The Effect of Beijing's Driving Restrictions on Pollution and Economic Activity*

Abstract

We evaluate the environmental and economic effects of Beijing's driving restrictions. Based on daily data from multiple monitoring stations, air pollution falls 19% during every-other-day and 8% during one-day-per-week restrictions. Based on hourly viewership data, the number of television viewers during the restrictions increases 1.7 to 2.3% for workers with discretionary work time but is unaffected for workers without, consistent with the restrictions' higher per-day commute costs reducing daily labor. Causal effects are identified from both time-series and spatial variation in air quality and intra-day variation in viewership. We provide possible reasons for the policy's success, including evidence of high compliance based on parking garage entrance records. Our results contrast with previous findings of no pollution reductions from driving restrictions and provide new evidence on commute costs and labor supply.

Keywords: Driving restrictions; externalities; environmental economics; pollution
JEL Classification: H23, D62, L51, J22, R41.

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This Draft: 8/25/2011

* Hongbin Cai, Yongmin Chen, Marvin Kraus, Stéphane Lambrecht, Katja Seim, Zhongmin Wang, and Michelle White provided helpful comments. We would like to thank Steven Q. Andrews for sharing the station-level data, Gula Tang for help with mapping and distance calculations, and Qing Gong, Mian Qing, and Wei Zhang for excellent research assistance. We thank seminar and conference participants at Southwestern University of Finance and Economics, Cheung Kong Graduate School of Business, Shanghai University of Finance and Economics, Beijing University, Renmin University, University of International Business & Economics, Zhejiang University, Xiamen University, University of Antwerp, and China Economist Society 2011 Annual Conference for helpful comments. All errors are our own.

1. Introduction

Driving restrictions have a long history as a way to reduce congestion. They date back to at least A.D. 125 when Julius Caesar banned horse-drawn vehicles from the narrow alleys around the Colosseum and the Roman Forum during the day because chariot traffic disrupted pedestrians.[1] In modern times, pollution reduction has emerged as an added rationale and such restrictions are now used in many cities around the world.[2] Despite the prevalence of driving restrictions, there is little empirical evidence of their effect on pollution and even less about their effect on economic activity. Empirical evidence is critical because such restrictions may be ineffective either due to non-compliance or compensating responses such as inter-temporal substitution of driving. At the same time, if effective, they impact economic activity by increasing commute costs and reducing workers' willingness to supply labor for given compensation.

We provide empirical evidence on the costs and benefits of driving restrictions instituted by the Beijing government in preparation for the 2008 Olympics. The restrictions prevented driving every other day based on license plate numbers. Their stringency was later reduced to one day per week, but they remain in place. On the benefits side, we find that the restrictions significantly reduced air pollution. Using daily data and a regression discontinuity design (RDD), our point estimates indicate that the every-other-day restrictions reduced total pollution by 19% and one-day-a-week restrictions by 8%. We find evidence of inter-temporal substitution of driving but the compensation is small relative to the primary reduction.

To rule out confounding factors besides auto usage, we use a differences-in-differences (DD) approach that combines the time-series variation with geographic variation in monitoring stations' locations. Stations closest to a road experience the largest drop in pollution and the drop becomes negligible at a distance consistent with the pollution's ambient properties. This means any confounding factors must be related to proximity to roads. We consider, and rule out, changes in gasoline prices, parking rates, number of taxis, emissions standards, and government-imposed working hours.

[1] See "The Cars that Ate London, Paris, Brussels, Amsterdam, Rome, Madrid, Vienna, Athens ..," *Time*, February 16, 2003 and "Fighting Traffic Congestion with Information Technology," *Issues in Science and Technology*, Fall 2002. Caesar's edict was later reversed due to the increased noise this created during the nighttime – early evidence of the inter-temporal substitution such restrictions can create.

[2] These include Santiago, Chile; Mexico City, Mexico; São Paulo, Brazil; Bogotá, Columbia; San Jose, Costa Rica; and several Italian cities. See Mahendra (2008) and "With Mixed Results, Cities Battle Traffic and Pollution," *Spiegel Online*, April 4, 2005.

Given the restrictions' benefit in reducing pollution, we investigate the cost they impose on economic activity. We show in a simple model that driving restrictions can reduce pollution, but, if so, the increased commute costs they create can reduce days worked per week for those who have discretionary work time (self-employed workers in our data). The effect on work day length is ambiguous because of changes in workers' commute modes (many workers prefer driving even if it is slower than public transit) and the consequent changes in congestion. However, it is possible that these workers fully compensate for fewer work days by increasing daily hours. Those with fixed work times (hourly workers in our data) must work specific hours. Therefore, the restrictions will affect neither their days worked nor daily hours conditional on their remaining employed.

Lacking direct measures of work time or daily traffic flows, we use a novel approach to indirectly measure labor supply. We rely on observed consumption of a major substitute – leisure time watching television (TV). Since the one-day-a-week driving restrictions apply during most workers' regular working hours (they initially apply from 6:00 a.m. to 9:00 p.m. and later from 7:00 a.m. to 8:00 p.m.), we examine viewership during the restricted hours to ascertain the effect on days worked but also examine viewership outside the restricted hours to determine if work day length more than compensates for effects on days worked.

Our empirical findings are consistent with the model's predictions. Viewership by self-employed workers increases by 11 to 15% during the one-day-a-week restricted hours, consistent with some workers with endogenous labor supply reducing days worked and substituting leisure in response to higher commute costs. Viewership increases slightly outside the restricted hours ruling out the possibility that longer work hours more than compensate for the decrease in days worked. While we cannot say with certainty that output is reduced as a result, for this not to be so would require increased efficiency during the fewer remaining work hours. Viewership by hourly employees, on the other hand, is unaffected during restricted hours consistent with these workers having no choice over number of days worked. Although daily work hours for these workers should also remain unchanged, their leisure time could change depending on changes in commute modes and congestion. We find a negligible increase in viewership outside the restricted hours.

Besides providing evidence on the restrictions' labor supply effects, the viewership results further corroborate our pollution results. They rule out confounding factors that decrease both public transit and auto commute times, such as expanded subway capacity, because leisure time would also increase for those with fixed work times.

The only other detailed economic analysis of driving restrictions is Davis (2008),[3] who finds no discernible effect on pollution from a similar policy in Mexico City.[4] Our work differs in three key respects. First, we use geographic in addition to time-series variation in pollution measures to identify the effects. Second, we examine the impact on work time. Third, while Davis (2008) only describes the penalties and detection methods used in Mexico City, we provide direct, detailed compliance evidence. In the absence of publicly-available violations data, we gathered data from a centrally-located Beijing parking garage. All parking garages in Beijing are required to record the time and license plate numbers of all entering cars but are not required to report offenders. Using this minute-by-minute data, we find a high level of compliance. This high level of compliance is one possible reason for the dramatic difference in effectiveness compared to Mexico City.

Chen, Jin, Kumar, and Shi (2011) employ DD estimation using nearby cities as a control group and find that Beijing's Olympics-related policies decreased pollution. The paper complements ours in that it finds that the driving restrictions were one of two effective policies, but differs in several respects. They explicitly examine only the effects of the brief, every-other-day restrictions[5] and do not consider labor supply effects. Also, their DD approach, which relies on satellite measures of pollution and distinguishes areas with higher road density, cannot rule out confounding factors that lower both auto and public transit congestion, such as expanded subway capacity. Our TV viewership results fulfill this role.

Our results imply that driving restrictions can effectively reduce air pollution, although at the cost of less work time by those with discretionary labor supply. Our study also adds to the very small empirical literature on commute costs and labor

[3] Policy papers examining driving restrictions include Osakwe (2010); Cropper, Jiang, Alberini, and Baur (2010); and Cambridge Systematics, Inc. (2007).
[4] Salas (2010) finds that the Davis (2008) results are sensitive to assumptions about time window and time trend. Eskeland and Feyzioglu (1995) use data on gasoline consumption to conclude that the Mexico City restrictions increased driving but they do not control for any pre-existing time trend.
[5] See Table 11 which controls only for the every-other-day policy. In Table 12 the authors include time-period dummies that extend partially into the one-day-per-week policy and conclude that it becomes ineffective; however, the results show a sustained, although diminished, pollution decrease.

supply. Relating the two is important for evaluating how transport changes will affect worker productivity. In particular, our finding that driving restrictions reduce work time has important implications for tax policy. It implies that shifting from an income to a commuting-related tax will not necessarily help reduce the work-time distortion created by an income tax. We know of only one study that relates commute cost changes to work time changes while properly controlling for endogeneity. Gutierrez-i-Puigarnau and van Ommeren (2010) find a very small elasticity of labor supply with respect to commute distance. In contrast to their study, we distinguish workers with and without discretion over work time, allowing us to compare control and treatment groups as well as separately identify the effect on those with discretion. This is important since business owners and entrepreneurs, important sources of new jobs and innovations, often have such discretion.

2. Pollution-Relevant Policies

Air pollution and its health implications are a major concern in Beijing, which is ranked the thirteenth "most polluted city" in the world in 2004 for suspended particulates, the pollutant we examine.[6] Matus *et al.* (2011) estimate that the 2005 cost of suspended particulates for China in total was $22.4 billion (in 1997 USD). Beyond these economic costs, air pollution has been linked to infant mortality (Chay and Greenstone (2003) specifically for suspended particulates and Currie and Neidell (2005) for other types of air pollutants). Cars create about 50% of particulate air pollution, highlighting the importance of reducing their negative externalities in Beijing and China at large.

In preparation for the 2008 Summer Olympics, the Beijing government implemented many measures which might reduce air pollution. Figure 1 shows a timeline of the major policies implemented before, during, and after the Olympics. Besides the driving restrictions, these included bus fare reductions, subway line openings, and temporary factory closures. During the Olympic period itself all non-essential factories were closed as were many businesses; and migrant workers (those without hukuos) were sent back to their home towns. Besides these specific policies, the government began gradually moving many factories outside of Beijing beginning in the mid-1990s. Although the government may have had other goals (e.g., reduced congestion or easier commutes) for some policies, they all could affect air pollution.

[6] See "Beijing Pollution: Facts and Figures," *BBC News*, August 11, 2008.

The driving restrictions we study began on July 20, 2008 when odd-even (“OddEven”) restrictions allowed cars to drive only every-other-day. The OddEven policy applied seven days a week and to all hours except midnight to 3:00 a.m. These restrictions were lifted on September 20. On October 11, the government re-instated driving restrictions, now preventing cars from driving one-day-per-week (“OneDay”). The OneDay restrictions applied only on weekdays and initially only between 6:00 a.m. and 9:00 p.m. We call this policy period “OneDay69.” On April 11, 2009 the daily restricted period changed to apply between 7:00 a.m. and 8:00 p.m. and remained unchanged beyond the end of our sample period. We call this period “OneDay78” and use OneDay to apply to the combined OneDay69 and OneDay78 periods.

The OddEven and OneDay policies restricted vehicles based on the last digit of their license plate numbers. During the OddEven policy, license plates ending in odd numbers could drive only on odd-numbered dates and those ending in even numbers only on even-numbered. The OneDay policy applied to weekdays with two out of the ten plate numbers restricted each day so that the restrictions followed a weekly cycle. The pairing of digits remained the same week-to-week ((0, 5), (1, 6), (2, 7), (3, 8), (4, 9)) but the assignment of these pairs to weekdays were initially rotated each month and, beginning April 11, 2009, every thirteen weeks.

The OddEven and OneDay69 policies applied to all areas within and including the 5th Ring Road while the OneDay78 policy applied to all areas within but not including the 5th Ring Road (Figure 2 shows these areas). Police cars, taxis, ambulances, postal vehicles, and embassy cars were exempt although these are small in number.

We regressed our pollution measure on dummy variables for all of the policies in Figure 1. Although other policies may have been effective but drowned out statistically, the driving restrictions were the only policies that were significant. This is consistent with the results of Chen, *et al.* (2011) who find that plant closures and traffic control were the most effective of Beijing’s Olympics-related pollution reduction measures.

As Figure 1 shows, a number of policies occurred around the time of the driving restrictions. In particular, the opening of subway Line 8, although it serves only the Olympic Park area and has a length of only 4.8 kilometers, almost exactly coincided with the start of OneDay69. It is therefore critical to rule out confounding factors. To do so, we supplement our time-series evidence with DD results across different pollution monitoring locations and DD results using TV viewership across workers with and without discretionary work time.

3. Theoretical Background

In this section we discuss the relevant theoretical predictions that we test. Appendix A contains an illustrative model that predicts the short-run effects of Beijing's driving restrictions on pollution and economic activity. We outline the model here and discuss its main results but direct the reader to the appendix for details. The model considers two groups of workers: those with discretionary work time and those with fixed work times.[7] Since most Beijing workers with fixed work times must arrive at work by 8:30 a.m. and stay until 5:30 p.m.,[8] we assume a fixed and equal number of daily work hours for them.

Within each group there is a distribution of workers with heterogeneous commute times and costs, wages, and non-wage income. In the first stage, each worker chooses their optimal commute mode (auto, public transit, or not working if they have discretion over work time). In stage two, each chooses work time, leisure time, and goods consumption to maximize utility given their first-stage choice. Workers consider how their commute mode choice affects their utility so we solve the model by backward induction. For each worker, commute modes differ in their monetary cost, time, and non-monetary disutility. The last allows for the fact that some workers prefer one commute mode over the other even if it requires more time and greater monetary cost. Examples of non-monetary disutility are expending effort to commute, bearing the burden of a crowded subway, or inhaling exhaust fumes while in traffic.

We modify a standard Cobb-Douglas labor supply function to accommodate commute mode choice and distinguish restricted from non-restricted days. We assume a linear wage function but comment on relaxing this assumption below. We model the OddEven restrictions and consider each worker's utility over a representative two-day period: one non-restricted and one restricted day. On the restricted day the worker suffers a penalty for driving. Absent the policy, the two days are identical. We consider the OddEven policy because it is simpler to model than and generates the

[7] The restrictions apply to non-commuters but they likely have greater flexibility for inter-temporal substitution. Including non-commuters, as our pollution data does, will bias us toward finding no effects. Since our viewership data is comprised only of workers the model applies directly to it. According to the 3rd Beijing Transportation Comprehensive Survey (Beijing Transportation Research Center, 2006), 48% of daily Beijing travelers across all modes are commuters.

[8] After our sample period (beginning April 12, 2010) official working hours became 9 a.m. to 6 p.m.

same intuition as the OneDay policy.[9] After solving the model for each worker we examine the aggregate effects on pollution and work time across the distributions of workers. The model considers only first-order effects but we comment on second-order effects due to changes in congestion below. The model assumes:

(A) Absent the restrictions, commute times and costs are low enough that it is optimal for all workers to work both days.
(B) Compliance costs are small enough that workers do not leave the workforce[10] or transition between jobs with discretionary and fixed work times.
(C) Wages and house prices do not adjust, workers do not move their residences or change their workplace (*i.e.*, commute times and costs are fixed), and workers do not purchase a second car to comply with the restrictions.[11]
(D) The penalty is great enough that it is never optimal to drive on a restricted day.
(E) License plate numbers are uniformly distributed with half restricted each day.

The driving restrictions affect work time on both an extensive margin (days worked) and an intensive margin (daily work hours conditional on working that day). Workers who are indifferent between working and staying home on a particular day determine the extensive margin. Workers who are indifferent between extending and not extending their daily work time determine the intensive margin. Extensive margin effects are relevant for pollution effects because they determine the number of aggregate daily auto trips. Leisure (and therefore TV viewership) is affected on both margins since it depends on both the number of days and daily hours worked.

Those with discretion may choose to work either "full time" (both days) or "reduced time" (one day). Assumption (A) and diminishing marginal utility of consumption ensure that the worker will at most remain home on the restricted day. We consider only a representative two-day period so all restricted days are identical. As a result, "reduced time" means taking every other day off from work. A more general model with random variation in daily productivity and leisure options would allow for less

[9] It is straightforward to adapt the model to the OneDay policy and the results differ only in magnitude. The commute costs it imposes are lower making "reduced time" less likely. However, declining marginal utility makes "reduced time" more likely because goods consumption suffers less from not working one day out of five rather than one day out of two. A full analysis of the OneDay model is available from the authors.

[10] Gibbons and Machin (2006) discuss the theoretical effect of increased commute costs on the labor participation/non-participation margin. Black, Kolesnikova, and Taylor (2010) find that female labor force participation rates are lower in cities with longer commute times consistent with women as the primary margin of labor supply adjustments.

[11] Eskeland and Feyzioglu (1995) model this last effect. Due to the integer nature of car purchases, some households are on the margin between zero and one car while others are on the margin between one and two. Driving restrictions reduce the service flow from owning a single vehicle and can lead the former to sell their vehicle but the latter to buy another vehicle.

regular and extreme reductions. This simple model is adequate since we do not use it for calibration or direct estimation. We first discuss the theoretical implications for the extensive margin as it relates to both pollution and work time.

Extensive Margin Effects: Absent the restrictions both days are identical and workers in both categories work "full time" by Assumption (A) and choose the same commute mode on both days. Whether a worker chooses to commute by public transit or auto depends on the costs and times they face for each, their return from working as determined by their wage, and the consumption their non-wage income provides.

For those with fixed work times, the restrictions have no impact on the extensive margin since they do not control their work times. They must work each day for specific hours and will take public transit on the restricted day regardless of their preferred mode when unconstrained. Therefore,

Implication 1: Across all workers with fixed work times, days worked (the extensive margin) and therefore days spent entirely on leisure are unchanged due to the policy.

The extensive margin effect for workers with discretionary work time depends on their preferred commute mode absent the restrictions. Those who prefer public transit are unaffected and will continue taking public transit both days. Given Assumption (D), workers who prefer to drive can either take public transit or not work on their restricted day.[12] Some will choose the latter due to the higher commute costs and instead substitute to leisure activities, including watching TV. There are two ways in which the higher commute costs may manifest themselves (Appendix C provides the details). First, ignoring non-monetary disutility from commuting, "reduced time" is preferable if public transit is sufficiently slower or more costly than driving. Second, even if public transit is cheaper and faster, "reduced time" is preferred if public transit is sufficiently unpleasant (non-monetary disutility is high). Therefore,

Implication 2: Across all workers with discretionary work time, days worked (the extensive margin) decrease and days spent entirely on leisure increase due to the policy.

These are the first-order effects on the extensive margin. Second-order effects may attenuate these. Auto congestion will decline and public transit congestion will

[12] Appendix B shows that it is not optimal to work on the restricted day and instead stay home on the non-restricted day under fairly general conditions.

increase. This will induce some people to drive who otherwise would take public transit on their non-restricted day.

Given Assumption (D) and that all workers continue to work on their non-restricted day, the effects on pollution are straightforward. One-half of workers in each category who prefer to drive cannot do so on a given day. Therefore,
Implication 3: Total auto commutes and pollution decrease due to the policy.

Because our model does not consider non-work driving and assumes all days are work days, there is no possibility of inter-temporal substitution. In a more general model, workers may drive more on their non-restricted day because they cannot on the restricted day.[13] This will attenuate the pollution effects and lower empirical estimates.

Intensive Margin Effects (Workers with Fixed Work Times): Although the restrictions do not affect work hours for workers with fixed work times, they may affect daily leisure time due to altered commute modes. Those who took public transit absent the restrictions will still do so and their daily leisure time is unaffected. For those who prefer to drive absent the restrictions, leisure is unaffected on non-restricted days since they continue to drive. However, on restricted days they are forced to take public transit. Their leisure time increases if public transit commuting is faster than auto and decreases if not. Since our empirical data on leisure includes both commute modes, we are interested in the aggregate effect. Intensive margin effects are zero for those who normally take public transit and ambiguous for those who normally drive; therefore,[14]
Implication 4: Daily hours spent working (the intensive margin) across all workers with fixed work times is unaffected by the policy. However, daily hours spent on leisure could either increase or decrease due to the policy.

Intensive Margin Effects (Workers with Discretionary Work Time): Intensive margin effects for workers with discretionary work time vary depending on whether they choose to work "full time" or "reduced time" and whether they prefer taking public transit or driving. Workers who prefer public transit absent the restrictions continue to work "full time" and take public transit both days so their work and leisure time remain the same. Those who prefer driving and choose to work "full

[13] Under the OneDay policy the restrictions also do not apply on the weekends allowing for more inter-temporal substitution. We allow for this in our empirical tests.
[14] The second-order effects (increased public transit and decreased auto commute times) of the restrictions also impact Implications 4 and 5 but do not change the ambiguity of the implications.

time,” on the other hand, must commute by public transit on the restricted day. As a result, daily leisure time increases or decreases depending on whether public transit commute times and costs are less or more than those by car. Unlike those with fixed work times, commute costs matter because daily labor supply is discretionary. Due to diminishing marginal utility, the worker equalizes leisure time across the work days and shares the difference in commute times and costs across the restricted and non-restricted days.

For workers with discretion who work “reduced time,” leisure time most likely decreases on the non-restricted day. Leisure time can increase if non-wage income is high but this is unlikely. In general, leisure time will decrease because workers will compensate for working fewer days by working longer daily hours. Since our empirical data on leisure time includes “full-” and “reduced-time” workers using either commute mode, we are interested in the aggregate effect. Intensive margin effects are zero for those who take public transit, ambiguous for those who work “full time” and normally drive, and ambiguous but likely positive for those who work “reduced time.” Therefore,

Implication 5: Daily hours spent working (the intensive margin) across all workers with discretionary work time could either increase or decrease due to the policy. As a result, daily hours spent on leisure could either increase or decrease due to the policy.

Our results for those choosing “reduced-time” are consistent with Gutiérrez-i-Puigarnau and van Ommeren (2009), who consider a general, concave wage function. Commute costs are fixed per daily trip so workers reduce the number of trips and generally spread these costs over longer daily hours. Allowing for a concave wage function in our model would lead to a smaller share of workers working “reduced time” and a smaller increase in daily work hours because declining marginal productivity of work would lead to a decline in wages with longer daily work hours.

4. Data

We use two primary data sets. The first is a daily measure of Beijing air pollution at both an aggregate and individual monitoring-station level. The second is an hourly measure of TV viewership by different categories of Beijing residents. We supplement these with control variables thought to affect air pollution and TV viewership. Our sample is from January 1, 2007 to December 31, 2009. This provides us with 1,096 total days of which 547 days occur before OddEven, 62 during OddEven, 21 between OddEven and OneDay, 182 days during OneDay69, and 265 days during OneDay78. This provides a fairly symmetric window – approximately 1.5 years both before and during the policy regimes. Appendix E provides descriptions and Table 1 summary statistics for all variables.

Pollution Data: Our pollution measure is the daily Beijing Air Pollution Index (API) published by the State Environmental Protection Agency (SEPA) and Beijing Environmental Protection Bureau (BJEPB). We use the API at both the individual monitoring-station[15] and aggregate levels. The latter is a simple average of the station-level APIs. Station composition varied a little over time. In 2007 the aggregate API is based on 28 stations. Five stations are dropped and four added for a net total of 27 stations to compute the aggregate API in 2008 and 2009. Figure 2 shows locations of monitoring stations in 2008 and 2009. Chen, *et al.* (2011) provide evidence on the accuracy of the Beijing API using independent satellite data.

The API is intended to provide specific advice on behavior (*e.g.,* not exercising or spending time outdoors) and ranges from 0 to 500 with higher values indicating stronger pollution concentrations and more harmful effects (see USEPA (2009) for details). Its value depends on concentrations of three different pollutants which affect proper breathing: particulate matter (PM_{10}), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). An API is calculated for each of the three pollutants but only the maximum one is reported. To compare the relative severity of the three pollutants, the concentration of each is rescaled before choosing the maximum.[16] PM_{10} is converted to the API based on the piecewise linear function shown in Table 2.

The maximum pollutant is identified only if the API exceeds 50. We focus on PM_{10} since it is the predominant pollutant on 917 of the 953 days with an API above 50. PM_{10} is the ambient concentration (in $\mu g/m^3$) of particulates smaller than 10μm. Since there are 143 days when the API is below 50 and the maximum pollutant is unidentified and 29 days when the worst pollutant is other than PM_{10},[17] we estimate two different specifications. In one we include all days regardless of pollutant type. In the other we allow our policy variables to have a differential effect when the API is

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[15] We thank Steven Q. Andrews for making this data available to us. Our description of the pollution data is based on Andrews (2008).
[16] Specifically, for the daily, station-level API an average concentration at each station for each of the three pollutants is first calculated across 24 hourly readings. Each of the three is converted to an API measure and the maximum is the daily API reading for that station. For the aggregate API, an average is taken across all stations of the average daily concentration at each station for each pollutant and then each is scaled to an API. The maximum API of the three pollutants is the daily aggregate API.
[17] The other 7 days when the API is above 50 the pollutant identity is missing.

below versus above 50 and when a pollutant other than PM_{10} is predominant. In our sample, the API ranges from 12 to 500 and averages 91.

Various sources create particulate matter, but autos are the major contributor in most urban areas. Autos create PM_{10} through emissions and by creating road dust.[18] Hao, Wang, Li, Hu, and Yu (2005) find that approximately 53% of Beijing's PM_{10} is attributable to motor vehicles – 23% due to emissions and 30% due to road dust.[19] As a rough rule of thumb, therefore, autos create half of the air pollution we measure.

TV Viewership Data: We use TV viewership to measure how driving restrictions affect work time. In the absence of data on work and total leisure time, viewership is a good proxy for two reasons. First, it is a large component of leisure and therefore a big substitute for work time.[20] Second, using viewership will bias us against finding any effect due to the restrictions. Outdoor activities are likely to become more attractive under the restrictions because auto congestion and pollution are reduced. Since TV viewership is consumed indoors it becomes relatively unattractive compared to other leisure.[21]

Our viewership measure is CSM Media Research's "Television Audience Measurement" (TAM) database, the most comprehensive TV ratings data in China. TAM measures the number of people watching each TV program and commercial. We aggregate to the hourly level across all channels. TAM's Beijing ratings are based on a panel of households, although the data is captured at the individual level. Panelist data is collected through a "PeopleMeter," an electronic device installed inside the TV that detects when it is on and, if so, to what channel it is tuned. Each panelist household has a remote-control device to enter which members are currently watching, which is displayed on the screen for confirmation. This provides individual- rather than household-level data. CSM's Beijing data covers an area very similar to that subject to the driving restrictions. It includes all areas inside the 5th Ring Road and only a small part of the outside suburban area.

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[18] Some governments measure $PM_{2.5}$, which includes only smaller particulates (below 2.5 μm) and does not capture road dust.

[19] Jiang, X. ("23% of PM10 in Beijing Comes From Vehicular Emissions," *Road Traffic and Safety*, 1, 45, 2006 (in Chinese)) and Dong, Liu, and Che (2008) corroborate this breakdown, finding that 23% and 24% respectively of Beijing's PM_{10} is due to auto emissions. Cui, Deng, and Guo (2009) estimate that autos create 62% of all air pollutants, including PM_{10}.

[20] A 2008 survey conducted by the Beijing Statistics Bureau (2009) estimates that the average Beijing resident spends 7.6 hours working, 1.4 hours commuting, 1.8 hours on household chores, and 3.5 hours on leisure activities during a work day. TV watching comprises 1.9 hours or 54% of total leisure time.

[21] TV viewing on mobile devices is extremely limited during our sample period.

TAM provides viewership data for seven different employment categories. We use two categories for which we can ascertain the degree of control that its members have over their work time. Those in the "self-employed" category likely have discretion over their work time. The "hourly workers" category includes mainly hourly employees who have fixed work times. The work time of an "hourly worker" could vary at their employer's discretion but only in the upward direction in the form of overtime. We do not utilize the other five TAM categories either because we do not have specific predictions for them or we are uncertain whether they have control over their work time.[22] CSM also conducts an establishment survey estimating the number of individuals in each category with TV access so that viewership rates can be translated into numbers of individuals watching TV. Table 1 provides summary statistics for each category. On average, across all hours there are 91 thousand "self-employed" and 149 thousand "hourly workers" watching TV although the number varies greatly across hours.

Control Variables: In our pollution regressions, we include a variety of daily weather variables known to affect particulate matter (see USEPA, 2010) all taken from China Meteorological Data Sharing Service System. We include dummies for the four quartiles of the daily maximum wind speed.[23] Higher wind speeds lower pollutant levels. Beijing air quality is greatly affected by wind direction. Northerly winds carry local pollutants while Easterly and Southeasterly bring pollutants from the Eastern coastal and mid-China cities (Wiedensohler, *et al.*, 2007). To control for this flexibly, we use dummies for the four directional quadrants and interact these with the four wind speeds. We include the daily hours of sunshine to control for the amount of atmospheric solar radiation, which allows ozone to form creating secondary pollutants.

Humidity can interact with pollutants to create secondary ones so we include daily average humidity. Precipitation has opposing effects. Rain can interact with existing pollutants to create secondary ones, but can also wash pollutant particles from the air and minimize their formation. To control for either possibility, we include total daily rainfall. Finally, we control for daily maximum surface temperature, which has an

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[22] For brevity we call TAM's "proprietor/private" category as "self-employed" and for clarity we refer to "workers" as "hourly workers." The unused categories are "unemployed," "cadres/managers," "junior civil servants," "students," and "other."

[23] Maximum is across averages during all ten-minute periods of the day. We experimented with using average daily speed, wind gusts (maximum speed during any three-second period), and maximum level directly. Quartiles of maximum daily speed provided the best fit of all these.

indeterminate effect on particulate matter since it depends primarily on whether a temperature inversion is created.

We include dummy variables to allow for different driving behavior on weekends and holidays and monthly dummies to allow for seasonal effects. We also include a dummy for the Olympic period. Since this largely coincides with the OddEven policy period and temporary factory closures, we will emphasize our OneDay results. To control for the other government policies discussed earlier and any pre-existing trend, we include a flexible daily time trend. Since this is an imperfect control, we supplement our RDD regressions with station-level and viewership DD regressions, both of which provide evidence that the driving restrictions cause the pollution effects.

For the viewership regressions, we include daily weather variables that might affect the desire to remain indoors watching TV rather than being outside. These include total rainfall, average wind speed, total hours of sunshine, and average surface temperature. We use daily measures even though our regressions are at the hourly level because we assume households decide whether to go to work based on daily expected weather. We include hourly dummies to capture intra-day variation in the appeal of other leisure activities (including sleep) and TV program quality. Similarly, we include weekend and holiday dummies to capture program differences and the appeal of outdoor options during these times. We include monthly dummies to capture seasonality in outdoor activity, and a dummy for the Olympic period since programming differed greatly then. To control for any pre-existing trend prior to the policy change we include a flexible daily time trend.

5. Effect of Driving Restrictions on Pollution

Implication 3 predicts that traffic density and therefore pollution should decline during the policy periods. To test this we employ an RDD method using the aggregate Beijing API. Intuitively, our test determines if any pre-existing time trend in pollution is altered during the policy periods conditional on the control variables. Since coincident factors may confound these results, we provide additional evidence based on DD estimates using station-level API data. This geographic variation allows us to relate the policy impact to each station’s distance from a major road. We find that these local API measures dropped less due to the policies for stations further from a major road than they did for those closer and that the effects dissipate at a distance consistent with the atmospheric behavior of PM_{10}.

Effect on Aggregate Pollution: To determine the effect of the driving restrictions on aggregate pollution we employ an RDD method. We allow for a potential discontinuity in each of the policy regimes (OddEven, OneDay69, and OneDay78 denoted by OE, $OD69$, and $OD78$):

$$\begin{aligned}(1)\qquad \log\left(API_t^A\right) &= \alpha + \beta_1 \log\left(API_{t-1}^A\right) + \sum_{i=1}^{11}\beta_{2i} m_{t\in i} + \sum_{k=1}^{K}\beta_{3k} Z_{tk} + \sum_{l=1}^{L}\beta_{4l} t^l + \beta_5 WE_t + \\ &\beta_6 HO_t + \beta_7 OE_t + \beta_8 OD69_t + \beta_9 OD78_t + \left(\beta_{10} OD69_t + \beta_{11} OD78_t\right) * WE_t + \varepsilon_t^A.\end{aligned}$$

API_t^A is the aggregate API on day t, m_t are monthly dummies designed to capture any seasonality not captured by the weather controls, Z_t contains weather and other control variables, WE_t is a weekend dummy, and HO_t is a holiday dummy. We include the lagged API to allow for persistence in air conditions across days. The vector β_4 captures any pre-existing time trend using an L^{th}-order polynomial function of days t. β_5 captures any differences in pollution on weekends and β_6 does the same during holidays. β_{7-9} are the primary coefficients of interest and capture any discontinuity due to the policies. β_{10-11} capture any inter-temporal substitution to weekends within the OneDay policy periods. We expect β_{10-11} to be weakly positive.

Column 1 of Table 3 shows a baseline regression with no time trend. The OddEven and OneDay coefficients are both negative and highly statistically significant. In Columns 2 and 3, we introduce linear and quadratic time trends. The monthly dummies remain so that any identified time trend is of seasonally-adjusted data. None of the time trend coefficients is significant under either the linear or quadratic specifications and an F-test (the bottom row of Table 3) reveals that the time trend coefficients are not jointly significant.[24] The main difference from the baseline results is that the OneDay coefficient is larger. This is because the OneDay policy variable is highly correlated with a time trend. This indicates the importance of our station-level and viewership evidence presented later which do not rely exclusively on time-series variation. To be conservative, we focus on the smaller effects of the baseline model.

Both policy variables are highly statistically significant and show a decrease in pollution during the restricted periods (Appendix F shows this visually). The aggregate API was 19.3% lower during the OddEven restrictions and the 95% confidence interval is 14.9 to 23.6%. With perfect compliance, no substitution to non-restricted hours, and a linear relationship between the number of cars and pollution,

[24] We experimented with higher-order time trends and found the coefficients were jointly insignificant up to a 7^{th}-order. The results are also robust to using year dummies rather than a time trend and allowing different time trends during the pre-treatment and policy periods as suggested in Angrist and Pischke (2009, page 255). There was also a four-day period (August 17 to 20, 2007) when odd-even restrictions were tested. Setting the OddEven variable to one for these days yields very similar results.

we would expect about a 25% decrease during the OddEven period (traffic reduced by 50%[25] and 50% of PM_{10} produced by motor vehicles).[26] The aggregate API was 7.9% lower with a 95% confidence interval of 5.2 to 10.7% during the OneDay policy. We would expect about a 10% decline (traffic reduced by 20% each day and 50% of PM_{10} created by motor vehicles). These estimates are consistent with a high level of compliance. We control separately for substitution to weekends and find that the API increases 9.7% during OneDay weekends. Although this percentage increase is similar to the weekday decrease, the weekend API is lower and applies to two days rather than five so that overall pollution declines.

Of the control variables, approximately 31% of the API persists day to day. Even after controlling for this, a Durbin-Watson test revealed that the residuals exhibited order-one autocorrelation so we use Newey-West standard errors with a one-day lag in all aggregate API regressions.[27] The API was significantly lower during the Olympics, consistent with the decreased business, construction, and resident population during that time. A one-degree temperature increase is associated with a 4.8% increase in the API – consistent with greater ozone and secondary pollution creation. A one-percent increase in humidity increases the API by 0.5%, consistent with humidity acting to create secondary pollutants. Rainfall has no significant effect, but each additional hour of sunshine decreases the API by 3.3%.

Wind direction has no significant effect, but wind speed does with the two middle quartiles leading to less pollution. This bowl-shaped effect may be due to moderate wind speeds preventing the build-up of pollution but very high wind speeds bringing in particulate matter from the nearby Gobi desert. API is 8.4% lower on weekends but not significantly different on holidays. In unreported coefficients, four of the nine interactions between wind speed and direction are significant and ten of the eleven monthly dummies are significant with December and January having the highest (worst) API levels and July and August having the best conditional on weather.

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[25] As we describe in Section 2, very few cars are exempt from the restrictions.

[26] Substitution effects are likely small since the restrictions applied except from midnight to 3:00 a.m. Pollution rises convexly with car density because congestion causes cars to spend more time idling and a longer time traveling the same distance (see Arnott and Kraus, 2003; Small and Verhoef, 2007). During the OneDay policy, a larger adjustment for inter-temporal substitution is required because the OneDay restrictions do not apply in the late evening and early morning hours.

[27] We ran the baseline regression using OLS and the standard errors were very similar. Since aggregate API is constrained at a maximum of 500 we also ran a Tobit regression. The results were almost identical. We do not use this as our primary specification because we cannot control for autocorrelation.

Column 4 shows the results of estimating the baseline regression but distinguishing between OneDay69 and OneDay78. This is demanding since the only change in the policy from OneDay69 to OneDay78 is slightly shorter restricted hours. Coefficients on the non-policy variables are virtually identical. The two OneDay policy coefficients are very statistically significant. The point estimates indicate a 7.4% drop in the API during the OneDay69 restrictions and 8.3% during OneDay78. However, an F-test rejects the hypothesis that the coefficients are unequal only at the 80% level.

Table 4 contains robustness checks. Column 1 repeats the baseline results from Table 3 for comparison except we no longer display the effects of wind speed or direction to conserve space. Column 2 introduces dummy variables to distinguish observations where sulfur dioxide is the worst pollutant ("SO2") or the API is below 50 and we do not know the primary pollutant ("Blue Sky"). We also interact these with the policy variables (there are no "SO2" days during the OddEven policy). The OddEven and OneDay effects are very similar: 18.9% and 8.8% decreases respectively. As expected, the "Blue Sky" dummy is highly significant and negative. The "SO2" dummy is significantly negative although we have no prior expectation on this. The only significant changes are that the API is less persistent across days and the Olympic variable is no longer significant consistent with many of the "Blue Sky" days occurring during the games.

Column 3 uses log PM_{10} as the dependent variable using the transformation in Table 2 to convert from the API. Because we must drop "Blue Sky" and "SO2" days, the number of observations falls to 916 and we cannot use Newey-West standard errors although we continue to include the lagged dependent variable even though the lag sometimes exceeds one day. The results are similar to the baseline API results.

Effect on Station-Level Pollution: The RDD results depend entirely on time-series variation and therefore could be due to contemporaneous, confounding factors. To reduce this possibility, we use geographic variation in the location of individual monitoring stations and apply a DD test.[28] These regressions test whether pollution decreased more for monitoring stations that were located closer to major roads than for stations located further away in response to the policies. The regression is:

[28] Another DD approach would be to use any non-uniformity in the plate number distribution and allow for differential effects in which plate numbers were restricted on a given day. However, plate numbers were assigned randomly by the Beijing Traffic Management Bureau for a uniform fee through March 9, 2009. Only after that could a plate number be selected from a set of available numbers for a fee. Since April 10, 2009 plates can be exchanged at no cost but only from a list of ten numbers.

$$\log\left(API_{st}^{S}\right)=\sum_{s=1}^{S}\alpha_s+\beta_1\log\left(API_{st-1}^{S}\right)+\sum_{i=1}^{12}\beta_{2i}m_{t\in i}+\sum_{k=1}^{K}\beta_{3k}Z_{tk}+\sum_{l=1}^{L}\beta_{4l}t^l+\beta_5 WE_t+ \tag{2}$$
$$\beta_6 OD_t*WE_t+\sum_{j=0}^{J}\left(\beta_{7j}OE_t+\beta_{8j}OD_t\right)*\left(Dist_s\right)^j+\varepsilon_{st}^{S},$$

where API_{st}^{S} is the daily API at station s on day t. As before, we include lagged API to capture persistence, monthly dummies to capture seasonality, control variables, a flexible time trend to capture any pre-existing trend, a weekend dummy to allow for differential effects, and an OneDay-weekend interaction to allow for inter-temporal substitution. Our DD estimator is implemented by including station-level fixed-effects $\left(\alpha_s\right)$ and a polynomial function of distance $\left(Dist_s\right)$ between each station and the nearest major road interacted with the policy variables. A positive coefficient for β_7 (β_8) indicates more pollution reduction for stations in closer proximity to a major road during the OddEven (OneDay) periods. Fixed-effects control for any time-constant, station-specific factors that affect pollution, including stationary sources of pollution such as a nearby factory as well as the baseline effect of distance. We use robust standard errors clustered at the station level to allow for general autocorrelation within stations and general heteroskedasticity.

We first confirm that results similar to those at the aggregate level are obtained with a station-level, fixed-effects regression (*i.e.*, we set $J=0$). We use a panel of 24 stations, 22 of which operated the entire time and two of which operated from 2008 to 2009.[29] There are a few missing observations because no API was reported for some days at some stations. Column 1 of Table 5 shows the results. We find similar effects to those from our aggregate API estimates, except that the magnitude of the OneDay coefficient is greater and the control variables are generally more significant. The OddEven policy reduces the API by 18.2% and the OneDay policy by 14.7%. We again find evidence of substitution to weekends with pollution 6.9% greater on weekends during the OneDay policy.

For our DD estimates, we use the minimum distance "as the crow flies" between a monitoring station and the nearest Ring Road.[30] We use only the eight monitoring

[29] A balanced panel would include only the 22 stations. We add the two stations because they are present during most of our time period and are located within the 4th Ring Road which adds identifying variation to our distance estimates below. The results using the balanced panel are very similar.
[30] Specifically, we use the Geographic Information System (GIS) software's ARCINFO command "Near" to compute the distance between the monitoring station and the nearest point on the road. The busiest roads in Beijing are segments (East, West, North, or South) of the four Ring Roads (2nd, 3rd, 4th, or 5th) according to 2006 data from the Beijing Transportation Research Institute. To ensure our results do not depend on the choice of Ring Roads, we re-estimated using distances from the nearest Class 1 road – any multi-lane highway with controllable entries and exits. The results were very similar.

stations within the 4th Ring Road for two reasons. First, using stations too far from major roads will bias against finding an effect because auto pollution will be dispersed widely enough that it will be indistinguishable from other pollution sources. Beijing's road network is densest inside the 4th Ring Road and monitoring stations within this area are sufficiently close to roads to detect the effect of distance. Table 1 confirms that stations within the 4th Ring Road are much closer to the nearest Ring Road than those outside. Second, none of the restrictions applied to the 6th Ring Road and the OneDay78 policy also did not apply to the 5th Ring Road. We would need to exclude these from our distance calculations since we do not know how traffic on them is affected. The restrictions decrease traffic if, absent the restrictions, it primarily feeds into the area within the 5th Ring Road. On the other hand, traffic increases if drivers use these roads more intensively to travel from one side of the city to the other while complying with the restrictions.[31] This ambiguity also rules out using monitoring stations outside the 5th Ring Road as a control group for those inside in a DD specification.

Column 2 of Table 5 shows the results of estimating Equation (2) using a linear function of distance $(J = 1)$. We include station fixed-effects and the same control variables. During the OddEven period pollution drops by 20.6% at the Ring Roads but the effect dissipates by 9.1 percentage points with each kilometer from the road. During the OneDay period pollution drops by 8.8% at the Ring Roads and dissipates by 5.8 percentage points with each kilometer. According to USEPA (2001, pp. 2 – 3), most PM_{10} emissions are deposited within a few kilometers of their release. Extrapolated slightly out of sample, our results imply that the pollution reduction dissipates at a distance of 2.3 kilometers for the OddEven policy and 1.5 kilometers for the OneDay policy. In Column 3 we allow for a quadratic function of distance $(J = 2)$. For the OddEven regime, both distance terms are significant, pollution drops at the Ring Road and the effect declines in distance with a minimum at 1.1 kilometers. The OneDay results are also significant with a minimum at 1.0 kilometers.

Policy Comparisons: We can perform "back-of-the-envelope" calculations to determine the increase in gasoline prices or auto registration fees necessary to achieve the same pollution reduction as the OneDay policy (8%). Cheung and Thomson (2004) estimate a long-run gasoline price elasticity of -0.56 in China using data from 1980 to

[31] We estimated the regression in Column 1 of Table 5 but distinguished stations outside the 6th Ring Road during the OddEven and OneDay69 policies and stations outside the 5th Ring Road during the OneDay78 policy. We found no differential effect on these stations consistent with the restrictions reducing traffic that otherwise would have fed into the area inside the 5th Ring Road.

1999. The gas price at the midpoint of our sample is about RMB 6 per gallon, implying that a long-run price increase of RMB 0.85 per gallon (14%) would be required to achieve the same pollution reduction if pollution falls linearly with gas consumption. Another alternative is to increase registration fees to reduce the stock of cars. If registration is one-time and transferrable across owners, a fee increase is equivalent to a vehicle price increase. Deng and Ma (2010) estimate an own-price elasticity of -9.2 for autos in China using annual data from 1995 to 2001. The authors note that this estimate is about three times greater than estimates from U.S. data, possibly due to auto price elasticities declining with rising incomes. Given income increases in China since 2001 it is useful to consider a range of elasticities from -3.0 to -9.2. If total miles driven falls linearly with car ownership and assuming an average car price of USD 15 thousand,[32] a license fee increase of USD 130 to 400 (RMB 858 to 2,631) would be required to obtain the same 8% pollution reduction. This compares to the current RMB 500 (USD 76) registration price in Beijing.[33]

Alternative Explanations: Our DD results show that the policies affected different stations differently depending on their distance from the Ring Roads. Given this, any confounding factors must be related to proximity to major roads. Before moving to our viewership results we consider some possibilities. Retail gasoline prices are regulated by the National Development and Reform Commission (NRDC) and changed somewhat during our sample period. Prior to December 19, 2008, the NRDC set a baseline price and allowed firms to charge a retail price within 8% of it. After this, NRDC imposed a retail price ceiling. The timing of the price changes is generally different than that of the driving restrictions, although there was a significant price drop around the start of the OneDay restrictions which would bias against our findings. We added log retail price to our baseline aggregate API regression and the results were very similar.[34]

[32] Unless otherwise noted, all exchange rate conversions performed at January 2011 rates (1 RMB = 0.152 USD). Most 2009 car purchasers targeted a car price of RMB 50 to 150 thousand according to “Annual Report of China Car Industry 2009 – 2010,” An, *et al.* (2010). The midpoint of this range yields USD 15.2 thousand.
[33] “Beijing’s Plan to Steer Clear of Traffic Jams,” *China Daily*, December 14, 2010.
[34] The price coefficient was insignificant in the regression. Price data taken from NDRC documents at the Beijing Development and Reform Council website (http://www.bjpc.gov.cn).

Regulated parking rates at public garages did not change during our sample period.[35] Private garages are allowed to charge market rates but this would bias against a reduction in driving. The number of official taxis in Beijing has remained constant at 66,646 since 2006 under a decision by the Beijing Council of Transportation under the "Tenth Five-Year Plan."[36] Taxi cab emissions have declined over time through replacement of older taxis and upgrading of existing equipment but this has occurred gradually and would be captured by our time trend. Staggered working hours were officially adopted in Beijing for those employed by social organizations, non-profit institutions, state-owned enterprises, and urban collective-owned enterprises but this did not take effect until April 12, 2010, after our sample period.

There were two changes in auto emissions regulations during our sample period. China's emissions standards are similar to European Standards I to V. From the beginning of our data through February 28, 2008 autos registered in Beijing had to conform to the Level III standard and have an on-board system that stops the vehicle if the limit is exceeded. From March 1, 2008 through the end of our sample, new vehicles had to meet the Level IV standard, which requires 30% lower maximum emissions. The timing of these changes differs from those of the driving restrictions and since the change applied only to new vehicles it would occur gradually and be captured by the time trend.

Beijing added subway capacity during our sample period (see Figure 1). The timings did not generally coincide with the OddEven and OneDay policies; however some of the effect that we measure could result from substitution from auto to public transit commuting. The following viewership results will eliminate this possibility.

6. Effect of Driving Restrictions on TV Viewership

We examine TV viewership for two reasons. The first reason is to provide evidence on the restrictions' effect on economic activity. Implications 1 and 2 predict that the restrictions should have different extensive margin effects on leisure time (and therefore TV viewership) for workers with and without discretion over labor supply. We use viewership measures for two different employment categories in the TAM data – "self-employed" and "hourly workers" – to test this. Second, it provides a

[35] According to parking regulations in, "Notice of Adjusting the Rates for Non-Residential Parking Lots in Beijing," Beijing Municipal Commission of Development and Reform (2010), File No. 144 (in Chinese) and "Notice of Adjusting the Rates of Motor Vehicle Parking Lots in Beijing," Beijing Bureau of Commodity Prices (2002), File No. 194 (in Chinese).

[36] According to *Beijing Statistic Yearbook* (2007, 2008, 2009), China Statistics Press.

means to rule out additional confounding factors that might explain the pollution reductions. We contrast the effects on viewership for workers with and without discretionary work time. Any factors that reduce both auto and public transit congestion, such as expanding subway capacity, increase TV viewership for both groups – an implication we can test.

Our comparison embeds RDD estimation within a DD design. We first estimate the policy's effect on each worker category using an RDD. This estimates whether there is a discontinuity in viewership during the policy periods relative to any pre-existing time trend conditional on control variables. We then use a DD design to see if the policy change affects the two groups of workers differently.

Since most workers' regular work hours occur during the restricted hours, we measure extensive margin effects by changes in aggregate TV viewing during restricted hours. Although extensive margin changes may extend outside the restricted hours if work day length exceeds the restricted period, they will certainly affect viewership inside the restricted hours. Therefore, we can restate our two main testable implications as:

Implication 1': During the policy period, TV viewership across all workers with fixed work times is unchanged during regular work (restricted) hours.

Implication 2': During the policy period, TV viewership across all workers with discretionary work time increases during regular work (restricted) hours.

Since changes in the intensive margin will manifest themselves primarily outside the restricted hours, we measure intensive margin effects by changes in aggregate TV viewership outside the restricted hours. Given the less-than-perfect correspondence between the extensive margin and the restricted hours and since theory is ambiguous about the intensive margin effects (see Implications 4 and 5), our primary goal in estimating the intensive margin effects is to see if they overwhelm those on the extensive margin.

To determine the restrictions' effect on viewership for each worker category we employ an RDD design. We allow for a potential discontinuity for each of the three policies (OddEven, OneDay69, and OneDay78). For the OneDay69 and OneDay78 policies we allow for intra-day discontinuities to estimate the effect on the extensive and intensive margins. We only allow for a daily discontinuity for the OddEven policy because intra-day work patterns were greatly disrupted by the Olympics. For the same reason, we will focus on the OneDay results. We estimate:

(3)
$$\log\left(View_{th}^{c}\right)=\beta_{1}\log\left(View_{t,h-1}^{c}\right)+\sum_{i=1}^{23}\beta_{2i}\alpha_{i=h}+\sum_{j=1}^{11}\beta_{3j}m_{t\in j}+\sum_{k=1}^{K}\beta_{4k}Z_{tk}+\sum_{l=1}^{L}\beta_{5l}t^{l}+$$
$$\beta_{6}WE_{t}+\beta_{7}Hol_{t}+\beta_{8}OE_{t}+\left(\beta_{9}OE_{t}+\beta_{10}OD69_{t}+\beta_{11}OD78_{t}\right)*WE_{t}+$$
$$\left(\beta_{12}OE_{t}+\beta_{13}OD69_{t}+\beta_{14}OD78_{t}\right)*Hol_{t}+\left(\beta_{15}OD69_{t}+\beta_{16}OD78_{t}\right)*RH_{th}+$$
$$\left(\beta_{17}OD69_{t}+\beta_{18}OD78_{t}\right)*NMH_{th}+\left(\beta_{19}OD69_{t}+\beta_{20}OD78_{t}\right)*NEH_{th}+\varepsilon_{th}^{c}.$$

$View_{th}^{c}$ is thousands of people watching TV on day t during hour h for worker category c ("self-employed" and "hourly workers"). We include lagged viewership because viewing is known to persist across programs (see Goettler and Shachar, 2001). This hourly dependency is separate from the daily time trend. The hourly dummies (α) capture baseline differences in hourly viewing and Z_t contains weather and other control variables. The vector β_5 captures any pre-existing time trend in daily viewership using an L^{th}-order polynomial function. β_6 and β_7 capture differences in weekend and holiday viewership before the policy and β_8 captures change in viewership during the OddEven regime. β_{9-11} capture difference in viewership on weekends during the different policy regimes while β_{12-14} do the same for holidays.

The primary coefficients of interest are β_{15-20}, which capture differences in viewership during the OneDay periods relative to the pre-existing trend. We divide the day into three time segments to separately estimate the effects on the extensive and intensive margins. RH_{th} equals one during restricted hours and zero otherwise. For non-restricted hours, NMH_{th} equals one during morning hours (midnight to 6:00 a.m. during OneDay69 and midnight to 7:00 a.m. during OneDay78) and NEH_{th} equals one during evening hours (9:00 p.m. to midnight during OneDay69 and 8:00 p.m. to midnight during OneDay78) and zero otherwise. We expect the extensive margin effects to be positive for "self-employed" $(\beta_{15}>0)$ and zero for "hourly workers" $(\beta_{16}=0)$. β_{17-20} capture effects on the intensive margin and our theory is ambiguous about these. We use morning and evening segments as a parsimonious way to distinguish non-restricted periods with very different viewing patterns. As a robustness check we allow for fully flexible, hour-by-hour effects as discussed below.

Table 6 displays the results of estimating Equation (3) for the "self-employed" and "hourly workers" categories. We employ a seventh-order polynomial function of days to control for any pre-existing trend – a choice we justify below. The residuals were found to have autocorrelation with a maximum lag of four hours, so we use Newey-West standard errors with a four-hour lag.

Effect on Viewership by Workers with Discretionary Work Time: Columns 1 and 2 display the results for "self-employed" workers. Viewership is persistent with 55% of viewers continuing to watch from the previous hour. Greater rainfall has a statistically significant effect but its magnitude is negligible. More hours of sunlight are associated with less TV viewership. "Self-employed" watch more TV on weekends, holidays, and during the Olympics. Viewership increases 11.6% during the OddEven policy but only by 2.4% during OddEven holidays. We do not have specific predictions for the OddEven period because the Olympics greatly altered regular work and leisure patterns then.

The primary coefficients of interest are those on the interactions between the OneDay policies and time segments. These represent the differential viewership during the policy periods relative to the pre-existing time trend and conditional on the control variables. Implication 2 predicts that average viewership during restricted hours will increase as marginal workers who normally drive will find it too costly to do so on their restricted day. In fact, viewership during the OneDay69 restricted hours is 10.8% higher with a t-statistic of 6.6 and 15.2% higher during the OneDay78 restricted hours with a t-statistic of 7.1. Thus, on the extensive margin, workers with discretionary labor supply work less and enjoy more leisure in the restricted periods.

Using TAM's data on the total number of Beijing workers in each category we can convert these percentage effects to absolute changes. On average, there are 102.1 thousand "self-employed" viewers during the OneDay69 restricted period. This implies an additional 11.0 thousand viewers per hour in the restricted OneDay69 hours relative to without the policy. Assuming that preferences for TV viewing and sensitivity to commute costs are uncorrelated, this extrapolates to 1.7% of the 656 thousand self-employed people in Beijing and 0.12% of the 9.2 million employed people.[37] During the OneDay78 restricted hours there are an average of 98.1 thousand viewers so our estimates imply an increase of 14.9 thousand additional "self-employed" viewers or 2.3% of all self-employed.

Theoretically, viewership outside the restricted hours (the intensive margin) can either increase or decrease. Those who do not work on their restricted day may compensate by working longer hours on non-restricted days; therefore, it is important to check whether intensive margin changes undo some or all of the extensive margin effects.

[37] Population data according to *The China Urban Statistic Yearbook 2009*, China Statistics Press. These calculations assume all Beijing residents have access to a TV. There were 134 color TVs per 100 households in Beijing in 2008 according to *Beijing Statistics Yearbook 2009*, China Statistics Press.

During the OneDay69 period, viewership is not significantly different outside the restricted hours. During the OneDay78 period, viewership increases in both the evening and morning hours. While not the only possibilities, this could be due to decreased auto congestion or a less-than-perfect correspondence between regular work hours and restricted hours (*i.e.*, regular work hours of "self-employed" would have exceeded the restricted hours had they not stayed home on their restricted day).

The intensive margin effects do not offset those on the extensive margin and the increased commute costs under the driving restrictions decrease total work hours. In total, the OneDay69 policy increases TV viewing by 165.2 thousand person-hours and the OneDay78 policy by 279.6 thousand.[38] Our estimates overstate the effects on work time if TV viewing became more attractive relative to other leisure during the policy periods. However, it is more likely that we understate the effects because increased commute costs increase other leisure activities besides TV watching. Our results imply that overall output fell unless productivity increased during the fewer hours not spent watching TV. Productivity may also be lower due to reduced social interactions in the workplace (see Arnott, 2007; Arnott, Rave, and Schöb, 2005).

Effect on Viewership by Workers with Fixed Work Times: Columns 3 and 4 display the results for "hourly workers." Consistent with predictions for the extensive margin (Implication 1), viewership is unaffected during the restricted hours of both the OneDay69 and OneDay78 periods. The point estimates are "tight zeroes" – they are not due to lack of variation in the data. These workers, having no discretion, must commute to work despite the restrictions and their leisure during work hours is unaffected. The results for the control variables in the "hourly workers" equation are similar to those for "self-employed" except that viewership is less persistent, is significantly lower on warmer days, and displays a greater differential on weekends and holidays. Viewership is higher during the OddEven period as it was for "self-employed," though the magnitude is smaller.

Theory is ambiguous about viewership changes on the intensive margin. Work day length will not be affected given fixed work times, but leisure time may decrease or increase depending on whether public transit commuting takes more or less time than by car. Empirically, we find no significant effect on viewership during OneDay69 non-restricted hours. For OneDay78, viewership increases 8.9% in the morning hours.

[38] For OneDay69 this equals 11.0 thousand additional viewers for 15 restricted hours. For OneDay78 this equals the sum of 14.9 thousand additional viewers for 13 restricted hours, 15.3 thousand for 4 evening hours, and 3.4 thousand for 7 morning hours.

Although this is a large percentage increase, it represents only 2.1 thousand additional viewers given the low viewership in morning hours. Viewership also increases by 4.0% in the evening hours. While not the only possibilities, this increase is consistent with lower auto congestion on non-restricted days allowing workers extra leisure time or shorter public transit than auto commute times on restricted days.

Robustness and Alternative Explanations: Appendix G shows the impact of the time trend on estimates of the policy/restricted-hours interaction coefficients. The top panel shows that for "self-employed," the coefficients on both the OneDay69 and OneDay78 interactions are positive and highly statistically significant. The effect of the time trend is in identifying the magnitude of the effect but the coefficients are quite stable at a 2nd-order time trend or higher.[39] In contrast, the "hourly worker" interaction effects, shown in the bottom panel, are small, inconsistent, and with two exceptions insignificant beginning with the 4th-order time trend.

To ensure robustness to the grouping of hours into restricted, non-restricted morning, and non-restricted evening hours; we re-estimated Equation (3) but interacted the OneDay69 and OneDay78 policy variables each separately with 24 hourly dummies for a total of 48 interactions. The results confirm our main estimates. Appendix H, Panel A plots the coefficients on the interaction terms between OneDay69 and the 24 hourly dummies for the "self-employed" category. Coefficients are plotted along the x-axis only if they are significant at the 10% level or better and the vertical lines demarcate the restriction period. Viewership is higher for eleven of the fifteen restricted hours relative to before the policy and all eleven are significant at the 5% level or better.[40] The decrease in the first restricted hour (6:00 – 7:00 a.m.) is consistent with workers shifting their commute earlier to comply with the restrictions.

Panel B graphs the coefficients on the interaction terms between OneDay69 and the 24 hourly dummies for the "hourly workers" category in the same format. The results again confirm our main estimates. Viewership is largely unaffected during the restricted period with only five of the thirteen hours showing an increase. There is also a decrease in the first hour of the restrictions (6:00 – 7:00 a.m.) consistent with workers shifting their morning commute earlier to comply with the restrictions.

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[39] More than a 7th-order time trend created collinearities between the time trend and control variables.
[40] Although the four significant effects in the early morning hours are large in percentage they are small in absolute terms. The average decrease from midnight to 4:00 a.m. is 4.0 thousand viewers per hour. The effect on absolute viewership is much greater during the restricted hours. The average increase from 7:00 a.m. to 7:00 p.m. is 12.8 thousand viewers per hour. These magnitudes are very similar to the average effects in the three time-segment model in Table 6.

Although we do not display them for brevity, the results for the interaction terms between OneDay78 and the hourly dummies are qualitatively similar although stronger. For "self-employed," viewership is significantly higher during all thirteen restricted hours and all are significant at the 1% level or better. For "hourly workers" viewership is not significantly different during any restricted hour.

Alternative explanations need to be consistent with the differing policy effects that we find for those with and without discretionary work time. This excludes greater subway capacity which would directly decrease public transit commute times and indirectly decrease auto commute times as commuters substitute from buses, taxis, or private cars to subways. While this could partially explain our pollution results, it is inconsistent with our intra-day viewership results. First, it conflicts with the increased viewership by the self-employed during restricted hours. Quicker auto and public transit commute times should stimulate daily labor supply. Second, shorter commute times should increase leisure time in non-restricted hours for both groups of workers (Appendix D shows this formally). While it does so for "self-employed" it does so for "hourly workers" only during the OneDay78 policy and only to a small degree.

An alternative interpretation, rather than explanation, of our findings is that employers compensated those with fixed work times for the increased commute costs caused by the restrictions while self-employed were unable to adjust market prices for their output to do so. While our theory model relies on lumpiness in labor supply (those without discretion must work either 40 or 0 hours), this would substitute a story of differences in labor- and product-market demand elasticities.

7. Reasons for Effectiveness

The only other systematic economic evaluation of driving restrictions is Davis (2008), which examines a similar one-day-per-week driving restriction in Mexico City. The study finds no effect from the restrictions, even in the short run, primarily because it stimulated an increase in the number of vehicles in use and a shift toward a greater proportion of high-emissions, used vehicles. In this section we offer reasons why the policy may have worked in Beijing. Most are speculative but we offer detailed evidence of high compliance in Beijing.

Both of the reasons that Davis (2008) cites for the failure of the policy in Mexico City are probably less relevant in Beijing. Although auto ownership is increasing quickly in Beijing, its cost still represents a significant fraction of income for most Beijing residents. In 2008, the average annual salary in Beijing was RMB 44,715 (USD 6,800) compared to USD 25,258 in Mexico City.[41] Therefore, purchasing a first vehicle in response to the reduced auto congestion created by the restrictions might be prohibitive. Also, since cars are not easily divisible (sharing is difficult), purchasing a second vehicle with a different plate number to satisfy the restrictions is expensive.

When cars are added in Beijing, they are also likely to be newer, lower-emissions vehicles. The number of vehicles in Beijing increased rapidly from 62 million in 1992 to 344 million in 2008.[42] This implies a younger auto stock compared to more developed countries where car ownership is a less recent phenomenon. Cars remain less prevalent in China than in developed countries. As of 2007, China had 24 cars per thousand people compared to 787 in the U.S. and 211 in Mexico.[43] This means cheaper, higher-emissions used cars are not as readily available, especially given Beijing's emissions standards for new vehicles.

Although our viewership results rule out Beijing's increase in public transit capacity as an explanation for our pollution results, it may play a complementary role. Greater capacity may have provided workers with better commuting options thereby lowering the cost of complying and limiting the labor supply decrease.

Compliance Evidence: Our pollution results are consistent with high compliance. It is uncertain whether compliance differences might explain the different findings in Beijing and Mexico City. Davis (2008) argues that penalties and monitoring in Mexico City are high but does not provide direct compliance evidence. In this section we present detailed evidence of high compliance in Beijing. Detection in Beijing can occur by any of 2,215 traffic surveillance cameras (one for every 7.7 square kilometers) or by one of about five thousand police officers directing traffic. Annually, the first violation triggers a loss of approximately RMB 595 (about USD 90), including an immediate fine and loss of several fee waivers. Subsequent violations incur a fine of RMB 100 (about USD 15). Violators also incur time costs and possibly psychic costs (Appendix I provides more detail on penalties and detection).

[41] Beijing data from "A Survey Report on Daily Time Allocation of Beijing Residents in 2008," Beijing Statistics Bureau (2009) (in Chinese) and Mexico City from http://mexico-city.co.tv/.
[42] Data from "Independent Environmental Assessment: Beijing 2008 Olympic Games," United Nations Environment Programme, February 2009 (page 42).
[43] Based on "Urban Population, Development and the Environment," United Nations Department of Economic and Social Affairs, United Nations Publication #ST/ESA/SERA/274 (2008).

To test the extent to which the penalties and detection probability ensure compliance, we obtained entrance records for a parking garage located within Beijing's 4th Ring Road. The garage serves a mall and office tower so that parkers are a mix of shoppers and workers. The police require that all Beijing garages record the entrance time to the minute and license plate of each entering car; however, they are not required to take any action against violators of the restrictions. We obtained one week's worth of data (June 27 to July 3, 2010) chosen at random among weeks not containing holidays or government meetings that might alter traffic. The garage's document retention policy prevented us from taking a sample within the time period of our main data.[44]

We divide the week's hours into three categories: restricted weekday, non-restricted weekday, and weekend (non-restricted). The sample week occurred during OneDay78 so we sampled restricted hours from weekday hours between 7:00 a.m. and 8:00 p.m. and non-restricted hours from weekdays between 9:00 p.m. and 6:00 a.m. We avoided sampling data from 6:00 – 7:00 a.m. and 8:00 – 9:00 p.m. because commuting from the 5th Ring Road to the inner part of Beijing can take up to one hour and therefore these hours could contain a mixture of restricted and non-restricted activity.

Since we do not know whether this garage represents Beijing traffic more generally, we only make within-garage comparisons. Weekend activity, when no drivers are restricted, should closely represent the plate number distribution absent restrictions. Although weekend driving may increase overall as drivers substitute from restricted weekdays, we expect this is fairly uniform across plate numbers. Therefore, we use the weekend as the expected distribution of plate numbers. We compare this expected distribution to the observed distribution during weekday restricted and weekday non-restricted periods. We discuss the regular (hourly) parking results first.

Our expected distribution contains 5,975 observations with at least 83 observations for each plate number, thus avoiding any small-sample issues. Figure 3 shows the expected distribution of plate numbers. The distribution is far from uniform because drivers can pay extra to choose a plate number. The number "4" is least popular as it is considered unlucky, while the number "9" is most popular because it is considered lucky. To check compliance, we can compare this expected distribution to each weekday's observed distribution.

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[44] Therefore the sample is not necessarily representative of the plate number distribution during the time period of our pollution and viewership data. In particular, over time drivers may have sought out less common plate numbers to avoid congestion.

We first compare the expected distribution to that observed during weekday restricted hours. For illustration, Figure 4 compares the expected (weekend) distribution to the observed distribution on Tuesday when plates "2" and "7" are restricted. The two restricted plates appear much less frequently than on the weekend and the other plates appear more frequently.[45] Appendix J analyzes data for all five weekdays and applies formal statistical tests. Overall, compliance with the driving restrictions is high. Of the ten restricted plate numbers during the week, eight are not significantly different from zero. Only plates "8," restricted on Wednesday, and "9," restricted on Friday, are significantly different from zero and only in proportions of 2.7% and 2.4% and at significance levels of 7.3% and 8.3%. A few cars entered the garage with no license plate – likely a method for avoiding detection by camera. However, their number was small, not exceeding 1.3% on any of the five days. Since the garage serves primarily professional businesses and an upscale mall we may understate compliance to the extent that the parkers are high income and less sensitive to penalties.

There is little evidence of inter-temporal substitution across weekdays. Only four of the forty non-restricted plates occur in a proportion greater than expected. Thus, drivers do not seem to compensate by driving more on non-restricted days. To check for intra-day substitution, we also compared the expected distribution to that for non-restricted weekday hours. Of the fifty combinations of day/plate numbers, only five occur in greater proportion than expected and only one ("2" on Tuesday) is restricted. Therefore, we find little evidence of intra-day substitution.[46]

The parking data separately identify monthly pass holders. The expected (weekend) distribution contains only 168 observations but there is much more data on weekdays, consistent with this group containing mostly workers. Compliance is also high among this group. Of the ten restricted plates none of them are statistically different from zero. As with regular parkers, we find little evidence of inter-temporal substitution across weekdays. Of the forty non-restricted plate/day observations, only six appear in significantly greater proportion than expected. There was insufficient data on monthly pass holders during non-restricted, weekday hours to perform statistical tests.

8. Conclusion

We find a significant pollution reduction due to Beijing's driving restrictions. We

[45] Figure 4 does not control for the fact that plates "2" and "7" should not occur under perfect compliance. Our detailed analysis in Appendix J does so.

[46] We cannot test for substitution to weekends because we cannot measure activity "but for" the restrictions.

identify the drop both inter-temporally and spatially, with larger drops at monitoring stations that are closer to major roads. Our spatial tests improve upon previous analyses by ruling out coincident policies unrelated to driving. Since most cities that monitor air pollution collect data from multiple locations to ensure representativeness, our approach can be used in other settings to improve identification of any policy change that can be related to stationary pollution sources.

We also devise a novel approach to overcome data limitations in measuring the effect of the driving restrictions on labor supply – measuring substitution to TV viewership. On average, workers with discretion over their work time increase their viewership during restricted hours, consistent with reduced work time due to higher commute costs. For workers with fixed work times, on the other hand, we find no significant effect. Since factors that reduce both auto and public transit congestion, such as expanded subway capacity, would increase TV viewership for all kinds of workers, we can also eliminate these as explaining the pollution reduction.

To explain the effectiveness of the driving restrictions we provide evidence that compliance is high and that inter-temporal substitution of driving is limited. We find only a minor degree of substitution to weekends and the parking garage data reveal no intra- or inter-day substitution. We conclude that driving restrictions can be effective in reducing pollution but at the cost of reduced work time. These are short-run effects. As incomes in China increase, demand for driving will increase and so will the number of cars.[47] Thus, to keep auto pollution levels constant may require further increases in driving costs (*e.g.*, by restricting driving more than one day per week). To the extent that sharing vehicles is costly, this will keep average driving costs high and reduce the equilibrium number of cars. As our results indicate, one cost of this would be further decreases in work time.

Although effective, the restrictions are not the most economically efficient way to reduce pollution. The restrictions arbitrarily reduce demand based on the last digit of a driver's license plate regardless of willingness to pay for driving. A more efficient allocation would result from increasing vehicle license fees. We provide rough calculations of the necessary increase in fees to accomplish an equivalent pollution reduction. Beijing has moved in this direction, beginning to limit the number of new

[47] Duranton and Turner (2009) provide empirical evidence that a fundamental law of auto congestion holds, in which a natural level of congestion is reached in the long run which equates driving demand and average cost of commuting as determined by road capacity.

car registrations in December 2010; however, it is too early to tell how binding the restrictions will be.

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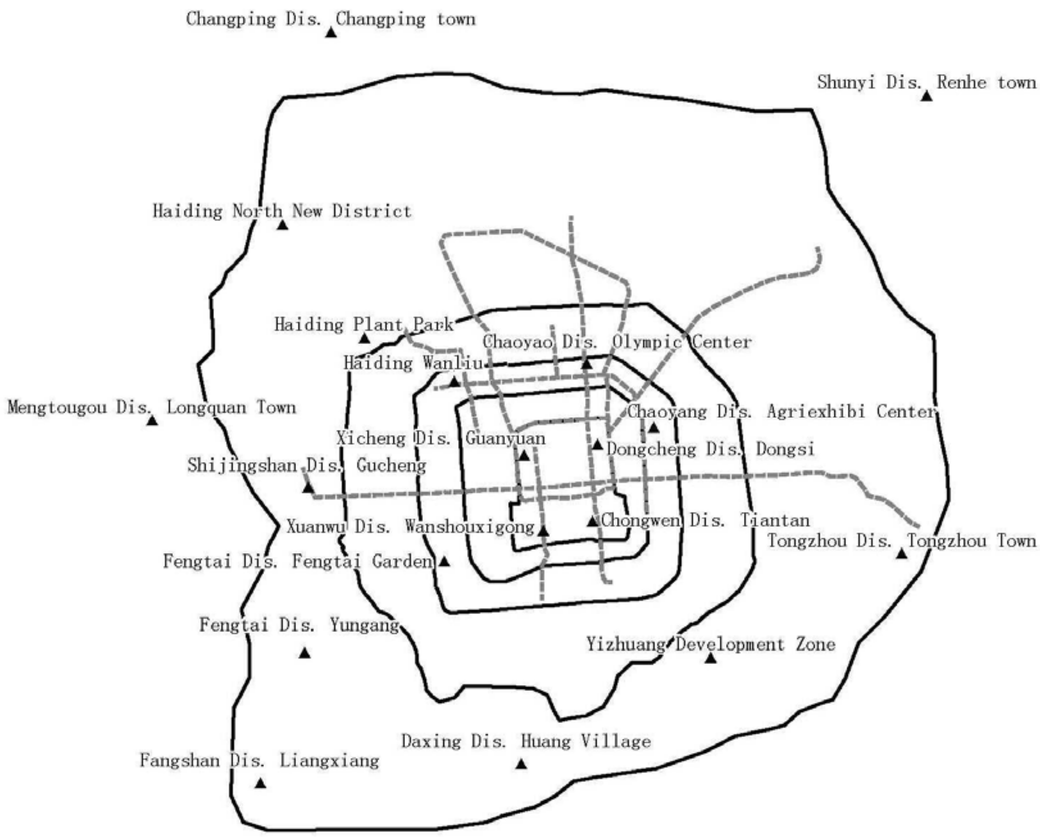
Figure 1 Timeline of Pollution-Reduction Policies

Bus Fare[1]	**01/01/07**	
Subway Fare[2]	**01/10/07**	
Subway Line 5[3]	**07/10/07**	
OddEven	**07/20/08**	**09/20/08**
Subway Line 10/Airport[4]	**07/19/08**	
Olympic Games	**08/08/08**	**08/24/08**
Factory Closures	**07/20/08**	**09/20/08**
Subway Line 8[5]	**10/09/08**	
OneDay69	**10/11/08**	**04/10/09**
OneDay78	**04/11/09**	**Present**
Subway Line 4[6]	**09/28/09**	

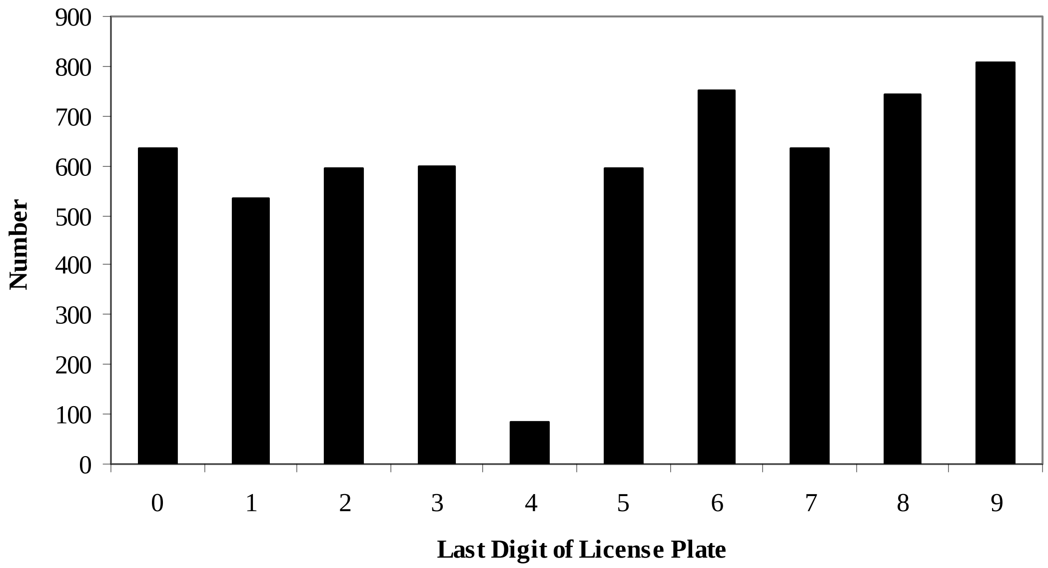
[1] Bus fares reduced from RMB 1 per trip to 0.4 for regular bus pass holders and to 0.2 for student pass holders. On January 15, 2008 an additional reduction on suburban routes went into effect – fares were lowered by 60% for adults and by 80% for students. "Suburban" routes connect the ten districts and counties outside the inner city with the eight city districts inside. [2] Subway fares reduced from RMB 2 per transfer to RMB 2 per trip regardless of number of transfers. [3] Subway Line 5 runs south to north. [4] Subway Line 10 runs southeast to northwest including the airport. [5] Subway Line 8 serves the Olympics Park area. It had been opened on a more limited basis earlier to serve Olympic athletes and tourists. [6] Subway Line 4 runs south to northwest.

Figure 2 Map of Beijing Traffic Restrictions and Monitoring Station Locations in 2008 and 2009



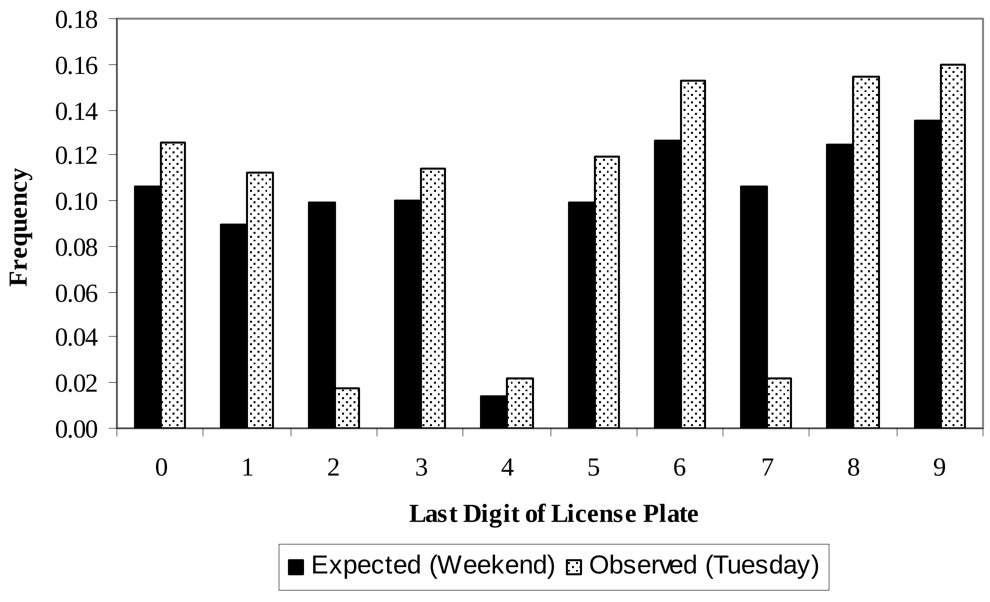
Map shows the locations of the monitoring stations (represented by triangles) within or close to the 6th Ring Road (additional stations are located outside the 6th Ring Road). The dashed lines are subway lines. The solid lines are the Ring Roads. The inner-most solid line (which partially overlaps with a subway line) is the 2nd Ring Road and expanding out from there are the 3rd, 4th, 5th, and 6th Ring Roads.

Figure 3 Expected (Weekend) Distribution of License Plate Numbers



Ending license plate numbers of autos entering a Beijing parking garage inside the 4th Ring Road on June 27 (Sunday) and July 3 (Saturday), 2010 collected by authors.

Figure 4 Expected (Weekend) versus Observed (Tuesday) Distribution of License Plate Numbers



Ending license plate numbers of autos entering a Beijing parking garage inside the 4th Ring Road collected by authors. Expected distribution based on June 27 (Sunday) and July 3 (Saturday), 2010. Observed distribution based on Tuesday, June 29, 2010 between the hours of 7:00 a.m. and 8:00 p.m. Plates "2" and "7" were restricted on Tuesday.

Table 1 Descriptive Statistics

Variable	N	Mean	Standard Deviation	Min	Max
Daily Aggregate Pollution Data					
Aggregate API	1,096	90.834	49.527	12.000	500.000
Log(Aggregate API)	1,096	4.392	0.486	2.485	6.215
PM_{10}	917	146.652	79.097	18.000	600.000
Log(PM_{10})	917	4.867	0.482	2.890	6.397
OddEven	1,096	0.075	0.263	0.000	1.000
OneDay	1,096	0.408	0.492	0.000	1.000
OneDay69	1,096	0.166	0.372	0.000	1.000
OneDay78	1,096	0.242	0.428	0.000	1.000
Olympics	1,096	0.016	0.124	0.000	1.000
Weekend	1,096	0.259	0.438	0.000	1.000
Holiday	1,096	0.071	0.257	0.000	1.000
Maximum Temperature	1,096	18.896	11.144	-6.900	39.600
Average Humidity	1,096	52.527	20.271	11.000	97.000
Total Rainfall	1,096	24.014	85.061	0.000	327.000
Sunshine	1,096	6.619	3.974	0.000	14.000
Wind Direction - Northeast	1,096	0.243	0.429	0.000	1.000
Wind Direction - Southeast	1,096	0.168	0.374	0.000	1.000
Wind Direction - Southwest	1,096	0.376	0.485	0.000	1.000
Wind Direction - Northwest	1,096	0.214	0.410	0.000	1.000
Max. Wind Speed - 1st Quartile	1,096	0.253	0.435	0.000	1.000
Max. Wind Speed - 2nd Quartile	1,096	0.249	0.433	0.000	1.000
Max. Wind Speed - 3rd Quartile	1,096	0.255	0.436	0.000	1.000
Max. Wind Speed - 4th Quartile	1,096	0.243	0.429	0.000	1.000
Daily Station-Level Pollution Data					
Station-Level API	25,482	90.227	50.751	6.000	500.000
Log(Station-Level API)	25,482	4.375	0.512	1.792	6.215
Station-Level Data					
Distance from Ring Road	24	8.210	11.884	0.406	38.578
Distance from Ring Road (w/i 4th Ring Road)	8	0.831	0.264	0.406	1.280
Viewership Data					
"Self-Employed" Viewership (thousands)	26,304	91	76	0	480
"Self-Employed" Log(thousands viewers)	26,304	4.042	1.179	0.000	6.176
"Salaried Workers" Viewership (thousands)	26,304	149	129	0	652
"Salaried Workers" Log(thousands viewers)	26,304	4.377	1.445	0.000	6.482
Total Rainfall	26,304	24.014	85.024	0.000	327.000
Average Wind Speed	26,304	2.212	0.915	0.500	6.700
Sunshine	26,304	6.619	3.972	0.000	14.000
Average Temperature	26,304	13.600	10.976	-9.400	31.600
Weekend	26,304	0.285	0.451	0.000	1.000
Holiday	26,304	0.071	0.257	0.000	1.000
Olympics	26,304	0.016	0.124	0.000	1.000
OddEven	26,304	0.075	0.263	0.000	1.000
OneDay69	26,304	0.166	0.372	0.000	1.000
OneDay78	26,304	0.242	0.428	0.000	1.000

See Appendix E for a description of the variables and their sources.

Table 2 Relationship between API and PM_{10}

API	PM_{10}	Conversion Formula
0 – 50	0 – 50	API = PM_{10}
50 – 200	50 – 350	API = (1/2)*PM_{10} + 25
200 – 300	350 – 420	API = (10/7)*PM_{10} – 300
300 – 400	420 – 500	API = (5/4)*PM_{10} – 225
400 – 500	500 – 600	API = PM_{10} – 100

Based on Andrews (2008).

Table 3 Effect of Driving Restrictions on Log Aggregate Beijing Daily API (2007 – 2009), N = 1,095

	Baseline	Linear Trend	Quadratic Trend	OneDay69 vs. OneDay78
Constant	3.0240 ***	3.0069 ***	3.0370 ***	3.0223 ***
	(0.1451)	(0.1475)	(0.1489)	(0.1446)
Lagged Log API	0.3124 ***	0.3127 ***	0.3114 ***	0.3123 ***
	(0.0300)	(0.0300)	(0.0300)	(0.0300)
OddEven	-0.1928 ***	-0.2174 ***	-0.2068 ***	-0.1946 ***
	(0.0436)	(0.0497)	(0.0512)	(0.0447)
OneDay	-0.0793 ***	-0.1308 **	-0.1481 **	
	(0.0273)	(0.0583)	(0.0591)	
OneDay*Weekend	0.0968 **	(0.0967) **	(0.0965) **	0.0968 **
	(0.0460)	(0.0458)	(0.0460)	(0.0460)
OneDay69				-0.0735 **
				(0.0332)
OneDay78				-0.0833 **
				(0.0334)
Olympics	-0.2105 ***	-0.2109 ***	-0.2107 ***	-0.2107 ***
	(0.0807)	(0.0805)	(0.0805)	(0.0808)
Weekend	-0.0843 ***	-0.0839 ***	-0.0837 ***	-0.0843 ***
	(0.0312)	(0.0310)	(0.0311)	(0.0312)
Holiday	-0.0745	-0.0775	-0.0774	-0.0745
	(0.0485)	(0.0485)	(0.0489)	(0.0484)
Maximum Temperature	0.0483 ***	0.0489 ***	0.0491 ***	0.0483 ***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Average Humidity	0.0050 ***	0.0050 ***	0.0050 ***	0.0050 ***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Total Rainfall	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sunshine	-0.0326 ***	-0.0327 ***	-0.0328 ***	-0.0326 ***
	(0.0041)	(0.0042)	(0.0042)	(0.0041)
Wind Direction - Southeast	0.0117	0.0135	0.0157	0.0110
	(0.0512)	(0.0512)	(0.0512)	(0.0514)
Wind Direction - Southwest	0.0300	0.0309	0.0323	0.0295
	(0.0416)	(0.0417)	(0.0417)	(0.0418)
Wind Direction - Northwest	-0.1809	-0.1819	-0.1736	-0.1822
	(0.1414)	(0.1406)	(0.1414)	(0.1422)
Max. Wind Speed - 2nd Quartile	-0.1955 ***	-0.2003 ***	-0.1990 ***	-0.1950 ***
	(0.0626)	(0.0628)	(0.0630)	(0.0625)
Max. Wind Speed - 3rd Quartile	-0.2260 ***	-0.2288 ***	-0.2275 ***	-0.2260 ***
	(0.0575)	(0.0574)	(0.0574)	(0.0575)
Max. Wind Speed - 4th Quartile	-0.0006	-0.0034	0.0025	-0.0010
	(0.0633)	(0.0632)	(0.0637)	(0.0635)
Adjusted R^2	0.5011	0.5017	0.5023	0.5011
Prob > F (Time Trend)		25.6	34.6	

Dependent variable is log of aggregate, daily API. Standard errors in parentheses. Newey-West standard errors with one-day lag used in all regressions. * = 10% significance, ** = 5% significance, *** = 1% significance. Month dummies and interactions between wind speed and wind direction included in all regressions. A linear time trend is included in Model 2 and a quadratic time trend in Model 3. The F-test is the joint significance level of the time trend variables.

Table 4 Effect of Driving Restrictions on Aggregate Daily Pollution Levels (2007 – 2009)

	Log(API)		
	Baseline	Blue Sky/SO_2	Log(PM_{10})
Constant	3.0240 ***	3.5581 ***	3.5957 ***
	(0.1451)	(0.1263)	(0.1406)
Lagged Log API (PM_{10})	0.3124 ***	0.2456 ***	0.2839 ***
	(0.0300)	(0.0255)	(0.0238)
OddEven	-0.1928 ***	-0.1887 ***	-0.2515 ***
	(0.0436)	(0.0322)	(0.0468)
OneDay	-0.0793 ***	-0.0877 ***	-0.1045 ***
	(0.0273)	(0.0234)	(0.0294)
OneDay*Weekend	0.0968 **	0.0499	0.0749
	(0.0460)	(0.0384)	(0.0540)
Olympics	-0.2105 ***	-0.0181	-0.1326 *
	(0.0807)	(0.0625)	(0.0790)
Weekend	-0.0843 ***	-0.0719 ***	-0.1198 ***
	(0.0312)	(0.0260)	(0.0348)
Holiday	-0.0745	-0.0364	-0.0769
	(0.0485)	(0.0380)	(0.0523)
Maximum Temperature	0.0483 ***	0.0319 ***	0.0480 ***
	(0.0036)	(0.0033)	(0.0040)
Average Humidity	0.0050 ***	0.0025 ***	0.0044 ***
	(0.0011)	(0.0009)	(0.0011)
Total Rainfall	-0.0001	-0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)
Sunshine	-0.0326 ***	-0.0254 ***	-0.0371 ***
	(0.0041)	(0.0033)	(0.0044)
Blue Sky		-0.7518 ***	
		(0.0555)	
Blue Sky*OddEven		0.2385 ***	
		(0.0738)	
Blue Sky*OneDay		0.0787	
		(0.0682)	
SO2		-0.2905 ***	
		(0.0705)	
SO2*OneDay		0.0984	
		(0.0905)	
Adjusted R^2	0.5011	0.6722	0.4742
N	1,095	1,095	916

Standard errors in parentheses. For Models 1 and 2, Newey-West standard errors with one-day lag are used. * = 10% significance, ** = 5% significance, *** = 1% significance. Month dummies, wind speed, wind direction, and interactions between wind speed and wind direction included in all regressions.

Table 5 Effect of Driving Restrictions on Log Daily API at Beijing Monitoring Stations, Fixed Effects Estimates (2007 – 2009)

	All Stations	Stations within 4th Ring Road: Linear Distance	Stations within 4th Ring Road: Quadratic Distance
Constant	2.9908 ***	2.9566 ***	2.9572 ***
	(0.0198)	(0.0162)	(0.0168)
Lagged Log API	0.3227 ***	0.3138 ***	0.3134 ***
	(0.0047)	(0.0035)	(0.0036)
OddEven	-0.1823 ***	-0.2063 ***	-0.3186 ***
	(0.0088)	(0.0223)	(0.0297)
OddEven*Distance		0.0911 ***	0.3824 ***
		(0.0291)	(0.0687)
OddEven*Distance^2			-0.1726 ***
			(0.0384)
OneDay	-0.1474 ***	-0.0884 ***	-0.1939 ***
	(0.0097)	(0.0226)	(0.0273)
OneDay*Distance		0.0578 **	0.3310 ***
		(0.0285)	(0.0690)
OneDay*Distance^2			-0.1620 ***
			(0.0404)
OneDay*Weekend	0.0690 ***	0.0782 ***	0.0782 ***
	(0.0039)	(0.0053)	(0.0053)
Olympics	-0.2244 ***	-0.2166 ***	-0.2166 ***
	(0.0088)	(0.0173)	(0.0173)
Weekend	-0.0587 ***	-0.0678 ***	-0.0677 ***
	(0.0030)	(0.0037)	(0.0037)
Holiday	-0.0738 ***	-0.0642 ***	-0.0643 ***
	(0.0034)	(0.0077)	(0.0077)
Maximum Temperature	0.0481 ***	0.0494 ***	0.0494 ***
	(0.0006)	(0.0005)	(0.0005)
Average Humidity	0.0045 ***	0.0049 ***	0.0049 ***
	(0.0002)	(0.0002)	(0.0002)
Total Rainfall	0.0000	0.0000 ***	0.0000 ***
	(0.0000)	(0.0000)	(0.0000)
Sunshine	-0.0328 ***	-0.0307 ***	-0.0307 ***
	(0.0011)	(0.0006)	(0.0006)
Adjusted R^2	0.4952	0.4960	0.4960
Number of Stations	24	8	8
N	25,390	8,319	8,319

Dependent variable is log of daily API at monitoring stations. Robust standard errors clustered at the station level in parentheses. * = 10% significance, ** = 5% significance, *** = 1% significance. Month dummies, wind speed quartiles, wind direction dummies, interactions between wind speed and wind direction included in all regressions. A quadratic time trend included in Model 1 and a cubic time trend in Models 2 and 3.

Table 6 Effect of Driving Restrictions on Log Hourly Television Viewership (2007 – 2009), N = 26,303

	"Self-Employed"		"Hourly Workers"	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Lagged Viewership	0.5507	(0.0081) ***	0.4373	(0.0094) ***
Total Rainfall	-0.0001	(0.0000) **	-0.0001	(0.0000) **
Average Wind Speed	0.0048	(0.0031)	0.0045	(0.0030)
Sunshine	-0.0024	(0.0007) ***	-0.0016	(0.0007) **
Average Temperature	-0.0009	(0.0009)	-0.0020	(0.0009) **
Weekend	0.0183	(0.0080) **	0.0709	(0.0082) ***
Holiday	0.0487	(0.0125) ***	0.1306	(0.0140) ***
Olympics	0.0971	(0.0196) ***	0.0902	(0.0229) ***
OddEven	0.1157	(0.0153) ***	0.0620	(0.0150) ***
OddEven*Weekend	-0.0118	(0.0174)	0.0329	(0.0198) *
OddEven*Holiday	-0.0916	(0.0399) **	-0.0640	(0.0422)
OneDay69*Weekend	0.0235	(0.0207)	0.0142	(0.0199)
OneDay69*Holiday	0.0979	(0.0319) ***	0.0060	(0.0379)
OneDay78*Weekend	0.0865	(0.0242) ***	0.0264	(0.0211)
OneDay78*Holiday	0.0718	(0.0389) *	-0.0310	(0.0320)
OneDay69*Restr. Hours	0.1079	(0.0164) ***	0.0147	(0.0163)
OneDay69*Non-Restr. Evening Hours	0.0074	(0.0165)	-0.0039	(0.0161)
OneDay69*Non-Restr. Morning Hours	-0.0533	(0.0355)	-0.0066	(0.0312)
OneDay78*Restr. Hours	0.1521	(0.0213) ***	-0.0231	(0.0187)
OneDay78*Non-Restr. Evening Hours	0.0761	(0.0206) ***	0.0402	(0.0180) **
OneDay78*Non-Restr. Morning Hours	0.1553	(0.0307) ***	0.0887	(0.0277) ***
R^2	0.8850		0.9291	

Dependent variable is log number of thousands of individuals watching television each hour. Newey-West standard errors with four-hour lag in parentheses. * = 10% significance, ** = 5% significance, *** = 1% significance. Hour and month dummies and a 7th-order polynomial expansion of a daily time trend included in both regressions.

Appendix A
Labor Supply Model with OddEven Driving Restrictions

Consider two groups of workers: those with discretionary work time (D) and those with fixed work times (F) in proportions λ^D and $\lambda^F = 1-\lambda^D$ respectively. Assumption (B) in the main text ensures that the restrictions do not change these proportions. The distribution of workers in each group is given by the cumulative density functions $G^D(\theta)$ and $G^F(\theta)$ where $\theta = \{w, Y, c_i, t_i, M_i\}$. w is hourly wage, Y is two-day non-wage income, and i is commute mode. Possible commute modes are auto $(i = A)$, public transit $(i = P)$, and for those with discretion, not working $(i = 0)$. For mode i, c_i is daily commute cost and t_i time (with $t_0 = c_0 = 0$). M_i is the worker's daily non-monetary disutility from commuting by mode i. Commuting by either mode is unpleasant: $M_P, M_A > M_0 = 0$. A worker's two-day utility conditional on commute choices (i for the non-restricted and j for the restricted day) is:

(A1) $$U_{ij}(\theta) = L_{Nij}^{\alpha} X_{Nij}^{1-\alpha} L_{Rij}^{\alpha} X_{Rij}^{1-\alpha} - M_i - M_j - \mathrm{I}_{Policy}\mathrm{I}_{j=A}Q;\ i, j \in \{A, P, 0\},$$

with $(0 < \alpha < 1)$. This distinguishes the restricted (R) and non-restricted (N) days. L is daily leisure hours and X daily consumption of other goods. We ignore across-day discounting and assume that utility derived from each two-day period is independent of other two-day periods. I is an indicator variable equal to one when the condition is true and zero otherwise and $Policy$ is a logical variable distinguishing the policy period. Q is expected penalty (monetary and psychic) in utility terms of driving a car while restricted. We solve the model by backward induction.

Second Stage: Discretionary Work Time: Ignoring the penalty Q, the worker's second-stage problem conditional on mode choices i and j is:

(A2) $$\underset{\left\{\substack{H_{Nij}, L_{Nij}, X_{Nij},\\ H_{Rij}, L_{Rij}, X_{Rij}}\right\}}{\mathrm{Max}} \quad U_{ij} = L_{Nij}^{\alpha} X_{Nij}^{1-\alpha} L_{Rij}^{\alpha} X_{Rij}^{1-\alpha} - M_i - M_j;\ i, j \in \{A, P, 0\} \quad st:$$

(A3) $$Y + w\left(H_{Nij} + H_{Rij}\right) - \left(X_{Nij} + c_i\right) - \left(X_{Rij} + c_j\right) = 0,$$

(A4a) $$T - \left(H_{Nij} + t_i\right) - L_{Nij} = 0,$$ (A4b) $$T - \left(H_{Rij} + t_j\right) - L_{Rij} = 0,$$

(A5a) $$H_{Nij} \geq 0 \leftarrow \kappa_N,$$ (A5b) $$H_{Rij} \geq 0 \leftarrow \kappa_R;$$

where T is total available hours per day, H is daily working hours, and the κ's are Kuhn-Tucker multipliers. Equation (A3) is the resident's two-day budget constraint with the price of X normalized to one. Equations (A4a) and (A4b) are the resident's day-by-day time constraints. We assume that the budget and time constraints bind but that the constraints on positive working hours may not. Substituting (A3) and (A4) the problem becomes:

(A6) $$\underset{\{H_{Nij}, X_{Nij}, H_{Rij}\}}{\mathrm{Max}} \ U_{ij} = \left(T - H_{Nij} - t_i\right)^{\alpha} X_{Nij}^{(1-\alpha)} \left(T - H_{Rij} - t_j\right)^{\alpha} \left(Y + wH_{Nij} + wH_{Rij} - X_{Nij} - c_i - c_j\right)^{1-\alpha} - M_i - M_j$$

The first-order conditions for the worker's problem are:

(A7a) $$\left[H_{Nij}\right]: \frac{\alpha\left(U_{ij} + M_i + M_j\right)}{T - H_{Nij} - t_i} = \frac{(1-\alpha)w\left(U_{ij} + M_i + M_j\right)}{Y + wH_{Nij} + wH_{Rij} - X_{Nij} - c_i - c_j},$$

(A7b) $$\left[H_{Rij}\right]: \frac{\alpha\left(U_{ij} + M_i + M_j\right)}{T - H_{Rij} - t_j} - \kappa = \frac{(1-\alpha)w\left(U_{ij} + M_i + M_j\right)}{Y + wH_{Nij} + wH_{Rij} - X_{Nij} - c_i - c_j},$$

(A8) $$\left[X_{Nij}\right]: \frac{(1-\alpha)\left(U_{ij} + M_i + M_j\right)}{X_{Nij}} = \frac{(1-\alpha)\left(U_{ij} + M_i + M_j\right)}{Y + wH_{Nij} + wH_{Rij} - X_{Nij} - c_i - c_j},$$

(A9a) $$[\kappa_R]: H_{Rij}\kappa_R = 0,$$ (A9b) $$[\kappa_N]: H_{Nij}\kappa_N = 0.$$

There are two cases to solve: "full time" $\left(H_{Nij}, H_{Rij} > 0; i, j \in \{A, P\}\right)$ and "reduced time" ($H_{Ni0} > 0$, $i \in \{A, P\}$; but $H_{Ri0} = 0$ or vice versa). Define, conditional on the commute mode choices i and j:

(A10a) $NT_{Ni} = T - t_i$ and $NT_{Rj} = T - t_j$,

(A10b) $NI_{ij} = \dfrac{Y - c_i - c_j}{w}$;

(A10c) $\Delta t_{ji} = t_j - t_i$,

(A10d) $\Delta c_{ji} = \left(c_j - ct_i\right)/w$.

NT_{Ni} and NT_{Rj} are the time available net of commuting on restricted and non-restricted days while NI_{ij} is the two-day, non-wage income net of commute costs. Δt_{ji} and Δc_{ji} are the difference in commute times and costs respectively on the restricted versus non-restricted days. Both NI_{ij} and Δc_{ji} are converted to hours based on the opportunity cost of time.

Case 1): "Full Time" $\left(H_{Nij}, H_{Rij} > 0; i, j \in \{A, P\}\right)$. Solving the model (the Optional Appendix contains a detailed solution), the results are:

(A11a) $H_{Nij} = (1-\alpha) NT_{Ni} - \dfrac{\alpha}{2}\left[NI_{ij} - \Delta t_{ji}\right]$,

(A11b) $H_{Rij} = (1-\alpha) NT_{Rj} - \dfrac{\alpha}{2}\left[NI_{ij} + \Delta t_{ji}\right]$;

(A12) $L_{Nij} = L_{Rij} = \alpha\left[NT_{Ni} + \dfrac{1}{2}\left(NI_{ij} - \Delta t_{ji}\right)\right]$,

(A13) $X_{Nij} = X_{Rij} = (1-\alpha) w\left[NT_{Ni} + \dfrac{1}{2}\left(NI_{ij} - \Delta t_{ji}\right)\right]$.

Two-day indirect utility is, where we re-introduce the penalty Q:

(A14) $U_{ij} = \left(kw^{(1-\alpha)}\right)^2\left(NT_{Ni} + \dfrac{NI_{ij}}{2} - \dfrac{\Delta t_{ji}}{2}\right)^2 - M_i - M_j - \mathrm{I}_{Policy}\mathrm{I}_{j=A}Q; i, j \neq 0$ where $\left(k = \alpha^{\alpha}(1-\alpha)^{(1-\alpha)}\right)$.

Leisure time is equated across the days. For workers who prefer public transit the work day lengths are the same: $H_{RPP} - H_{NPP} = 0$. For those who prefer driving, their restricted work day will be shorter or longer than their non-restricted depending on whether their public transit commute is longer or shorter than by car ($H_{RAP} - H_{NAP} = (\alpha - 1)\Delta t_{PA}$).

Case 2): "Reduced Time" *(*$H_{Ni0} > 0, i \in \{A, P\}$ *but* $H_{Rij} = 0$*).* We solve the model assuming zero hours on the restricted day. In this case $t_R = c_R = 0$. The results for instead working zero hours on the non-restricted days are symmetric but Appendix B shows that this is not optimal under fairly general conditions. Solving (the Optional Appendix contains a detailed solution), the results are:

(A15a) $H_{Ni0} = \dfrac{2}{1 + (1-\alpha)}\left[(1-\alpha) NT_{Ni} - \dfrac{\alpha}{2} NI_{i0}\right]$,

(A15b) $H_{Ri0} = 0$;

(A16a) $L_{Ni0} = \dfrac{\alpha}{1 + (1-\alpha)}\left[NT_{Ni} + NI_{i0}\right]$,

(A16b) $L_{Ri0} = T$;

(A17a) $X_{Ni0} = \dfrac{(1-\alpha) w}{1 + (1-\alpha)}\left[NT_i + NI_{i0}\right]$,

(A17b) $X_{Ri0} = \dfrac{(1-\alpha) w}{1 + (1-\alpha)}\left[NT_i + NI_{i0}\right]$.

Two-day indirect utility is:

(A18) $U_{i0} = \dfrac{\left(kw^{(1-\alpha)}\right)^2}{\left(1 + (1-\alpha)\right)^{1+(1-\alpha)}\alpha^{\alpha}}\left(NT_{Ni} + NI_{i0}\right)^{1+(1-\alpha)} T^{\alpha} - M_i$, where $\left(k = \alpha^{\alpha}(1-\alpha)^{(1-\alpha)}\right)$.

The worker cannot balance leisure or work time across restricted and non-restricted days. The results for $H_{Nij} = 0$ but $H_{Rij} > 0$ are obtained by replacing N with R, i with 0, and 0 with j.

Second Stage: Fixed Work Times: Since daily work hours are fixed $\left(H_{Nij} = H_{Rij} = \overline{H} > 0; i, j \in \{A, P\}\right)$, the worker chooses only L_{Nij}, L_{Rij}, X_{Nij}, and X_{Rij}. Solving, (the Optional Appendix contains a detailed solution), the results are:

(A19a) $L_{Nij} = T - \overline{H} - t_i$, (A19b) $L_{Rij} = T - \overline{H} - t_j$;

(A20) $X_{Nij} = X_{Rij} = w\left[\overline{H} + \frac{1}{2} NI_{ij}\right]$.

Two-day indirect utility is, where we re-introduce the penalty Q:

(A21) $$U_{ij} = w^{2(1-\alpha)}\left[\left(T - \overline{H} - t_i\right)\left(T - \overline{H} - t_j\right)\right]^{\alpha}\left(\overline{H} + \frac{NI_{ij}}{2}\right)^{2(1-\alpha)} - M_i - M_j - \mathrm{I}_{Policy}\mathrm{I}_{j=A}Q; i, j \neq 0.$$

The difference in leisure time on restricted versus non-restricted days depends on relative commute times for the chosen modes $\left(L_{Rij} - L_{Nij} = \Delta t_{ji}\right)$ but the difference is not shared across the two days.

This completes the second-stage solution for type θ. We now consider the first stage when each worker chooses their commute mode. Using the distributions of the θ's we can specify the share of each commute mode for both categories of workers: $s_{ij}^k, k \in \{D, F\}; i, j \in \{A, P, 0\}$. We solve the first stage with and without the restrictions.

First Stage – Without Restrictions: Without the restrictions, the two days are identical and the worker makes the same choice across days ($i = j$). The shares of each mode are $(k = D, F)$:

(A22a) $s_{AA}^k = \int\{\theta \,|\, U_{AA}(\theta) > U_{ii}(\theta); i = P, 0\} dG^k(\theta) d\theta$, (A22b) $s_{PP}^k = \int\{\theta \,|\, U_{PP}(\theta) > U_{ii}(\theta); i = A, 0\} dG^k(\theta) d\theta$,

where U_{ij} is given by (A14) and Assumption (A) in the main text implies $s_{00}^k = 0$ so that $s_{AA}^k + s_{PP}^k = 1$.

First Stage – With Restrictions: Assumption (D) in the main text ensures that Q is great enough that no workers drive on their restricted day so that $i \in \{A, P\}$ and $j \in \{P, 0\}$. Regardless of whether they have discretion or not, commuters who prefer public transit absent the restrictions will take public transit both days under the restrictions so that $\hat{s}_{PP}^k = s_{PP}^k; k \in \{D, F\}$ where we use hats to denote outcomes under the restrictions. This follows because $U_{PP}(\theta) > U_{AA}(\theta)$ implies $U_{PP}(\theta) > U_{AP}(\theta)$ in both Equations (A14) and (A21).

Workers who prefer to drive absent the restrictions will continue to drive on the non-restricted day. On the restricted day, those with fixed work times must take public transit on the restricted day so that $\hat{s}_{A0}^F = 0$ and $\hat{s}_{AP}^F = s_{AA}^F$. On the restricted day, those with discretion can either take public transit or not work. The shares doing each are:

(A23a) $\hat{s}_{AP}^D = \int\{\theta \,|\, U_{AP}(\theta) > U_{A0}(\theta)\} dG^D(\theta) d\theta$, (A23b) $\hat{s}_{A0}^D = \int\{\theta \,|\, U_{A0}(\theta) > U_{AP}(\theta)\} dG^D(\theta) d\theta$.

Given Assumption (B) in the main text, we know that $\hat{s}_{AP}^D + \hat{s}_{A0}^D = s_{AA}^D$ and if some commuters find it optimal to stay home when restricted $\left(\hat{s}_{A0}^D > 0\right)$ then $\hat{s}_{AP}^D < s_{AA}^D$.

Extensive Margin Effects: For those with fixed work times, there is no effect on the extensive margin since they have no control over work time (*i.e.*, $\hat{s}^F_{AP} = s^F_{AA}$ and $\hat{s}^F_{PP} = s^F_{PP}$). This yields **Implication 1** in the main text.

Assumption (A) implies that absent the restrictions no workers with discretionary work time stay home on the restricted day.[1] With the restrictions, this increases to $\lambda^D \hat{s}^D_{A0}/2$ – the density of workers choosing "reduced time." This yields **Implication 2** in the main text.

Under the restrictions, daily car density and pollution on Beijing roads decreases by $\frac{1}{2}\left(\lambda^D s^D_{AA} + \lambda^F s^F_{AA}\right)$. That is, half the drivers cannot drive on a given day. This yields **Implication 3** in the main text.

Intensive Margin Effects – Workers with Fixed Work Times: Those who took public transit absent the restrictions will still do so and their leisure time is unaffected $\left(\hat{L}_{NPP} - L_{NPP} = \hat{L}_{RPP} - L_{RPP} = 0\right)$ by Equation (A19). Those who prefer to drive, with density $\lambda^F s^F_{AA}/2$, are forced to take public transit and leisure is unaffected on non-restricted $\left(\hat{L}_{NAP} - L_{NAA} = 0\right)$ but affected on restricted days $\left(\hat{L}_{RAP} - L_{RAA} = -\Delta t_{PA}\right)$ by Equation (A19). Since intensive margin effects are zero for those who normally take public transit and ambiguous for those who normally drive, the total effect $\left(-\lambda^F s^F_{AA} \Delta t_{PA}/2\right)$ could be positive or negative. This yields **Implication 4** in the main text.

Intensive Margin Effects – Workers with Discretionary Work Time: Workers who prefer public transit absent the restrictions choose to work "full time" and there is no effect on leisure time: $\hat{L}_{NPP} - L_{NPP} = \hat{L}_{RPP} - L_{RPP} = 0$ by Equation (A12). Those who prefer driving absent the restrictions and choose to work "full time" must commute by public transit on the restricted day and their leisure time could increase or decrease depending on whether public transit commute times and costs are less than those by car or not: $\hat{L}_{NAP} - L_{NAA} = \hat{L}_{RAP} - L_{RAA} = -\alpha/2\left(\Delta c_{PA} + \Delta t_{PA}\right)$ by Equation (A12).

For workers who work "reduced time," leisure time most likely decreases on the non-restricted day. Equations (A12) and (A16a) imply:

(A24) $$\hat{L}_{NA0} - L_{NAA} = \frac{\alpha}{1+(1-\alpha)}\left[(\alpha-1)(T-t_A) + \frac{\alpha}{2}\frac{Y}{w} + (1-\alpha)\frac{c_A}{w}\right] \equiv \Upsilon .$$

That the expression in Equation (A24) can be positive (negative) is most easily seen by setting α close to one (zero). This expression is more likely positive the greater Y, c_A, or t_A. The total effect across all workers with discretionary work time is $\lambda^D\left[\hat{s}^D_{A0}\Upsilon - \hat{s}^D_{AP}\alpha/2\left(\Delta c_{PA} + \Delta t_{PA}\right)\right]$, which could be positive or negative. This yields **Implication 5** in the main text.

Appendix B
Non-Optimality of Staying Home on Non-Restricted Day

Working on the restricted day but not on the non-restricted is not optimal under at least two general cases:

Case 1: $M_A = M_P$ and $c_A > c_P$. For a worker who prefers to commute by auto, $U_{AA} > U_{PP}$ which by Equation (A14) implies:

(B1) $$\left(NT_{NA} + \frac{NI_{AA}}{2}\right)^2 > \left(NT_{NP} + \frac{NI_{PP}}{2}\right)^2 \Rightarrow (t_P - t_A) > \frac{2}{w}(c_A - c_P)$$. Now:

[1] In our data, this will not literally be zero due to multiple daily work shifts, vacations, and sick days.

(B2) $c_A > c_P \Rightarrow \frac{1}{w}(c_A - c_P) < \frac{2}{w}(c_A - c_P) \Rightarrow (t_P - t_A) > \frac{1}{w}(c_A - c_P)$ which implies:

(B3) $(NT_{NA} + NI_{A0}) > (NT_{NP} + NI_{P0}) \Rightarrow (NT_{NA} + NI_{A0})^{1+(1-\alpha)} > (NT_{NP} + NI_{P0})^{1+(1-\alpha)}$. This implies $U_{A0} > U_{P0}$ using Equation (A18).

Case 2: $t_A = t_P$ and $c_A = c_P$ but $M_A \neq M_P$. By Equation (A14) $U_{AA} > U_{PP} \Rightarrow M_P > M_A$. This implies $U_{A0} > U_{P0}$ using Equation (A18).

Assumption (A) in the main text ensures that the worker will remain home on at most the restricted day since the non-restricted day is unaffected and extra leisure is already enjoyed on the restricted day under "reduced-time" work.

Appendix C
Conditions for "Reduced-Time" Work for Discretionary Workers

We consider two cases:

Case 1: $M_A = M_P = 0$. Comparing Equations (A14) and (A18), $U_{A0} > U_{AP}$ when:

(C1) $$\frac{(NT_{NA} + NI_{A0})^{1+(1-\alpha)} T^{\alpha}}{\left(NT_{NA} + NI_{A0} - \frac{c_P}{2} - \frac{\Delta t_{PA}}{2}\right)^2} > \left(1 + (1-\alpha)\right)^{1+(1-\alpha)} \alpha^{\alpha}.$$

It follows immediately that this is more likely the greater c_P or Δt_{PA}.

Case2: $(M_P \gg 0)$. Since U_{A0} in Equation (A18) does not depend on M_P and U_{AP} in Equation (A14) is decreasing in M_P it follows directly that $U_{A0} > U_{AP}$ when M_P is sufficiently large $(M_P \gg 0)$.

Appendix D
Effect of Expanded Subway Capacity on Leisure Time

Expanded subway capacity reduces both public transit and auto commute times: $\tilde{t}_A < t_A$ and $\tilde{t}_P < t_P$, where tildes indicate outcomes after the expansion. Assume that the expansion has no effect on commute costs ($\tilde{c}_A = c_A$ and $\tilde{c}_P = c_P$) and does not change workers' optimal commute modes. Assuming all workers obey the restrictions and continue to work "full time" (*i.e.*, there is no extensive margin effect), compute the change in leisure time due to the subway expansion for each category of worker and commute mode. For those with discretionary work time who prefer driving and public transit respectively (by Equation (A12)):

(D1) $$\tilde{L}_{NAP} - L_{NAA} = \tilde{L}_{RAP} - L_{RAA} = \alpha\left[\left(t_A - \tilde{t}_A\right) + \frac{1}{2}\frac{c_A - c_P}{w} - \frac{1}{2}\left(t_P - \tilde{t}_A\right)\right],$$

(D2) $$\tilde{L}_{NPP} - L_{NPP} = \tilde{L}_{RPP} - L_{RPP} = \alpha\left(t_P - \tilde{t}_P\right).$$

For those with fixed work times who prefer driving and public transit respectively (by Equation (A19)):

(D3a) $\tilde{L}_{NAP} - L_{NAA} = \left(t_A - \tilde{t}_A\right)$, (D3b) $\tilde{L}_{RAP} - L_{RAA} = \left(t_A - \tilde{t}_P\right)$;

(D4) $$\tilde{L}_{NPP} - L_{NPP} = \tilde{L}_{RPP} - L_{RPP} = \left(t_P - \tilde{t}_P\right).$$

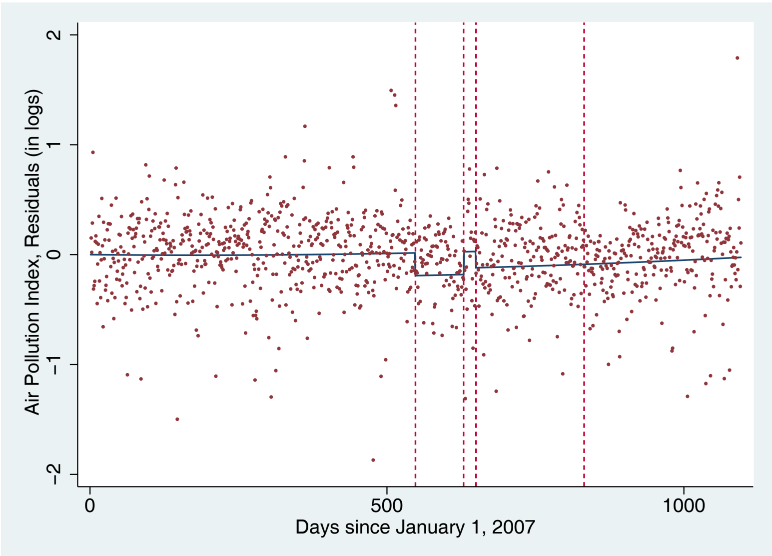
All of the expressions on the right-hand sides of Equations (D1) through (D4) are weakly decreasing in both $\tilde{t}_A$ and $\tilde{t}_P$ and are strictly decreasing in one of them for at least one commute mode within each group of workers. This implies that leisure time increases for both groups due to the expansion.

Appendix E
Variable Descriptions and Data Sources

Variable	Description	Frequency/ Availability	Data Source
Aggregate API	Aggregate Air Pollution Index; see text for detailed description.	Daily	SEPA and BJEPA
Station-Level API	Air Pollution Index from 24 monitoring stations.	Daily	Andrews (2008)
Maximum Temperature	Maximum daily temperature in celcius.	Daily	CMDSSS
Average Humidity	Average percent humidity over the day.	Daily	CMDSSS
Total Rainfall	Total rainfall over the day in centimeters.	Daily	CMDSSS
Wind Direction	Predominant direction of wind during the day divided into four quadrants (Northeast, Southeast, Southwest, Northwest).	Daily	CMDSSS
Max. Wind Speed	Maximum of the average wind speed over 15-minute increments across the day in meters per second.	Daily	CMDSSS
Sunshine	Number of total hours of sunlight during the day.	Daily	CMDSSS
Distance from Ring Road	Distance in kilometers of monitoring station from nearest Ring Road.	Once	Geographic Information System calculations
Average Wind Speed	Average daily wind speed in meters per second.	Daily	CMDSSS
Average Temperature	Average daily temperature in celsius.	Daily	CMDSSS
Television Viewership	Number of people in thousands watching television.	Hourly	CSM Media Research Television Audience Measurement (TAM)

CMDSSS refers to China Meteorological Data Sharing Service System, SEPA to State Environmental Protection Agency, and BJEPA to Beijing Environmental Protection Agency.

Appendix F
API Discontinuity due to Policies



Residuals from estimating Equation (1) in the main text without OE, $OD69$, $OD78$, and time trend. Moving left to right, the four vertical lines demarcate the beginning and end of the OddEven policy, the beginning of OneDay69 policy, and the beginning of OneDay78 policy. The fitted line allows for a quadratic time trend along with differing intercepts for the OddEven, OneDay69, and OneDay78 policy periods. The fitted line shows a large decrease in the API during the OddEven policy, a commensurate increase at its expiration, and then a smaller decrease during the OneDay69 and OneDay78 policy periods. The effects for the OneDay69 and OneDay78 policies are indistinguishable. The line also reflects a slight upward trend in the API over time (although it is not statistically significant).

Appendix G
Sensitivity of Policy Coefficients to Order of Polynomial Daily Time Trend in Regression of Log Hourly Television Viewership, N = 26,303

	0-Order	1-Order	2-Order	3-Order	4-Order	5-Order	6-Order	7-Order
"Self-Employed"								
OneDay69*Restricted Hours	0.1887 ***	0.1126 ***	0.1020 ***	0.1019 ***	0.1297 ***	0.1099 ***	0.1110 ***	0.1079 ***
	(0.0084)	(0.0107)	(0.0110)	(0.0138)	(0.0155)	(0.0159)	(0.0160)	(0.0164)
OneDay78*Restricted Hours	0.2708 ***	0.1566 ***	0.1044 ***	0.1043 ***	0.1410 ***	0.1476 ***	0.1488 ***	0.1521 ***
	(0.0088)	(0.0132)	(0.0184)	(0.0190)	(0.0206)	(0.0209)	(0.0209)	(0.0213)
χ^2 (Time Trend)		10.2	60.6	40.6	32.8	28.2	23.5	20.2
"Hourly Workers"								
OneDay69*Restricted Hours	0.1058 ***	0.0784 ***	0.0681 ***	0.0589 ***	0.0127	0.0310 **	0.0236	0.0147
	(0.0074)	(0.0106)	(0.0105)	(0.0135)	(0.0143)	(0.0158)	(0.0158)	(0.0163)
OneDay78*Restricted Hours	0.1407 ***	0.0994 ***	0.0487 ***	0.0425 **	-0.0185	-0.0246	-0.0326 *	-0.0231
	(0.0063)	(0.0134)	(0.0166)	(0.0174)	(0.0183)	(0.0184)	(0.0185)	(0.0187)
χ^2 (Time Trend)		3.6	17.9	12.5	22.0	19.0	18.0	15.6

Coefficents on selected policy variables in regression of log viewership on control variables and a polynomial time trend as in Table 6. Dependent variable is log number of thousands of individuals watching television each hour. Newey-West standard errors with four-hour lag in parentheses. * = 10% significance, ** = 5% significance, *** = 1% significance. All regressions include the control variables shown in Table 6 as well as hour and month dummies. The χ^2 value is the test statistic for the joint significance of the time trend variables.

Appendix H
Coefficients on Interaction between Policy Variables and Hourly Dummies

Panel A – "Self-Employed" Percentage Difference in Viewership during OneDay69 Period

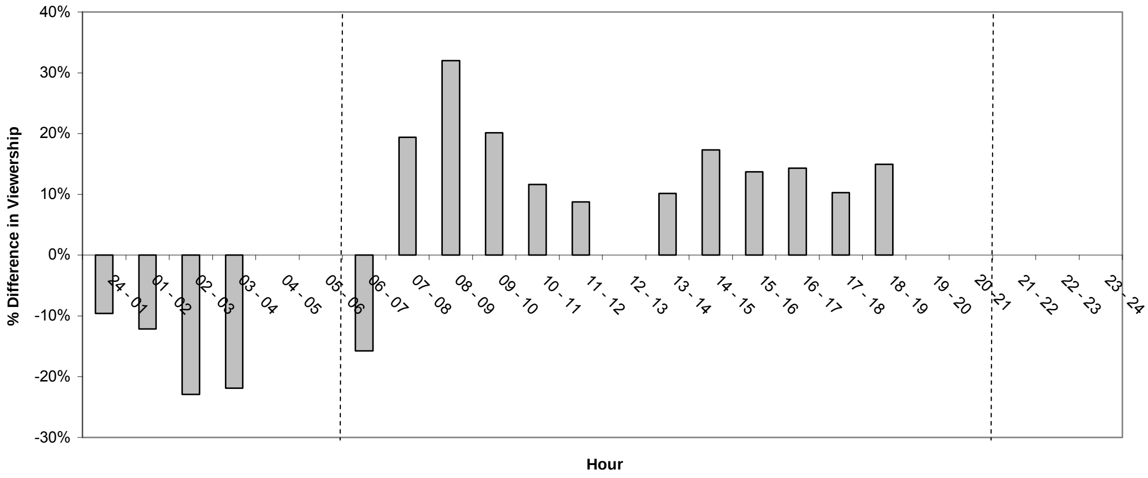


Chart shows coefficients on interactions between the OneDay69 policy variable and hourly dummies in the regression of Columns 1 and 2 of Table 6 but with OneDay69 and OneDay78 interacted with each hour separately. Coefficients are shown only if significant at the 10% level or better. The vertical dotted lines demarcate the restricted period.

Panel B – "Hourly Workers" Percentage Difference in Viewership during OneDay69 Period

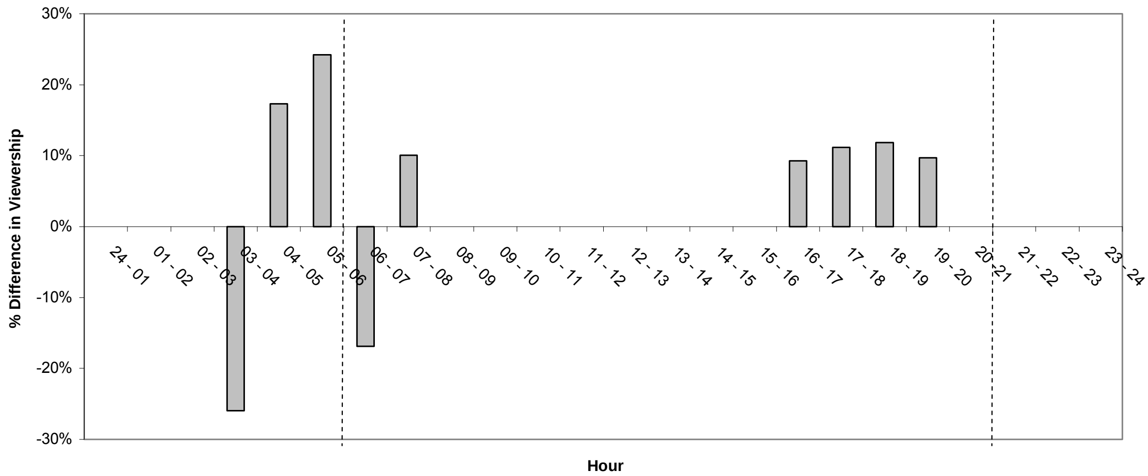


Chart shows coefficients on interactions between the OneDay69 policy variable and hourly dummies in the regression of Columns 3 and 4 of Table 6 but with OneDay69 and OneDay78 interacted with each hour separately. Coefficients are shown only if significant at the 10% level or better. The vertical dotted lines demarcate the restricted period.

Appendix I
Penalties for and Detection of Driving Restrictions Violations

Violation penalties include monetary and time costs and depend on the detection method. Violators are immediately fined RMB 100 and incur a time cost because payment requires going to the relevant police station for documentation and then to a bank to pay. The latter step can be done online but only if the recipient has an account at the Industrial and Commercial Bank of China. The driver can delegate these tasks to someone with a lower cost of time by loaning them their national identity card. If a police officer detects the violation, it must be paid within fifteen days or interest is accrued at RMB 3 per day. For violations detected by cameras there is no immediate deadline. Regardless of how detected, the fine must be paid before renewal of the vehicle's bi-annual registration. During our sample period, only one penalty could be issued per day.[2]

A first-time violation would also trigger the loss of several fee waivers. Those complying with the OddEven restrictions received a waiver of three months' vehicle taxes (about RMB 100)[3] and highway maintenance fees (about RMB 330).[4] During the OneDay period the waiver equaled one month's fees. During both the OddEven and OneDay periods, a driver received a discount on auto insurance equal to the number of days their car was restricted. Although the precise amount depended on individual premiums, the average reduction was RMB 65 during the OneDay69 period.[5]

Beijing had 1,958 traffic surveillance cameras as of March 31, 2009 and the number increased to 2,215 by the end of 2009. This equals 0.13 cameras per square kilometer if equally spaced.[6] As of October, 2010 Beijing had about five thousand police officers to direct traffic.[7]

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[2] As of December 24, 2010 the law was changed to allow multiple citations to be issued per day.
[3] Annual vehicle taxes ranged from RMB 300 to 600 depending on vehicle size according to Beijing Local Taxation Bureau Document Nos. 329 (2004) and 339 (2007).
[4] Until December 31, 2008, monthly highway maintenance fees for passenger vehicles were RMB 22 for each seat of capacity according to the Beijing Highway Bureau (http://www.ylfzhj.bj.cn). For a common passenger vehicle with five seats the monthly fees would therefore be RMB 110. After December 31, 2008, the fees were absorbed into fuel taxes and not affected by a violation.
[5] According to China Insurance Regulatory Commission Beijing Bureau (http://www.china-insurance.com/newscenter/newslist.asp?id=132329).
[6] Data taken from Beijing Traffic Management Bureau, accessed at http://www.bjjtgl.gov.cn. Density calculation based on Beijing's land area of 16,411 square kilometers.
[7] According to http://www.chinanews.com/gn/2010/10-11/2579335.shtml.

Appendix J
Detailed Compliance Results

Panel A: Comparison of Expected (Weekend) and Observed (Weekday) Distributions of Ending License Plate Numbers Entering Beijing Parking Garage during Restricted Hours (7:00 am - 8:00 pm) from June 27 to July 3, 2010 - Regular Parkers

The top panel shows the expected distribution from the two weekend days (June 27 and July 3). The second panel shows data for the Monday (June 28) restricted hours, when plate numbers “1” and “6” were banned:

- The first two rows show the observed distribution of plate numbers.
- The third row tests whether each plate’s proportion during the restricted hours is significantly greater than zero using a one-tailed test. Plain text indicates that the proportion is not significantly greater than zero (plates “1,” “4,” and “6”) and bold indicates that it is statistically greater than zero (all other plates).
- The fourth row tests whether the observed proportion of each non-restricted plate differs from the expected proportion using a two-tailed test. In doing so, we adjust the expected distribution for the fact that there should be no “1” and “6” plates (*i.e.*, we compute the expected proportion assuming only the presence of the eight other plates). Bold significance levels indicate that the plate appears in statistically greater proportion than expected (none), those in bold italics indicate that it appears in significantly lower proportion than expected (plates “2” and “3”) and those in plain text that it is not significantly different (all others).

The data for the other weekdays is in the same format. Restricted numbers are shown in boxes.

Distribution	0	1	2	3	4	5	6	7	8	9	Total	No Plate
Expected Distribution (Weekend)												
Number	635	534	594	597	83	593	753	636	743	807	5,975	96
Percentage	10.6%	8.9%	9.9%	10.0%	1.4%	9.9%	12.6%	10.6%	12.4%	13.5%	100.0%	1.6%
Observed Distributions												
Monday (1, 6 Restricted)												
Number	398	45	312	315	54	380	67	400	486	490	2,947	28
Percentage	13.5%	1.5%	10.6%	10.7%	1.8%	12.9%	2.3%	13.6%	16.5%	16.6%	100.0%	1.0%
Different from Zero (SL)[1]	**0.0%**	20.2%	**0.0%**	**0.0%**	15.8%	**0.0%**	10.6%	**0.0%**	**0.0%**	**0.0%**		
Different from Expected (SL)[2]	54.7%		***3.2%***	***3.7%***	67.3%	34.5%		50.8%	14.1%	93.8%		
Tuesday (2, 7 Restricted)												
Number	357	319	50	325	63	339	436	63	440	456	2,848	26
Percentage	12.5%	11.2%	1.8%	11.4%	2.2%	11.9%	15.3%	2.2%	15.4%	16.0%	100.0%	0.9%
Different from Zero (SL)[1]	**0.0%**	**0.0%**	17.2%	**0.0%**	11.6%	**0.0%**	**0.0%**	11.6%	**0.0%**	**0.0%**		
Different from Expected (SL)[2]	34.3%	29.6%		18.8%	**4.8%**	44.9%	46.7%		31.2%	35.5%		
Wednesday (3, 8 Restricted)												
Number	353	270	327	31	43	351	453	393	75	447	2,743	29
Percentage	12.9%	9.8%	11.9%	1.1%	1.6%	12.8%	16.5%	14.3%	2.7%	16.3%	100.0%	1.1%
Different from Zero (SL)[1]	**0.0%**	**0.0%**	**0.0%**	27.6%	20.4%	**0.0%**	**0.0%**	**0.0%**	**7.3%**	**0.0%**		
Different from Expected (SL)[2]	35.4%	***4.7%***	30.4%		30.7%	26.4%	15.2%	**8.2%**		30.9%		
Thursday (4, 9 Restricted)												
Number	382	375	333	369	0	409	492	372	526	79	3,337	29
Percentage	11.4%	11.2%	10.0%	11.1%	0.0%	12.3%	14.7%	11.1%	15.8%	2.4%	100.0%	0.9%
Different from Zero (SL)[1]	**0.0%**	**0.0%**	**0.0%**	**0.0%**	N/A[4]	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**8.3%**		
Different from Expected (SL)[2]	29.9%	14.9%	***3.8%***	56.4%		22.1%	71.4%	13.6%	**5.7%**			
Friday (0, 5 Restricted)												
Number	69	349	340	373	46	68	402	348	497	533	3,025	39
Percentage	2.3%	11.5%	11.2%	12.3%	1.5%	2.2%	13.3%	11.5%	16.4%	17.6%	100.0%	1.3%
Different from Zero (SL)[1]	10.2%	**0.0%**	**0.0%**	**0.0%**	20.0%	10.6%	**0.0%**	**0.0%**	**0.0%**	**0.0%**		
Different from Expected (SL)[2]		26.8%	33.8%	66.6%	60.9%		***2.2%***	***8.8%***	**7.4%**	10.5%		

Ending license plate numbers of autos entering a Beijing parking garage inside the 4th Ring Road collected by authors. [1] SL = significance level. Bold indicates significantly greater than zero (at the 10% level or better) using a one-tailed equality of proportions test. [2] SL = significance level. Bold indicates significantly greater (at the 10% level or better) than expected proportion (assuming restricted plates occur in proportion zero) using a two-tailed equality of proportions test and bold, italics significantly lower. [3] No observations - significance level is undefined. Boxes indicate restricted plate numbers on that day.

Panel B: Comparison of Expected (Weekend) and Observed (Weekday) Distributions of Ending License Plate Numbers Entering Beijing Parking Garage during Non-Restricted Weekday Hours (9:00 pm - 6:00 am) from June 27 to July 3, 2010 - Regular Parkers

The top panel shows the expected distribution from the two weekend days (June 27 and July 3). The second panel shows data for the Monday (June 28) non-restricted hours:

- The first two rows show the observed distribution of plate numbers.
- The third row provides test statistics comparing the observed proportion of each plate to the expected based on a two-tailed test. Bold font indicates that the observed proportion is significantly greater than expected (none), bold italics lower (none), and plain text not significantly different (all plates).

The data for the other weekdays is in the same format. Numbers restricted during the restricted hours of that day are shown in boxes.

Distribution	0	1	2	3	4	5	6	7	8	9	Total	No Plate
Expected Distribution (Weekend)												
Number	635	534	594	597	83	593	753	636	743	807	5,975	96
Percentage	10.6%	8.9%	9.9%	10.0%	1.4%	9.9%	12.6%	10.6%	12.4%	13.5%	100.0%	1.6%
Observed Distributions												
Monday (1, 6 Restricted)												
Number	7	3	4	2	1	3	7	4	7	4	42	2
Percentage	16.7%	7.1%	9.5%	4.8%	2.4%	7.1%	16.7%	9.5%	16.7%	9.5%	100.0%	4.8%
Different from Observed (SL)[1]	20.6%	68.4%	92.8%	25.9%	58.5%	54.8%	42.9%	81.4%	40.8%	45.1%		
Tuesday (2, 7 Restricted)												
Number	13	9	2	9	1	4	11	6	14	7	76	2
Percentage	17.1%	11.8%	2.6%	11.8%	1.3%	5.3%	14.5%	7.9%	18.4%	9.2%	100.0%	2.6%
Different from Observed (SL)[1]	**7.0%**	37.9%	**3.4%**	59.3%	95.7%	17.6%	62.6%	43.9%	11.7%	27.5%		
Wednesday (3, 8 Restricted)												
Number	7	4	2	6	2	5	9	5	5	5	50	2
Percentage	14.0%	8.0%	4.0%	12.0%	4.0%	10.0%	18.0%	10.0%	10.0%	10.0%	100.0%	4.0%
Different from Observed (SL)[1]	44.2%	81.7%	16.1%	63.7%	11.9%	98.6%	25.3%	88.3%	60.3%	47.0%		
Thursday (4, 9 Restricted)												
Number	1	2	4	0	0	2	8	1	1	0	19	0
Percentage	5.3%	10.5%	21.1%	0.0%	0.0%	10.5%	42.1%	5.3%	5.3%	0.0%	100.0%	0.0%
Different from Observed (SL)[1]	44.8%	80.9%	10.7%	14.6%	60.5%	93.0%	**0.0%**	44.7%	34.4%	***8.5%***		
Friday (0, 5 Restricted)												
Number	6	9	13	10	3	3	14	9	11	5	83	0
Percentage	7.2%	10.8%	15.7%	12.0%	3.6%	3.6%	16.9%	10.8%	13.3%	6.0%	100.0%	0.0%
Different from Observed (SL)[1]	31.7%	54.6%	**8.5%**	53.5%	**8.9%**	***5.5%***	24.6%	95.3%	82.3%	***4.7%***		

Ending license plate numbers of autos entering a Beijing parking garage inside the 4th Ring Road collected by authors.[1] SL = significance level. Bold indicates significantly greater (at the 10% level or better) than expected proportion using a one-tailed equality of proportions test, bold italics indicates significantly less (at the 10% level or better) than expected proportion using a two-tailed equality of proportions test. Boxes indicate restricted plate numbers on that day.

Panel C: Comparison of Expected (Weekend) and Observed (Weekday) Distributions of Ending License Plate Numbers Entering Beijing Parking Garage during Restricted Hours (7:00 am - 8:00 pm) from June 27 to July 3, 2010 - Monthly Parkers

The top panel shows the expected distribution from the two weekend days (June 27 and July 3). The second panel shows data for the Monday (June 28) restricted hours, when plate numbers “1” and “6” were banned:

- The first two rows show the observed distribution of plate numbers.
- The third row tests whether each plate’s proportion during the restricted hours is significantly greater than zero using a one-tailed test. Plain text indicates that the proportion is not significantly greater than zero (plates “1,” “4”, and “6”) and bold indicates that it is statistically greater than zero (all other plates).
- The fourth row tests whether the observed proportion of each non-restricted plate differs from the expected proportion using a two-tailed test. In doing so, we adjust the expected distribution for the fact that there should be no “1” and “6” plates (*i.e.*, we compute the expected proportion assuming only the presence of the eight other plates). Bold significance levels indicate that the plate appears in statistically greater proportion than expected (plates “3” and “5”), those in bold italics indicate that it appears in significantly lower proportion than expected (plate “8”) and those in plain text that it is not significantly different (all others).

The data for the other weekdays is in the same format. Restricted numbers are shown in boxes.

Distribution	0	1	2	3	4	5	6	7	8	9	Total	No Plate
Expected Distribution (Weekend)												
Number	14	20	15	7	1	9	27	20	29	26	168	3
Percentage	8.3%	11.9%	8.9%	4.2%	0.6%	5.4%	16.1%	11.9%	17.3%	15.5%	100.0%	1.8%
Observed Distributions												
Monday (1, 6 Restricted)												
Number	46	3	46	56	6	60	6	60	58	70	411	1
Percentage	11.2%	0.7%	11.2%	13.6%	1.5%	14.6%	1.5%	14.6%	14.1%	17.0%	100.0%	0.2%
Different from Zero (SL)[1]	**0.8%**	44.1%	**0.8%**	**0.1%**	38.3%	**0.1%**	38.3%	**0.1%**	**0.1%**	**0.0%**		
Different from Expected (SL)[2]	96.9%		77.4%	**1.6%**	57.6%	**3.3%**		66.7%	***1.3%***	31.0%		
Tuesday (2, 7 Restricted)												
Number	26	27	3	21	3	28	36	5	44	42	235	3
Percentage	11.1%	11.5%	1.3%	8.9%	1.3%	11.9%	15.3%	2.1%	18.7%	17.9%	100.0%	1.3%
Different from Zero (SL)[1]	**3.6%**	**3.1%**	42.2%	**7.6%**	42.2%	**2.6%**	**0.5%**	37.1%	**0.1%**	**0.1%**		
Different from Expected (SL)[2]	78.7%	39.3%		17.3%	61.9%	***9.3%***	28.4%		58.1%	80.7%		
Wednesday (3, 8 Restricted)												
Number	36	29	51	3	3	43	36	49	11	51	312	2
Percentage	11.5%	9.3%	16.3%	1.0%	1.0%	13.8%	11.5%	15.7%	3.5%	16.3%	100.0%	0.6%
Different from Zero (SL)[1]	**1.5%**	**4.2%**	**0.1%**	43.2%	43.2%	**0.4%**	**1.5%**	**0.1%**	26.3%	**0.1%**		
Different from Expected (SL)[2]	66.0%	10.3%	12.7%		80.4%	**2.6%**	***2.4%***	73.6%		51.9%		
Thursday (4, 9 Restricted)												
Number	25	23	21	27	0	34	38	26	31	11	236	2
Percentage	10.6%	9.7%	8.9%	11.4%	0.0%	14.4%	16.1%	11.0%	13.1%	4.7%	100.0%	0.8%
Different from Zero (SL)[1]	**4.3%**	**5.8%**	**7.6%**	**3.1%**	N/A[4]	**0.8%**	**0.3%**	**3.6%**	**1.5%**	23.2%		
Different from Expected (SL)[2]	72.1%	25.2%	68.3%	**2.4%**		**1.2%**	58.2%	46.0%	***8.8%***			
Friday (0, 5 Restricted)												
Number	1	47	41	54	3	9	66	61	59	66	407	4
Percentage	0.2%	11.5%	10.1%	13.3%	0.7%	2.2%	16.2%	15.0%	14.5%	16.2%	100.0%	1.0%
Different from Zero (SL)[1]	48.0%	**0.7%**	**1.6%**	**0.2%**	44.1%	32.6%	**0.0%**	**0.1%**	**0.1%**	**0.0%**		
Different from Expected (SL)[2]		54.1%	99.5%	**0.4%**	93.7%		58.5%	65.0%	15.1%	72.0%		

Ending license plate numbers of autos entering a Beijing parking garage inside the 4th Ring Road collected by authors. [1] SL = significance level. Bold indicates significantly greater than zero (at the 10% level or better) using a one-tailed test. [2] SL = significance level. Bold indicates significantly greater (at the 10% level or better) than expected proportion (assuming restricted plates occur in proportion zero) using a two-tailed test and bold, italics significantly lower. 3 No observations - significance level is undefined. Boxes indicate restricted plate numbers on that day.