10} amount to at least RMB 1.18 billion in urban China.

The rest of the paper is organized as follows. Section 2 provides a heuristic model to show that removing a toll will increase traffic flow and therefore vehicle emissions and air

[7] During the past few years, Spring Festival holiday includes seven days, Tomb-Sweeping Day three, Labor Day three, and National Day seven. The exact dates for those holidays, announced by the State Council according to the calendar, change each year with the calendar. The National Day holiday in 2012 includes eight days.

pollution. Section 3 introduces the data and Section 4 the econometric models. Section 5 presents the results and Section 6 concludes.

2 Illustrative model

Arnott and Kraus (2003) provide an excellent introduction to highway congestion pricing theory. This section adds vehicle pollution externalities to their model. We consider only short-run effects of toll policy and therefore assume road capacity is fixed. The simple model shows that social efficiency requires a toll equal to the sum of congestion and pollution externalities. Although congestion pricing has been implemented in some cities, vehicle emission pricing is rarely implemented and may be more complicated in both theory and practice (Anas and Lindsey, 2011; Coria, *et al*., 2013). Our simple model is intended to provide economic intuition for our econometric models.[8]

Suppose each driver drives from point A to point B over a stretch of highway. Trip time T depends on the traffic flow-capacity ratio: $T = T(\frac{N}{S}),$ with $T' > 0$ and $T'' > 0$ where S is the maximum capacity of the highway and is assumed to be fixed in the short run, N the hourly traffic flow uniformly passing any point on the highway, $\frac{N}{S}$ the flow-capacity ratio, and "′" the first order derivative. Assume hourly vehicle emissions, E, depend positively on both the flow capacity ratio and the traffic flow: $E(\frac{N}{S}, N)$. If c is the constant, hourly vehicle operating cost from A to B, then the total user cost or trip cost per hour f is

$$f = f(\frac{N}{S}, N) = c + vT(\frac{N}{S}) + \lambda E(\frac{N}{S}, N), \quad (1)$$

where v is the monetary value of travel time per hour and λ the health or disutility cost of vehicle emissions in dollars. The total user cost across all drivers is $C(N, S) = Nf$. The marginal social cost of adding one more vehicle on the road is

$$\frac{\partial C}{\partial N} = f + N\frac{\partial f}{\partial N} = f + Nv\frac{\partial T}{\partial N} + N\lambda\frac{\partial E}{\partial N}, \quad (2)$$

where the first term on the right-hand side is the marginal private cost, the second the congestion externality, and the third the pollution externality. If the government charges a toll τ , the full trip price to the user, P, is the individual trip cost plus the toll:

$$P = f(\frac{N}{S}, N) + \tau. \quad (3)$$

[8] For other types of road pricing with emissions, see Verhoef (2000), Johansson-Stenman (2006), Yin and Lawphongpanich (2006), and Bigazzi and Figliozzi (2013).

The trip demand function is $N(P) = N(f(\frac{N}{S}, N) + \tau)$, which determines the equilibrium flow rate (the number of trips in equilibrium) : $N = \hat{N}(S, \tau)$. In the short run, given capacity *S*, the social planner maximizes the total hourly social surplus on the highway which is the difference between total benefit (the area under the inverse trip demand curve) and total user costs up to the equilibrium flow rate:

$$\underset{\tau}{Max} \int_0^{\hat{N}(S,\tau)} P(n)dn - C(\hat{N}(S,\tau), S). \quad (4)$$

From the first-order condition with respect to τ, combining with equations (2) and (3), we can obtain the following result:

$$\tau = Nv\frac{\partial T}{\partial N} + N\lambda\frac{\partial E}{\partial N}. \quad (5)$$

Equation (5) says that the optimal toll should be set equal to the sum of congestion and pollution externalities.

Figure 1 illustrates further the intuition of the relation between the highway toll and congestion and pollution externalities. Without any toll, the number of vehicles on the road is N_0. With a toll equal to the congestion externality, the number of vehicles on the road is N^* and with a toll equal to the sum of congestion and pollution externalities the number of vehicles on the road is further reduced to N^{**}. In the absence of any toll, drivers consider only their private user cost and ignore the congestion and pollution externalities, leading to excessive travel relative to the socially optimal level. A toll can be charged to obtain this optimal level of traffic flow.

Although we do not know whether the highway toll charged by local governments in China is greater or less than the sum of the congestion and pollution externalities, we do know that after it is lifted, traffic flow will increase to N_0 generating more congestion and vehicle emissions than before. Many highways pass through only the outskirts of cities; however, intra-city trips are often consumed along with inter-city trips (e.g., driving from a suburban residence to the inner city). Therefore, increased traffic flow on highways also increases vehicle emissions in cities where highway trips originate, pass through, or terminate. Increased traffic flow on highways may alter drivers' route choice and this may change the distribution of pollutants over space in cities. We focus on the air quality at the city level and quantify by how much air pollution increases due to the lifting of the highway toll on passenger vehicles in Chinese cities.

3 Data

The two main data sets we use are the daily air pollution index (API) data and the daily weather conditions for major cities in China.

The city-level aggregate API ranges from 0 to 500 and depends on the concentrations of three pollutants measured at monitoring stations within a city: PM_{10}, nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). [9]A higher API indicates stronger pollution concentrations and more harmful health effects.[10] The Ministry of Environmental Protection of China (MEP) publishes the daily API for 120 major cities.[11] Chen, *et al*. (2012) confirm that the API is highly correlated with two alternative measures of air pollution: visibility reported by the China Meteorological Administration and Aerosol Optical Depth from the U.S. National Aeronautics and Space Administration satellites. The API data have been used in a few empirical studies (Chen, *et al*., 2013; Lin, *et al*., 2011; Viard and Fu, 2013). We choose a sample period from January 1, 2011 to December 31, 2012.[12] After January 1, 2013, the MEP stops publishing the API and switches to a new air quality index (AQI) for 74 cities. [13] Our two-year sample period provides consistent API data and also a comparison group of days in 2011.

When the API is above 50, the major pollutant is identified. PM_{10} is the major pollutant for most of the days in most of cities and vehicles are the major creator of PM_{10} in cities. For example, approximately 53% of Beijing's PM_{10} is attributable to motor vehicles: 23% due to auto emissions and 30% road dust (Hao, *et al*., 2005). PM_{10} has a linear piecewise relationship with API (Andrew, 2008):

$$PM_{10} = API,\ 0 \le API \le 50;$$
$$PM_{10} = 2*API - 50,\ 50 \le API \le 200;$$
$$PM_{10} = (7/10)*API + 210,\ 200 \le API \le 300;$$
$$PM_{10} = (4/5)*API + 180,\ 300 \le API \le 400;$$
$$PM_{10} = API + 100,\ 400 \le API \le 500.$$

We use both the API and the imputed PM_{10} to test the effect of waiving highway tolls.

Weather conditions influence emissions and air quality. PM_{10} concentration is affected by precipitation and wind speed (Rost, *et al*., 2009; Jones, *et al*., 2010) and ozone is not easily formed on cloudy, cool, rainy, or windy days. [14] Daily weather conditions include wind speed, humidity, temperature, and precipitation and are downloaded from the web site

[9] Each monitoring station records the concentrations of the three pollutants multiple times each day. A daily API for each pollutant is calculated at each station. A mean API across stations in a city for each pollutant is then calculated and the maximum of these three means is the city-level aggregate API for that day. Source: the Ministry of Environmental Protection of China web site: http://web.archive.org/web/20041018003319/http://www.sepa.gov.cn/quality/background.php (in Chinese). Viard and Fu (2013) provide more discussion of the calculation of API.

[10] An API below 100 has no health implications. An API between 101and 200 indicates slight to light pollution causing slight irritations. An API between 201and 300 indicates moderate to heavy pollution and healthy people will be noticeably affected. An API above 300 indicates severe air pollution creating strong irritations and even healthy people will experience reduced endurance in activities.

[11] The data can be downloaded from the MEP web site: http://datacenter.mep.gov.cn/report/air_daily /air_ dairy.jsp.

[12] Expanding the sample to include 2009 and 2010 data generates similar results but doesn't help model identification since tolls are charged all over 2009 and 2010.

[13] The new data set is at http://datacenter.mep.gov.cn/airdesc.jsp.

[14] See http://www.epa.gov/airtrends/weather.html.

www.wunderground.com. [15] The weather data also include visibility which is closely related to air pollution. According to Malm (1999), "visibility" is defined as "the greatest distance at which an observer can just see a black object viewed against the horizon sky." Visibility depends on the density of particulates that scatter and absorb light and has an inverse linear relationship with air quality (Malm, 1999). Huang, *et al*. (2009) find that visibility (and humidity) predicts PM_{10} very well in Shanghai from 2004 to 2005 period. Environmental economic studies have used visibility as a proxy for air pollution, such as Du, *et al*. (2014).

By the end of 2008, about 95% of expressways in China are tolled (Lin, 2012). Toll rates differ across provinces, highways, and vehicle types: tolls range from RMB 0.26 to 4.75 per vehicle per kilometer, RMB 0.025 to 0.165 per ton per kilometer, or RMB 3 to 100 per vehicle each time passing through an expressway. For passenger vehicles with seven or fewer seats, the toll rate can be RMB 0.26 to 0.9 per vehicle per kilometer or RMB 3 to 50 per vehicle each time.[16] Because of this complexity of the toll rate structure we need to construct a "toll index" for each city to estimate the toll elasticity of air pollution.

Merging the air pollution and weather data and dropping cities without any tolled expressways passing by provides a final sample of 98 cities. Figure 2 shows the map of these 98 cities and the highways connecting them. Table 1 presents the summary statistics of key variables. Compared with the National Day holiday period in 2011 when highway tolls are charged, during the National Day holiday period in 2012 when tolls are waived, on average API is 12 higher, PM_{10} is 19 ug/m^3 higher, and visibility is 0.4 km lower, suggesting stronger air pollution from eliminating tolls. Changes of traffic flow on highways are expected to provide consistent evidence but such data currently are not publically available in China.

4 Model specification

During the 2012 National Day holiday, from September 30 to October 7, highway tolls are waived for passenger vehicles with seven or fewer seats. This is the first time that the highway toll has been waived nationwide and also the only days it is waived during 2012. Since both production and consumption activities generate air pollution and holidays alter the proportion of these two types of activities, we need to separate the holiday effect. We use the 2011 National Day holiday, from October 1 to October 7, during which highway tolls are charged, as a control group.

Our main model is a city fixed effect, panel data model:

$$P_{it} = \alpha_i + \beta_1 Nationalday + \beta_2 Notoll + \gamma W_{it} + \theta X_{it} + f(t) + \varepsilon_{it}, \qquad (1)$$

[15] Wind direction information is missing in the historical data. If the main wind direction is relatively constant in a city, the city fixed effect in our model can partially control for this.

[16] Toll rates are set by provincial governments. We assemble the toll rate data for 2011-2012 from each provincial government's web site.

where the dependent variable P_{it} is one of the three measures of air pollution in city i on day t: logarithm of air pollution index, PM_{10}, or visibility. Independent variables are defined as follows:

α_i: city fixed effect.

Nationalday: a dummy variable set to 1 if a day is among one of the National Day holidays (October 1 to 7, 2011 and September 30 to October 7, 2012).

Notoll: a dummy variable set to 1 if on a day highway tolls are waived (September 30, 2012 to October 7, 2012).

W_{it}: a vector of daily weather variables for city i on day t including maximum wind speed (kilometers per hour), precipitation (millimeters), average humidity (in percentage), and average temperature (centigrade).

X_{it}: a vector of other control variables including a weekend dummy, eleven month dummies, year 2012 dummy, and a dummy for holidays other than National Day holidays.

$f(t)$: a flexible polynomial time trend term controlling for unobserved confounding factors or trends that may affect daily air quality. Without loss of generality, we consider asymmetric time trends before, during, and after the *Notoll* period. Using symmetric trend generates very similar results.

ε_{it} is the error term; β_1, β_2, γ, and θ are coefficient vectors to be estimated. Since we have controlled for the National Day holiday effect, the coefficient of *Notoll*, β_2, captures the effect of removing highway tolls on air pollution. This interpretation is analogous to a differences-in-differences approach. In estimation standard errors are clustered at the city level to control for within-city correlation of API.

Model (1) has a few special cases. First, if we estimate Model (1) by year and consider National Day holiday as an exogenous "policy", then we can compare whether the effects of this "policy" are qualitatively different across years. Second, if we choose a small window before and after this "policy", Model (1) can be estimated following the regression discontinuity design method since such an estimation can show whether the trend in air quality has a "jump" during and after the "policy" period.[17] Finally, as a robustness check, we also estimate a city fixed effect model assuming each city has a separate time trend by interacting each city dummy with flexible time trend terms. These interaction terms absorb unobserved, city-specific, time-varying factors that affect air quality.

[17] For an introduction to regression discontinuity design method, see Angrist and Pischke (2009) or Lee and Lemieux (2010). For applications of this method in the time series context, see Davis (2008), Chen and Whalley (2012), and Viard and Fu (2013).

5 Results

5.1 Suggestive results

We first estimate Model (1) separately for the 2011 and 2012 sub-samples. We must drop the *Notoll* variable because a toll is charged on all days of 2011 and in 2012 the days without tolls coincide with the National Day holiday. We treat the National Day holiday as an exogenous "policy" and apply the regression discontinuity design (RDD) method, using flexible time trends to control for unobserved confounding factors that affect urban air pollution. These estimates can show whether the National Day holidays affect air pollution differently in 2011 and 2012.

Table 2 presents the results. The dependent variable is the logarithm of API. All control variables are included but only the coefficients of *Nationalday* are reported. Panel 1 shows that in 2011 the API decreases by between 9% and 21% during National Day holiday compared with a regular workday. [18] These estimates are robust up to the fifth order time trend. [19]However, Panel 2 shows that in 2012 the API decreases by at most 5% during the National Day holiday and the estimates are not stable across different order of time trends. Since the only difference between these two National Day holiday periods is that highway tolls are waived during the 2012 National Day holiday, Table 2 results suggest that eliminating tolls substantially increases air pollution.

To check whether the above suggestive results are sensitive to the window width before and after the "policy", we also employ the RDD method to estimate the difference in air pollution before, during, and after the National Day holidays with a symmetric, narrow window. Specifically, we regress log(API) on the *Nationalday* dummy, weekend dummy, four daily weather variables, city fixed effects, and linear and quadratic time trends before, during, and after the "policy", using a small window of seven days before, during, and after the National Day holiday in 2011. [20] We estimate the same model using a small window of eight days before, during, and after the National Day holiday in 2012.

Table 3 reports the results. Panel 1 shows that in 2011 air pollution falls by between 8% and 11% during the National Day holiday compared with the seven days before and after the National Day; however, in 2012, air pollution increases by between 3% to 7% during the National Day holiday compared with the eight days before and after the National Day. Since the only difference is the removing of tolls in the 2012 National Day holiday period, these small-window RDD results are consistent with the Table 2 results.

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[18] Using data for 2009 and 2010, we find that air pollution falls by between 7% and 18% during the National Day holidays depending on model specifications. This suggests that the trend of holiday effect is relatively stable before 2012.

[19] Higher order time trends are not feasible because of extremely high correlations between some time trend terms.

[20] Higher order time trends cannot be added because of the short sample period.

As a visual demonstration, we apply the RDD method and estimate the effect of National Day holiday on air pollution for Shanghai, China's largest city. Figure 3 shows the symmetric quadratic trend seven days before, during, and after the 2011 National Day holiday. The trend shifts down slightly during the National Day holiday period (the coefficient of *Nationalday* dummy is -0.171 and statistically insignificant). Similarly, Figure 4 shows the symmetric quadratic trend eight days before, during, and after the 2012 National Day holiday. In contrast, the trend jumps upward significantly during the National Day holiday period (the coefficient of *Nationalday* dummy is 0.363 and statistically significant at the 10% level). These demonstrations may be interpreted with caution since the sample sizes are just 21 and 24 days, respectively, and for only one city. Nevertheless, they provide suggestive evidence on the effect of removiing tolls on air pollution. To take into account city heterogeneity and longer-term effect, we apply the panel differences-in-differences (DID) method in the next subsection.

5.2: Results from panel DID design

Table 4 reports the estimate results of our main Model (1) using pooled 2011 and 2012 data. Column 1 does not include any time trend; flexible time trend terms are added to Column 2 through Column 5, from linear, asymmetric time trends before, during, and after the "policy" period up to the fourth-order.[21] The coefficients of *Nationalday* and *Notoll* dummies are stable and statistically significant at the 1% level across all columns. During a regular National Day holiday period in these two years, air pollution decreases by 20% to 25% across cities; however, removing highway tolls during the 2012 National Day holiday period increases air pollution by 20% to 23%, almost exactly offsetting the pollution reduction from the National Day holiday. Since we have conditioned on the 2011 National Day holiday effect and used city fixed effects and flexible time trends to control for unobserved confounding factors that may affect air quality, the 20% to 23% increase in air pollution can be interpreted as the causal effect of removing highway tolls.

Air pollution is created by both production and consumption activities. During weekends and holidays, production activities are cut down but consumption and leisure activities increase significantly. Whether air pollution will increase or decrease during weekends and holidays is an empirical question (Li, *et al.*, 2010). Table 4 shows that the coefficients on *Weekend* are close to zero and never significant, suggesting that weekend pollution is similar to workdays. The coefficients on *Other holidays* suggest that during other holidays air pollution is 3% higher than a regular workday. The coefficients on the *Year* 2012 dummy suggest that air quality improves significantly over 2011. The coefficients on the four weather condition variables are as expected and are stable across model specifications.

[21] Time trends higher than 5^{th} order cannot be added due to high collinearity between time trend terms.

The local features and different development stages of cities in China contribute differently to vehicle emissions (Huo, *et al*., 2011). Therefore, it is important to control for both city fixed effects and city-specific time trends. Table 5 presents the results of estimating Model (1) with city-specific time trends. We interact city fixed effects with linear, asymmetric time trends before, during, and after the "policy" period in Column 2; with both linear and quadratic time trends in Column 3; and with linear, quadratic, and cubic time trends in Column 4. The results are very similar to those in Table 4: removing highway tolls increases air pollution by 21% to 24%. Since the interaction of city fixed effects with flexible time trends captures non-parametrically unobserved, city-specific, time-varying factors that affect air quality, such as growth in income and car ownership, industry composition, and environmental regulations, we believe Table 5 provides compelling evidence that eliminating tolls substantially increases air pollution.

5.3 PM_{10} and visibility results

Panel 1 of Table 6 reports the effect of waiving highway tolls using Model (1) with the logarithm of PM_{10} level as the dependent variable. The coefficients are fairly stable using different order time trends. Compared with a regular workday, PM_{10} decreases by 25% to 32% during a regular National Day holiday period but increases by 25 to 30%, or by 20.9 to 26.8 $\mu g/m^3$, when highway tolls are waived. [22] We obtain similar results using up to the third order city-specific time trends.

This finding has important health implications. A large number of epidemiologic studies have shown that particulate matter is an important risk factor for cardiopulmonary disease and mortality. Acute or short-term exposures to particulate pollution can exacerbate existing cardiovascular and pulmonary disease, increase hospital admissions, and hasten death (Brook, *et al*., 2004; Brunekreff and Holgate, 2002; Pope, 2000). In the short run, the welfare cost of pollution exposure includes reduced activity days (for example, due to hospitalization) and acute mortality. Matus, *et al*. (2012) provide an exposure-response (ER) function of 0.0541 additional restricted activity days per year-adult-$\mu g/m^3$ increase in PM_{10} concentration and an ER function of a 0.06% increase in the mortality rate per $\mu g/m^3$ increase in PM_{10} concentration in China. Using employment and wage data for all cities at or above the prefecture level (that is, excluding small cities) in 2011, a back-of-envelope calculation shows that the welfare loss of reduced activity days due to increased PM_{10} concentration during the eight days without tolls is RMB 1.183 to 1.517 billion (see Appendix A).

[22] The mean PM_{10} for workdays (excluding weekends and holidays) is 83.6 $\mu g/m^3$.

Visibility and air pollution are closely related and suspended particulate matter is the main cause of visibility degradation (Diederen, *et al*., 1985; Hyslop, 2009). Panel 2 of Table 6 reports the effect of waiving highway tolls on visibility where we have replaced the dependent variable in Model (1) with the logarithm of visibility level (measured in kilometers). The coefficients on *Nationalday* and *Notoll* are stable and statistically significant at least at the 5% level across all the columns. Specifically, visibility increases by 12% to 14% during a regular National Day holiday break but decreases by 6% to 11% or 0.7 to 1.3 kilometers when highway tolls are removed during the 2012 National Day holiday break.[23] Using city-specific time trends generates very similar results.

This visibility effect has implications for road safety. Studies have found that bad visibility is associated with more road vehicle accidents, more severe injuries, and more vehicles involved in crashes (Abdel-Aty, *et al*., 2011; Edwards, 1998; Zhang, *et al*., 2013). Our results therefore imply that removing highway tolls increases not only air pollution but also the frequency and severity of traffic accidents. Reduced visibility also implies lower amenity and aesthetic values for urban residents (Loehman, *et al*., 1994; Delucchi, *et al*., 2002).

5.4 Testing the intertemporal shift of travel demand

Although the city-specific time trend models provide compelling evidence that eliminating tolls significantly increases air pollution, this effect may be overestimated if trips originally scheduled shortly after the National Day holiday simply shift forward to the holiday period when tolls are waived. This intertemporal displacement effect is termed "harvesting effect" in the environmental health literature (Deschênes and Moretti, 2009), implying that air quality will be improved right after the "no toll" policy period since the number of trips will have reduced. To test this harvesting effect, we add a dummy variable set to one if a day is one of the eight days right after the "no toll" policy period and re-estimate Model (1). Panel 1 of Table 7 reports the results. The coefficients on *Nationalday* and *Notoll* variables are almost identical to those in Table 4, and the coefficients on "*Eight days after no toll*" variable is positive in all five columns and statistically significant in three columns. This provides no evidence for the harvesting effect.

The harvesting effect can run the opposite way, meaning that some trips originally scheduled before the "no toll" period will be delayed and shift backward to the "no toll" period so that drivers can avoid highway tolls. This implies that the number of trips right before the "no toll" policy should decrease and so does air pollution. We add another dummy variable set to one if a day is one of the eight days right before the "no toll" policy period and re-estimate all models in Panel 1. Panel 2 shows the results: The coefficients on

[23] The mean visibility for workdays (excluding weekends and holidays) is 11.6 kilometer.

Nationalday and *Notoll* variables are very similar to those in Panel 1 and the coefficients on both "*Eight days before no toll*" and "*Eight days after no toll*" variables are positive and significant except one case. This further confirms that there is little harvesting effect. One possible interpretation is that in China the majority of employers rarely offer flexible, paid holidays except the nation-wide official holidays.[24] Therefore, workers have to take their vacations during those official holidays.[25] Removing tolls reduces travel cost and therefore induces more travels during the "no toll" period.

5.5 Estimate the toll elasticity of pollution

Highway tolls vary across provinces, highways, and vehicle types. If charged per vehicle per kilometer on passenger vehicles, tolls range from RMB 0.26 to 0.9, an average of 0.58. As a rough rule of thumb, Table 4 results imply that raising the toll on passenger vehicles from zero to RMB 0.58 per vehicle per kilometer can reduce urban air pollution by 20%.

To be more informative, we replace *Notoll* dummy by the weighted toll rate in each city to estimate the toll elasticity of pollution. We manually collect the toll rate of each highway in each city, then use the length of each highway as weight to compute the weighted average of highway toll for each city. In our city sample, the mean weighted roll rate is RMB 0.4 per kilometer and the maximum 0.76. [26]

Table 8 reports the results of panel data models where *Notoll* dummy is replaced by weighted toll rate in each city. The estimated coefficients of weighted toll rate are all significant at the 1% level and stable, ranging from -0.31 to -0.49 with a mean value of -0.40. To translate this coefficient to elasticity, we assume the toll rate increases by RMB0.04, or 10% from the current mean value, thus the air pollution will decrease by 1.6% (-0.40*0.04), an elasticity of 0.16, which is close to the estimates of semi-elasticity between 0.20 and 0.23 in Table 4. This finding should be informative for local governments to design congestion toll policy in the near future.

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[24] "China has fewest paid vacation days in world", online at http://www.china.org.cn/china/2011-08/02/content_23125687.htm.

[25] Another possible interpretation is that some people may expect that highways will be crowded during the "no toll" holidays and thus shift their trips forward; some other people may have to postpone their trips back home due to traffic congestion during the holiday period. The presence of either case will underestimate the *Notoll* effect.

[26] In our sample there are four cities, Haikou, Kelamayi, Lasa, and Sanya that charge no highway toll. Both Haikou and Sanya are in Hainan province that charge higher gasoline taxes than do other provinces.

6 Conclusion

Vehicles generate congestion and pollution externalities. A toll can be charged to alleviate congestion and reduce vehicle emissions. In the absence of a toll the number of vehicles on the road will exceed the optimal number that maximizes social welfare. Chinese city governments charge tolls to finance highways. For passenger vehicles with seven or fewer seats, these tolls range from RMB 0.26 to 0.9 per vehicle per kilometer. When highway tolls are waived nationwide for passenger vehicles during the 2012 eight-day National Day holiday period, urban air pollution increases by 20%; PM_{10} increases by 25%; and visibility decreases by one kilometer. These effects are not overestimated since we find little evidence that drivers shift their trips from before and after "no toll" periods to the "no toll" period. We estimate the toll elasticity of air pollution to be 0.16. Our findings suggest that the policy of eliminating tolls during holidays generates a significant loss of social welfare: the welfare loss from reduced working days due to the negative health effect of an increase in PM_{10} concentration during the "no toll" period is estimated to be at least RMB 1.183 billion.

Although due to data availability we are unable to quantify how much the optimal toll should be during the national holidays, this study does provide the first empirical evidence on the effect of road pricing on air pollution in China; it also complements the scant literature on empirical studies of the environmental effect of road pricing. Some Chinese cities, notably Beijing, Shanghai, Guangzhou, and Xiamen, are discussing the feasibility of charging congestion tolls to alleviate traffic congestion and air pollution. Our study provides a timing and useful reference to the policymakers of those cities.

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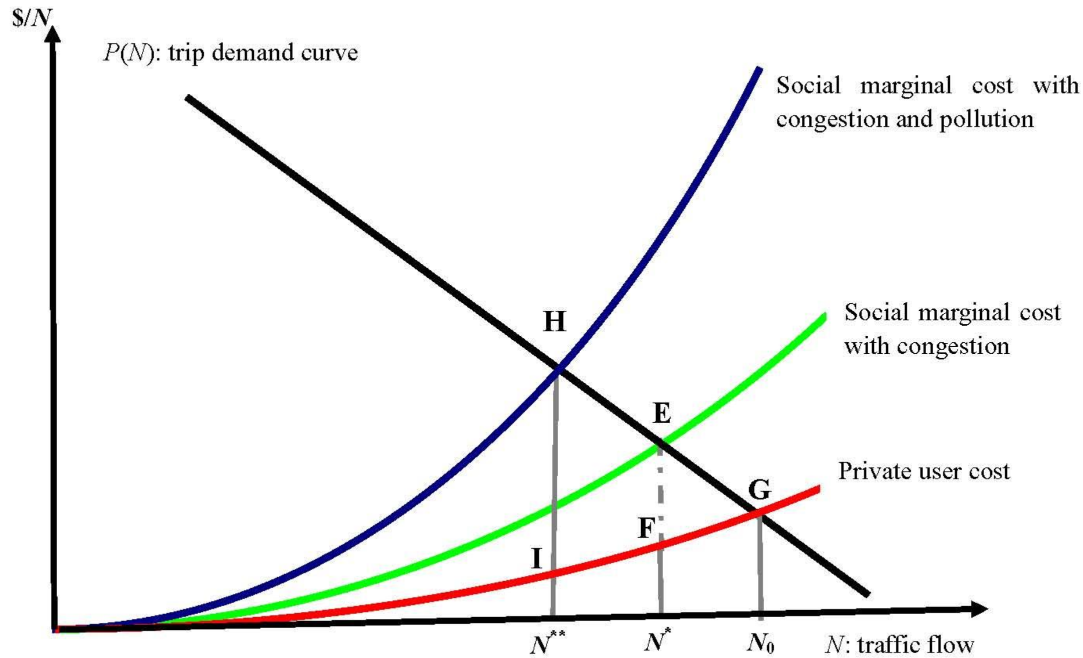

Figure 1: Optimal toll, congestion and pollution externalities

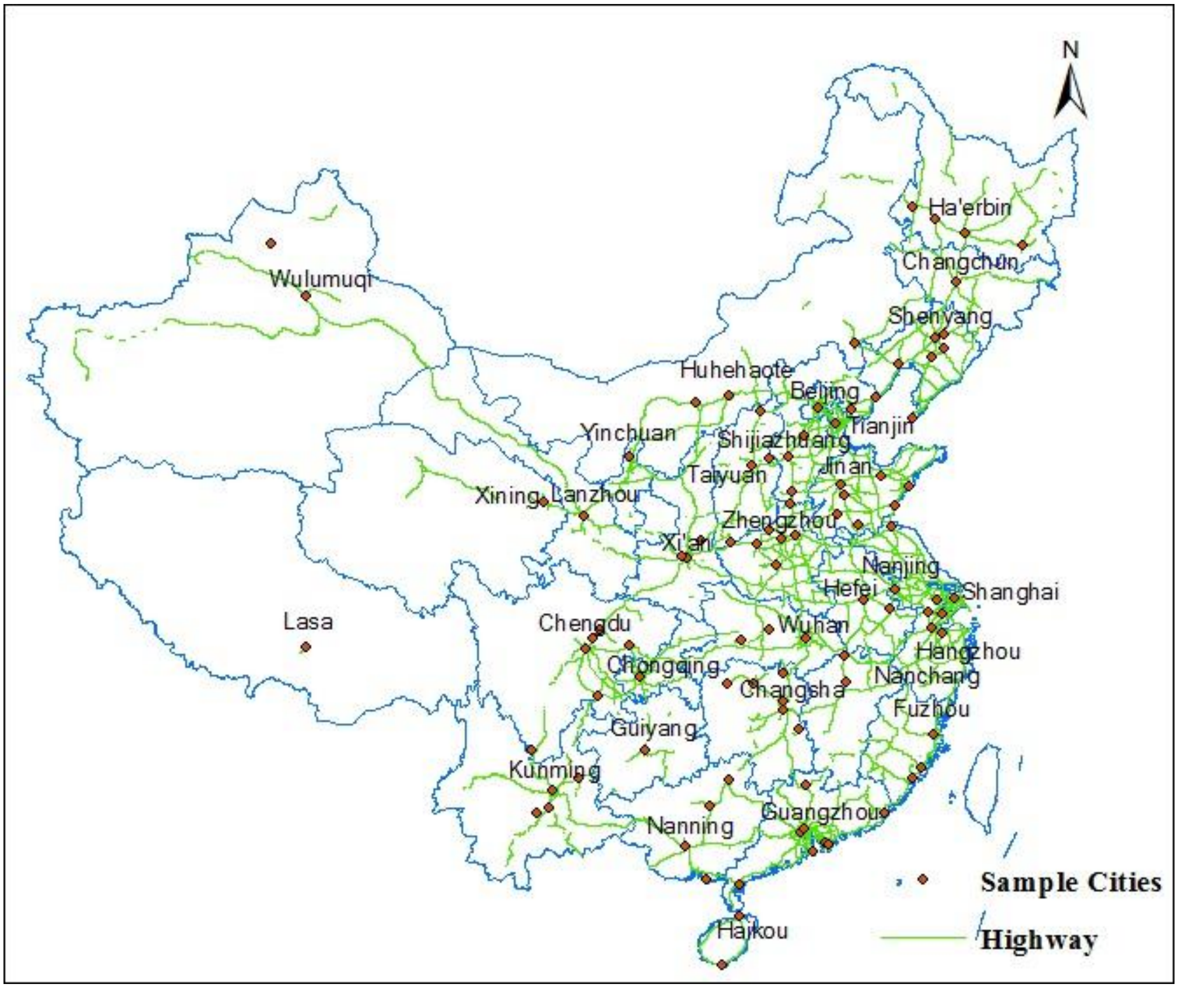

Figure 2: Cities in our sample and highways connecting them

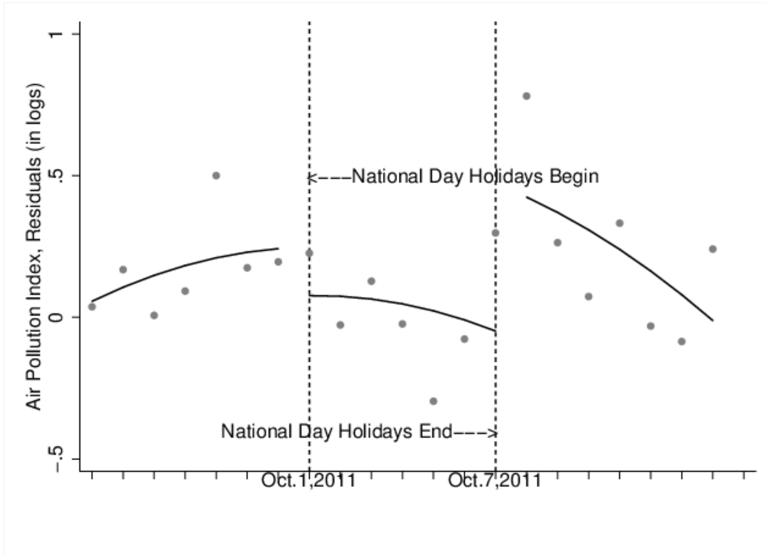

Figure 3: Time trends seven days before, during, and after the 2011 National Day holidays in Shanghai

The plotted dots are the sum of residuals from estimating Equation (1) in the main text without *Notoll* dummy and the linear and quadratic time trend. The fitted line allows for a quadratic time trend.

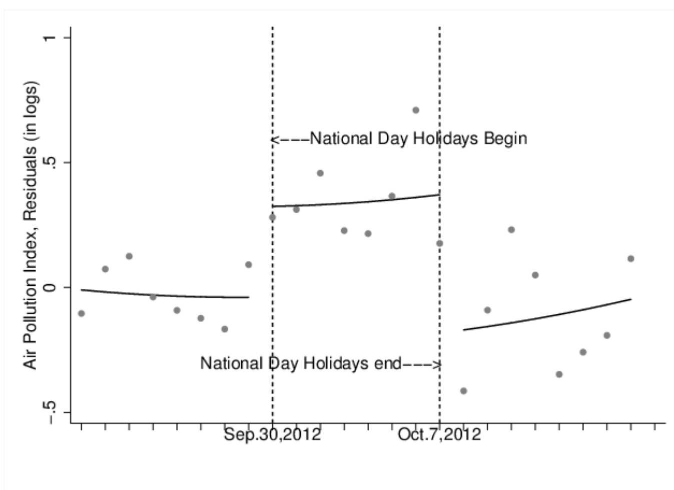

Figure 4: Time trend eight days before, during, and after the 2012 National Day holidays in Shanghai

The plotted dots are the sum of residuals from estimating Equation (1) in the main text without *Notoll* dummy and the linear and quadratic time trend. The fitted line allows for a quadratic time trend.

Table 1: Summary statistics

Variable	Mean (standard deviation): 2011-2012	2011 National Day holiday period	2012 National Day holiday period	*t* test statistic
Air pollution index	65.7(27.5)	55.2	67	-10.0
PM_{10} (μg/m^3)	84.1 (48.1)	67	86	-9.1
Visibility(km)	11.6 (7.3)	12.2	11.8	1.1
Maximum wind speed (km/hour)	7.9 (4.5)	8.1	6.3	7.7
Precipitation (mm)	1.4 (6.0)	1.6	0.5	4.0
Average humidity (%)	61.1 (20.3)	62.6	59.9	3.0
Average temperature (cel.)	14.6 (11.4)	16.5	18.2	-7.5
National day holiday dummy	0.02(0.14)			
Notoll dummy	0.01 (0.10)			
Weekend dummy	0.29 (0.45)			
Other holidays dummy	0.05 (0.23)			

Note: The *t* test statistics in the last column tests whether the means of a variable in the 2011 and 2012 National Day holiday periods are equal.

Table 2: National Day holiday effect by year

Variable	1 No time trend	2 1^{st} order time trend	3 2^{nd} order time trend	4 3^{rd} order time trend	5 4^{th} order time trend	6 5^{th} order time trend
	Panel 1: Dependent variable: log(API). Sample period: 2011					
Nationalday	-0.206^{***}	-0.182^{***}	-0.113^{***}	-0.115^{***}	-0.099^{***}	-0.085^{***}
	(-8.64)	(-8.16)	(-5.12)	(-5.20)	(-4.27)	(-3.36)
Adjusted R^2	0.371	0.372	0.382	0.386	0.386	0.386
	Panel 2: Dependent variable: log(API). Sample period: 2012					
Nationalday	-0.047^{***}	-0.041^{***}	-0.008	-0.008	-0.006	0.039^{***}
	(-2.71)	(-2.45)	(-0.45)	(-0.48)	(-0.37)	(-2.26)
Adjusted R^2	0.399	0.399	0.403	0.403	0.403	0.406

Note: Weather variables, month-of-year dummies, weekend dummy, other holidays dummy, and city fixed effects are included. Column 1 does not include any time trend terms. Columns 2 to 6 include polynomial time trend terms up to the fifth order. *t* statistics are in the parentheses. Standard errors are clustered at the city level. Superscripts "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively. Sample sizes for 2011 and 2012 are 34,738 and 35,672, respectively.

Table 3: Symmetric window RDD results

Variable	1 No time trend	2 1^{st} order time trend	3 2^{nd} order time trend
	Panel 1: Symmetric window (seven days) before, during, and after National Day holiday in 2011		
Nationalday	-0.086***	-0.076***	-0.106***
	(-3.30)	(-2.77)	(-3.37)
Adjusted R^2	0.479	0.517	0.518
Sample size	2,058	2,058	2,058
	Panel 2: Symmetric window (eight days) before, during, and after National Day holiday in 2012		
Nationalday	0.030**	0.054***	0.066***
	(2.05)	(3.50)	(3.10)
Adjusted R^2	0.394	0.513	0.513
Sample size	2,352	2,352	2,352

Note: Dependent variable is log(API). Weather variables, weekend dummy, and city fixed effects are included. In Panel 1, the sample includes 7 days before, during, and after the National Day holiday in 2011. In Panel 2, the sample includes 8 days before, during, and after the National Day holiday in 2012. *t* statistics are in the parentheses. Standard errors are clustered at the city level. Superscripts "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Panel data regression results

Variable	1	2	3	4	5
Nationalday	-0.246***	-0.237***	-0.220***	-0.212***	-0.198***
	(-9.66)	(-9.47)	(-8.96)	(-8.49)	(-8.54)
Notoll	0.232***	0.226***	0.204***	0.215***	0.195***
	(6.67)	(6.01)	(5.64)	(5.55)	(5.35)
Other holidays	0.029***	0.033***	0.034***	0.034***	0.035***
	(4.78)	(5.41)	(5.64)	(5.67)	(5.73)
Weekend	-0.000	-0.001	-0.001	-0.001	-0.001
	(-0.19)	(-0.34)	(-0.44)	(-0.49)	(-0.38)
Year 2012	-0.020**	-0.288***	-0.333***	-0.316***	-0.339***
	(-2.42)	(-3.30)	(-3.81)	(-3.59)	(-3.83)
Maximum wind speed	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(-10.06)	(-10.10)	(-10.15)	(-10.15)	(-10.14)
Precipitation	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-4.17)	(-4.18)	(-4.24)	(-4.25)	(-4.20)
Average humidity	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-4.35)	(-4.29)	(-4.21)	(-4.17)	(-4.20)
Average temperature	0.011***	0.011***	0.011***	0.011***	0.011***
	(6.51)	(6.53)	(6.60)	(6.61)	(6.61)
Asymmetric time trend	No	1st order	2nd order	3rd order	4th order
Adjusted R^2	0.372	0.373	0.374	0.374	0.375

Note: Dependent variable is log(API).All models also include month-of-year dummies and city fixed effects. Column 1 does not include time trend. Columns 2 to 5 include time trend before, during, and after the "no toll" period up to the fourth order. *t* statistics are in the parentheses. Standard errors are clustered at the city level. Superscripts "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively. Sample size: 70,400.

Table 5: Results from city-specific time trend regressions

Variable	1	2	3	4
Nationalday	-0.246***	-0.238***	-0.222***	-0.213***
	(-9.66)	(-9.58)	(-9.08)	(-8.67)
Notoll	0.232***	0.227***	0.212***	0.235***
	(6.67)	(6.06)	(5.85)	(6.15)
Asymmetric time trend	No	1st order	2nd order	3rd order
Adjusted R^2	0.373	0.394	0.407	0.423

Note: Dependent variable is log(API). All models also include weather variables, month-of-year dummies, year dummy, weekend dummy, other holidays dummy, and city fixed effects; Columns 2-4 also include linear, quadratic, and cubic time trend before, during, and after the “no toll” period and their interactions with city fixed effects. These coefficients are not reported. *t* statistics are in the parentheses. Standard errors are clustered at the city level. Superscripts “***”, “**”, and “*” indicate significance at the 1%, 5%, and 10% levels, respectively. Sample size: 70,400.

Table 6: PM_{10} and visibility results

Variable	1	2	3	4	5
			Panel 1: Dependent variable: log(PM_{10})		
Nationalday	-0.318***	-0.304***	-0.280***	-0.270***	-0.253***
	(-10.15)	(-9.89)	(-9.26)	(-8.74)	(-8.82)
Notoll	0.301***	0.288***	0.254***	0.270***	0.249***
	(6.75)	(6.03)	(5.52)	(5.54)	(5.38)
Asymmetric time trend	No	1st order	2nd order	3rd order	4th order
Adjusted R^2	0.366	0.366	0.367	0.367	0.368
Sample size			70,400		
			Panel 2: Dependent variable: log(visibility)		
Nationalday	0.135***	0.133***	0.143***	0.138***	0.119***
	(6.10)	(5.88)	(6.43)	(5.88)	(5.28)
Notoll	-0.103***	-0.057**	-0.113***	-0.101***	-0.085***
	(-3.80)	(-2.04)	(-3.88)	(-3.20)	(-2.63)
Asymmetric time trend	No	1st order	2nd order	3rd order	4th order
Adjusted R^2	0.690	0.690	0.690	0.690	0.691
Sample size			69,534		

Note: All models include weather variables, month-of-year dummies, year dummy, weekend dummy, other holidays dummy, and city fixed effects. Columns 2 to 5 also include time trend before, during, and after the "no toll" period up to the fourth order. *t* statistics are in the parentheses. Standard errors are clustered at the city level. Superscripts "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Testing the intertemporal shift of travel demand

Variable	1	2	3	4	5
			Panel 1		
Nationalday	-0.239***	-0.226***	-0.213***	-0.206***	-0.198***
	(-9.86)	(-9.54)	(-9.07)	(-8.58)	(-8.68)
Notoll	0.232***	0.223***	0.202***	0.214***	0.195***
	(6.66)	(6.03)	(5.61)	(5.56)	(5.29)
Eight days after no toll	0.047**	0.064***	0.042*	0.035	0.003
	(2.15)	(2.80)	(1.91)	(1.52)	(0.12)
Asymmetric time trend	No	1st order	2nd order	3rd order	4th order
Adjusted R^2	0.373	0.372	0.374	0.374	0.375
			Panel 2		
Nationalday	-0.240***	-0.228***	-0.216***	-0.208***	-0.199***
	(-9.88)	(-9.62)	(-9.17)	(-8.65)	(-8.75)
Notoll	0.236***	0.231***	0.217***	0.238***	0.212***
	(6.72)	(6.18)	(5.93)	(5.98)	(5.47)
Eight days before no toll	0.092***	0.089***	0.070***	0.072***	0.034**
	(7.00)	(6.61)	(5.10)	(5.13)	(2.20)
Eight days after no toll	0.049**	0.064***	0.046**	0.046**	0.011
	(2.21)	(2.79)	(2.06)	(1.95)	(0.48)
Asymmetric time trend	No	1st order	2nd order	3rd order	4th order
Adjusted R^2	0.373	0.372	0.374	0.374	0.375

Note: Dependent variable is log(API). All models include weather variables, month-of-year dummies, year dummy, weekend dummy, other holidays dummy, and city fixed effects. Columns 2 to 5 also include asymmetric time trend before, during, and after the "no toll" period up to the fourth order. *t* statistics are in the parentheses. Standard errors are clustered at the city level. Superscripts "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively. Sample size: 70,400.

Table 8: Toll elasticity of pollution

Variable	1	2	3	4	5
Nationalday	-0.230***	-0.223***	-0.209***	-0.200***	-0.188***
	(-9.73)	(-9.64)	(-9.19)	(-8.63)	(-8.58)
Weighted toll rate	-0.490***	-0.425***	-0.352***	-0.347***	0.313***
	(-7.10)	(-5.16)	(-3.58)	(-3.06)	(-2.68)
Asymmetric time trend	No	1st order	2nd order	3rd order	4th order
Adjusted R^2	0.372	0.373	0.374	0.374	0.375

Note: All models include weather variables, month-of-year dummies, year dummy, weekend dummy, other holidays dummy, and city fixed effects. Columns 2 to 5 also include asymmetric time trend before, during, and after the "no toll" period up to the fourth order. *t* statistics are in the parentheses. Standard errors are clustered at the city level. Superscripts "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively. Sample size: 70,400.

Appendix A:

According to the *China Urban Statistical Yearbook 2012* published by the China Statistical Press, in 2011, the total employment in all Chinese cities at or above the prefecture level is 268.1984 million; the average annual wage is RMB42,790.9. With 48 working weeks per year and 5 days a week, the daily wage is about RMB178. Matus, *et al*. (2012) estimate an exposure-response function of 0.0541 additional restricted activity days per year-adult-$\mu g/m^3$ increase in PM_{10} concentration. Since waiving highway tolls during the eight-day National Day holiday period in 2012 increases PM_{10} by 20.9 to 26.8 $\mu g/m^3$, evaluating the value of a restricted day at the daily average wage level, this amounts to RMB 1.183 to 1.517 billion welfare loss during those eight days due to the increase of PM_{10}.