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The Effects of Driving Restrictions on Travel Demand

Evidence from Beijing

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Abstract

We examine the effect of Beijings driving restrictions on travel demand. Since April 11, 2009, one day each week, a car may not be used within the 5th Ring Road from 7 am to 8 pm, with the restricted day depending on the license plate number. Using the 2010 Beijing Household Travel Survey data, we find that driving restrictions decrease the probability of auto use about 10%, much lower than expected. Some households find other ways to use cars during the restricted period, mainly substitute towards unrestricted period, area, or vehicles. Men, workers with fixed work schedules, and low-income drivers are more likely to seek out ways to use cars. This suggests differential demand for auto use and willingness to pay for it, which is not addressed by the current policy. Driving restrictions alter the travel patterns of even non-drivers, who reduce their trips on days when congestion is higher (i.e. on days that restrict plates ending in 4, since relatively few plates display this unlucky number).

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1 Introduction

Driving restrictions have been implemented in cities around the world for decades.[2] During the 2008 Olympics, the Beijing municipal government banned half of the vehicles every day according to the last digit of 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 effective till now (hereafter the One-day restrictions).

A number of empirical studies have questioned the effectiveness of such policies. Using 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 (2011) show that the One-day restrictions in Beijing reduce PM10 concentrations by 8%, while Lin, Zhang and Umanskaya (2011) find no significant effect for the same policy.[3] 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).[4]

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 in Mexico City. Both Salas (2010) and Gallego, Montero and Salas (2011) indicate that the adaptations take 9 to 11 months: the program

[2]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).

[3]The former uses the daily air pollution index (API) of Beijing from Jan 1, 2007 to Dec 31, 2009, while the latter uses the API data from Jul 20, 2007 to Oct 31, 2009.

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

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 trips across individuals and across days in a week (Eskeland and Feyzioglu, 1997). However, few studies have attempted to identify such variations, probably due to lack of micro data. One exception is the study by Viard and Fu (2011) that examines the relationship between driving restriction and labor supply indirectly using hourly TV viewership between workers with and without discretionary work time in Beijing.

This article measures the effects of the One-day restrictions on individual travel demand using the 2010 Beijing Household Travel Survey data. We compare travel behaviors between drivers with restricted car use on the survey day and unrestricted drivers, controlling for demographic and location variables. This methodology is justified because driving restrictions are exogenously imposed upon drivers. However, the effect identified here is somewhat overestimated because auto use frequency of unrestricted drivers should be higher than that under no restrictions due to the inter-temporal substitution in travel demand. Our focus is on the differential effects of driving restrictions across individuals, rather than on the average effects of driving restrictions and the associated welfare change, since we have no information about travel behaviors of these drivers before the restrictions were imposed.

Driving restrictions aim to reduce auto use and encourage travel by public transit or non-motorized modes. As such, for drivers with restricted car use, the share of auto trips is expected to decrease proportionally while the use of bicycle and public transit increases. Nevertheless, drivers may find ways to circumvent the restrictions, mainly substitute towards unrestricted period, area, or vehicles, for example driving before/after the restrictions start/end, driving outside the restricted area, carpool, using additional cars, or simply noncompliance, if the utility in doing so exceeds that from switching to public transit or other options. All these tend to offset the intended effect of driving restrictions. Our analysis shows that driving restrictions do reduce auto use, and the share of bus and bicycle/e-bicycle travel increases by 4.3% and 2.2%, respectively.

But the effect is lower than the expected 20% less car use. For drivers with restricted car use, the autos share of all travel is still higher than 50%. We also find evidence of inter-temporal substitution in travel demand within a restricted day. Driving restrictions decrease auto use during the unrestricted period (before 7am or after 8pm) by only 3 percentage points, much less than the 10 percentage points during the restricted period.

The utilities from driving relative to alternative options are different across drivers. We find that those who attach more value to driving are more likely to continue using auto even facing driving restrictions. The estimation results confirm the individual heterogeneity in WTP for auto trips. For example, under driving restrictions, drivers with discretionary work time rely less on auto than those with fixed work time.

The One-day restrictions alter the travel patterns of even non-drivers (those who have no car) in Beijing. In China, there are fewer cars with 4- an unlucky number- as the last digit of license plate, which makes the restrictions uneven within a week, i.e. more congestion on days that restrict plates ending in 4. This has imposed unnecessary compliance costs on non-drivers. Our results indicate that they decrease their trip frequency on such days considering the higher time costs- the outcome of the inter-temporal substitution in travel demand within a week.

This study contributes to the literature in three respects. First, it examines the direct effect of driving restrictions on travel demand, 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. The finding of this study lends empirical support to the claim that driving restrictions do not address the variation in WTP for auto use. Third, the analysis shows how driving restrictions affect non-drivers due to cultural issues.

The rest of this article is organized as follows. Section 2 introduces the background of Beijings driving restrictions. Section 3 summarizes the 2010 Survey data. In Section 4, mode choice is examined to identify the overall effects of driving restrictions on auto use. In Section 5, we analyze how the adjustments in auto use vary across individuals. The effect of restrictions on non-drivers is addressed in Section 6. Section 7 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 0am to 3am) according to the last digit of license plate (odd or even) from Jul 20 to Sep 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 Oct 11, 2008 (Figure 1). On Apr 11, 2009, driving restrictions were further relaxed; they were not applied on the 5th Ring Road, and the time period was reduced to 7am-8pm. The relaxed restrictions remain effective till now. In this study, we measure the effect of the latest restrictions because the 2010 Survey records individual travel behaviors in fall 2010. The main focus is on households who live within the restricted area. For simplicity, we refer to the area within the 5th Ring Road as the Beijing central city.

[Figure 1 about here.]

On each weekday, two last digits of 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 Apr 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. But driving restrictions are not uniform within a week 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

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

last digit (Figure 2), much lower than that of other digit pairs (their average share is 21.6%).[6] Therefore, there is more congestion on days that restrict 4&9, an observation that has been widely reported in the media. In this study, we examine how people adjust their travel behaviors when facing the restrictions.

[Figure 2 about here.]

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. 1,085 out of 1,911 Traffic Analysis Zones (TAZs) in the whole Beijing City are selected. In each TAZ, 10 to 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 the one-day travel diary of all respondents, 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 identified and the last digit of 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 Sep 8 and Oct 31, 2010, which we use to control for the weekly variation in travel patterns.

To investigate the effects of driving restrictions 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. The trip mode is identified as the mode of the trip segment that has the longest duration (we use duration because distance is unavailable

[6] The government or firm provided 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.

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 lack of park and ride facilities in Beijing.

Of 46,900 sampled households, 26.7% have one vehicle, and 2.2% have at least two vehicles. In this study, we mainly focus on weekday travel behaviors of drivers in households who live within the 5th Ring Road and have only one vehicle, whether privately provided or not. The final sample includes 5,123 drivers with complete information. Summary statistics are 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 to 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 research institutes), teachers, or self-employed, who usually have discretionary work time. Only 12% of the drivers do not have any public transit pass, which enables bus riders to enjoy a 60% discount on bus fares.

[Table 1 about here.]

To control for the spatial variation in travel behaviors and examine the location-specific effect of driving restrictions, we construct several location variables on the basis of the TAZ where a driver lives. We divide the Beijing City into downtown (two innermost districts) and suburb by administrative boundaries (Figure 1). 31% of these drivers live in downtown. One well-known fact about Beijing is the insufficient provision of public facilities and infrastructure such as public transit in the southern part, with the Chang'an Avenue as the boundary. Of these drivers, slightly more than half live in the northern part. We also approximate the air distance to the closest subway station from each drivers residence (the centroid of the TAZ where one lives) to control for accessibility to subway.

For these drivers, their survey days are almost uniformly distributed among different weekdays. Linking the last digit of license plate to ones survey day, we find that about 1/5 of these drivers (990 out of 5,123) cannot use their cars on the survey day. For 18% (17%) of them, the survey day is just one day before (after) their auto use is restricted. These are used to test whether there is any inter-temporal substitution of travel demand.

On average, a driver makes 2.56 trips on a weekday, of which there are 1.61 auto trips. Only 10% of these drivers have no trip at all on the survey day, while 40% have no auto trip.

The 2010 Survey spans two periods with different rules that assign digit pairs to weekdays (Table 2). In the first period, vehicles with last digit as 4 or 9 are restricted for use on Friday, while in the second period, these same vehicles are restricted on Monday. Using this, we examine how people change their travel patterns in response to the relatively high traffic flow on days that restrict 4&9.

[Table 2 about here.]

4 The effects on auto use

Modal split on weekdays for two groups of drivers, those with restricted and unrestricted car use on the survey day, is presented in Table 3. As expected, the autos share of all travel by restricted drivers is about 10% lower than unrestricted drivers.

[Table 3 about here.]

For trips made by both groups of drivers, we estimate a binary logit model of mode choice:

$$log(\frac{P_{i,t}}{1-P_{i,t}}) = \gamma_0 + \gamma_1 Restrict_i + \gamma_2 x_i + \gamma_3 z_t, \tag{4.1}$$

where $P_{i,t}$ indicates whether a trip t by person i is made by auto, x_i is the vector of covariates that vary across individuals such as gender, age and occupation, and z_t is the vector of covariates that vary across trips including trip purpose and timing. The coefficient of interest, γ_1, is the effect of driving restrictions on the probability of auto use for a trip.

We estimate six equations. In addition to weekday dummies, Equation I includes only the restriction dummy. Equation II and III add demographic and location variables as well as the trip purpose dummies. Since driving restrictions are effective only between 7am and 8pm, drivers with their auto use restricted may choose to travel before 7am or after 8pm. In Equation IV to VI, we add an interactive term, the product of the restriction dummy and a dummy indicating whether a trip is made during the unrestricted period on the survey day.[7] Standard errors are clustered by the pair of origin-TAZ and destination-TAZ in Equation III and VI, and by person in other equations.

The estimation results, reported in Table 4, show that driving restrictions significantly decrease the probability of auto use by nearly 10% for an average trip. The estimates of demographic and location variables conform to our expectations. Male drivers are more likely to use auto for a trip. The probability of auto use increases with income. People who hold public transit bus, live far away from subway stations, or live in downtown, drive less. Here we dont intend to analyze causality due to data limitations.

[Table 4 about here.]

When their car use is restricted, some drivers switch to bus, bicycle/e-bicycle, and taxi. The share of bus trips by drivers with restricted car use is higher than unrestricted drivers by 4.3%, and the share of bicycle/e-bicycle trips is 2.2% higher (Table 3). These changes in travel mode are what the government has expected.

Nevertheless, for drivers with car use restricted on the survey day, the autos share of all travel is still higher than 50% (Table 3). This shows that two years after the implementation of driving restrictions, households adaptations, to which policymakers didnt pay enough attention, have made the policy less effective than anticipated. According to our calculations, of 1,346 auto trips

[7] A trip is assumed to occur before 7am or after 8pm if any part of this trip lies within the unrestricted period.

made by restricted drivers, only 13% (175 trips) are by carpool (60 trips), traveling outside the 5th Ring Road (9 trips), or during the unrestricted period (113 trips). The estimates of the interactive term in Column IV to VI of Table 4 confirm the inter-temporal substitution in travel demand towards unrestricted period. Driving restrictions decrease auto use for trips during the unrestricted period by only 3 percentage points, much less than the 10 percentage points for trips during the restricted period.

The other 87% auto trips can be explained by having access to additional cars. Overall, of 990 restricted drivers, nearly half (472 drivers) drive at least once within the restricted area between 7am and 8pm when their car use is restricted. This implies that they use a car probably not reported in the 2010 Survey. For example, drivers can rent a car or borrow a car from nearby friends/relatives like retired parents. Drivers can also use a government/firm provided car. We believe that quite a few households didnt report such cars as requested. In the 2010 Survey, government/firm provided cars account for only 4.6% of all vehicles, much lower than the 13.1% in the 2005 Survey. Another explanation is simply noncompliance because of the low fine at that time (100 RMB, about 15$ per day).[8] However, we cannot differentiate these two cases due to data limitations, and there is no official data on the noncompliance ratio in 2010.

To illustrate how adaptations such as buying another car would offset the intended effects of driving restrictions, we make a similar analysis of households who own two vehicles and live within the 5th Ring Road. They are classified into two groups: households with one car restricted on the survey day, and those with both unrestricted. The autos share of all travel by the former (64.3%) is even higher than that by the latter (61.9%). Looking at the purpose of auto trips, the former has more drop off/pick up trips (20.4%) than the latter (14.9%), since the unrestricted car now needs to serve the entire family. However, the option to buy another car has more or less been ruled out in Beijing by a strict car registration lottery program implemented since Jan

[8]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.

1, 2011.[9]

5 The differential effects on trip frequency

In this section, we investigate the effects of driving restrictions on auto trip frequency and more importantly, how the adjustments in auto use vary across individuals. Driving restrictions are expected to increase the ratio of drivers who make no auto trip on the survey day. But there would be no remarkable difference in auto trip frequency between restricted drivers who have access to additional cars and unrestricted drivers. For now we consider all auto trips, whether they are between 7am and 8pm or not, within the restricted area or not, etc., because all of them suggest a relatively high WTP for auto use.

As seen in Table 5, restricted drivers on average make 1.36 auto trips per day, significantly lower than the 1.67 trips of unrestricted drivers. 47.3% of restricted drivers make no auto trip on the survey day, higher than 38.0% of unrestricted drivers. Excluding drivers having no auto trip, the average daily auto trip frequency of the former is lower than the latter, however, only marginally significantly.

[Table 5 about here.]

We therefore decompose a drivers travel decision-marking process into two steps: i) whether to make any auto trip on the survey day; and ii) the number of auto trips given auto use. The first step is estimated using a binary logit model:

$$log(\frac{P_i}{1-P_i}) = \gamma_0 + \gamma_1 Restrict_i + \gamma_2 x_i, \tag{5.2}$$

where P_i indicates whether person i make at least one auto trip on the survey day, and x_i is the vector of covariates that vary across individuals. The coefficient of interest, γ_1, is the effects of

[9] The chance to win a registration was 35 to 1 in July 2011, according to a report by Reuters at http://www.reuters.com/article/2011/07/28/us-china-cars-lottery-idUSTRE76R21R20110728, retrieved Jun 8, 2012.

driving restrictions on the probability of auto use for a person. Given that auto trip frequency is count data, the second step is estimated using a zero-truncated Poisson model (see Cameron and Trivedi, 1998):

$$Pr(y_i) = \begin{cases} \frac{\lambda_i^{y_i}}{y_i!(e^{\lambda_i}-1)} & n \in N \\ 0 & elsewhere \end{cases}, \tag{5.3}$$

$$log(\lambda_i) = \gamma_0 + \gamma_1 Restrict_i + \gamma_2 x_i,$$

where y_i is auto trip frequency. 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. Barmby and Doornik, 1989; Ma and Goulias, 1999).

For both models, we estimate four equations respectively. In addition to weekday dummies, Equation I includes only the restriction dummy as the explanatory variable to identify the overall effects of driving restrictions. Equation II adds date dummies- whether being surveyed one day before or after ones car use is restricted, to examine whether there is any inter-temporal substitution in auto use during a 3-day time window. Demographic and location variables are added in Equation III. In Equation IV, several interactive variables, the product of the restriction dummy and the demographic/location variable, are further included to investigate how the adjustments in auto use vary across individuals. Standard errors are clustered by TAZ where one lives in all equations.

The estimation results of Model (5.2) are presented in Table 6. The estimates of demographic and location variables in Column III and IV conform to our expectations. The probability of auto use increases with income. Those who dont work or have a flexible work schedule rely less on auto. Having a public transit pass, or living near subway stations, is negatively associated with the probability of auto use. Similarly, drivers who live in the northern part where there is relatively sufficient provision of public transit rely less on auto. Gender, age, and household structure have no significant effect on the probability of auto use given auto ownership.

[Table 6 about here.]

The results in Column I to III show that driving restrictions significantly decrease the probability of auto use on the survey day by 8.3%-9.1%, which is consistent with the findings in Section 4. The actual effect would be somewhat smaller, since the counterfactual here is auto use of unrestricted drivers on the survey day, which should be higher than that before the restrictions were imposed due to the inter-temporal substitution in travel demand. Such substitution also tends to offset the intended effects of driving restrictions. Though we find no evidence of inter-temporal substitution in auto use in a 3-day time window (Column II to IV), it is possible that drivers increase auto use in all unrestricted weekdays.[10]

The estimates of interactive variables in Column IV show that the effects of driving restrictions vary across individuals. Male drivers put more effort in circumventing the restrictions. The probability of auto use of a male driver decreases by only 5 percentage points, while that of a female driver decreases by about 18 percentage points (Figure 3). High-income drivers seem not very enthusiastic about getting around the restrictions. Under restrictions, the probability of auto use for a high-income driver decreases by 27 percentage points, while it is only 18 percentage points for a low-income driver (Figure 3). Our explanation is that high-income people i) have more control over their schedule and ii) have more discretionary auto use that could be eliminated, as indicated by the estimates of income variables. The same argument applies to drivers living in the southern part. Under restrictions, they decrease auto use more than those living in the north. And as expected, the probability of auto use for drivers with discretionary work time decreases by 25 percentage points, more than the 17 percentage points for those with fixed work time (Figure 3). In addition, drivers who live near subway stations are less likely to circumvent the restrictions, though not significant.

[Figure 3 about here.]

Such differential effects provide evidence of the cross-individual variation in WTP for auto use, which is not addressed by driving restrictions on the basis of license plate. In this sense, using

[10]We add date dummies in Model (4.1), but still find no evidence of inter-temporal substitution in a 3-day time window.

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 were not too high relative to that of driving restrictions. As another option, increasing parking price may not work well in Beijing since many employers provide free parking for their workers.

Next, we examine the effects of driving restrictions on auto trip frequency conditional on auto use. As seen in Column I to III of Table 7, the estimates of the restriction dummy are as expected negative, but the effects are not significant, since here drivers with restricted car use have found ways to circumvent the restrictions. As expected, high-income drivers, and drivers who have a kid of age 6-12 make more auto trips. Drivers who dont work make more auto trips because they have more discretionary time and thus assume more household duties, e.g. grocery shopping. Drivers who live far away from subway stations or live in suburb use auto more.

[Table 7 about here.]

We cannot identify the exact way in which a driver circumvents the restrictions, but the travel diary data enable us to identify those who substitute their travel towards unrestricted period. For drivers who make at least one auto trip on the survey day, we divide their auto trips into two groups- trips made between 7am and 8pm and trips before 7am or after 8pm, and estimate a Poisson model respectively (see Cameron and Trivedi, 1998):

$$\begin{aligned} Pr(y_i) &= \frac{\lambda_i^{y_i}}{y_i! e_i^{\lambda}}, \\ log(\lambda_i) &= \gamma_0 + \gamma_1 Restrict_i + \gamma_2 x_i, \end{aligned} \tag{5.4}$$

where y_i is auto trip frequency by person i during the restricted period or during the unrestricted period, and γ_1 is still the coefficient of interest.

The estimates of the restriction dummy, reported in Column IV to VII of Table 7, indicate why the overall effects on auto trip frequency given auto use is not significant. Drivers with their auto use restricted on the survey day make 0.04 more auto trips during the unrestricted period than those unrestricted, though not significant. Such adaptations- driving during off peak hours- will not offset the congestion mitigation effects of driving restrictions.

Robustness check: We perform a series of robustness tests that mainly address the concern over model specification. First, we use the Poisson model and the negative binomial model to analyze the effects on auto trip frequency without distinguishing drivers who make no auto trip and those who have at least one auto trip. The estimation results, not reported here, validate the differential effects of driving restrictions.

Second, we consider zero-inflated models given the high ratio of drivers who have no auto trip in the survey. This type of models suggests that the zero observations come from two sources: 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 car 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. But we cannot distinguish these two effects using a cross-sectional dataset.

Third, we try other dependent variables such as auto trip frequency, which doesnt change the results much. We also use work trip frequency and non-work trip frequency as the dependent variable, but do not obtain more interesting results.

Last, we calculate total auto trip duration for each sampled driver, which serves as an approximate measure of vehicle miles traveled (VMT), and then estimate an OLS model with the same covariates in Model 2 and 3. The estimation results, not reported here, show that drivers with their auto use restricted on the survey day have less auto use than those unrestricted by about 14 minutes, which translates to 7 km assuming an average speed of 30 km/h.[11] Again, we cannot make welfare evaluation since we have no information about travel behaviors before driving restrictions were imposed. The results also confirm the cross-individual variation in WTP for auto use.

[11]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).

6 The effects on non-drivers

In this section, we examine whether people decrease their trip frequency due to the relatively high traffic flow on days that restrict 4&9. Here we again use a Poisson model of trip frequency:

$$\begin{aligned} Pr(y_i) &= \frac{\lambda_i^{y_i}}{y_i! e_i^{\lambda}}, \\ log(\lambda_i) &= \gamma_0 + \gamma_1 Day49_i + \gamma_2 x_i, \end{aligned} \tag{6.5}$$

which is similar to Model (5.4), but now γ_1 shows the difference in trip frequency between days that restrict 4&9 and other weekdays.

We first look at drivers in households who live within the 5th Ring Road and have only one car with license plate not ending in 4 or 9 and unrestricted on the survey day. Among 3,581 drivers thus selected, about 23.6% are surveyed on days that restrict 4&9. However, no matter what model forms used and what control variables included, there is no evidence of inter-temporal substitution in trip frequency or auto trip frequency, i.e. lower trip frequency or the lower probability of going out/auto use on days that restrict 4&9.

We then look at non-drivers (people in households who have no cars) who live within the 5th Ring Road. Summary statistics are presented in Table 8. Excluding back-home trips, non-drivers on average make 1.16 trips on the survey day, and about 20% of them are surveyed on days that restrict 4&9. Four equations are estimated. Equation I and III include only the dummy that indicates whether the respondent is surveyed on days that restrict 4&9, in addition to weekday dummies. Demographic and location variables are added in Equation II and IV. Observations on four rainy days during the survey period are excluded in Equation III and IV since people make fewer trips when it is rainy.

[Table 8 about here.]

As seen in Table 8, non-drivers significantly decrease their trip frequency on days that restrict 4&9, controlling for the weekly variation. Using the estimation results in Column II, the average trip frequency of a non-driver is 1.10 when the digit pair 4&9 is restricted, lower than the 1.16

if instead another digit pair is restricted. This shows that the uneven restrictions have imposed unnecessary compliance costs on non-drivers who were supposed to benefit from restrictions; they have to make inter-temporal substitution in their daily activities. The estimates of demographic and location variables in Column II and IV all conform to our expectations. For example, young, high-income people, and those who live in downtown make more trips.

The difference in the estimated 4&9 effects between drivers and non-drivers can be explained by i) less leeway drivers have due to auto reliance and driving restrictions, since now they can adjust their auto use in only four weekdays, and ii) the relatively low elasticity of auto travel demand to traffic volume, since congestion hinders buses more than cars (Kutzbach, 2009).

As a robustness test, we try alternative model forms suitable for count data. First, the negative binomial model, though not recommended given the underdispersion of trip frequency in this sample, presents the qualitatively same results. Also, the likelihood-ratio test doesnt prefer this model to the Poisson model. Second, because about 20% of non-drivers make no trip on the survey day, zero-inflated Poisson models are estimated, with the same explanatory variables employed in both the inflate part and the Poisson part. The estimation results, not reported here, validate the inter-temporal substitution in trip frequency of non-drivers. For Equation I and III, the Vuong test doesnt prefer the zero-inflated model to the Poisson model. But for Equation II and IV, the Vuong test prefers the zero-inflated model. The estimation results indicate that people are more likely to stay at home on days that restrict 4&9, and even if they go out, they tend to make fewer trips, assuming that the uneven restrictions decrease the log count of trip frequency in a linear way. In addition, using the overall trip frequency as the dependent variable doesnt change our findings.

However, we should be cautious about the identified 4&9 effects for non-drivers. Of all travel by non-drivers, 42.6% are by foot, 25.1% by bus, 17.2% by bicycle, and 5.7% by subway. Among these modes, bus is more likely to be stuck in traffic. So we calculate auto trip frequency of non-drivers by these four modes, and estimate Model (6.5) respectively. The estimates, not reported here, show that people do make fewer bus trips on days that restrict 4&9, but the magnitude is not higher than that of the other modes. This finding is a little surprising, though we could argue that high traffic more or less affects the experience of other modes due to air pollution, lack of bicycle lanes, and peoples reliance on the combination of bus and subway.

We also find no evidence of inter-temporal substitution in travel demand within a 4&9 restricted day (e.g. avoiding peak hour traffic), by comparing the daily trip distribution by hourly group on different weekdays. A regression of the morning peak hour trip ratio on the day49 dummy (not reported here), for all trips, all auto trips, or only trips of non-drivers, shows that there is no extended peak hour on days that restrict 4&9. Here the morning peak hour is defined as 7am-8am or 6: 30am-8: 30am.

7 Conclusions

This article examines the effects of Beijings driving restrictions on individual travel demand. Our findings cast doubt on the effectiveness of this policy. First, driving restrictions do decrease auto use and some drivers switch to other modes like bus as expected. Households adaptations, however, have greatly offset the intended effects of restrictions. Driving restrictions decrease the probability of auto use by less than 10 percentage points, and the autos share of all travel by drivers with restricted car use on the survey day is still higher than 50%.

Second, the differential effects of driving restrictions provide evidence of the cross-individual variation in WTP for auto use, which is not addressed by driving restrictions on the basis of license plate. For example, under restrictions, the probability of auto use for a high-income driver decreases by 28 percentage points, while it is only 19 percentage points for a low-income driver. The probability of auto use for drivers with discretionary work time decreases more than those with fixed work time.

Third, the uneven restrictions, which cause more congestion on days that restrict 4&9, alter the travel patterns of non-drivers. This has imposed compliance costs on non-drivers: they decrease their trip frequency on such days due to the higher time cost.

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- a lucky number in China. However, such smarter policy designs cannot eliminate the 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. 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; and ii) the effects on firms or retailers location choice, e.g. whether high-tech firms moves out of the restricted area. Longitudinal data are required to support such studies.

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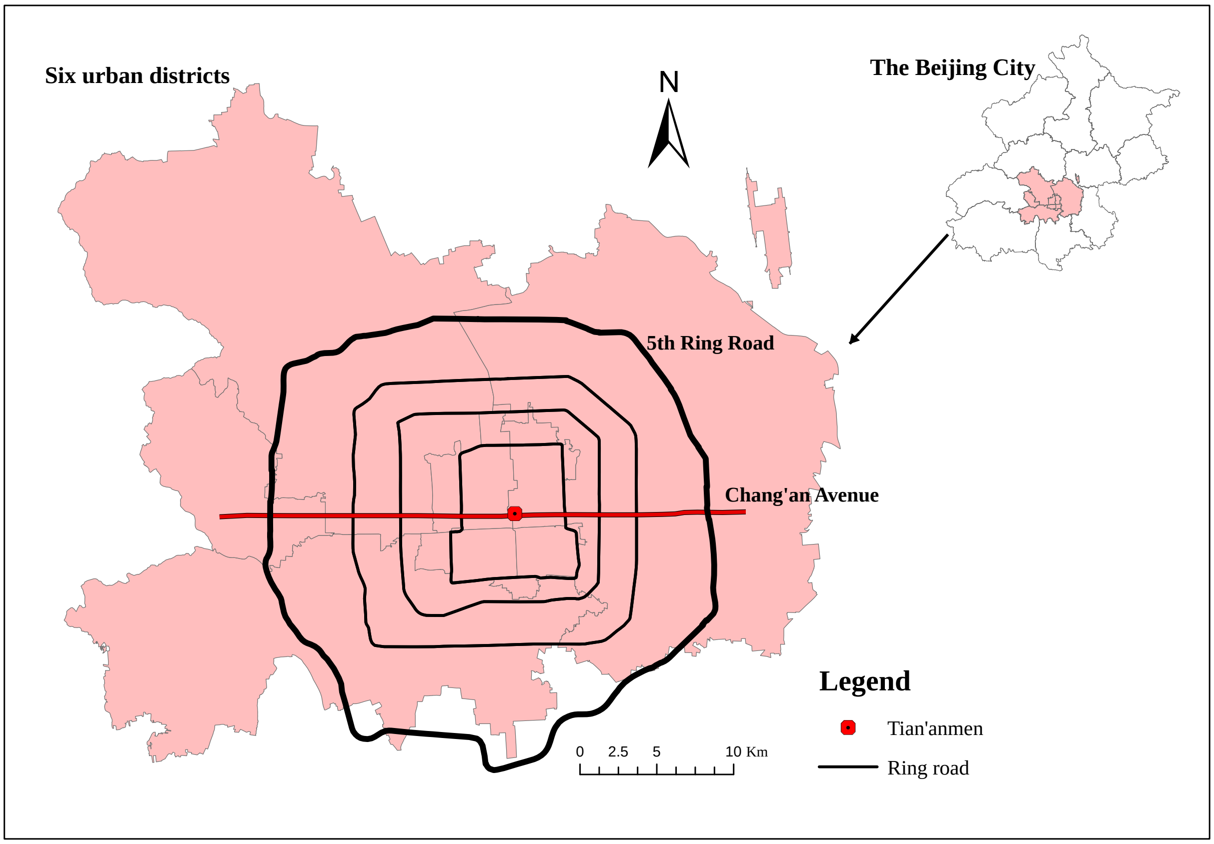

Figure 1: The map of the Beijing City, six urban districts and Ring Roads

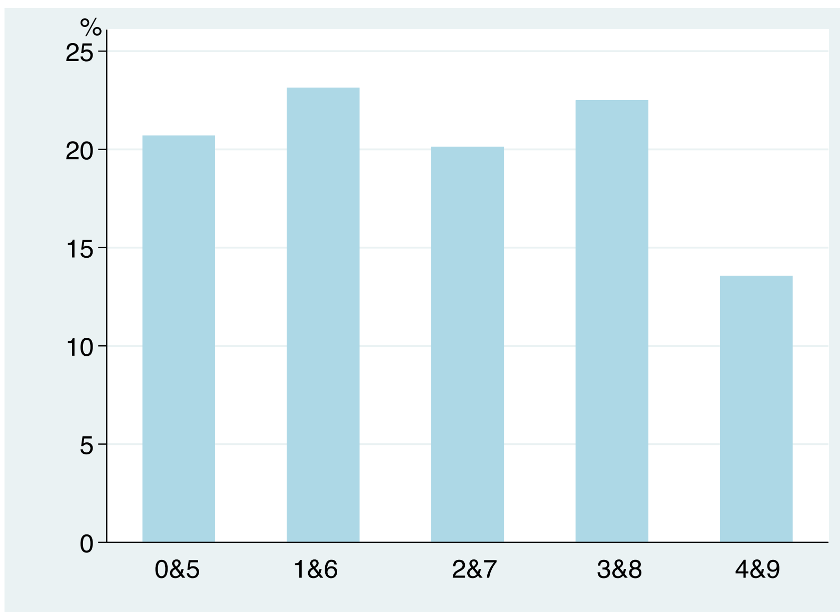

Figure 2: The share of vehicles with different last digits in the 2010 Survey

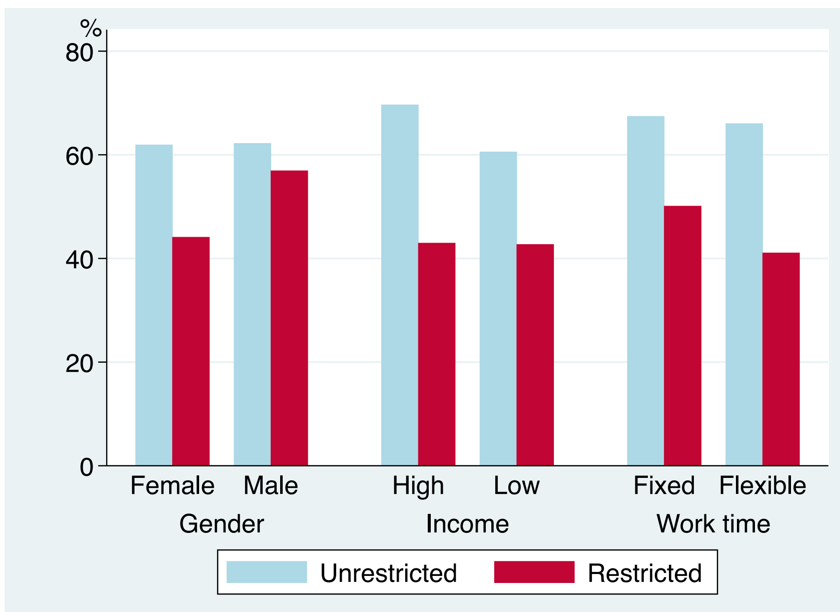

Figure 3: The estimated probability of auto use for an average driver

Table 1: Summary statistics of 5,123 drivers

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	Whether having at least one kid of age 6 to 12	0.14	0.35	0	1
IncomeLow	Annual household income less than 50,000 RMB ($7,550 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
Monthpass	Whether having any public transit pass	0.88	0.33	0	1
Location					
Subway	Air distance to the closest subway station from the centroid of one'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 Street or not	0.51	0.50	0	1
Survey day					
Mon/Tue/Wed/Thu/Fri		22%, 22%, 22%, 16%, 18%			
Restriction					
Restrict	Auto use restricted on the survey day, or not	0.19	0.39	0	1
BeforeRestrict	Surveyed one day before/after one's car use is restricted, or not	0.18	0.39	0	1
AfterRestrict		0.17	0.38	0	1
Trip frequency					
TripCount	Number of total trips	2.56	1.6	0	12
Trip	Whether having at least one trip	0.9	0.29	0	1
AutoTripCount	Number of total auto trips	1.61	1.65	0	12
Auto	Whether having at least one auto trip	0.6	0.49	0	1

Table 2: 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
Oct 10 - Oct 31, 2010	4&9	0&5	1&6	2&7	3&8

Table 3: Modal split of drivers with their car use restricted and those unrestricted

Mode	Restricted (990 drivers)		Unrestricted (4,133 drivers)		Difference in share (%)
	Frequency	**Percent (I)**	**Frequency**	**Percent (II)**	**I - II**
Walk	382	15.5	1,653	15.5	0
Bicycle	181	7.4	617	5.8	1.6
Electric bicycle	41	1.7	116	1.1	0.6
Motor	10	0.4	20	0.2	0.2
Subway	88	3.6	384	3.6	0
Bus	270	11	718	6.7	4.3
Firm/school bus	43	1.8	111	1	0.7
Taxi	57	2.3	92	0.9	1.5
Illegal taxi/motor	0	0	8	0.1	-0.1
Pick-up/truck	41	1.6	58	0.6	1.2
Car	1,346	54.7	6,887	64.5	-9.8
Other	0	0	7	0.1	-0.1
Total	2,459	100	10,671	100	

The statistics here are calculated for drivers in households who live within the 5th Ring Road and have only one vehicle.

Table 4: Estimation results of the mode choice model for trips

Dependent variable	Whether a trip is made by auto					
N = 13,088	**(I)**	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**
Restrict	-0.093***	-0.095***	-0.095***	-0.100***	-0.102***	-0.102***
	(0.018)	(0.016)	(0.011)	(0.018)	(0.017)	(0.012)
Restrict*Bef7Aft8				0.073*	0.073*	0.073**
				(0.042)	(0.040)	(0.037)
Bef7Aft8				0.045**	0.037**	0.037**
(whether a trip is made before 7am or after 8pm)				(0.018)	(0.017)	(0.016)
Male		0.052***	0.052***		0.051***	0.051***
		(0.015)	(0.011)		(0.015)	(0.011)
Age		-0.001**	-0.001***		-0.001**	-0.001***
		(0.001)	(0.000)		(0.001)	(0.000)
Kids		-0.060***	-0.060***		-0.058***	-0.058***
		(0.019)	(0.013)		(0.019)	(0.013)
IncomeMed		0.031**	0.031***		0.032**	0.032***
		(0.015)	(0.011)		(0.015)	(0.011)
IncomeHigh		0.069***	0.069***		0.070***	0.070***
		(0.019)	(0.013)		(0.019)	(0.013)
HourFlexible		-0.009	-0.009		-0.008	-0.008
		(0.017)	(0.013)		(0.017)	(0.013)
HourZero		-0.135***	-0.135***		-0.132***	-0.132***
		(0.023)	(0.017)		(0.023)	(0.017)
Monthpass		-0.159***	-0.159***		-0.158***	-0.158***
		(0.023)	(0.017)		(0.023)	(0.017)
Subway		0.020***	0.020***		0.020***	0.020***
		(0.005)	(0.005)		(0.005)	(0.005)
Downtown		-0.036**	-0.036***		-0.036**	-0.036***
		(0.015)	(0.013)		(0.015)	(0.013)
North		-0.010	-0.010		-0.010	-0.010
		(0.014)	(0.012)		(0.014)	(0.012)
Trip purpose dummies	No	Yes	Yes	No	Yes	Yes
Standard errors clustered by	Person	Person	OD-TAZs	Person	Person	OD-TAZs
Log likelihood	-8958.4	-7990.9	-7990.9	-8588.1	-7962.2	-7962.2

The average marginal effect reported. Standard errors in parenthesis. * = 10% significance, ** = 5% significance, *** = 1% significance. Weekday dummies and constant included in all regressions.

Table 5: Auto trip frequency of drivers with restricted and unrestricted car use

5,123 sampled drivers	**No. of obs.**	**Daily auto trip frequency**		
		Mean	**SD**	**t-value mean comparison**
Restricted drivers	990	1.36	1.6	-5.27***
Unrestricted drivers	4,133	1.67	1.66	
Restricted drivers having at least one auto trip	522 (52.70%)	2.58	1.3	-1.76*
Unrestricted drivers having at least one auto trip	2,562 (62.00%)	2.69	1.3	

* = 10% significance, ** = 5% significance, *** = 1% significance.

Table 6: Estimation results of the binary logit model of auto use

Dependent variable	Auto, whether having any auto trip			
N = 5,123	**(I)**	**(II)**	**(III)**	**(IV)**
Restrict	-0.091***	-0.085***	-0.083***	-0.163***
	(0.018)	(0.019)	(0.018)	(0.062)
BeforeRestrict		0.025	0.027	0.026
		(0.020)	(0.020)	(0.020)
AfterRestrict		-0.003	-0.001	-0.001
		(0.020)	(0.020)	(0.020)
Male			0.025	0.003
			(0.017)	(0.018)
Age			-0.001	-0.001
			(0.001)	(0.001)
Kids			-0.011	-0.014
			(0.019)	(0.022)
IncomeMed			0.038**	0.049***
			(0.015)	(0.017)
IncomeHigh			0.072***	0.090***
			(0.021)	(0.024)
HourFlexible			-0.029	-0.014
			(0.018)	(0.019)
HourZero			-0.238***	-0.243***
			(0.023)	(0.024)
Monthpass			-0.104***	-0.104***
			(0.021)	(0.021)
Subway			0.022***	0.022***
			(0.007)	(0.007)
Downtown			-0.009	-0.001
			(0.018)	(0.019)
North			-0.031*	-0.044**
			(0.017)	(0.018)
Restrict*Male				0.114***
				(0.043)
Restrict*IncomeMed				-0.052
				(0.036)
Restrict*IncomeHigh				-0.088*
				(0.048)
Restrict*HourFlexible				-0.068*
				(0.040)
Restrict*HourZero				0.036
				(0.053)
Restrict*North				0.057**
				(0.034)
Log likelihood	-3426.4	-3425.4	-3297.5	-3286.7

The average marginal effect reported. Standard errors clustered by residence-TAZ in parenthesis. * = 10% significance, ** = 5% significance, *** = 1% significance. Weekday dummies and constant included in all regressions. Restrict*Kids, Restrict*Subway, and Restrict*Downtown included in Equation IV but insignificant.

Table 7: Estimation results of the count model of auto trip frequency

Dependent variable	Number of auto trips			Number of auto trips before 7am or after 8pm		Number of auto trips between 7am and 8pm	
Model	Zero-truncated Poisson			Poisson		Poisson	
N = 3,084	**(I)**	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**	**(VII)**
Restrict	-0.134	-0.100	-0.106	0.0400	0.038	-0.155**	-0.161**
	(0.079)	(0.083)	(0.083)	(0.026)	(0.026)	(0.064)	(0.064)
BeforeRestrict		0.066	0.058				
		(0.079)	(0.079)				
AfterRestrict		0.082	0.104				
		(0.087)	(0.086)				
Male			0.059		0.044*		0.009
			(0.063)		(0.025)		(0.052)
Age			0.002		0.003***		-0.001
			(0.003)		(0.001)		(0.002)
Kids			0.450***		-0.025		0.412***
			(0.082)		(0.034)		(0.067)
IncomeMed			-0.006		-0.039*		0.038
			(0.063)		(0.022)		(0.050)
IncomeHigh			0.290***		-0.037		0.284***
			(0.083)		(0.029)		(0.068)
HourFlexible			-0.006		0.009		-0.013
			(0.075)		(0.026)		(0.063)
HourZero			0.403***		-0.003		0.352***
			(0.105)		(0.040)		(0.091)
Monthpass			0.039		-0.053*		0.091
			(0.085)		(0.029)		(0.068)
Subway			0.039*		-0.005		0.039**
			(0.023)		(0.008)		(0.018)
Downtown			-0.190**		-0.013		-0.143
			(0.074)		(0.025)		(0.058)
North			-0.061		-0.019		-0.034
			(0.067)		(0.024)		(0.052)
Log likelihood	-4877.1	-4876.5	-4839.8	-2041.3	-2028.2	-5051.1	-5017.9

For only those who made at least one auto trip on the survey day.
The average marginal effect reported. Standard errors clustered by residence-TAZ in parenthesis. * = 10% significance, ** = 5% significance, *** = 1% significance.
Weekday dummies and constant included in all regressions.

Table 8: Estimation results of the Poisson model of trip frequency for non-drivers

Dependent variable	**mean**	**SD**	**All observations**		**Excluding observations on rainy days**	
Trip frequency excluding back-home trips	1.16	0.97	N = 32,170		N = 26,044	
			(I)	**(II)**	**(III)**	**(IV)**
Day49 (surveyed on days that restrict 4&9, or not)	0.21	0.40	-0.061***	-0.057**	-0.065**	-0.060*
			(0.023)	(0.022)	(0.032)	(0.031)
Male	0.47	0.50		-0.016*		-0.014
				(0.009)		(0.010)
Age	47.80	19.60		-0.001**		-0.001*
				(0.000)		(0.000)
Kids	0.10	0.29		0.207***		0.216***
				(0.023)		(0.025)
IncomeMed	0.28	0.45		0.015		0.005
				(0.016)		(0.018)
IncomeHigh	0.05	0.22		0.055*		0.064*
				(0.030)		(0.034)
HourFlexible	0.08	0.26		-0.011		-0.014
				(0.027)		(0.027)
HourZero	0.56	0.50		-0.253***		-0.243***
				(0.015)		(0.016)
Monthpass	0.95	0.22		0.217***		0.213***
				(0.034)		(0.038)
Subway	1.6	1.26		0.021		0.024*
				(0.014)		(0.013)
Downtown	0.41	0.49		0.082**		0.084**
				(0.033)		(0.034)
North	0.52	0.50		-0.060*		-0.058*
				(0.032)		(0.032)
Log likelihood			-42308.1	-41933.1	-34118.4	-33829.4

The average marginal effect reported. Standard errors clustered by residence-TAZ in parenthesis. * = 10% significance, ** = 5% significance, *** = 1% significance. Weekday dummies and constant included in all regressions.