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The effects of driving restrictions on travel behavior evidence from Beijing

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ABSTRACT

We examine the effects of Beijing's driving restrictions on individual travel behavior. The restrictions prohibit drivers from using their vehicles one weekday per week on the basis of the license plate number. Using the 2010 Beijing Household Travel Survey data, we find that driving restrictions have significant effects on auto trip frequency and thus vehicle miles traveled, suggesting substitution toward other modes. We also find evidence of the differential effects across subgroups of drivers. This suggests a variation in willingness to pay for auto use, which is not addressed by the restrictions. Three adaptation mechanisms–substitution toward unrestricted hours/days, having access to an unrestricted vehicle, and noncompliance–have been at work that mitigate the policy's effect. Driving restrictions cause more congestion on days that restrict plates ending in "4" (an unlucky number) and thus have an unanticipated consequence on non-drivers, who reduce their trips on such days.

1. Introduction

Driving restrictions have been implemented in cities around the world for decades.[1] During the 2008 Olympics, the Beijing municipal government banned half of the vehicles every day according to the last digit of the license plate to alleviate both air pollution and travel congestion. The restrictions were then relaxed by preventing driving one weekday per week (7am–8pm), but remain in effect till now.

A number of empirical studies have questioned the effectiveness of such policies. Employing a regression discontinuity design, Davis (2008) finds no evidence that the "One Day without a Car" program in Mexico City has improved air quality, using data from the monitoring stations. Viard and Fu (2015) show that the one-day restrictions in Beijing reduce PM10 concentrations by 8%, though Lin et al. (2011) find no significant effect for the same policy.[2] As for traffic flow, Grange and Troncoso (2011) show that the additional restriction in Santiago, which bans more cars on the basis of a permanent restriction, decreases traffic flow by 5.5%, much lower than the ratio of vehicles restricted for use. Comparing traffic between periods with and without restrictions, a report by the Beijing Transportation Research Center claims that the one-day restrictions increase travel speed about 15% during peak hours and decrease daily traffic flow on main roads by only 2.8%–4.1% (Beijing Transportation Research Center, 2011).[3]

Households' adaptations to the policy, e.g., purchasing additional cars, often make the policy effective only in the short run. Eskeland and Feyzioglu (1997) and Davis (2008) confirm this by examining gasoline sales and vehicle ownership at the aggregate level in Mexico City. Gallego et al. (2013) indicate that the adaptations take 9–11 months: the program in Mexico City reduced air pollution only at the beginning, followed by a gradual increase in pollutant concentration.

Another criticism of driving restrictions is the neglect of heterogeneity in willingness to pay (WTP) for auto use across individuals and across weekdays (Eskeland and Feyzioglu, 1997). However, few studies have attempted to identify such variations due to the lack of micro data. One exception is the study by Viard and

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[1] Most of them are Latin American cities such as Mexico City. For a brief review on related policies in these cities, see Grange and Troncoso (2011).

[2] The former uses the daily air pollution index (API) of Beijing from January 1, 2007 to December 31, 2009, while the latter uses API data from July 20, 2007 to October 31, 2009.

[3] A summary is available at http://www.bjjtw.gov.cn/gzdt/dtxx/200904/t20090402_32864.htm (in Chinese), retrieved June 8, 2012. The two periods for comparison are: October 2008 to February 2009 (with restrictions), and October to November 2007 (without restrictions).

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0094-1190/

Fu (2015) that examines the relationship between driving restriction and labor supply indirectly using hourly TV viewership of workers with and without discretionary work time in Beijing.

This article is among the first to use micro data to measure the effects of driving restrictions on individual travel behavior. Using the 2010 Beijing Household Travel Survey data, we test a number of hypotheses derived from a simple conceptual framework. Consider a utility-maximizing driver who chooses a combination of mode and departure time for a specific activity, with no travel as an outside option. Given a penalty incurred on using a restricted vehicle during restricted hours, we expect substitution toward (i) other modes, (ii) unrestricted hours/days, or (iii) no-travel, no substitution if (iv) an unrestricted vehicle is available, and (v) noncompliance. Substitution toward other modes or no-travel suggests a decrease in auto trip frequency and thus vehicle miles traveled (VMT). Substitution toward no-travel suggests also a decrease in total trip frequency. Substitution toward unrestricted hours/days, having access to an unrestricted vehicle, and noncompliance are the three adaptation mechanisms that mitigate the policy's effect.

We basically compare travel behavior between drivers with restricted vehicles on the survey day and unrestricted drivers, controlling for demographic and location variables. This methodology is justified since driving restrictions can be taken as a valid quasi-experiment; we show that license plate assignment and thus being restricted or not is not related to any characteristics of drivers. It provides an upper bound of driving restrictions' effects compared to the no-restrictions case. First, the intertemporal substitution may increase auto use on unrestricted days. Second, the speed improvements may attract some of the latent demand to drive on unrestricted days (Vickrey, 1969).[4]

We first investigate the effects of driving restrictions on auto trip frequency and VMT as well as total trip frequency at the driver level. We find that driving restrictions decrease auto trip frequency about 0.25–0.30 per day (15.5%–18.6% of the average), which suggests a substantial degree of substitution between modes. A back-of-the-envelope calculation shows that the deterrent effect of driving restrictions on daily VMT of drivers who live within the restricted area is 17.8 million km. However, driving restrictions have no significant effect on total trip frequency, suggesting less substitution toward no-travel than toward other modes probably due to the low utility of no-travel. We also present evidence of the differential effects of driving restrictions across subgroups of drivers. For example, drivers with flexible work time are more sensitive to the restrictions, i.e., more likely to make zero auto trips, than those with fixed work time.

We then explore the three adaptation mechanisms, mainly by examining driving restrictions' effect on mode choice/auto use at the trip level. First, substitution towards unrestricted hours is not important because driving restrictions do not significantly encourage auto use during unrestricted hours. In contrast, Gibson and Carnovale (2015) find that drivers respond to road pricing by shifting trips toward unpriced times, using a quasi-experiment in Milan, Italy. However, we provide suggestive evidence of substitution toward unrestricted days; auto trip frequency on weekdays adjacent to a driver's restricted day is higher than other weekdays by 0.10 (6.0% of the average). Second, driving restrictions have no significant effect on auto use for drivers in households with two or more vehicles. So having access to an employer provided vehicle would mitigate the policy's effect. Third, the magnitude of driving restrictions' effect on auto use is significantly smaller for shorter trips, which provides suggestive evidence of noncompliance because the probability of being caught is lower for shorter trips.

[4] We thank an anonymous referee for pointing this out.

We also examine an unanticipated consequence of driving restrictions. In China, there are fewer cars with "4", an unlucky number, as the last digit of the license plate. It makes the restrictions uneven across weekdays, i.e., more congestion on days that restrict plates ending in "4". We find substitution of activities/trips toward other days for non-drivers (people in households who have no vehicle): total trip frequency on days that restrict the numbers 4&9 is significantly lower than other weekdays by about 0.09 (4.3% of the average).

This study contributes to the literature in three respects. First, it examines the direct effect of driving restrictions on travel behavior, which is rarely studied in the literature of driving restrictions. Second, it is among the first to examine individual response to driving restrictions in terms of auto use. Using micro data, the paper not only shows the differential effects of driving restrictions across subgroups of drivers but also explores three adaptation mechanisms that mitigate the policy's effect. Third, it provides evidence of the unanticipated consequence on non-drivers of driving restrictions in Beijing.

The rest of this article is organized as follows. Section 2 provides policy background. Section 3 summarizes the data. Section 4 describes a simple conceptual framework and our estimating equations. Section 5 discusses the results. Section 6 concludes.

2. Driving restrictions in Beijing

During the 2008 Beijing Olympics, the Beijing municipal government implemented driving restrictions to alleviate both air pollution and travel congestion. The restrictions banned half of the vehicles off the road every day (except midnight to 3am) according to the last digit of the license plate (odd or even) in the whole city from July 20 to September 20, 2008.

The government relaxed driving restrictions after the Olympics. New restrictions prevented entry within the 5th Ring Road one weekday per week (from 6am to 9pm) since October 11, 2008 (Fig. 1). On April 11, 2009, driving restrictions were further relaxed; they were not applied on the 5th Ring Road, and the restricted hours were reduced to 7am–8pm. The relaxed restrictions remain in effect till now. In this study, we measure the effects of the latest restrictions since the 2010 Survey records individual travel behaviors in fall 2010. The main focus is on households who live within the restricted area.

On each weekday, two last digits of the license plate are restricted, following the pairs of 0&5, 1&6, 2&7, 3&8, and 4&9, which have been the same throughout. The rule that assigns these digit pairs to weekdays changes every thirteen weeks after April 11, 2009. Driving restrictions apply to all private and public vehicles except police cars, fire trucks, ambulances, buses, taxis, and other vehicles authorized by the government.

At the end of 2010, there were about 4.8 million registered vehicles in Beijing.[5] Thus on average nearly one million vehicles are restricted for use every weekday. However, driving restrictions are not uniform across weekdays because there are fewer cars with license plate ending in "4", an unlucky number in China. Out of 14,625 vehicles reported by all sampled households in the 2010 Survey, there are only 2.4% with "4" as the last license digit, and thus only 13.6% with "4" or "9" as the last digit (Table 3), much lower than the average share, 21.6%, of other digit pairs.[6] Therefore,

[5] See the website of the Beijing Traffic Management Bureau at http://www.bjjtgl.gov.cn/publish/portal0/tab118/ (in Chinese), retrieved June 8, 2012.

[6] The government or firm owned vehicles account for less than 5% of all reported vehicles. In the following we do not differentiate between public and private vehicles since driving restrictions treat them equally.

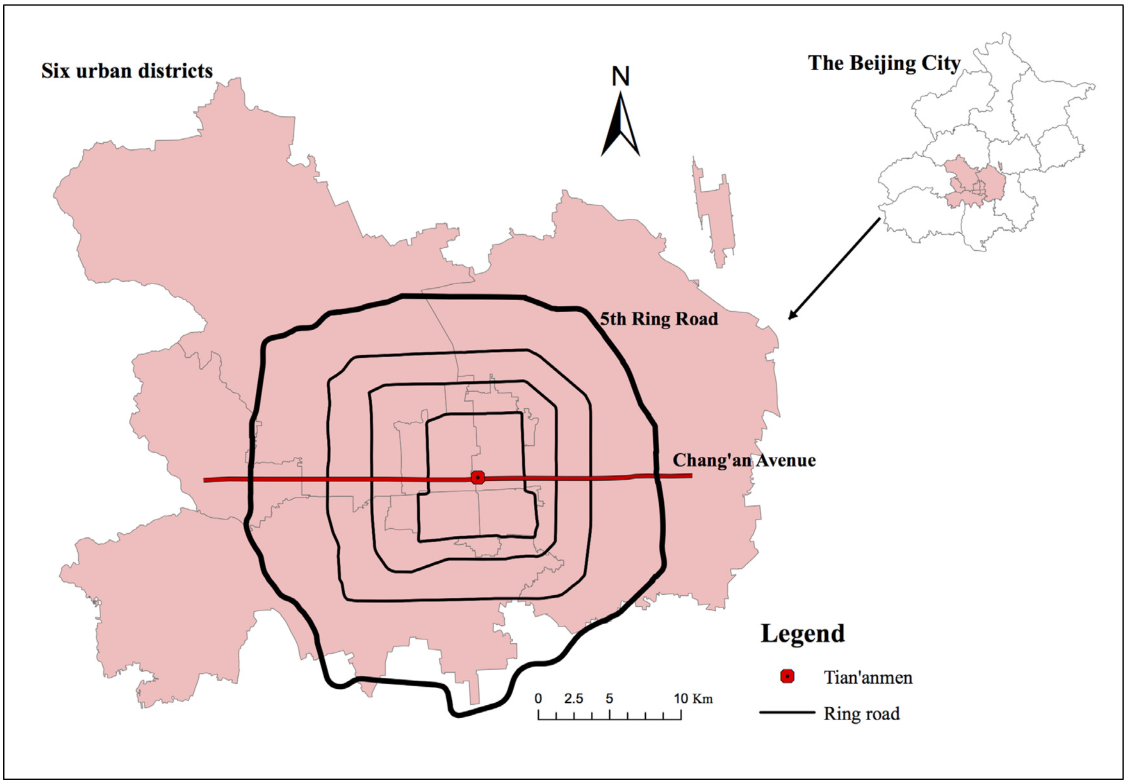

Fig. 1. The map of the Beijing City, six urban districts and Ring Roads. Note: Since April 11, 2009, driving restrictions prevent entry within the 5th Ring Road (not applied on it) one weekday per week (7am–8pm). The northern part within the 5th Ring Road, with Chang'an Avenue as the boundary, has better transit access.

there is more congestion on days that restrict 4&9, an observation that has been widely reported in the media.

3. Data

The Beijing municipal government has organized four large-scale household travel surveys respectively in 1986, 2000, 2005 and 2010. The recent 2010 Survey adopts a multistage sampling strategy with a target of 1% sampling rate. 1085 out of 1911 Traffic Analysis Zones (TAZs) in the whole Beijing City are selected. In each TAZ, 10–50 households are selected to take a face-to-face interview. The final sample size is 46,900 households with 116,142 persons in the whole city.

The 2010 Survey provides a one-day travel diary of all household members, household information including household structure, income, and residential location at the TAZ level, as well as personal information including gender, age, occupation, etc. For every vehicle these households use, the main user is self-reported by the households and the last digit of the license plate is recorded, which tells us whether the vehicle is restricted for use on the survey day. These households were surveyed on different days between September 8 and October 31, 2010, which we use to control for the weekly variation in travel behavior.

To investigate driving restrictions' effects on trip frequency, we generate a trip dataset on the basis of the original trip segment dataset. Here a trip is defined as traveling between two anchor destinations with a specific purpose (e.g., commuting, shopping) excluding transfer. In total there are 253,584 trips in the 2010 Survey data. For a trip, the mode is identified as the mode of the trip segment that is part of this trip and has the longest duration (distance unavailable except the origin-TAZ and the destination-TAZ). In case there are two or more segments that have the same length of duration, we choose the one with the highest mobility. For example, the mobility of car is higher than that of bus. Using other methods to identify the main mode will not change the results in this study, because 38,008 out of 38,657 auto trip segments are identified as an auto trip without combining any other mode, probably due to the lack of park and ride facilities in Beijing.

Of 46,900 sampled households, 33,363 (71.1%) have no vehicle, 12,503 (26.7%) have one vehicle, and 1034 (2.2%) have at least two vehicles (Table A.1). Here we include both private and government/firm provided vehicles. We then divide the sampled households by whether they live within the 5th Ring Road or not, because driving restrictions are in effect within this area. This area (approximately 1085 km^2, 6.7% of the whole Beijing City) is often referred to as the Beijing Metropolitan Area, or the Beijing central city as in the Beijing Urban Master Plan (2004–2020) (Beijing Institute of City Planning, 2004).[7] We also exclude 14 households with household income unavailable and then 12,664 households who were surveyed on weekends because driving restrictions are in effect on only weekdays.

We construct three location variables on the basis of the TAZ where a household lives, to control for the spatial variation in travel behavior and examine the location-specific effects of driving restrictions. First, we divide the Beijing City into downtown (two innermost districts) and suburb by administrative boundaries (Fig. 1). Second, we approximate the air distance to the closest subway station from the centroid of the residence-TAZ. Third, one well-known fact about the Beijing central city is the insufficient provision of infrastructure such as public transit in the southern part, with Chang'an Avenue as the boundary (Fig. 1).[8]

[7] In the 2010 Survey, 90.9% of commuting trips originating from the central city end in the central city, while this ratio is only 23.2% for commuting trips originating from outside the central city.

[8] For example, the average distance to subway station of 2622 drivers in the northern part is 1.32 km, significantly lower than the 2.31 km for 2501 drivers in the southern part (mean comparison t-statistics 26.23).

Table 1
Summary statistics of 5123 drivers in one-vehicle households within the restricted area.

Variable	Definition	Mean	SD	Min	Max
Demographic					
Male	Male 1, female 0	0.77	0.42	0	1
Age		40.75	10.63	18	98
Kids	Having at least one kid aged 6–12 or not	0.14	0.35	0	1
IncomeLow	Annual household income less than 50,000 RMB ($7550 by the exchange rate at the end of 2010)	0.34	0.47	0	1
IncomeMed	50,000–100,000 RMB ($15,100)	0.47	0.50	0	1
IncomeHigh	More than 100,000 RMB	0.18	0.39	0	1
HourFlexible	Worker with discretionary work time or not	0.19	0.39	0	1
HourFixed	Worker with fixed work time or not	0.69	0.46	0	1
HourZero	Retired/Unemployed or not	0.13	0.33	0	1
Location					
DistSubway	Air distance to the closest subway station from the centroid of a driver's residence-TAZ (km)	1.80	1.44	0.27	8.04
Downtown	Living in two downtown districts (*DongCheng* and *XiCheng*) or not	0.31	0.46	0	1
North	Living to the north of Chang'an Avenue or not	0.51	0.50	0	1
Survey day					
Mon/Tue/Wed/Thu/Fri		22%, 22%, 22%, 16%, 18%			
Restriction					
Restrict	Vehicle restricted on the survey day or not	0.19	0.39	0	1
AdjacentRestrict	Survey day adjacent to a driver's restricted day or not	0.36	0.48	0	1
Trip frequency					
TripCount	Total trip frequency	2.56	1.60	0	12
Trip	Having at least one trip or not	0.90	0.29	0	1
AutoTripCount	Auto trip frequency	1.61	1.65	0	12
Auto	Having at least one auto trip or not	0.60	0.49	0	1

We mainly use three different samples in the estimations: (i) drivers, (ii) trips made by the drivers, and (iii) non-drivers. The first sample, used for identifying driving restrictions' effects on auto trip frequency, trip frequency, and VMT, covers drivers–the self-reported main user of a vehicle in the 2010 Survey–in one-vehicle households surveyed on weekdays. We investigate driving restrictions' effects for 5123 drivers within the restricted area and 3874 drivers out of the restricted area separately.[9] We expect that driving restrictions affect mainly the former drivers, with descriptive statistics presented in Table 1. Nearly 80% of these drivers are male, their average age is 41, and 14% of them have at least one kid of age 6–12. About 34% are classified as low-income, 47% as middle-income, and 18% as high-income. Nearly 20% of them are semi-government employees (*ShiYe DanWei* in Chinese, such as researchers and teachers) or self-employed, who usually have discretionary work time. 31% of these drivers live in downtown, and slightly more than half live in the northern part.

For these drivers, their survey days are almost uniformly distributed among different weekdays. About 1/5 of these drivers (990 out of 5123) cannot use their vehicles from 7am to 8pm on the survey day. Here the "Restrict" dummy equals 1 if a driver's vehicle is restricted on the survey day. For 35% of them, the survey day is just one day before or after the restricted day, which we use to test whether there is any intertemporal substitution of auto trips toward unrestricted weekdays.

The second sample, used for exploring drivers' adaptation mechanisms, covers the trips made by sampled drivers surveyed on weekdays. In specific, we look at three sub-samples: 13,088 trips by the 5123 drivers in one-vehicle households within the restricted area, 11,201 trips by the 3874 drivers in one-vehicle households out of the restricted area, and 183 trips by 61 drivers in households within the restricted area who have at least two vehicles. As seen in Table 1, a driver of the first group on average makes 2.56 trips per weekday, of which there are 1.61 auto trips. Only 10% of the first group have no trip at all on the survey day, while 40% have no auto trip.

[9] A few households do not report the main vehicle user in the 2010 Survey data.

The third sample, used for examining the effects of the uneven restrictions on trip frequency, includes 32,170 non-drivers in no-vehicle households who live within the restricted area and were surveyed on weekdays. Summary statistics of these non-drivers are presented in Table 9. A non-driver on-average makes 2.11 trips per weekday. 21% of them were surveyed on days that restrict 4&9.

4. Estimation

We use a simple conceptual framework on the basis of activity-based travel theory to illustrate how driving restrictions affect individual travel behaviors (e.g., Bowman and Ben-Akiva, 2001). Consider a utility-maximizing driver i who chooses a combination of mode m and departure time d for a specific activity, with no activity/travel as an outside option. A utility component specific to driving restrictions is given by

$$z_{imd} = Penalty * I(i\ being\ restricted) * I(m = auto)$$
$$I(d \in [7am, 8pm]) * Probability(getting\ caught), \tag{4.1}$$

where $I()$ is an identity function.

This cost arises from a penalty incurred with a non-zero probability on using a restricted vehicle during restricted hours. Given that modes and times are not perfect substitute, we expect substitution toward (i) other modes, (ii) unrestricted hours/days, or (iii) no-travel outside option. The key parameters here are the degree of substitution between modes and between times, and the utility of the outside option (relative to the utility of activity itself). There would be no substitution if (iv) an unrestricted vehicle (e.g., employed provided vehicles) was easily available, since no penalty is incurred. Also, given that the cost (*Penalty*Probability*) is finite, we expect (v) non-compliance that decreases with size of penalty and with probability of getting caught.

Substitution toward other modes or no-travel outside option implies a decrease in auto trip frequency and thus VMT. Substitution towards no-travel option implies also a decrease in total trip frequency. To investigate driving restrictions' effect on auto trip frequency, trip frequency, and VMT we estimate the following model at the driver level using the first sample:

$$y_i = \gamma_1 Restrict_i + \gamma_2 Restrict_i * x_i + \gamma_3 x_i + \epsilon_i, \tag{4.2}$$

Table 2
Summary statistics of drivers with restricted and unrestricted vehicles.

N	Restricted drivers		Unrestricted drivers		
	990		4,133		
Variable	Mean	SD	Mean	SD	t-stats
Male	0.79	0.41	0.77	0.42	−1.27
Age	40.71	0.17	40.89	0.33	−0.47
Kids	0.14	0.01	0.14	0.01	0.40
IncomeLow	0.34	0.01	0.35	0.02	−0.80
IncomeMed	0.48	0.01	0.45	0.02	1.91*
IncomeHigh	0.18	0.01	0.20	0.01	−1.48
HourFlexible	0.18	0.01	0.20	0.01	−1.26
HourFixed	0.69	0.01	0.67	0.01	1.17
HourZero	0.13	0.01	0.13	0.01	−0.17
DistSubway	1.81	0.02	1.79	0.05	0.24
Downtown	0.31	0.01	0.31	0.01	−0.25
North	0.51	0.01	0.51	0.02	0.40
Auto trip frequency	1.36	1.60	1.67	1.66	−5.27***
N: drivers having at least one auto trip	522		2,562		
Auto trip frequency	2.58	1.30	2.69	1.30	−1.76*

The statistics are calculated for drivers in one-vehicle households who live within the restricted area.
* = 10% significance, ** = 5% significance, *** = 1% significance.

where y_i is daily auto trip frequency, trip frequency, or VMT of the driver i, and x_i is a vector of covariates that vary across drivers such as gender, age, occupation, and survey day of the week. The coefficients of interest, γ_1 and γ_2, capture the average effect of driving restrictions and the differential effects across subgroups of drivers.

For auto trip frequency, the magnitude of γ_1 increases with the degree of substitution between modes, decreases with that between times, and increases with the utility of no-travel if it is above certain level. The effect of driving restrictions would be largest if there was prefect substitution between modes and no substitution between times, without taking into account the utility of no-travel. The differential effects of driving restrictions (the variation in WTP for auto use) arise from the variation in the degree of substitution between modes and between times as well as the variation in the utility of no-travel. For trip frequency, the magnitude of γ_1 also increases with the utility of no-travel if this utility is above certain level.

Substitution toward unrestricted hours/days, having access to an unrestricted vehicle, and noncompliance are the three adaptation mechanisms of drivers that suggest no decrease in overall auto trip frequency. Driving restrictions would have little effect on auto trip frequency if there was prefect substitution between times and no substitution between modes, if every driver had access to an unrestricted vehicle, or if the probability of getting caught was zero. To explore these adaptation mechanisms we estimate a binary logit model of mode choice at the trip level using the second sample:

$$log\left(\frac{P_{i,t}}{1-P_{i,t}}\right) = \gamma_1 Restrict_i + \gamma_2 Restrict_i * z_t + \gamma_3 x_i + \gamma_4 z_t, \quad (4.3)$$

where $P_{i,t}$ is the probability that a trip t by the driver i is made by auto, and z_t is a vector of covariates that vary across trips like trip purpose. γ_1 captures the effect of driving restrictions on the probability of auto use conditional on a trip.

First, for substitution toward unrestricted hours, we estimate Model (4.3) for trips made from 7am to 8pm and trips before 7am or after 8pm separately. γ_1 would be significantly negative for the former and significantly positive for the latter, if the degree of substitution between times was large enough. Similarly, we estimate Model (4.2) respectively for auto trip frequency from 7am to 8pm and that before 7am or after 8pm. We also add the "AdjacentRestrict" dummy in Model (4.2) to test substitution toward unrestricted days. Second, to illustrate how having access to an unrestricted vehicle would mitigate the policy's effect (γ_1 not significant), we estimate Model (4.3) using trips made by drivers in households with two or more vehicles. Third, for noncompliance, we add the restriction dummy interacted with trip distance in Model (4.3). We expect γ_2 to be negative in this case because the probability of being caught is smaller for shorter trips.

In the estimations we exploit the fact that the restrictions target only some of the drivers on each weekday on the basis of the license plate and compare travel behaviors between two groups of drivers–drivers with restricted auto use on the survey day and those unrestricted, controlling for demographic and location variables. Though the license plates are not randomly allocated given people's favorable (unfavorable) attitude toward lucky numbers "6" and "8" (unlucky number "4"), this is still a valid quasi-experiment. Our identification strategy is based on the assumption that license plate assignment and thus being restricted or not is not related to any characteristics of drivers. We show this by first presenting the summary statistics of two groups of drivers and t-statistics of mean comparison. As seen in Table 2, these two groups of drivers are very similar, except that the median-income share is slightly higher for restricted drivers. We further divide these drivers into five groups by pairs of last digit of the license plate. We add driver group dummies in the following estimations even though there is not much difference across groups of drivers (Table A.2). In this sense, license plate numbers, or the restrictions, are almost randomly assigned.

For both drivers and non-drivers, the congestion on days that restrict 4&9 can be seen as an exogenous shock. Given the increase in time cost on such days, we expect substitution of activities/trips toward other days. To examine the effects of uneven restrictions on trip frequency for both drivers and non-drivers we estimate the following model at the person level using the third sample:

$$y_i = \gamma_1 Day49_i + \gamma_2 x_i + \epsilon_i, \quad (4.4)$$

where y_i is trip frequency of the person i on the survey day. The "Day49" dummy equals one if a person is surveyed on days that restrict vehicles with last digit as "4" or "9". Luckily, the 2010 Survey spans two periods with different rules that assign digit pairs to weekdays (Table 3). 4&9 vehicles are restricted on Friday in the

Table 3
Vehicle restriction rules during the 2010 survey.

Last digit restricted	Mon	Tue	Wed	Thu	Fri
Sept 8–Oct 9, 2010	0&5	1&6	2&7	3&8	4&9
The share of vehicles in the 2010 survey	20.7%	23.1%	20.1%	22.5%	13.6%
Oct 10–Oct 31, 2010	4&9	0&5	1&6	2&7	3&8

first period and on Monday in the second period. We use this to identify uneven restrictions' effect on trip frequency.

5. Results

5.1. Effect on auto trip frequency, trip frequency and VMT

Auto trip frequency: We first estimate a series of linear models of daily auto trip frequency (Model (4.2)). The estimation results are presented in Table 4. In addition to weekday dummies and driver group dummies by last digit of the license plate, Columns I and IV include only the restriction dummy to identify the average effect of driving restrictions on auto use frequency. Columns II and V add demographic and location variables as well as a date dummy that equals one if the survey day is adjacent to a driver's restricted day. In Columns III and VI, several interactive variables between the restriction dummy and the demographic/location variable are further included to investigate the differential effects across subgroups of drivers. Columns I–III are estimated using drivers in one-vehicle households who live within the restricted area, and Columns IV–VI using drivers in one-vehicle households out of the restricted area. Standard errors are clustered by residence-TAZ in all columns.

The estimates of demographic and location variables conform to our expectations. For example, auto trip frequency increases with

Table 4
Effect of driving restrictions on auto trip frequency.

Dependent variable	auto trip frequency					
	Drivers within the restricted area			Drivers out of the restricted area		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Restrict	−0.297***	−0.254***	−0.484**	−0.057	−0.062	−0.026
	(0.057)	(0.061)	(0.191)	(0.074)	(0.079)	(0.188)
AdjacentRestrict		0.103*	0.101*		0.019	0.018
		(0.057)	(0.057)		(0.074)	(0.073)
Male		0.105*	0.047		0.162*	0.162*
		(0.056)	(0.062)		(0.083)	(0.089)
Age		−0.003	−0.002		−0.003	−0.003
		(0.002)	(0.002)		(0.003)	(0.003)
Kids		0.221***	0.246***		0.499***	0.569***
		(0.073)	(0.084)		(0.092)	(0.105)
IncomeMed		0.093*	0.116**		0.149**	0.103
		(0.052)	(0.057)		(0.073)	(0.081)
IncomeHigh		0.346***	0.398***		0.162	0.221*
		(0.071)	(0.080)		(0.114)	(0.123)
HourFlexible		−0.079	−0.069		0.050	0.062
		(0.065)	(0.068)		(0.084)	(0.099)
HourZero		−0.508***	−0.519***		−0.550***	−0.509***
		(0.084)	(0.094)		(0.094)	(0.109)
Downtown		−0.118**	−0.119**			
		(0.055)	(0.060)			
DistSubway		0.082***	0.083***		0.014***	0.014***
		(0.019)	(0.019)		(0.003)	(0.003)
North		−0.121**	−0.164***			
		(0.055)	(0.060)			
Restrict*Male			0.314**			−0.010
			(0.139)			(0.192)
Restrict*IncomeMed			−0.108			0.230
			(0.117)			(0.166)
Restrict**IncomeHigh			−0.251			−0.244
			(0.167)			(0.260)
Restrict*HourFlexible			−0.049			−0.054
			(0.142)			(0.192)
Restrict*HourZero			0.058			−0.194
			(0.178)			(0.231)
Restrict*North			0.216*			
			(0.112)			
N	5123	5123	5123	3874	3874	3,874
R^2	0.01	0.04	0.04	0.00	0.04	0.04

Standard errors clustered by residence-TAZ in parentheses. Equations I–III are estimated using drivers in one-vehicle households who live within the restricted area, while Equations IV–VI using drivers in one-vehicle households out of the restricted area. Weekday dummies, driver group dummies, and constant included in all regressions. Restrict*Downtown included in Equation III but insignificant. Restrict*Kids and Restrict*Subway in Equations III and VI but insignificant. The "Downtown" dummy and the "North" dummy do not apply to the area out of the 5th Ring Road and are not included in Equations V and VI.
* = 10% significance, ** = 5% significance, *** = 1% significance.

Table 5
Effect of driving restrictions on a driver's auto use on one weekday.

Dependent variable	having at least one auto trip or not					
	Drivers within the restricted area			Drivers out of the restricted area		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Restrict	−0.089***	−0.081***	−0.159***	−0.023	−0.023	−0.054
	(0.018)	(0.018)	(0.062)	(0.020)	(0.020)	(0.047)
AdjacentRestrict		0.018	0.017		0.007	0.007
		(0.016)	(0.016)		(0.018)	(0.018)
Male		0.030*	0.008		0.061***	0.050**
		(0.017)	(0.018)		(0.020)	(0.023)
Age		−0.001*	−0.001*		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Kids		−0.010	−0.012		0.023	0.043*
		(0.019)	(0.022)		(0.021)	(0.024)
IncomeMed		0.034**	0.045***		0.018	0.012
		(0.016)	(0.017)		(0.017)	(0.019)
IncomeHigh		0.068***	0.087***		0.012	0.038
		(0.021)	(0.024)		(0.026)	(0.029)
HourFlexible		−0.030	−0.015		0.012	0.004
		(0.019)	(0.020)		(0.022)	(0.026)
HourZero		−0.238***	−0.243***		−0.210***	−0.204***
		(0.023)	(0.024)		(0.020)	(0.023)
DistSubway		0.023***	0.023***		−0.000	−0.000
		(0.007)	(0.007)		(0.001)	(0.001)
Downtown		−0.009	−0.006			
		(0.017)	(0.019)			
North		−0.033*	−0.045**			
		(0.017)	(0.018)			
Restrict*Male			0.112**			0.053
			(0.044)			(0.048)
Restrict*IncomeMed			−0.049			0.030
			(0.036)			(0.041)
Restrict*IncomeHigh			−0.088*			−0.105*
			(0.048)			(0.061)
Restrict*HourFlexible			−0.072*			0.044
			(0.040)			(0.052)
Restrict*HourZero			0.032			−0.023
			(0.053)			(0.056)
Restrict*North			0.058*			
			(0.034)			
N	5123	5123	5123	3874	3874	3,874

The average marginal effect reported. Standard errors clustered by residence-TAZ in parentheses. Equations I–III are estimated using drivers in one-vehicle households who live within the restricted area, while Equations IV–VI using drivers in one-vehicle households out of the restricted area. Weekday dummies, driver group dummies, and constant included in all regressions. Restrict*Downtown included in Equation III but insignificant. Restrict*Kids and Restrict*Subway in Equations III and VI but insignificant. The "Downtown" dummy and the "North" dummy do not apply to the area out of the 5th Ring Road and are not included in Equations V and VI.
* = 10% significance, ** = 5% significance, *** = 1% significance.

distance to subway station.[10] The results in Columns I and II show that driving restrictions significantly decrease auto trip frequency for drivers within the restricted area by 0.25–0.30 per weekday, which is 15.5%–18.6% of the average and suggests a substantial degree of substitution between modes. As expected, driving restrictions have no significant effect for those out of the restricted area (Columns IV and V). The estimates of the interactive variables in Column III show that the magnitude of the effects is significantly different between male and female drivers, as well as between drivers in the northern part and those in the southern part.

Driving restrictions are expected to increase the ratio of drivers who make no auto trip on the survey day. As seen in Table 2, 47.3% of restricted drivers make no auto trip on the survey day, higher than the 38.0% of unrestricted drivers. But conditional on that a driver has made any auto trip, there would be not much difference in auto trip frequency between restricted drivers (2.58 auto trips) and those unrestricted (2.69 auto trips). We therefore estimate a binary logit model of whether a driver makes any auto trip on the survey day, with the estimation results presented in Table 5. The estimates in Columns I–II show that driving restrictions significantly decrease the probability of making at least one auto trip on one weekday by 8.1%–8.9% for a driver within the restricted area, but have no significant effect for a driver out of the restricted area.

The estimates of interactive variables in Column III confirm the differential effects of driving restrictions. The probability of making at least one auto trip on one weekday for an "average" male driver decreases by only 5 percentage points (from 62.3% to 56.9%), while that for a female driver decreases by about 18 percentage points (from 61.4% to 43.6%). This suggests that the degree of substitution between modes for male drivers is lower than that for female drivers. The probability of making at least one auto trip for drivers with flexible work time decreases by 25 percentage points (from 65.9% to 40.6%), more than the 17 percentage points for those with fixed work time (from 67.4% to 50.1%), partly because the former can choose to stay at home when their vehicle is re-

[10] No causality can be inferred because of the interplay between residence location decision and travel behavior. For example, Colwell et al. (2002) investigate the effects of the frequency and the length of recreation trips on the spatial distribution of consumers.

Table 6
Effect of driving restrictions by subgroups of drivers.

Dependent variable	having at least one auto trip or not			
	Estimate	SE	Sample mean	Proportional change (%)
Baseline	−0.089***	(0.018)	[0.602]	14.8
Male	−0.060***	(0.021)	[0.610]	9.8
Female	−0.157***	(0.039)	[0.576]	27.3
Flexible work time	−0.145***	(0.040)	[0.603]	24.0
Fixed work time	−0.069***	(0.022)	[0.645]	10.7
High income	−0.118***	(0.040)	[0.657]	18.0
Low income	−0.059*	(0.030)	[0.558]	10.6
North	−0.061**	(0.027)	[0.575]	10.6
South	−0.101***	(0.025)	[0.631]	16.0
With kids	−0.077	(0.053)	[0.601]	12.8
Without kids	−0.082***	(0.020)	[0.602]	13.6

All coefficients are from separate logit regressions for different subgroups of drivers in one-vehicle households who live within the restricted area, with demographic and location variables, weekday dummies, driver group by last digit dummies, and constant included. Standard errors clustered by residence-TAZ in parentheses. The average marginal effect and the sample mean of auto use reported.
* = 10% significance, ** = 5% significance, *** = 1% significance.

stricted. This can be explained by a higher utility from no-travel for the former drivers than for the latter. High-income drivers are also more sensitive to the restrictions. The probability of making at least one auto trip for a high-income driver decreases by 27 percentage points (from 69.5% to 42.8%), while it is only 18 percentage points for a low-income driver (from 60.8% to 42.9%). There are two explanations about the higher sensitivity of high-income drivers. First, the degree of substitution between times is lower for high-income drivers than that for low-income drivers since high-income drivers may have a tighter activity schedule. Second, the marginal utility of no-travel (relative to the activity itself) is higher for high-income drivers given the higher baseline auto use rate. The second explanation can also explain the larger effect on drivers living in the southern part; the baseline level of a driver in the southern part is higher about 6 percentage points than in the northern part. In addition, driving restrictions' effect is larger for drivers who live closer to subway stations, though not significant.[11]

To further demonstrate the magnitude of the effects across subgroups of drivers, we estimate the effect of driving restrictions for each subgroup separately and compare the estimated effect to the average probability of having at least one auto trip within each group. For a similar subgroup analysis, see Grönqvist and Niknami (2014). Table 6 presents the results. Similarly, the proportional decrease in the probability of having at least one auto trip is larger for female drivers, drivers with flexible work time, and high-income drivers.

Such differential effects provide evidence of the variation in WTP for auto use across subgroups of drivers, which is not addressed by driving restrictions on the basis of the license plate. In this sense, using market-based measures such as congestion pricing for entry within the 5th Ring Road would incur overall welfare gains, if the implementation cost of congestion pricing was not too high relative to that of driving restrictions (Vickrey, 1963; Arnott et al., 1993). As another option, increasing parking price may not work well in Beijing since a number of employers provide free parking for their workers.

Trip frequency: Similarly, we estimate a series of linear models of daily trip frequency (Model (4.2)). As expected, driving restrictions have no significant effect for drivers who live out of the restricted area (Columns IV and V of Table A.3). For drivers within the restricted area, the estimates of the restrictions dummy are significant in only Column I, and the magnitude (0.10, or 4.0% of the average) is much small than that of the effect on auto trip frequency (0.30) (Table 4).[12] This suggests less substitution toward no-travel than toward other modes, probably because the utility of no-travel is quite low.

Vehicle miles traveled: We calculate total daily auto trip duration for each sampled driver, which serves as an approximate measure of vehicle miles traveled (VMT), and then estimate a series of linear models (Model (4.2)). The estimation results, reported in Table A.4, show that drivers with restricted vehicles have less auto use than those unrestricted by about 13 minutes per day, which translates to 6.5 km assuming an average speed of 30 km/h.[13]

We then do a back-of-the-envelope calculation of the effect on daily VMT of drivers who live within the restricted area. In the 2010 Survey, 8367 of 14,625 vehicles belong to sampled households within the restricted area. So out of 4.8 million registered vehicles in the Beijing City, about 2.7 million vehicles belong to households within the restricted area. This implies that the deterrent effect of driving restrictions on daily VMT of drivers who live within the restricted area is 17.8 million km.

5.2. Adaptation mechanisms

To explore the three adaptation mechanisms–substitution toward unrestricted hours/days, having access to an unrestricted vehicle, and noncompliance–we investigate the effect of driving restrictions on mode choice at the trip level. Modal split on weekdays for two groups of drivers, those with restricted and unrestricted vehicles on the survey day, is presented in Table 7. As expected, the auto's share of all travel by restricted drivers is about 10% lower than unrestricted drivers. When their vehicle is restricted, some drivers substitute toward modes like bus and bicycle/e-bicycle. The share of bus trips by restricted drivers is higher by 4.3% than unrestricted drivers, and the share of bicycle/e-bicycle trips is 2.2% higher (Table 7). This is consistent with the findings of substitution toward other modes in Section 5.1.

We estimate a series of binary logit model of whether a trip is made by auto (Model (4.3)). The estimation results of Panel 1 in Table 8 show that driving restrictions significantly decrease the auto use probability of an average trip by nearly 10% for drivers in one-vehicle households who live within the restricted area, but have no significant effect for drivers out of the restricted area.

Nevertheless, for restricted drivers within the restricted area, the auto's share of all travel is still higher than 50% (Table 7), much higher than expected. This suggests that two years after the implementation of driving restrictions, drivers' adaptations have made the policy less effective than anticipated.[14]

Substitution toward unrestricted hours/days: We first examine whether driving restrictions encourage substitution toward un-

[11] We also add the restriction dummy interacted with vehicle engine capacity in Column III of Table 5, but do not find any significant result (coefficient 0.060, and standard error 0.041).

[12] We try also work trip frequency and non-work trip frequency, but do not find any significant results.

[13] Within the 5th Ring Road, the average speed on expressway and major trunk roads during morning peak hours in 2010 is 35.1 km/h and 22.2 km/h, respectively, and 30.2 km/h and 19.7 km/h during evening peak hours (Beijing Transportation Research Center, 2011, p.47).

[14] We also look at the 2009 Beijing Household Travel Survey data. The 2009 Survey samples only 3203 households in the whole Beijing City and thus is not comparable to the 2010 data. However, for drivers in households who live within the restricted area and have the only vehicle restricted on the survey day, the ratio of those who make at least one auto trip is 22.8% in 2009, much lower than the 52.7% in 2010. It suggests that people have been learning to adapt to the restrictions.

Table 7
Modal split of trips by drivers with their vehicles restricted and those unrestricted.

Mode	Restricted (990 drivers)		Unrestricted (4133 drivers)		Difference in share (%)	
	Frequency	Percent (I)	Frequency	Percent (II)	I - II	t-stats
Walk	382	15.5	1653	15.5	0.0	−1.28
Bicycle	181	7.4	617	5.8	1.6	1.28
Electric bicycle	41	1.7	116	1.1	0.6	1.92*
Motor	10	0.4	20	0.2	0.2	1.30
Subway	88	3.6	384	3.6	0.0	−0.56
Bus	270	11.0	718	6.7	4.3	4.68***
Firm/school bus	43	1.8	111	1.0	0.7	2.07**
Taxi	57	2.3	92	0.9	1.5	4.34***
Illegal taxi/motor	0	0.0	8	0.1	−0.1	−0.85
Pick-up/truck	41	1.6	58	0.6	1.2	1.72*
Car	1346	54.7	6887	64.5	−9.8	−5.34***
Other	0	0.0	7	0.1	−0.1	−0.98
Total	2459	100.0	10,671	100.0		

The statistics here are calculated for drivers in one-vehicle households who live within the restricted area. The t-statistics of mean comparison are calculated for the share of each mode.
* = 10% significance, ** = 5% significance, *** = 1% significance.

Table 8
Effect of driving restrictions on mode choice.

Dependent variable	auto trip or not			
Panel 1	Trips by drivers in one-vehicle households who live			
	Within the restricted area		Out of the restricted area	
	(I)	**(II)**	**(III)**	**(IV)**
Restrict	−0.092***	−0.094***	−0.007	−0.010
	(0.017)	(0.016)	(0.018)	(0.017)
Controls	No	Yes	No	Yes
N	13,088	13,088	11,177	11,177
Panel 2	Drivers in one-vehicle households within the restricted area			
	Trips$\in$ [7am, 8pm]	Trips$\notin$[7am, 8pm]	All trips	
	(V)	**(VI)**	**(VII)**	**(VIII)**
Restrict	−0.136***	−0.025	−0.091***	−0.092***
	(0.017)	(0.035)	(0.019)	(0.018)
AdjacentRestrict			0.001	(0.006)
			(0.017)	(0.016)
Controls	Yes	Yes	No	Yes
N	11,864	1224	13,088	13,088
Panel 3	Drivers in one-vehicle households within the restricted area			
	All trips			
	(IX)	**(X)**	**(XI)**	**(XII)**
Restrict	−0.038	−0.043	−0.040*	−0.044**
	(0.028)	(0.027)	(0.022)	(0.021)
Duration (min)	0.002***	0.002***		
	(0.000)	(0.000)		
Restrict*Duration	−0.001**	−0.001**		
	(0.001)	(0.001)		
Distance (km)			0.015***	0.014***
			(0.001)	(0.001)
Restrict*Distance			−0.006***	−0.006***
			(0.002)	(0.002)
Controls	No	Yes	No	Yes
N	13,088	13,088	13,088	13,088
Panel 4	Trips by drivers in households with two or more vehicles and live within the restricted area			
			(XIII)	**(XIV)**
Restrict: 1 some but not all vehicles restricted, 0 all unrestricted			−0.034	−0.061
			(0.097)	(0.092)
Controls			No	Yes
N			183	183

The average marginal effect reported. Standard errors clustered by resident-TAZ in parentheses. Weekday dummies and trip purpose dummies included in all equations. Driver group dummies included in all equations except Equations XIII and XIV. Controls include demographic and location variables.
* = 10% significance, ** = 5% significance, *** = 1% significance.

restricted hours by estimating a mode choice model (Model (4.3)) for trips made from 7am to 8pm and trips before 7am or after 8pm separately. As seen in Column VI of Table 8, driving restrictions have no significant effect on auto use for trips during unrestricted hours.

We also estimate linear models of auto trip frequency during restricted hours and that during unrestricted hours (similar to Column II of Table 4), respectively, for drivers in one-vehicle households who live within the 5th ring Road. The estimates show that a restricted driver makes significantly fewer auto trips by 0.26 (stan-

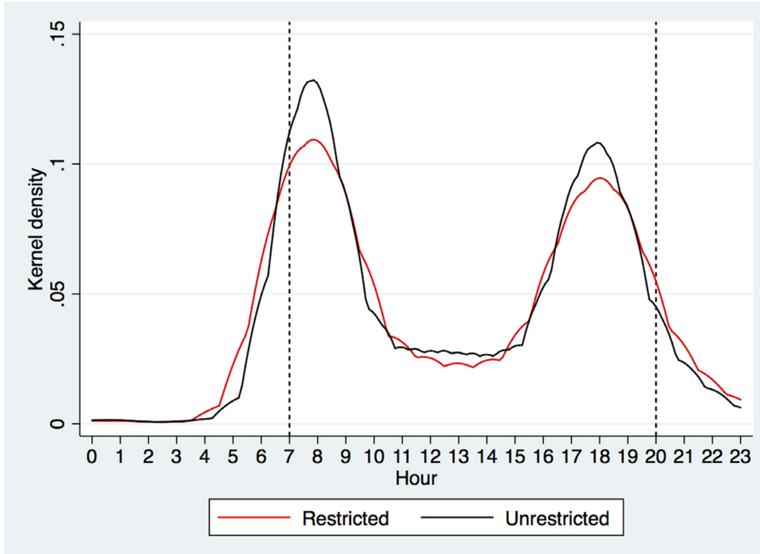

Fig. 2. The Kernel density distribution of auto trips by arrival time. Note: Drivers with their vehicles restricted on the survey day have a slightly higher share of trips before 7am or after 8pm than unrestricted drivers.

dard error 0.09) during restricted hours, and makes no more trips during unrestricted hours (coefficient −0.01, standard error 0.02).[15] Fig. 2 shows the Kernel density distribution of auto trips by arrival time for both restricted and unrestricted drivers. Restricted drivers have a slightly higher share of auto trips during unrestricted hours than unrestricted drivers. In sum, we do not find strong evidence of substitution toward unrestricted hours, which suggests a low degree of substitution between times.

We then test substitution toward unrestricted days by estimating Model (4.2) with the "AdjacentRestrict" dummy added.[16] As seen in Columns VII and VIIII of Table 8, the probability of auto use of a trip on weekdays adjacent to a driver's restricted day is not significantly higher than that on other unrestricted weekdays. Looking at auto trip frequency, the probability that a driver makes at least one auto trip is also not higher on adjacent weekdays (Columns II and III of Table 5). However, the estimates in Columns II and III of Table 4 provide suggestive evidence of substitution toward adjacent weekdays. On weekdays adjacent to the restricted day, a driver makes 0.10 more auto trips (6.0% of the average) than other unrestricted weekdays.

Auto trips during unrestricted hours (113 trips), in the unrestricted area (9 trips) and carpool (60 trips), account for only 13% of all auto trips made by restricted drivers. Of 990 restricted drivers, nearly half (472 drivers) have at least one auto trip within the restricted area during restricted hours. This suggests that the other two mechanisms–using an unrestricted vehicle and noncompliance are at work.[17]

Using an unrestricted vehicle: To illustrate how having access to an unrestricted vehicle would mitigate the policy's effect, we examine mode choice of trips (Model (4.3)) by drivers in households who live within the restricted area and have two or more vehicles. We basically compare auto use between drivers with some but not all vehicles restricted and those with no vehicles restricted.[18] As seen in Panel 4 of Table 8, driving restrictions have no effect on auto use if a restricted driver have access to an unrestricted vehicle. But we need caution to derive implications given the small sample size.

We then take a closer look at two-vehicle households who live within the restricted area. We classify these households into two groups–households with one vehicle restricted on the survey day and those with both unrestricted. The auto's share of all travel by the former (64.3%) is even higher than that by the latter (61.9%). Decomposing these auto trips by purpose, we find that the former households have more drop off/pick up trips (20.4%) than the latter (14.9%), suggesting that the unrestricted vehicle now serves the entire family.

So where do drivers with their only vehicle restricted find an unrestricted vehicle? One explanation is the availability of employer-provided vehicles. Quite a few households may not report such vehicles as requested. In the 2010 Survey, government/firm provided vehicles account for only 4.6% of all vehicles, much lower than the 13.1% in the 2005 Survey. Renting a car is not an option in 2010 since its cost is much higher than the noncompliance penalty–the third mechanism discussed below.

Different from the Mexico City, the option to buy another vehicle has been ruled out in Beijing by a strict car registration lottery program implemented since January 1, 2011. The chance to win a registration was 35 to 1 in July 2011, according to a Reuters report.[19] Before that there was no restriction on auto purchase at all in Beijing. However, the low rate of multiple vehicle ownership (2.2% of all households) in the 2010 survey implies that purchasing additional vehicles may not have been a suitable option for most households at that time.

Noncompliance: The third mechanism is simply noncompliance given the low penalty at that time–100 RMB (about 15$) per day.[20] Because there are no official data on noncompliance, we

[15] We get similar results by estimating a Poisson model.

[16] It is likely that drivers substitute toward all other weekdays rather than adjacent weekdays, but we cannot test this using the 2010 Survey data.

[17] We cannot distinguish these two mechanisms because the 2010 Survey does not tell us which vehicle a driver uses for a specific trip, and there are no official data on the noncompliance ratio in 2010.

[18] It is not common that a household have all vehicles restricted on the same day since the government allows such households to change the license plate of their vehicles. In the 2010 Survey, of 1034 households with two or more vehicles, only 16 have all vehicles restricted on the same day.

[19] http://www.reuters.com/article/2011/07/28/us-china-cars-lottery-idUSTRE76R21R20110728, retrieved Jun 8, 2012.

[20] Although the Beijing police department claimed that a vehicle could be fined multiple times on one day, drivers seemed to have different perceptions according to news reports.

Table 9
Effect of uneven restrictions on trip frequency of non-drivers.

Dependent variable	mean	SD	Non-drivers within the restricted area		Excluding those surveyed on rainy days	
Trip frequency	2.11	1.57	N = 32,170		N = 26,044	
			(I)	(II)	(III)	(IV)
Day49 (surveyed on days that restrict 4&9 or not)	0.21	0.40	−0.090** (0.037)	−0.085** (0.036)	−0.098* (0.051)	−0.090* (0.050)
Male	0.47	0.50		−0.018 (0.016)		−0.015 (0.018)
Age	47.80	19.60		−0.001** (0.001)		−0.001 (0.001)
Kids	0.10	0.29		0.366*** (0.041)		0.385*** (0.045)
IncomeMed	0.28	0.45		0.001 (0.027)		0.013 (0.030)
IncomeHigh	0.05	0.22		0.026 (0.047)		0.038 (0.053)
HourFlexible	0.08	0.26		−0.027 (0.048)		−0.029 (0.045)
HourZero	0.56	0.50		−0.384*** (0.026)		−0.374*** (0.028)
DistSubway	1.60	1.26		0.035 (0.023)		0.039* (0.023)
Downtown	0.41	0.49		0.164*** (0.056)		0.167*** (0.058)
North	0.52	0.50		−0.107** (0.054)		−0.102* (0.055)
R^2			0.00	0.03	0.00	0.02

Standard errors clustered by residence-TAZ in parentheses. Weekday dummies and constant included in all regressions. Equations I–II are estimated using all people in households who live within the restricted area and have no vehicles, while Equations III and IV exclude people in households who were surveyed on four rainy days.
* = 10% significance, ** = 5% significance, *** = 1% significance.

use an alternative way to show how noncompliance would offset the intended effect of the restrictions. We expect noncompliance for shorter trips, e.g., from home to kindergarten to pick up kids, because the probability of being caught by police/camera in this case is lower. We test this by adding the restriction dummy interacted with trip distance/duration in Model (4.3). Here trip distance is calculated as the linear distance between the centroids of origin-TAZ and destination-TAZ multiplied by a correction factor of 1.67, because the road distance is larger than the linear distance (Couture, 2015).[21] The estimates in Panel 3 of Table 8 show that the magnitude of driving restrictions' effects on auto use is significantly smaller for shorter trips, though in general people are more likely to use auto for longer trips. This provides suggestive evidence of noncompliance, because a restricted driver, if having access to an unrestricted vehicle, would not use auto for mainly short trips.

Experienced drivers may be able to find routes to avoid traffic cameras. So we use the density of minor road (30 km/h design speed) in both origin-TAZ and destination-TAZ as a proxy for the probability of getting caught, because traffic cameras are mainly installed on main roads. We also add an interactive term between the minor road density and trip distance. But we do not find further evidence of noncompliance.

5.3. Effect of uneven restrictions

An unanticipated consequence of driving restrictions is the congestion on days that restrict 4&9. To examine whether people have lower activity/trip frequency on such days, we estimate a series of linear models of trip frequency (Model (4.4)) respectively for drivers and non-drivers.

We first look at drivers in households who live within the restricted area and have only one vehicle with license plate not ending in "4" or "9" and unrestricted on the survey day. Among the 3581 drivers thus selected, about 23.6% are surveyed on days that restrict 4&9. We try different model specifications such as OLS and Poisson, but there is no evidence of substitution toward other days in terms of trip frequency or auto trip frequency. We also add interactions between the "Day49" dummy and the demographic/location variables to test whether there are differential effects across subgroups of drivers, but do not find any significant results.

We then look at non-drivers (people in households who have no vehicles) who live within the restricted area, with summary statistics presented in Table 9. Non-drivers on average make 2.11 trips per weekday, and about 20% of them are surveyed on days that restrict 4&9. As seen in Table 9, non-drivers have significantly lower trip frequency on days that restrict 4&9, controlling for the weekly variation. We get similar results if people surveyed on four rainy days are excluded (Columns III and IV of Table 9). Using the estimation results in Column II, an average non-driver makes 2.04 trips on days that restrict 4&9, lower than the 2.13 trips on other weekdays. This provides evidence of an additional compliance cost on non-drivers.

The decrease in trip frequency of non-drivers arises from the increase in travel disutility: (i) larger travel time would discourage bus use; (ii) greater hazard and pollution might deter walking and bicycling; and (iii) there may be greater congestion on bus and subway because drivers substitute to these modes.[22] We compare the modal split of non-drivers on days that restrict 4&9 and on other weekdays (Table 10). The three modes that have lower shares on days that restrict 4&9 are: walk (lower by 0.3%, or 0.04 trips per person), bicycle (lower by 0.5%, or 0.02 trips per person), and bus

[21] The distance of trips within the same TAZ is zero in this case. Excluding such trips, we get qualitatively the same estimation results.

[22] We thank an anonymous referee for pointing this out.

Table 10
Modal split of trips by non-drivers on days that restrict 4&9 and on other weekdays.

Mode	4&9 restricted days (6630 persons)		Other weekdays (25,540 persons)		Difference in share (%)	
	Frequency	Percent (I)	Frequency	Percent (II)	I - II	t-stats
Walk	5764	42.4	23,275	42.7	−0.3	−1.65*
Bicycle	2282	16.8	9413	17.3	−0.5	−1.88*
Electric bicycle	459	3.4	1743	3.2	0.2	0.82
Motor	39	0.3	116	0.2	0.1	1.56
Subway	787	5.8	3120	5.7	0.1	0.02
Bus	3385	24.9	13,672	25.1	−0.2	−1.14
Firm/school bus	303	2.2	1137	2.1	0.1	0.85
Taxi	202	1.5	690	1.3	0.2	1.87*
Illegal taxi/motor	19	0.1	25	0.1	0.0	3.81***
Pick-up/truck	8	0.1	38	0.1	0.0	−0.47
Car	215	1.6	844	1.6	0.0	0.12
Other	126	0.9	464	0.8	0.1	0.73
Total	13,589	100.0	54,537	100.0		

The statistics here are calculated for all people in households who live within the restricted area and have no vehicles. The t-statistics of mean comparison are calculated for the share of each mode.
* = 10% significance, ** = 5% significance, *** = 1% significance.

(lower by 0.2%, or 0.02 trips per person). For the other modes such as subway, the absolute change in terms of trip frequency is less than 0.004. We also estimate Model (4.4) for walk, bicycle, bus, and subway trip frequency separately. The estimates confirm that non-drivers make significantly fewer trips by walk and by bicycle. All these lend empirical support to the second explanation.

The difference in the estimated “4&9” effects between drivers and non-drivers can be explained by (i) a lower elasticity of auto travel to traffic volume than bus travel, since congestion hinders buses more than cars (Kutzbach, 2009), (ii) greater hazard and pollution that deter walking and bicycling, and (iii) a lower degree of substitution between times for drivers since they can substitute auto trips between only four weekdays.

5.4. Robustness checks

We perform a series of robustness tests including (i) trying different model specifications; (ii) clustering standard errors at different levels; (iii) placebo test; and (iv) adding sample weights.

Auto trip frequency, trip frequency, and VMT: First, we estimate a Poisson model and a negative binomial model of auto trip frequency and trip frequency.[23] The estimation results with auto trip frequency as the dependent variable are presented in Table A.5. The magnitude of the estimates of the restriction dummies and related interactive terms, reported in Columns III–VI, are slightly larger than that of the linear model results in Columns I and II. For trip frequency, we get similar conclusions (not reported here).

Second, we do a placebo test for both auto trip frequency and VMT by randomly choosing a restriction rule and find no significant results (Columns I–IV of Table A.6).

Third, we construct two types of sample weights using the 2010 Census data, available at the district level, because there is no official weight for the 2010 Beijing Household Travel Survey. We construct Weight I using the district population, and Weight II using the population by gender and age intervals at the district level.[24] The estimates of the linear models of auto trip frequency using both weights, reported in Columns VII–X of Table A.5, are quite similar to the base results in Columns I and II.

Mode choice: First, we use an OLS model instead of binary logit and get similar results. Second, we try clustering standard errors by person, origin-TAZ, destination-TAZ, and pair of origin-TAZ and destination-TAZ, and get qualitatively the same results (not reported here). Third, we do a placebo test and do not find any significant results (Columns V–VI of Table A.6). Fourth, adding sample weights do not change the estimation results much (Table A.7).

Uneven restrictions: First, we estimate a Poisson model and a negative binomial model of trip frequency of non-drivers, and get qualitative similar results (Columns II and III in Table A.8). We also estimate a zero-inflated Poisson model, with the same explanatory variables employed in both the inflate part and the Poisson part, because 20% of non-drivers make no trip on the survey day. The estimates, not reported here, validate the intertemporal substitution in trip frequency of non-drivers. Second, the estimates of the “Day49” dummy after adding two types of sample weights are significantly negative (Columns IV and V in Table A.8), though the magnitude is smaller than that of the base results.

6. Conclusions

This article examines the effects of Beijing’s driving restrictions on individual travel behavior. First, driving restrictions decrease auto trip frequency of drivers in one-vehicle households who live within the restricted area about 0.25–0.30 per weekday (15.5%–18.6% of the average), suggesting a substantial degree of substitution between modes. A back-of-the-envelope calculation shows that the deterrent effect of driving restrictions on daily VMT is 17.8 million km. However, driving restrictions have no significant effect on total trip frequency, suggesting less substitution toward no-travel than toward other modes probably due to the low utility of no-travel. We also present evidence of the differential effects of driving restrictions across subgroups of drivers by gender, income, etc.

[23] See Cameron and Trivedi (1998). The Poisson model, and its variants or more generalized forms such as the negative binomial model and the zero-inflated models, have been widely used in the trip/activity frequency analysis (e.g., Okoruwa et al., 1988; Barmby and Doornik, 1989; Ma and Goulias, 1999).

[24] There are mainly two reasons that cause the deviation of the survey sample from the population. First, the sample ratio is higher in six urban districts. Second, the sample ratio for people aged 15–24 is lower probably because the 2010 Survey does not include university students who live on campus. We prefer Weight I over Weight II because (i) the second issue would not affect the representativeness of our results since almost all university students who live on campus have no vehicle, and because (ii) university students have different travel behaviors than those of the same age.

There are mainly three adaptation mechanisms–substitution toward unrestricted hours/days, having access to an unrestricted vehicle, and noncompliance. First, we find no evidence of substitution toward unrestricted hours but suggestive evidence of substitution toward unrestricted days. Auto trip frequency on weekdays adjacent to the restricted day is higher than other weekdays by 0.10 (6.0% of the average). Second, we show that having access to an unrestricted vehicle would offset the intended effect of driving restrictions, since driving restrictions have no effect on auto use for drivers in households with two or more vehicles. Third, we provide suggestive evidence of noncompliance by showing that driving restrictions' deterrent effect is significantly smaller for shorter trips with a lower probability of getting caught.

Driving restrictions have an unanticipated consequence on non-drivers. Since there is more congestion on days that restrict the numbers 4&9, total trip frequency of non-drivers on such days is significantly lower than other weekdays by about 0.09 (4.3% of the average).

The program in Beijing has been emulated in Hangzhou, Chengdu, and other cities in China. Of them, Hangzhou City has addressed the concern over uneven restrictions by using a different digit pairs that combine "4" and "6". However, such policy designs cannot eliminate other compliance costs associated with driving restrictions. Theoretically, market-based measures such as congestion pricing currently implemented in London and Singapore are recommended, because the price mechanism allows more auto use by people with a higher WTP. Also, the payments collected could be used for improving public transit (Kidokoro, 2010). A welfare evaluation of driving restrictions and a hypothetical congestion-pricing program for entry within the 5th Ring Road could be done using the travel survey data.

More research is needed to understand: (i) the long-term effects of driving restrictions, if any, in switching a "high auto-use" driver into a "low auto-use" one;[25] and ii) the effects on firm's or retailers' location choice, e.g., whether high-tech firms move out of the restricted area. Longitudinal data are required to support such studies.

[25] Drivers who make no trips on the survey day consists of: (i) "low auto-use" drivers who use public transit or non-motorized modes for daily travel, and (ii) "high auto-use" drivers who use their vehicles frequently but not on a daily basis. In this case, driving restrictions are expected to have two types of effects: (i) short-term effects that restrict auto use of "high auto-use" drivers one weekday per week, and (ii) long-term effects that switch a "high auto-use" driver into a "low auto-use" driver. For example, a driver may change his/her main travel mode after acquiring a better knowledge of alternative modes. Using a longitudinal dataset, we may distinguish these two effects.

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Appendix

Table A1
Sample selection.

Number of vehicles	Number of households	Living within the restricted area	
		Yes	No
0	33,363	20,777 (14,537)	13,286 (9720)
1	12,503	7082 (5217)	5421 (3983)
≥ 2	1034	627 (459)	407 (306)
Total	46,900	27,786	19,114

In parentheses are the numbers of households excluding those with household income unavailable or being surveyed on weekends.

Table A2
Summary statistics of drivers by pairs of last digit of the license plate.

Last digit *N*	0&5 1047	1&6 1193	2&7 1027	3&8 1148	4&9 708
Male	0.78	0.77	0.76	0.77	0.77
	(0.41)	(0.42)	(0.43)	(0.42)	(0.42)
Age	40.75	40.52	40.60	41.06	40.84
	(10.78)	(10.72)	(10.58)	(10.55)	(10.45)
Kids	0.14	0.12	0.13	0.16	0.15
	(0.35)	(0.33)	(0.34)	(0.37)	(0.35)
IncomeLow	0.36	0.33	0.34	0.35	0.33
	(0.48)	(0.47)	(0.47)	(0.48)	(0.47)
IncomeMed	0.45	0.50	0.48	0.45	0.48
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
IncomeHight	0.19	0.16	0.18	0.20	0.19
	(0.39)	(0.37)	(0.38)	(0.40)	(0.39)
HourFlexible	0.21	0.19	0.17	0.18	0.17
	(0.41)	(0.40)	(0.38)	(0.38)	(0.38)
HourFixed	0.66	0.69	0.70	0.69	0.71
	(0.48)	(0.46)	(0.46)	(0.46)	(0.45)
HourZero	0.13	0.12	0.12	0.13	0.12
	(0.34)	(0.32)	(0.33)	(0.34)	(0.32)
DistSubway	1.78	1.77	1.81	1.87	1.78
	(1.40)	(1.45)	(1.46)	(1.47)	(1.41)
Downtown	0.28	0.34	0.30	0.32	0.31
	(0.45)	(0.47)	(0.46)	(0.46)	(0.46)
North	0.51	0.49	0.53	0.50	0.54
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)

The statistics are calculated for drivers in one-vehicle households who live within the restricted area. SD in parentheses.

Table A3
Effect of driving restrictions on trip frequency.

Dependent variable	trip frequency					
	Drivers within the restricted area			Drivers out of the restricted area		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Restrict	−0.095*	−0.037	−0.197	−0.016	0.009	0.154
	(0.057)	(0.060)	(0.161)	(0.076)	(0.081)	(0.203)
AdjacentRestrict		0.130**	0.128**		0.069	0.068
		(0.058)	(0.058)		(0.071)	(0.071)
Male		−0.097*	−0.164***		−0.181**	−0.150*
		(0.050)	(0.055)		(0.076)	(0.080)
Age		0.004*	0.004*		0.010***	0.010***
		(0.002)	(0.002)		(0.004)	(0.004)
Kids		0.472***	0.468***		0.580***	0.636***
		(0.077)	(0.080)		(0.085)	(0.095)
IncomeMed		0.048	0.074		0.126*	0.078
		(0.052)	(0.056)		(0.071)	(0.075)
IncomeHigh		0.265***	0.292***		0.311***	0.358***
		(0.063)	(0.071)		(0.102)	(0.117)
HourFlexible		−0.086	−0.074		−0.014	0.015
		(0.065)	(0.067)		(0.071)	(0.087)
HourZero		−0.166**	−0.116		−0.313***	−0.295**
		(0.084)	(0.093)		(0.111)	(0.116)
Downtown		−0.029	−0.042			
		(0.064)	(0.068)			
DistSubway		0.032	0.031		0.033***	0.033***
		(0.021)	(0.021)		(0.003)	(0.003)
North		−0.125**	−0.147**			
		(0.058)	(0.062)			
Restrict*Male			0.358***			−0.170
			(0.128)			(0.198)
Restrict*IncomeMed			−0.132			0.241
			(0.119)			(0.155)
Restrict*IncomeHigh			−0.125			−0.194
			(0.157)			(0.247)
Restrict*HourFlexible			−0.060			−0.151
			(0.142)			(0.197)
Restrict*HourZero			−0.260			−0.073
			(0.193)			(0.280)
Restrict*North			0.105			
			(0.111)			
N	5123	5123	5123	3874	3874	3874
R^2	0.00	0.02	0.02	0.00	0.06	0.06

Standard errors clustered by residence-TAZ in parentheses. Equations I–III are estimated using drivers in one-vehicle households who live within the restricted area, while Equations IV–VI using drivers in one-vehicle households out of the restricted area. Weekday dummies, driver group dummies, and constant included in all regressions. Restrict*Downtown included in Equation III but insignificant. Restrict*Kids and Restrict*Subway in Equations III and VI but insignificant. The "Downtown" dummy and the "North" dummy do not apply to the area out of the 5th Ring Road and are not included in Equations V and VI.
* = 10% significance, ** = 5% significance, *** = 1% significance.

Table A4
Effect of driving restrictions on VMT.

Dependent variable	total auto trip duration (minutes)		
	Drivers within the restricted area		
N=5,123	(I)	(II)	(III)
Restrict	−13.777***	−12.765***	−20.488**
	(2.717)	(2.908)	(8.662)
AdjacentRestrict		2.687	2.523
		(3.015)	(3.023)
Male		7.653***	6.587**
		(2.766)	(2.977)
Age		−0.124	−0.125
		(0.109)	(0.109)
Kids		0.015	−0.599
		(3.278)	(3.727)
IncomeMed		1.512	2.625
		(2.708)	(3.075)
IncomeHigh		11.621***	14.425***
		(3.566)	(4.130)
HourFlexible		−5.272	−2.627
		(3.263)	(3.703)
HourZero		−28.777***	−29.965***
		(3.814)	(4.089)
DistSubway		3.702***	3.709***
		(0.990)	(0.991)
Downtown		0.108	1.891
		(2.982)	(3.305)
North		−5.750**	−7.001**
		(2.836)	(3.088)
Restrict*Male			5.600
			(5.984)
Restrict*IncomeMed			−4.865
			(6.272)
Restrict*Incomehigh			−14.050*
			(7.683)
Restrict*HourFlexible			−13.511**
			(6.148)
Restrict*HourZero			6.226
			(8.191)
Restrict*North			5.992
			(5.199)
R^2	0.01	0.03	0.04

Standard errors clustered by residence-TAZ in parentheses. All equations are estimated using drivers in one-vehicle households who live within the restricted area. Weekday dummies, driver group dummies, and constant included in all regressions. Restrict*Downtown, Restrict*Kids, and Restrict*Subway included in Equation III but insignificant.
* = 10% significance, ** = 5% significance, *** = 1% significance.

Table A5
Robustness check: effect on auto trip frequency.

Dependent variable	auto trip frequency					
N=5,123	Drivers in one-vehicle households who live within the restricted area					
Model	Base: OLS		Poisson		Negative binomial	
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**
Restrict	−0.254***	−0.484**	−0.274***	−0.613**	−0.275***	−0.620**
	(0.061)	(0.191)	(0.068)	(0.250)	(0.068)	(0.247)
Restrict*Male		0.314**		0.422**		0.417**
		(0.139)		(0.189)		(0.190)
Restrict*IncomeMed		−0.108		−0.115		−0.108
		(0.117)		(0.137)		(0.138)
Restrict*IncomeHigh		−0.251		−0.206		−0.190
		(0.167)		(0.177)		(0.181)
Restrict*HourFlexible		−0.049		−0.081		−0.090
		(0.142)		(0.165)		(0.163)
Restrict*HourZero		0.058		−0.053		−0.032
		(0.178)		(0.275)		(0.279)
Restrict*North		0.216*		0.205		0.201**
		(0.112)		(0.127)		(0.128)
R^2	0.01	0.04				
Model	OLS+Weight I		OLS+Weigh II			
	(VII)	**(VIII)**	**(IX)**	**(X)**		
Restrict	−0.250***	−0.528***	−0.212***	−0.565***		
	(0.066)	(0.200)	(0.069)	(0.212)		
Restrict*Male		0.328**		0.357**		
		(0.155)		(0.158)		
Restrict*IncomeMed		−0.067		−0.030		
		(0.130)		(0.139)		
Restrict*IncomeHigh		−0.287*		−0.302*		
		(0.170)		(0.180)		
Restrict*HourFlexible		−0.082		−0.019		
		(0/148)		(0.155)		
Restrict*HourZero		0.057		0.006		
		(0.197)		(0.213)		
Restrict*North		0.204*		0.183*		
		(0.116)		(0.123)		
R^2	0.04	0.04	0.04	0.04		

Standard errors clustered by residence-TAZ in parentheses. All equations are estimated using drivers in one-vehicle households who live within the restricted area. Demographic and location variables, weekday dummies, driver group dummies, and constant included in all regressions. Restrict*Downtown, Restrict*Kids, and Restrict*Subway included in all regressions.
* = 10% significance, ** = 5% significance, *** = 1% significance.

Table A6
Robustness check: placebo test.

Dependent variable	auto trip frequency		VMT		auto trip or not	
Sample	5,123 drivers				13,088 trips	
Model	OLS				Logit	
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**
Restrict	0.040	0.036	2.648	2.430	0.014	0.011
	(0.059)	(0.058)	(3.196)	(3.217)	(0.017)	(0.017)
Controls	No	Yes	No	Yes	No	Yes
R^2	0.00	0.04	0.00	0.03		

The average marginal effect reported for Columns V and VI. Standard errors clustered by residence-TAZ in parentheses. Equations I–IV are estimated using drivers in one-vehicle households who live within the restricted area. Equations V–VI are estimated using the trips by these drivers. Weekday dummies and driver group dummies included in all equations. Trip purpose dummies included in Columns V and VI. Controls include demographic and location variables.
* = 10% significance, ** = 5% significance, *** = 1% significance.

Table A7
Robustness check: mode choice.

Dependent variable	auto trip or not					
Model	Base: Logit		Logit+Weight I		Logit+Weight II	
N=13,088 trips	**(I)**	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**
Restrict	−0.092***	−0.094***	−0.086***	−0.088***	−0.079***	−0.082***
	(0.017)	(0.016)	(0.018)	(0.064)	(0.018)	(0.018)
Controls	No	Yes	No	Yes	No	Yes

The average marginal effect reported. Standard errors clustered by residence-TAZ in parentheses. All equations are estimated using the trips by drivers in one-vehicle households who live within the restricted area. Weekday dummies, trip purpose dummies, and driver group dummies included in all equations. Controls include demographic and location variables.
* = 10% significance, ** = 5% significance, *** = 1% significance.

Table A8
Robustness check: effect of uneven restrictions on trip frequency of non-drivers.

Dependent variable	trip frequency				
Model	Base: OLS	Poisson	Negative binomial	OLS+Weight I	OLS+Weight II
N=32,170	**(I)**	**(II)**	**(III)**	**(IV)**	**(V)**
Day49	−0.085**	−0.086**	−0.086**	−0.068****	−0.072**
	(0.036)	(0.037)	(0.037)	(0.039)	(0.0035)
R^2	0.00			0.03	0.03

The average marginal effect reported for Columns II and III. Standard errors clustered by residence-TAZ in parentheses. All equations are estimated using people in households who live within the restricted area and have no vehicles. Demographic and location variables as well as weekday dummies included in all equations. * = 10% significance, ** = 5% significance, *** = 1% significance.

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