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Driving Delhi?
Behavioural Responses to Driving Restrictions*

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This paper examines two related hypotheses: the ability of urban drivers to effectively bypass policies that restrict road traffic, and whether these behavioural responses render such policies ineffective. I study an unexpected, large scale driving restriction policy experiment in Delhi. In the short run, around half of the affected drivers are able to lawfully bypass it by switching to existing unrestricted private travel modes. However, consistent with high marginal rates of congestion, the policy also led to a precisely estimated decrease in average driving travel time excess delay. I provide suggestive evidence that both effects are broadly similar during a second, anticipated round of the policy. Methodologically, this paper makes two contributions: traffic congestion is quantified using rich data from Google Maps, and short-term driving substitution patterns are identified using panel daily driver data and the essentially random assignment of odd and even license plates.

1 Introduction and setting

Large cities across the developing world face problems of road traffic congestion and pollution. Driving restrictions or road rationing measures are a popular class of policies that aim to directly reduce congestion and pollution. These policies consist of barring drivers of private cars to access public roads only on certain days, usually based on the digits of their license plate or on special stickers. Such a policy was famously introduced in Mexico City in 1990 to reduce air pollution (Davis 2008), and later implemented under various forms in Santiago, Chile, Bogota, Colombia, Quito, Ecuador, and Beijing, China. During January and April 2016, the Delhi government implemented, on a trial basis, a driving restriction policy based on license plate numbers, with the stated goal to decrease air pollution by reducing the number of cars on the road.

There is a sizeable literature studying the aggregate impact of these policies, with mixed findings. The early near-consensus was that these policies are not effective at denting pollution and congestion (Eskeland and Feyzioglu 1997, Davis 2008, de Grange and Troncoso 2011, Bonilla 2013, Gallego et al 2013). Two more recent paper find that restrictions are successful at reducing CO and PM10 in Quito and Beijing, respectively (Carrillo et al 2015, Viard and Fu 2015).

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This research on aggregate outcomes is often accompanied by considerable scepticism due to the possibility of strong behavioural responses from some drivers.[2] A common hypothesis is that some drivers will bypass the policy by buying an additional vehicle, which may allow them to drive every day if the license plate numbers have different parity. This concern is also widespread in the popular and policy discourse regarding these policies. A second, stronger claim is that these behavioural responses render the policy ineffective. Of course, the second statement does not follow automatically from the first.

In fact, the existing literature does not provide reliable empirical evidence in support of the first statement either. The idea that drivers may purchase another vehicle was proposed by Eskeland and Feyzioglu (1997) regarding Mexico City's "Hoy no Circula" policy. However, the authors find that a calibrated model of car ownership is unable to reproduce a considerable effect size. Davis (2008) focuses on the same policy and uses yearly registration and purchase data and a regression discontinuity approach to argue that the policy led to a jump in vehicle registrations around its introduction in 1990. However, upon closer inspection the yearly car registration time series are strongly collinear with Mexico's GDP, and a placebo test using GDP as the outcome variable produces very similar (and yet implausible) results.[3] These concerns put into question whether the policy really led to a jump in vehicle registrations.

Overall, the existing literature has limited evidence on how drivers respond to driving restrictions.[4] In particular, one natural question is how drivers react in the short term in terms of travel behaviour, specifically what alternatives (if any) are available for their travel on days when their main vehicle is not allowed on the road. A natural concern is the inefficiency that driving restrictions introduce by disrupting commuters' daily habits, which may lead drivers to alternate – and possibly costly, lengthy or unfamiliar – travel modes. This can lead to cancelled trips and reductions in labour supply, in addition to being a direct welfare cost.

This paper studies how drivers in Delhi responded to two rounds of a large scale, short-term driving restrictions policy in Delhi. The analysis relies on individual, daily behaviour data collected through a driver phone survey, based on a sample of drivers recruited in person prior to the policy. Individual data, including information on the days when each driver is restricted, is informative about how drivers change or cancel trips, reduce labour supply, and substitute to different travel modes on restricted days, as well as to explore sources of heterogeneity in these responses. This type of analysis is complementary to the existing literature on aggregate impacts, and can improve researchers' and policy makers' understanding of the consequences of driving restriction policies.

The results show that most (but not all) drivers are able to find alternative transport modes, over short periods of time and with little advance notice. However, roughly half of the drivers induced to change their behaviour continue to use private vehicles such as other household vehicles or auto rickshaws, which shows that short term responses may indeed dampen the effect of the policy. Between a quarter and a third switch

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[2] A related but distinct finding from the urban transportation literature is that over the long run drivers exhibit a flat demand curve with respect to road capacity (Duranton and Turner 2012). That is, that paper argues that increasing road capacity leads to more or less commensurate increases in traffic as measured by vehicle kilometers travelled.

[3] This argument is displayed graphically in Appendix Figure 1. Panel (A) reproduces Figure 9 in Davis (2008, page 69), which uses an RD strategy to identify a 0.19 log point jump in car registrations at the time of the driving restrictions policy, significant at 5%. Panel (B) depicts a placebo check: it uses the same specification but uses log GDP as outcome variable; the RD model finds a similar coefficient of 0.17 log points, significant at 10%. This result is not surprising given that the correlation between log GDP and log vehicle registrations is 91%.

[4] One notable exception is Viard and Fu (2015), who use TV viewership data to argue that driving restrictions in Beijing led workers with flexible hours to increase leisure time, and thus likely reduce their labour supply.

to public transit, with a larger effect where public transport is a better alternative, that is where the excess travel time of using public transit relative to driving is lower.

We also find that around a quarter of affected drivers cancelled all travel, with a significant fraction of work or business trips also cancelled. Data from before and after the policy suggests that this effect is an absolute decrease in labour supply, as opposed to moving trips and work from restricted towards unrestricted days.

Thus, this study highlights the existence of many different short-term behavioural responses to driving restrictions, including private alternative travel modes that are readily available and that likely reduce the policy's effectiveness.

A second contribution of this study is to use rich, crowd-sourced data on road traffic congestion collected from Google Maps, to precisely quantify the impact of driving restrictions on congestion. The results point to a moderately sized, precisely estimated reduction in traffic congestion due to Odd-Even, which is furthermore fairly constant across the two rounds of the policy. Most existing studies use air pollution measurements as a proxy for vehicle flows. This approach makes sense given the stated goal of many policies to reduce air pollution, and the correlation between car flows and pollution. However, there are advantages to studying traffic congestion directly. Traffic congestion is a central mediating factor and thus it is important to measure it directly: the usual policy goal is to reduce emissions from cars on the road. Traffic is also a more stable outcome compared to air pollution, which is influenced – in complex ways – by other factors such as weather and wind. Indeed, I show that the Google Maps data is remarkably precise and responds quickly to the lifting of the driving restrictions policy, as well as to special events such as national holidays.

The rest of this paper is organized as follows. Section 2 describes the setting, Delhi's Odd-Even policy experiment, as well as the data sources and empirical strategies. Section 3 describes the aggregate results on traffic congestion, section 4 presents the results on driver behaviour, and section 5 concludes.

2 Setting, data and empirical strategy

2.1 The Odd-Even policy in Delhi

Delhi is consistently ranked as one of the most polluted cities in world in terms of annual average concentration of PM2.5 (WHO 2014). In order to check the high pollution and congestion levels, the Delhi Government implemented a two-week trial driving restriction policy based on license plate numbers in January 2016. A second two-week round was implemented in April 2016.

The policy restricted the use of cars with license plate ending in an odd number ("odd cars") on even days, and even cars on odd days. The private cars affected by the policy were not allowed on roads between 8am and 8pm on restricted days. Restrictions applied from Monday to Saturday. The policy applied to cars circulating in the Delhi area, formally the Delhi National Capital Territory, which excludes the nearby cities of Gurgaon, Faridabad, Noida, Ghaziabad, etc. Several groups of vehicles and drivers were exempted: hybrid cars or cars running on compressed natural gas (CNG), motorcycles and three-wheelers, single women drivers, women drivers accompanied by women only or by children up to the age of 12, private taxi fleets, emergency vehicles, and a very small number of professions (Central Government politicians, etc.). The policy was announced on December 5th 2015, less than a month prior to its launch. Moreover, the government clarified that this is a trial period (January 1-15th).

In early February 2016, the government announced a second round that was implemented between April 15th and 30th 2016. The same rules applied, and again the government made it clear that the policy would only apply for a short period of 15 days.

The explicit short-term nature of the Odd-Even policy implies that this paper identifies short-term policy responses and impacts, before long-term decisions, such as purchasing a second car or becoming familiar with a public transit route, can take effect. The second round was announced with longer advance notice, and drivers has more experience due to the first round. In principle, a comparison of the impacts during the two rounds may thus be informative of how driver responses and the policy impact change due to longer advance notice. However, other factors that may affect the policy's impact also differ between the two rounds, most notably average temperature.[5]

2.2 Traffic congestion data

This paper uses a data set of road traffic conditions that covers 150 routes across Delhi (Appendix Figure 1). For each route, that is for each origin destination combination, we collected from Google Maps the distance and travel time for the quickest route under current (live) traffic conditions. The queries were made at 20 minute intervals throughout the day, daily, for each route. We have near complete data for the month of January 2016, and between April 15th and May 15th 2016. The exact routes were chosen to broadly cover the major road corridors in Delhi.

Google predicts current traffic conditions using a proprietary algorithm applied to historic as well as current crowd-sourced location and speed data from Android smartphone users on the road.[6] One concern with using this data source to measure changes in traffic congestion is that, in principle, predicted current traffic may rely strongly on historical patterns, instead of accurately reflecting current conditions. Note that this type of inertia will tend to bias downward any observed difference in congestion between periods with and without the Odd-Even policy. In practice, qualitatively there is little evidence of inertia, and the results in Figure 1 show that daily congestion levels respond quickly to new events, such as the end of the Odd-Even policy, and a national holiday.

To measure traffic congestion, the analysis focuses on travel time delay and travel time excess delay. Travel time delay is defined as the time it takes to travel on a certain route, expressed in minutes per kilometre. Travel time excess delay is the delay above and beyond what it would take during conditions without any congestion. In this paper, I use night-time minimum travel time on a route as a proxy of the travel delay without congestion.[7] To compute an average travel time excess delay across Delhi, for most of the analysis this variable is averaged on each route and day between 8am and 8pm (when the Odd-Even policy applies), and then averaged over the 150 routes in the dataset.

It is important to note that this unweighted average of travel time excess delay is not the average delay experienced by commuters in Delhi. To compute that quantity, it would be necessary to have more specific data on travel routes for all commuters, including those using buses and motorcycles (which are not in our survey sample). Broadly speaking, the measure used here will tend to underestimate excess delay, because

[5] The average January daily mean temperature is 14.3°C, whereas in April it is 28.8°C.

[6] https://googleblog.blogspot.ro/2009/08/bright-side-of-sitting-in-traffic.html

[7] Specifically, for each route the night-time travel time is defined as the average over days of the daily minimum travel time on that route. This is almost always achieved during the night. Note that Delhi only allows trucks to drive in the city during the night, and night-time truck speeds may in practice be higher than congestion-free car travel speeds would be. If this is true, it means I am overestimating travel time excess delay, and underestimating any impact due to the policy.

areas with higher excess delay also have higher traffic and likely more commuters, so the weight should be higher.

While travel delay and excess delay only measure travel time, they are strongly informative about overall traffic volumes. Indeed, transportation engineers have long established a relationship between the volume of traffic on a road or in an area, and average speed (Geroliminis and Daganzo 2008). Unfortunately, a quantitative calibration of this relationship is not available for Delhi.

The empirical strategy to estimate the impact of the Odd-Even policy is to compare times during and after the Odd-Even policy. The time period used in the analysis is January 1st-31st, and April 15th-30th. Both intervals include roughly two weeks covered by the Odd-Even policy, followed by two weeks without the policy. January 26th, a national holiday, is excluded from the analysis presented in Table 1; note that the travel time on that day is the lowest in the entire sample, as can be seen from Figure 1.

2.3 Driver monitoring surveys

Daily driver behaviour and other outcomes were measured using phone surveys on a sample of drivers in Delhi. The respondents were recruited in gas stations (petrol pumps) across Delhi. There were two rounds of recruitment in late December 2015 and late March-early April 2016, prior to the two rounds of the Odd-Even policy.[8] Gas stations were sampled from a listing of petrol pumps in Delhi.[9] The sampling in January was not explicitly random; instead gas stations were chosen to cover a wide geographic area, as well as neighbourhoods of all socio-economic strata. Gas stations during the second round were randomly sampled from the listing.[10]

The drivers were recruited between 9am-6pm and invited to participate in a survey about the odd-even policy. Drivers were eligible if three conditions were satisfied: (1) their car used petrol or diesel (not CNG, not hybrid), (2) they owned the car, (3) the car was typically used in Delhi at least three times per week on average. Cars driven by a hired/professional driver were included in the survey only if the owner was present and agreed to respond. Women, although exempted from conforming to the policy, were included in the baseline survey, although they are excluded from the analysis reported below. The fraction of women respondents is 7%. The short baseline survey recorded demographic characteristics (age, gender, education, main activity), information about the usual commute, number and type of vehicles owned by the household, as well as opinions on the policy and planned response to the policy. For drivers from households with at least two cars, and in order to avoid confusion, we label the car used when the driver was first recruited into the sample as the "primary car." Drivers from households with multiple cars may still be affected by the policy, because the other cars may be used by other household members and thus not necessarily readily available. Surveyors recorded the car make and license plate parity. A mobile phone recharge of 100 Indian Rupees (~1.5 USD) was offered as compensation to survey participants. At the end of the survey, respondents were asked for their consent to be contacted by phone for follow-up surveys. A total of 556

[8] Additional recruitment took place on Sundays while the policy was in effect. Note that the Odd-Even policy does not apply on Sundays, which means that we expect a balanced mix of license plate holders.

[9] Car gas or petrol distribution in Delhi is controlled by three state-owned companies (India Oil Corporation, Hindustan Petroleum, and Bharat Petroleum). The listing was compiled using locations with the `gas_station` tag in Google Maps. CNG stations were removed. A list of locations from the Indian Oil Corporation website was also used.

[10] However, the surveyor teams often did not receive permission to survey in a gas station, in which case they re-located to the nearest station that had not yet been visited.

and 494 eligible male drivers with valid phone numbers were recruited prior to the first and second rounds of the policy. During the second round, the response rate among drivers we approached was at least 46%.[11]

The main data used in the analysis comes from follow-up phone surveys. We conducted phone surveys while the policy was in effect, as well as during one week before and one week after the second round of the policy (in April and May). Respondents were asked about the first important trip completed on the day of the call, such as (onward) morning commute, their satisfaction with the commute, origin and destination location, duration, distance covered and departure time, modes of transportation, as well as any inconveniences experienced during travel.[12] The respondents were asked if they had *cancelled* any trips on the same day, and the purpose of the cancelled trip. Respondents were compensated with a mobile phone recharge worth between 30 and 50 Indian Rupees (~0.50-0.75 USD) for each phone survey. We aimed to complete multiple phone surveys per participant, covering both odd and even days.

After the survey, we geocoded trip origin and destination as well as home and work locations for most of the drivers in the sample. For each driver, we also ran Google Maps API travel time queries between his home and work locations, using as departure time the average time mentioned in his phone surveys. We ran separate queries for driving, using public transit, and using metro (and walking) only. These predicted travel times are used in Section 4.5 to identify respondents who face high relative public transit travel times.

Descriptive Statistics. Table 2 and Appendix Table 3 provide some descriptive statistics on the number of respondents and response rate, respondent demographics and commuting related variables.

The sample is roughly evenly divided between the 18-30 and 30-50 age groups, with very few driver respondents above 50 years old. Private employed and self-employed are the largest categories by main activity. Around 34% and 52% of drivers report having an un-restricted vehicle and at least a motorcycle, respectively. Respondents generally support the odd-even policy, with 69% saying it is a good or very good policy for Delhi. Appendix Table 3 contains more information on response rates during the two recruitment periods and during the phone survey.

Balance. The comparison of the odd and even license plate holders is shown in Appendix Table 1. Of all respondents, 48.8% have odd license plates, which is statistically not distinguishable from 50%. Each of the other columns compares the average value of the column variable among odd and even license plate holders. There is no evidence that the groups are systematically different, and a χ^2 test of join significance returns a p-value of 0.22. Panels B and C look at the January and April driver samples differently, and find no systematic evidence of imbalance.

2.4 Empirical Strategy

The daily driver outcome data described above allows us to understand how driver behaviour and other outcomes differ between restricted and unrestricted days. However, the specific form of the Odd-Even driving restrictions imply that we are identifying short-term, day to day, substitutions effects, not automatically the overall impact of the policy. To understand this precisely. we begin with a simple potential outcomes model. Let t and i index (week)days and drivers, and assume t covers both days when the Odd-Even policy is in effect, and days when it is not. Let Y_{it} denote a daily driver outcome, such as whether i travels to work on day t. The $Restricted_{it}$ dummy is equal to one for odd license plate owners on even

[11] Some drivers who refused to participate were ineligible, so this is a lower bound on the response rate.
[12] For calls made before noon, surveyors asked about trips completed on the previous day. For calls made on Monday morning, the reference day was chosen to be the previous Friday.

days during the policy, and vice versa, and zero otherwise. The $Unrestricted_{it}$ dummy is defined similarly. Both dummies are defined to be equal to zero when the policy is not in effect. η_t is a day t effect constant across individuals, and μ_i is an individual effect constant across time. The potential outcomes model is:

$$Y_{it} = \gamma_0 + \gamma_R \cdot Restricted_{it} + \gamma_U \cdot Unrestricted_{it} + \mu_i + \eta_t + \epsilon_{it}$$

This model specifies that drivers may have different average outcomes when the policy is not in effect (γ_0), when it is in effect and they are unrestricted on that particular day ($\gamma_0 + \gamma_U$), and when they are restricted ($\gamma_0 + \gamma_R$). The overall average impact of the Odd-Even policy on Y is $(\gamma_R + \gamma_U)/2$. To identify it, we need data before and after the policy, and certain assumptions on the daily effects η_t are necessary. Specifically, we need to assume that η_t is on average the same during certain periods with and without the policy, or that it does not change abruptly when the policy begins or ends.

The policy can lead to overall changes in the outcome Y, as well as to reallocation or substitution between restricted and unrestricted days. In other words, the model allows drivers to behave differently without the policy and on unrestricted days during the policy. For example, a driver may shift some trips from restricted days during the policy to adjacent unrestricted days. This presence of this effect is identified by a non-zero coefficient γ_U. We explore these issues in section 4.

In this paper we focus mainly on identifying the difference between restricted and unrestricted days during the policy. When restricting to t when the policy is in effect, $Unrestricted_{it} = 1 - Restricted_{it}$, so we can rewrite the above equation as:

$$Y_{it} = Y_0 + \beta \cdot Restricted_{it} + \eta_t + \epsilon_{it}$$

Here $Y_0 = \gamma_0 + \gamma_U$ and $\beta = \gamma_R - \gamma_U$. The coefficient β identifies the average effect of a restricted day, relative to an unrestricted day.

Underlying this model are two groups which are alternatively treated, namely odd and even license plate holders. Assuming that the odd/even number plates are as-good-as-randomly assigned,[13] β identifies the substitution pattern in each of the two groups. In this case, a cross-sectional comparison on a particular day (t) of owners of odd and even vehicles, will causally estimate β. The following three equations estimate the same effect:

(1) $Y_{it} = \beta Even_i + \varepsilon_{it}$ for t odd during Odd Even,
(2) $Y_{it} = \beta Odd_i + \varepsilon_{it}$ for t even during Odd Even,
(3) $Y_{it} = \beta Restricted_{it} + \varepsilon_{it}$ for all t during Odd Even.

Moreover, if η_t is not correlated with $Even_t$, the next two equations also consistently estimate β:

(4) $Y_{it} = \beta Even_t + \varepsilon_{it}$ for i odd,
(5) $Y_{it} = \beta Odd_t + \varepsilon_{it}$ for i even.

The balance check included in Appendix Table 1 is intended as a verification of whether the odd and even license holders appear to be similar of baseline characteristics.

[13] There is no known incentive to choose odd rather than even numbers prior to the policy.

However, note that even if the odd- and even-license plate holders are different and react differently to the policy, the panel version of equation (3) consistently identifies the appropriate population parameter β.[14] This specification uses repeated restricted and unrestricted observations for the same driver, and includes day and driver fixed effects.

(6) $$Y_{it} = \mu_i + \beta Restricted_{it} + \eta_t + \varepsilon_{it}.$$

In practice, we find very little difference in point estimates between equations (3) and (6), while the panel estimates generally are less precise.

3 The impact of the Odd-Even policy on traffic congestion

The lifting of the Odd-Even policy led to an immediate, precisely estimated, and stable increase in road traffic congestions levels. Figure 1 plots daily average travel delay (between 8am and 8pm) over the 150 routes in the sample, during the two rounds of driving restrictions, and during two-week intervals following the two rounds. For each round, average travel delay is broadly stable across days during the policy, and it jumps on the first weekday after the policy ends. The higher level generally persists over the entire two weeks following the policy.

Table 1 quantifies the impact of the Odd-Even policy on average travel time excess delay. The first column compares the average excess delay during and after the policy. The second and third columns include time trends in a regression discontinuity setting. Route fixed effects account for persistent differences between different routes, and standard errors are clustered at the date level.[15]

The results point to a reduction of around 0.10-0.12 minutes/km. Given the average excess delay of 1.1-1.2 minutes/km without the policy, this effect size represents 9-10% of average excess delay. On a trip that normally would take 40 minutes, this corresponds to a 1.7-minute average reduction in travel time. While this may appear small, to get a better sense of the magnitude of this effect, consider the following benchmarks. First, excess delay is usually around 33% lower on Sundays compared to weekdays, implying that the driving restrictions policy was about a third as effective as typical Sunday traffic. The London Congestion Charge is another point of reference. Implemented since 2003, that policy required 4 wheelers to pay 5 GBP per day to enter the restricted area. That policy led to a 30% reduction in excess delay (Transport for London 2006). The point is not to directly compare Delhi and London. However, this provides some level of guidance for what is a reasonable goal for an effective traffic reduction policy.

Commuters tend to perceive small objective differences in travel time as important. Indeed, the drivers we surveyed reported significantly less inconvenience due to road traffic congestion during Odd-Even, compared to the weeks immediately before and after. Moreover, this pattern holds equally among drivers who initially held a negative view about the Odd-Even policy, suggesting that these are indeed perceived

[14] Indeed, consider the following potential outcomes model that allows odd- and even-license plate holders to differ:

$$Y_{it} = (Y_0^{even} + \beta^{even} \cdot Odd_t)Even_i + (Y_0^{odd} + \beta^{odd} \cdot Even_t)Odd_i + \mu_i + \eta_t + \epsilon_{it}$$

Using the definition of $Restricted_{it} = Odd_i \cdot Even_t + Even_i \cdot Odd_t$, we can rewrite as:

$$Y_{it} = \left(Y_0^{even} \cdot Even_i + \frac{\beta^{odd} - \beta^{even}}{2} \cdot Odd_i + Y_0^{odd} \cdot Odd_i + \mu_i\right) + \frac{\beta^{odd} + \beta^{even}}{2} Restricted_{it} + \eta_t + \frac{\beta^{even} - \beta^{odd}}{2} Odd_t + \epsilon_{it}$$

This model can be implemented empirically using equation (6), and the coefficient β will identify the average impact $\frac{\beta^{odd} + \beta^{even}}{2}$ in the population.

[15] Two-way clustering at the date and route level leads to smaller estimated standard errors.

changes in traffic congestion, as opposed to opinion influenced by support for the policy. See section 4.4 and Table 7 for more details.

The Odd-Even policy reduced traffic congestion during both rounds when it was in effect. Travel times were slightly lower overall during the second round, and the impact was also slightly lower. However, this difference is not statistically significant (p-value of 0.32), so there is no evidence that driving restrictions became less effective during the second round, when drivers had more advance notice and ability to prepare for the policy.

These aggregate effects on excess delay reflect a combination of several different effects. They include the primary reduction in odd or even cars on the road, as well as any potential increases in use of other vehicles as drivers substitute to other travel modes. These substitution patterns are explored in the following section using daily data on driver behaviour. Additionally, these results include potential responses from drivers not directly affected by the policy, who may have increased their travel behaviour due to the perceived decrease in traffic congestion. However, even net of these offsetting factors, driving restrictions seem to have decreased travel times in Delhi.

4 Driver Behaviour and Substitution Patterns

Driving restrictions may have potentially multifaceted consequences in terms of the travel and labour supply behaviour of the affected drivers. In this section I use data on daily driver behaviour to explore these responses.

4.1 Compliance and direct impact of the Odd-Even policy

Table 3 presents the impact of driving restrictions on whether the respondent uses his primary car, as a function of whether the policy restricts the respondent from using the car on that day. The table also serves as an identification check by implementing the various specifications described in section 2.4. The outcome variable is whether the respondent used their primary car on the reference day.[16] For each completed phone survey, the "Restricted Day" variable captures whether the respondent was not allowed to drive on the reference day due to the Odd-Even policy. The first two columns restrict the sample to respondents whose primary car has an odd license plate and respectively even license plate (equations (4) and (5)). The next two columns restrict the sample to odd and even reference days (equations (1) and (2)). The last two equations pool all the data respectively without and with individual and reference day fixed effects.

All entries in Table 3 show large, strongly significant decreases in car usage on restricted days. On average, during the first round of the policy 51% of drivers use their primary car on an unrestricted day, versus 18% on a restricted day. The numbers for the second round are 43% and 10%, respectively.[17]

The coefficients in the first four columns are similar in size but not exactly equal. They vary between 28% and 38%, and some pairs of coefficients are statistically significantly different. These differences are driven by the fact that drivers of even cars seem more likely to drive on unrestricted days, compared to drivers of odd cars. This difference is statistically significant only during the second round. Overall, these differences may stem from differences between average behaviour between drivers of odd and even cars; however, they do not seem to suggest any overall pattern that would put into question the rest of the analysis in this

[16] Respondents were asked about their behaviour on the reference day, which was most often the day of the phone survey. If the survey started before noon, the reference day was "yesterday," or the last weekday preceding the phone survey.

[17] Note that a fraction of trips on restricted days occur before 8am, so they are not non-compliant; repeating the same analysis restricting to trips between 8am and 8pm leads to lower non-compliance but overall similar results.

paper. Regardless of the reason for this discrepancy, as explained in section 2.4, the pooled empirical specification identifies the correct population average effect.

The results in the fifth column show an average 33% decrease in primary car usage on restricted days, and adding individual and reference day fixed effects in the last column does not change these estimates. For the rest of this paper we use the specification in the fifth column. We have checked that adding fixed effects as in the last column does not change the point estimates, while typically increasing standard errors.

The pooled results are remarkably similar between the two rounds. While driving was overall less likely in April (consistent with the lower traffic congestion levels identified in section 3), the impact on restricted days was virtually identical, and non-compliance lower.

Table 3 only covers the period during the Odd-Even policy. Thus, the identified effect represents a combination of absolute decreases in use of primary cars, as well as substitution between restricted and unrestricted days. For example, it is possible that drivers shifted trips using their primary car to unrestricted days, in which case the previous estimates would overestimate the impact of the policy. Conversely, competing demands for unrestricted cars on unrestricted days may lead drivers to use their primary cars less on unrestricted days compared to without the policy, and thus the previous estimates would underestimate the impact of the policy. To parse out these relative contributions, Appendix Table 2 includes data one week before and one week after the second round of Odd-Even. The first column includes separate dummies for the week before and the week after the policy, while the second columns pools them together. The omitted category in both cases is unrestricted days during the policy. We find that even on unrestricted days during the policy, drivers are less likely to use their primary car, compared to the period without the policy. This effect size is large, at 10 percentage points on average. In other words, the odd-even policy seems to have reduced primary car use on unrestricted days as well on restricted days.

4.2 Driver substitution patterns

The previous section established that among drivers who typically use their primary car on unrestricted days, Odd-Even shifted a significant share away from that behaviour. This section studies the travel behaviour of these drivers that replaces the use of primary cars.

The four columns in Table 4 analyse four mutually exclusive travel behaviour categories, using the same specification as in the fifth column in Table 3. On restricted days, around 33 percentage points fewer drivers use their primary car. Of these, around 14 percentage points switch to using other private vehicles, namely another (unrestricted) car or a motorcycle, or a taxi or auto rickshaw. Another 10-11 percentage points of drivers switch to public transport, namely the Delhi metro, carpool (as a passenger) or bus.[18] Finally, between 8 and 10 percentage points of drivers cancel all trips during the reference day. This final category suggests a potential real economic cost of driving restrictions.

These results suggest that the Odd-Even policy was partly successful to shift drivers towards public transit, and to make some drivers cancel their trips. However, the policy was also partly offset when drivers turned to other more familiar travel modes. Thus, almost half (41-43%) of the drivers who are induced away from using their primary car turn to using a different private vehicle for their commute, either another vehicle owned by their household, a borrowed vehicle or a hired vehicle. These alternatives will intuitively tend to reduce the effectiveness of the policy, because they have similar traffic externalities compared to their

[18] In cases where the driver reports using both private and public modes on the same trip, we code it as a public transport mode. This applies to 3-4% of all drivers.

primary car. Nevertheless, motorcycles and auto rickshaws may have lower traffic externalities, while their impact on pollution emissions is unclear.

To understand the extent of substitution between restricted and unrestricted days, Appendix Table 2 includes data from the weeks immediately before and after the second round of the policy. The results show that drivers were more likely to use other private vehicles on unrestricted days during Odd-Even compared to without the policy, by 6 percentage points on average (column 4). However, overall use of any private vehicle (combining the first two categories), is still lower by 4 percentage points on unrestricted days compared to without Odd-Even.

In other words, the Odd-Even policy led drivers to use private vehicles less even on unrestricted days, not only on restricted days. This is consistent with higher competition for unrestricted private vehicles, for example from family members and friends. Empirically, this effects seems to dominate the ability of drivers to shift trips using private vehicles from restricted towards unrestricted days. It is worth emphasizing that these results rely on taking the weeks before and after the second round of the policy as a valid counterfactual for the policy.

Finally, Appendix Table 2 also shows that public transport was higher on unrestricted days than without Odd-Even, again consistent with higher competition over private options, and indicating that the overall impact of Odd-Even on public transport use is higher than the one identified in Table 4. The last two columns offer suggestive evidence that some drivers cancelled trips on unrestricted days during Odd-Even.

Zooming in within the broad categories included in Table 4 reveals interesting patterns. Table 5 presents these results; odd and even columns show results from the first and second rounds, respectively. Panel A breaks down travel using household vehicles into primary car, other car, and motorcycle. In January, few drivers used other cars, both on restricted and unrestricted days, and the main substitution was towards motorcycles, from 9% to 16% on unrestricted and restricted days, respectively. During the second round in April, by contrast, other cars starts from a higher baseline, although the sum of primary and other cars is virtually the same during the two rounds (54% and 53.1% respectively). Moreover, the shift to other cars is more pronounced while that to motorcycles muted. It is not clear whether this happened because drivers had more time to find arrangements to use other cars during the second round, or because of other factors that were different between the two rounds, such as much hotter weather in April.

Panel B in Table 5 breaks down public transit into bus, metro and carpool. Few drivers in our sample use the bus, and Odd-Even shifts only a small percentage into using this mode of transport. This is also true for carpool, yet the impact on restricted days is more tightly estimated. During both rounds, the Delhi metro is the most popular public transport option, and usage roughly doubles on restricted days, from around 5-9% to 10-15%.

Panel C reveals a small, marginally detectable increase in taxis, as well as a larger increase in auto rickshaws of roughly the same magnitude as the increase in metro usage.

4.3 Travel behaviour and labour supply

The results in Table 4 and Appendix Table 2 already showed that drivers cut back on trips on restricted days. Here we explore this issue in more detail. Table 6 has the results. The first four columns measure whether drivers made any trip on the reference day, and if they made any trip with a work or business purpose.[19] The phone survey also included a question towards the end regarding cancelled trips; the other four columns in Table 6 measure whether the driver reported cancelling any trip on the reference day, and if they reported cancelling any work or business purpose trip.

The results show that drivers make fewer trips on restricted days, and if anything this effect is stronger during the second round of the policy. The reduction is significant in size, around 10-14% of the mean on unrestricted days. Columns 1 and 2 in Panel B also include data on the weeks before and after the policy, and the results do not suggest that drivers shift trips from restricted to unrestricted days. If anything, drivers seem to make fewer trips on unrestricted days compared to without the policy, although this result is not statistically significant. The results in columns 5 and 6 are very similar and with the opposite sign, as expected. This serves as a validity check, and suggests that drivers are truthful and do not exaggerate about cancelled trips. Overall, this evidence shows that the Odd-Even policy led to a lower number of trips on restricted days, which was not compensated by more trips on unrestricted days.

Moving on to work and business trips, columns 3 and 4 present a very similar situation. Drivers make fewer work trips on restricted days, and this appears to be an absolute decrease rather than a reallocation between restricted and unrestricted days. Surprisingly, the negative effect is significantly stronger during the second round of the policy. One possible interpretation is that stronger enforcement of the Odd-Even policy during the second round of the policy forced some drivers to cancel trips. Once again, results on cancelled trips broadly agree with the results on trips made.

Overall, the evidence in Table 6 shows that the Odd-Even policy had real economic costs by reducing labour supply and economic activity by employed and self-employed drivers. Note that this reduction may be efficient. Indeed, in the presence of inefficiently high traffic congestion levels – which is the textbook prediction due to road traffic externalities – it may be efficient for some drivers to cancel their trips. However, it is also possible that drivers with high value of travel but low access to travel alternatives were forced to cancel their trips. A full social welfare analysis is beyond the scope of this paper.

4.4 Driver satisfaction and perceived congestion levels

One major concern with driving restrictions – as well as with related policies such as congestion pricing – is the inconvenience effect it may have on drivers. On the other hand, the purported reduction in traffic congestion and air pollution may lead to more satisfying commutes. This section investigates the impact of driving restrictions on commute satisfaction and perceptions of road traffic congestion.

The challenge when studying these outcomes is that we only observe them when drivers make a trip. Moreover, traffic congestion perceptions may be influenced by the type of vehicle and whether the respondent was driving or was being driven. To correct for these potential issues, each regression in this table controls for the travel mode (primary car, other car, motorcycle, auto rickshaw, metro). In addition, even numbered columns report results from regressions that also include driver fixed effects.[20]

The first two columns report results on commute satisfaction. In both rounds, satisfaction was slightly lower on restricted days. This results should again be qualified by the fact that there were fewer trips overall on restricted days, which means we may be underestimating the negative effect on restricted days. Importantly, drivers expressed significantly lower satisfaction during the weeks immediately before and after the second round of the policy. This finding seems more robust, both because the effect size is larger, roughly

[19] During the phone survey, surveyors first asked whether the respondent made any trip, and then classified the trip purpose into: work or business, to help family members of friends travel, for household chores, for leisure, an unexpected or emergency trip.
[20] Note that the controls vary at the driver-day level and thus they are still relevant with driver fixed effects.

consistent before and after the policy, and because the selection issue is smaller (recall that in Table 6 we did not find a large difference in trips during and before/after Odd-Even).

The phone survey also asked drivers if they experienced any kind of inconvenience during their commute.[21] Complaints regarding inconvenience due to road traffic congestion stand out, especially during the period without odd-even. Columns 3-6 in Table 7 report the results. As one would expect, there is no difference between restricted and unrestricted days after we control for travel modes. However, the fraction of drivers who complain about traffic congestion is much higher before and after the second round of Odd-Even, and these differences are highly significant and symmetric. They are also unaffected by using driver fixed effects, indicating that the same driver tends to complain much less about traffic congestion during the policy.

Another important challenge with the subjective outcomes in this table is that they may in principle be coloured by respondents' overall opinion about the policy. Most drivers in our sample (69%) are of the opinion that Odd-Even is good or very good for Delhi, and this opinion may lead to censor their reports of inconveniences experienced during their commute.

To explore this possibility, the last two columns in the table restrict the sample to drivers who said during the baseline survey that the Odd-Even policy is a bad or a very bad policy for Delhi. The results are essentially unchanged, suggesting that the change in perceived traffic congestion was not due to respondents defending their support for the policy.

The results reviewed in this section suggest that the Odd-Even policy had a large positive effect on how drivers perceived traffic conditions. Together with the results in Section 3 on the aggregate impact of driving restrictions on traffic congestion, these results suggest that even apparently small changes in average travel time excess delay can lead to large changes in satisfaction.

4.5 Heterogeneity in private and public transit use

The original goal of the Odd-Even policy was to encourage more drivers to use public transport instead of their private vehicles. As shown in Table 4, the policy only partly achieved this goal. This section explores sources of heterogeneity in usage of private versus public transport modes. The two rounds of the policy are pooled in these results.

The results in this section should be interpreted with care. They document differences (or lack thereof) in impact of the Odd-Even policy among groups with different characteristics, such as drivers who do or do not own another car. However, these impact differences are not causal, as these groups likely differ in many other characteristics than the ones we choose to focus on.

Table 8a reports results on the impact of driving restrictions among drivers depending on whether they own another car (Panel A), and as a function of the length of their commute (Panel B). The first column in panel A shows that most of the switching to other cars happens among drivers who own another car, as one would naturally expect. The second and third columns show that this effect carries over to use of any private vehicle, and use of public transport. This implies that drivers without another car do not substitute towards other private vehicles (such as motorcycles); instead, they substitute mostly towards public transport. There does not appear to be any difference in the total number of trips, as shown in the fourth columns. Panel B

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[21] Surveyors were asked to code the type of inconvenience based on the respondents' answer among the following options: "Reached my destination late," "Price hike by auto/taxi etc.," "Had to change the timing of my trip (leave early or late)," "Traffic congestion on the road," "Congestion in the public transportation," "Was exhausted because of the commute," "Got lost/ was stranded," "Faced physical or verbal harassment," "Paid fine for driving restricted vehicle."

does not reveal any differential patterns between drivers who face a long (driving) trip between their home and work locations, as predicted using Google Maps data.

Table 8b reports results interacted with the quality of public transport. For each driver with valid geocoded home and work locations, we compute the ratio of public transit travel time to driving travel time, as predicted by Google Maps. In general, public transport is slower. Indeed, on average in our sample it is 75% slower, the median is 65% slower, and only 5% of drivers have a faster commute by public transit. We label drivers with above-median travel time ratio as "slow transit." We repeat the same exercise for the ratio of travel time using the metro and walking only, and construct a "slow metro" dummy.

We do not find any evidence that drivers who face high public transit travel times have different behaviours in terms of private vehicle usage. Indeed, the first two columns in Panel A exhibit very small coefficients and no significant differences for Slow transit and its interaction with Restricted Day. Column 3 shows that these two groups are not on average more or less likely to use public transit on unrestricted days. However, drivers who have slow transit options are 8 percentage points less likely to switch to public transit on restricted days, from a base of 14 percentage points for those with fast transit options. The last column in Panel A shows that drivers with slow transit are marginally less likely to travel in general, yet there is no evidence that they are even less likely to travel on restricted days. Overall, this evidence suggests that access to fast public transit may be an important factor to enable drivers to switch to such modes.

Panel B in Table 8b explores whether direct, fast metro links specifically matter for drivers' response to the Odd-Even policy. The results do not point to any special role of metro linkages, above and beyond general transit quality as measured in Panel A. Note that these results do not rule out a causal effect of access to fast metro on public transit use in general.

5 Conclusion

Thanks to their simplicity and relative ease of implementation, driving restrictions area a popular policy for governments of large, polluted and congested cities across the world. They are also one of the most studied urban transportation policies, yet there is considerably more that we need to understand about their impact and about how drivers respond to transportation policies in general.

This study used newly available, rich data on traffic congestion across Delhi, as well as daily individual data on driver behaviour and an empirical strategy that exploits the specific design of driving restrictions as a natural experiment. The results show that drivers use several travel mode alternatives at their disposal, even in the short term. In particular, many drivers are able to use other private vehicles on restricted days, which likely tends to offset the impact of the policy on congestion. This behaviour is broadly similar during two rounds of the policy, one of which was unexpected and the other had a longer advance notice. The same adaptive behaviour also seems to shield drivers away from very negative consequences on satisfaction and inconveniences. In fact, drivers generally perceive traffic congestion to be significantly lower during the policy versus before and after, and this is a robust result. A significant fraction of drivers switch to public transport, and heterogeneity analysis shows that ownership of other private vehicles and public transit travel time matter; both characteristics are strong predictors of whether drivers switch to public transit during driving restrictions. We also find that a significant fraction of drivers cancelled trips, including work and business trips, due to the restrictions.

This study also finds that, despite a complex pattern on behavioural responses from drivers, the Odd-Even policy had a clearly detectable, moderately sized negative impact on traffic congestion. This is consistent with theory – there is no general reason why behavioural responses to a policy will undo its effects completely. However, this finding speaks directly to a major concern discussed in the literature, as well as among policy-makers, namely that behavioural responses may completely offset the impact of driving restriction policies. The explicitly short-term nature of the Odd-Even policy means that these findings do not apply directly to driving restrictions that are implemented permanently. However, the stability of the results between two rounds of the policy suggests that anticipation effects are small.

The use of crowd-sourced traffic congestion data from Google Maps holds another promise for the study of urban transportation policies. It seems that this data is less volatile compared to air pollution data, which is the usual outcome measure for studying to impact of driving restrictions policies, while also reacting quickly to changes such as the Odd-Even policy. These features imply that traffic data is well suited for event study analysis of policy pilots, even over short periods of time. Combined with separate research on the general link between traffic congestion and air pollution levels, this type of data may help to better understand the impact of urban transportation policies on air pollution.

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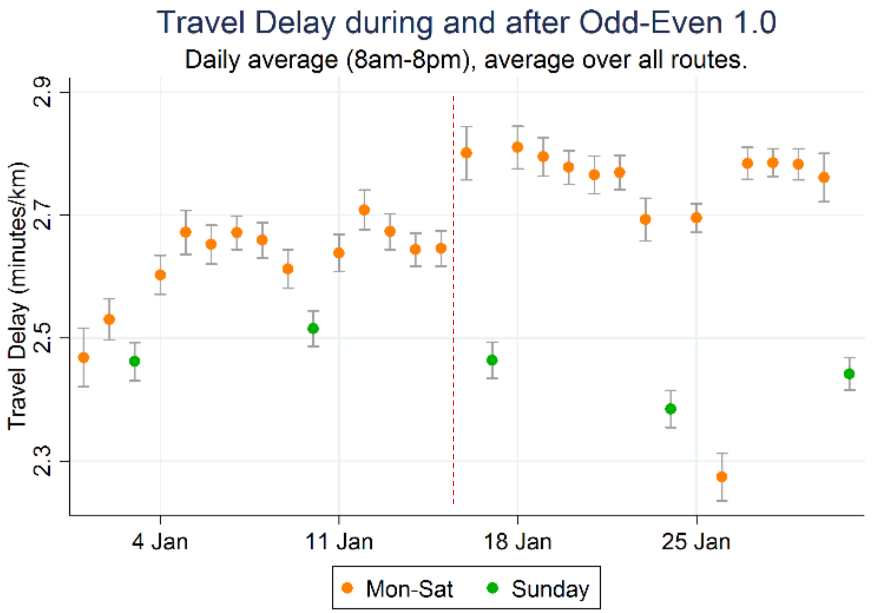
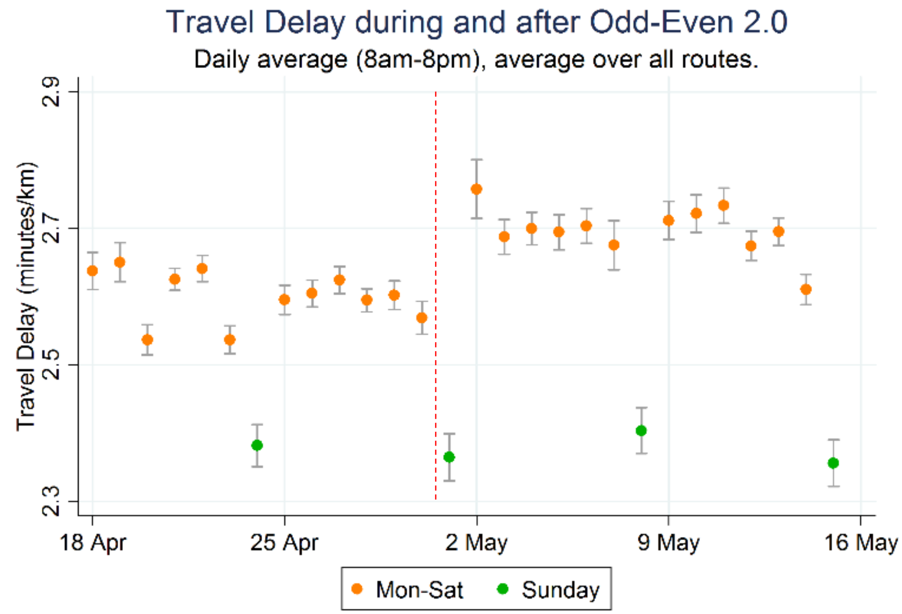
7 Figures



Panel (A)



Panel (B)

Figure 1. Travel Time Delay during and after driving restrictions

Figure notes. Each panel shows average daily travel delay (expressed in minutes/km) averaged between 8am and 8pm and over 150 routes in the sample. The two rounds of Odd-Even took place during January 1-15th and April 15-30th respectively. Each confidence interval is computed over 150 daily averages, after taking out route fixed effects in the entire dataset. Average nighttime travel time in the sample is 1.6 minutes/km. January 26th, a national holiday, and January 1st and 2nd, are dropped from the analysis in Table 1.

8 Tables

Table 1. The Impact of Restrictions on Travel Time Excess Delay (minutes/km)

	(1)	(2)	(3)
Dependent Variable:		Travel Time Excess Delay	
		Panel A. First round (January)	
Odd-Even	-0.116***	-0.124***	-0.121***
	(0.018)	(0.037)	(0.037)
Control mean	1.171	1.171	1.171
Observations	3,600	3,600	3,600
		Panel B. Second round (April)	
Odd-Even	-0.096***	-0.143***	-0.141***
	(0.015)	(0.032)	(0.032)
Specification: time trend	None	Linear on either side	Quadratic
Control mean	1.1	1.1	1.1
Observations	3,450	3,450	3,450

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table Notes. This table reports the impact of Odd-Even on travel time excess delay from regressions that include the (two week) Odd-Even period and two weeks after the policy. Specifically, the sample covers 150 routes within Delhi and the following dates: January 4-31st in panel A, and April 18th – May 15th in Panel B. Sundays and January 26th (national holiday) are dropped. The dependent variable, daily travel time excess delay (expressed in minutes/km) is obtained from the travel time after subtracting average night-time travel time for that route. It is then averaged between 8am and 8pm for each route and day. Standard errors clustered at the date level in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Driver Survey Descriptive Statistics

	(1) Mean	(2) Observations that satisfy condition	(3) Total Observations
Panel A. Number of Respondents			
Respondents reached during phone surveys		956	
Phone surveys		4178	
Panel B. Demographics			
Age			
18-29 years old	41.5%	397	956
30-49 years old	53.6%	512	956
over 50 years old	4.9%	47	956
College degree	69.4%	663	956
Occupation			
Private employment	39.0%	373	956
Self-employed	41.8%	400	956
Government employee	6.0%	57	956
Student	8.3%	79	956
Other	3.9%	37	956
Panel C. Vehicle ownership			
Primary car has odd license plate	48.8%	467	956
Primary car age (years)	5.2	-	312
Household has another car	33.6%	321	956
Household has motorcycle	52.0%	496	953
Believes Odd-Even policy is good or very good for Delhi	69%	381	554

Table Notes. This table reports sample descriptive statistics from the baseline (recruiting) survey and the follow-up (phone) survey. More detailed information on response rates is available in Appendix Table 3.

Table 3. The Impact of Restrictions on Daily Usage of Primary Car

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Used Primary Car					
Individual and Reference Day Fixed Effects:						Yes
Sample:	Odd license plate cars only	Even license plate cars only	Odd days only	Even days only	Full	Full
Panel A. First Round (January)						
Restricted Day	-0.284***	-0.378***	-0.332***	-0.331***	-0.331***	-0.344***
	(0.0349)	(0.0359)	(0.0368)	(0.0373)	(0.0251)	(0.0330)
Observations	676	677	707	646	1,353	1,353
P-value on Restricted Day	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Mean on Unrestricted Days	0.485	0.531	0.485	0.531	0.507	0.507
Mean on Restricted Days	0.201	0.153	0.153	0.201	0.176	0.176
Panel B. Second Round (April)						
Restricted Day	-0.314***	-0.358***	-0.288***	-0.384***	-0.336***	-0.325***
	(0.0278)	(0.0304)	(0.0298)	(0.0296)	(0.0206)	(0.0347)
Observations	751	772	773	750	1,523	1,523
P-value on Restricted Day	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Mean on Unrestricted Days	0.396	0.467	0.396	0.467	0.431	0.431
Mean on Restricted Days	0.083	0.108	0.108	0.083	0.096	0.096

Table Notes. This table reports results on primary car use behaviour as a function of whether today is restricted or unrestricted under the Odd-Even policy. In the first column, the sample includes only observations from drivers whose primary car has an odd license plate, on both odd (unrestricted) and even (restricted) days. The second column includes only observations from even license plate drivers. The third and fourth columns restrict the sample to odd and even calendar days, respectively. The last two columns use the full sample; the last column includes reference day and driver fixed effects in the specification. Standard errors, clustered at the driver level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4. The Impact of Restrictions on Private and Public Modes of Travel

	(1)	(2)	(3)	(4)
Dependent variable:	Used Primary car	Used any other private mode	Used public transit	Made any trip
	Panel A. First Round (January)			
Restricted Day	-0.331***	0.141***	0.115***	-0.0756***
	(0.0251)	(0.0207)	(0.0211)	(0.0214)
Observations	1,353	1,353	1,353	1,353
P-value on Restricted Day	<0.001	<0.001	<0.001	<0.001
Mean for Unrestricted Days	0.507	0.138	0.153	0.798
Mean for Restricted Days	0.176	0.279	0.268	0.723
	Panel B. Second Round (April)			
Restricted Day	-0.336***	0.138***	0.0950***	-0.0984***
	(0.0206)	(0.0210)	(0.0147)	(0.0222)
Observations	1,523	1,523	1,523	1,523
P-value on Restricted Day	<0.001	<0.001	<0.001	<0.001
Mean for Unrestricted Days	0.431	0.201	0.077	0.711
Mean for Restricted Days	0.096	0.339	0.172	0.613

Table Notes. This table reports results on travel behaviour as a function of whether today is restricted or unrestricted under the Odd-Even policy. The four columns correspond to four mutually exclusive outcome variables: whether the respondent used his primary car on the reference day, whether they used any other private vehicle (but did not use any public transport), whether they used public transit, and whether they did not make any trip at all (not that the fourth column captures trips *made*). Standard errors, clustered at the driver level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. The Impact of Restrictions on All Modes of Travel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy Round:	January (First)	April (Second)	January (First)	April (Second)	January (First)	April (Second)	January (First)	April (Second)
Panel A. Trips Using Household Vehicles								
Dependent Variable:	*Used any household vehicle*		*Used primary car*		*Used other car*		*Used motorcycle*	
Restricted Day	-0.226***	-0.214***	-0.331***	-0.336***	0.0259**	0.0918***	0.0767***	0.0286**
	(0.0264)	(0.0234)	(0.0251)	(0.0206)	(0.0111)	(0.0170)	(0.0159)	(0.0138)
Observations	1,353	1,523	1,353	1,523	1,353	1,523	1,353	1,523
P-value on Restricted Day	<0.001	<0.001	<0.001	<0.001	0.020	<0.001	<0.001	0.039
Mean Unrestricted Days	0.624	0.618	0.507	0.431	0.033	0.100	0.087	0.092
Mean Restricted Days	0.398	0.404	0.176	0.096	0.059	0.192	0.163	0.120
Panel B. Trips by Public Transport (or Carpool)								
Dependent Variable:	*Used public transit*		*Used bus*		*Used metro*		*Used carpool*	
Restricted Day	0.111***	0.0848***	0.0184	0.0266***	0.0658***	0.0531***	0.0282**	0.0165**
	(0.0213)	(0.0144)	(0.0124)	(0.00809)	(0.0162)	(0.0119)	(0.0109)	(0.00675)
Observations	1,353	1,523	1,353	1,523	1,353	1,523	1,353	1,523
P-value on Restricted Day	<0.001	<0.001	0.136	0.001	<0.001	<0.001	0.010	0.014
Mean Unrestricted Days	0.152	0.072	0.054	0.021	0.085	0.049	0.024	0.011
Mean Restricted Days	0.263	0.157	0.072	0.048	0.151	0.102	0.052	0.027
Panel C. Trips by Hired Vehicles								
Dependent Variable:	*Used taxi or autorickshaw*		*Used taxi*		*Used autorickshaw*			
Restricted Day	0.0788***	0.0598***	0.0104	0.0126*	0.0683***	0.0484***		
	(0.0155)	(0.0129)	(0.00757)	(0.00665)	(0.0140)	(0.0113)		
Observations	1,353	1,523	1,353	1,523	1,353	1,523		
P-value on Restricted Day	<0.001	<0.001	0.168	0.058	<0.001	<0.001		
Mean Unrestricted Days	0.038	0.041	0.014	0.012	0.024	0.029		
Mean Restricted Days	0.117	0.101	0.025	0.025	0.092	0.078		

Table Notes: This table reports results on travel behaviour as a function of whether today is restricted or unrestricted under the Odd-Even policy. Survey respondents were free to report multiple travel modes at the same time, so categories are not mutually exclusive. Standard errors, clustered at the driver level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. The Impact of Restrictions on Travel Behaviour and Labour Supply

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Made any trip today		Made work trip today		Cancelled any trip today		Cancelled work trip today	
Panel A. First Round (January)								
Restricted Day	-0.076***		-0.027		0.066***		0.045***	
	(0.021)		(0.024)		(0.016)		(0.013)	
Observations	1,353		1,353		1,353		1,353	
P-value on Restricted Day	0.000		0.262		0.000		0.001	
Mean for Unrestricted Days	0.798		0.632		0.0682		0.044	
Panel B. Second Round (April)								
Restricted Day	-0.101***	-0.101***	-0.090***	-0.090***	0.0804***	0.0804***	0.050***	0.050***
	(0.022)	(0.022)	(0.023)	(0.023)	(0.016)	(0.016)	(0.013)	(0.013)
Week before Odd-Even	0.013		-0.042		-0.0028		-0.0050	
	(0.024)		(0.026)		(0.014)		(0.011)	
Week after Odd-Even	0.036*		0.054**		-0.024**		-0.016*	
	(0.021)		(0.022)		(0.011)		(0.0095)	
Not Odd-Even		0.027		0.015		-0.016		-0.012
		(0.019)		(0.020)		(0.011)		(0.009)
Observations	2,825	2,825	2,825	2,825	2,825	2,825	2,825	2,825
P-value on Restricted Day	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mean for Unrestricted Days	0.731	0.731	0.594	0.594	0.058	0.058	0.038	0.038

Table Notes: This table reports results on travel behaviour before, during and after the Odd-Even policy. Panel B includes data during the weeks immediately before and after the Odd-Even policy in April 2016. The first four columns measure reported trips that were made, while the other four columns measure reported trips cancelled. Standard errors, clustered at the driver level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7. The Impact of Restrictions on Commute Satisfaction and Perceived Congestion

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:					Baseline opinion: Odd-Even is bad for Delhi	
Dependent variable:	Commute satisfaction		Reported road traffic congestion inconvenience		Reported road traffic congestion inconvenience	
Panel A. First Round (January)						
Restricted Day	-0.0461***	-0.0311*	-0.00295	-0.0102	0.0137	-0.00839
	(0.0153)	(0.0162)	(0.0107)	(0.0110)	(0.0222)	(0.0253)
Travel mode controls	Yes	Yes	Yes	Yes	Yes	Yes
Driver FE		Yes		Yes		Yes
Ref day FE		Yes		Yes		Yes
Observations	2,034	1,765	2,876	2,701	704	693
P-value on Restricted Day	0.00258	0.0557	0.782	0.354	0.536	0.740
Unrestricted mean	0.867	0.883	0.0962	0.0934	0.115	0.114
Restricted mean	0.809	0.817	0.0774	0.0766	0.112	0.109
Panel B. Second Round (April)						
Restricted Day	-0.0355*	-0.0303	0.00825	0.00707	0.0530	0.0200
	(0.0183)	(0.0208)	(0.0150)	(0.0154)	(0.0349)	(0.0362)
Week before Odd-Even	-0.163***	-0.204***	0.151***	0.166***	0.164***	0.185***
	(0.0222)	(0.0242)	(0.0210)	(0.0221)	(0.0483)	(0.0488)
Week after Odd-Even	-0.0852***	-0.0940***	0.119***	0.132***	0.130***	0.149***
	(0.0169)	(0.0188)	(0.0190)	(0.0198)	(0.0434)	(0.0440)
Travel mode controls	Yes	Yes	Yes	Yes	Yes	Yes
Driver FE		Yes		Yes		Yes
Observations	1,962	1,763	2,825	2,735	524	504
Unrestricted mean	0.760	0.763	0.208	0.209	0.216	0.217

Table Notes: This table reports results on driver satisfaction before, during and after the Odd-Even policy. The first two columns measure a binary commute satisfaction, while the last four columns use an indicator for whether the driver mentioned traffic congestion when asked about any commute inconveniences experienced during his trip. The last two columns restrict the sample to observations from drivers who reported at baseline that in their opinion the Odd-Even policy is “bad” or “very bad” (as opposed to “good” or “very good”) for Delhi. All regressions include controls for the following travel modes: primary car, other car, motorcycle, auto rickshaw, and metro. In addition, even numbered columns also include driver fixed effects, and in panel A reference day fixed effects (these are not included in Panel B due to collinearity with dummies for the week before and after Odd-Even). Standard errors, clustered at the driver level, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8a. Heterogeneity in Private and Public Transport Use

	(1)	(2)	(3)	(4)
Dependent Variable:	Used other car	Used any private mode	Used public transit	Made any trip
Panel A. Other car ownership				
Restricted Day	0.028***	-0.230***	0.118***	-0.100***
	(0.010)	(0.022)	(0.017)	(0.019)
Has other car	0.083***	0.046	-0.041**	0.005
	(0.018)	(0.031)	(0.019)	(0.026)
Restricted Day x Has other car	0.112***	0.114***	-0.075***	0.029
	(0.028)	(0.037)	(0.026)	(0.033)
Observations	2,876	2,876	2,876	2,876
Fraction with other car	0.320			
Panel B. Trip Duration				
Restricted Day	-0.348***	-0.149***	0.067***	-0.072**
	(0.033)	(0.037)	(0.024)	(0.033)
Trip duration (hours)	-0.030	-0.023	0.072**	0.026
	(0.044)	(0.042)	(0.028)	(0.035)
Restricted Day x Trip duration	0.013	-0.061	0.053	-0.006
	(0.050)	(0.054)	(0.039)	(0.045)
Observations	2,589	2,589	2,589	2,589
Mean trip duration (hours)	0.592			

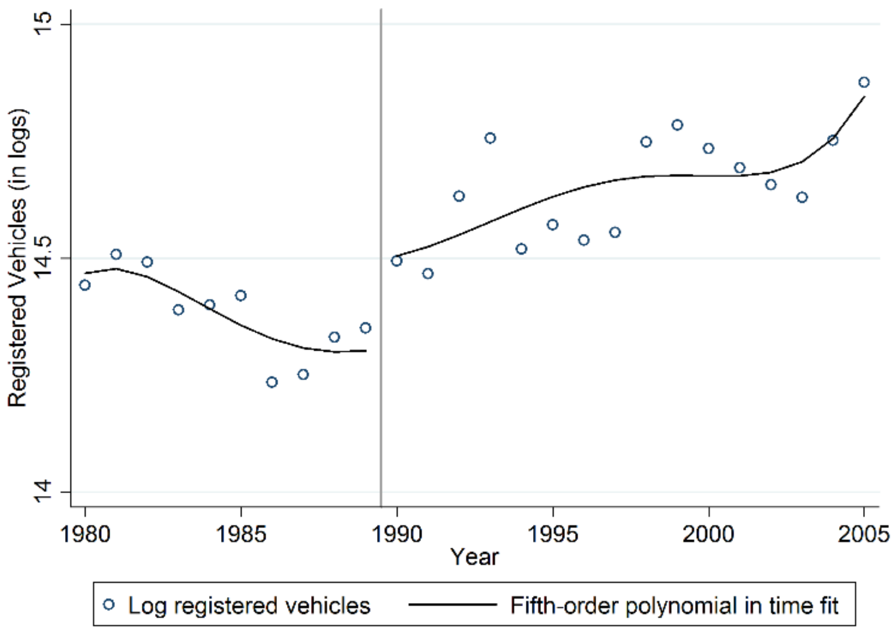
Table Notes: This table explores heterogeneity in travel behaviour according to car ownership status, and predicted trip duration. Panel A includes a dummy, and its interaction with "Restricted Day," for whether the driver reported that his household owns another car (other than the primary car). Panel B controls for the predicted trip duration (in hours) by car between the driver's home and work, and its interaction with "Restricted Day." The trip duration prediction is obtained from the Google Maps API. The sample pools the January and April data during the Odd-Even restrictions. Standard errors, clustered at the driver level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8b. Heterogeneity in Private and Public Transport Use

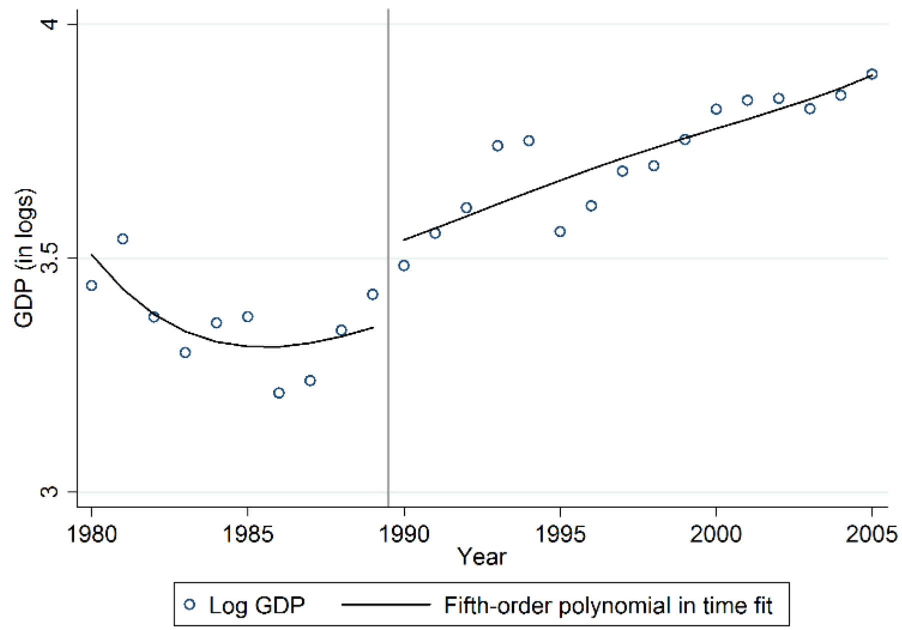
Dependent Variable:	(1) Used Primary Car	(2) Used any private mode	(3) Used public transit	(4) Made any trip
Panel A. Relative speed of Public Transit				
Restricted Day	-0.338***	-0.212***	0.141***	-0.064***
	(0.027)	(0.026)	(0.021)	(0.022)
Slow transit	0.032	-0.026	-0.026	-0.045*
	(0.032)	(0.031)	(0.020)	(0.025)
Restricted Day x Slow transit	-0.003	0.050	-0.080***	-0.022
	(0.037)	(0.038)	(0.028)	(0.032)
Observations	2,589	2,589	2,589	2,589
Fraction with slow transit	0.547			
Panel B. Relative Speed of Metro				
Dependent Variable:	Used Delhi Metro	Used Delhi Metro	Used public transit	
Restricted Day	0.094***	0.095***	0.137***	
	(0.017)	(0.018)	(0.022)	
Slow transit	-0.029*	0.021	0.035	
	(0.017)	(0.032)	(0.042)	
Restricted Day x Slow transit	-0.066***	-0.075**	-0.112**	
	(0.022)	(0.037)	(0.045)	
Slow metro		-0.066**	-0.075*	
		(0.032)	(0.042)	
Restricted Day x Slow metro		-0.004	0.037	
		(0.037)	(0.045)	
Observations	2,589	2,283	2,283	
Fraction with slow metro:	0.499			

Table Notes: This table explores heterogeneity in travel behaviour according to the quality of public transit. Panel A includes a dummy, and its interaction with "Restricted Day," for whether the ratio between the predicted public transit trip duration, and the predicted driving duration, between the driver's home and work locations, is above median. Panel B also includes a similarly defined dummy for predicted duration by metro and walking only. The sample pools the January and April data during the Odd-Even restrictions. Standard errors, clustered at the driver level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

9 Appendix Figures



Panel (A)



Panel (B)

Figure Notes. The two figures plot yearly vehicle registration in Mexico City (in logs) in Panel A, and yearly Mexico's GDP in current US (in logs) in Panel B. In each panel, the fitted line comes from a regression with 5th order time trends. GDP data from World Development Indicators.

Appendix Figure 1. Placebo check for the impact of the "Hoy no circula" policy in Mexico City on vehicle registration

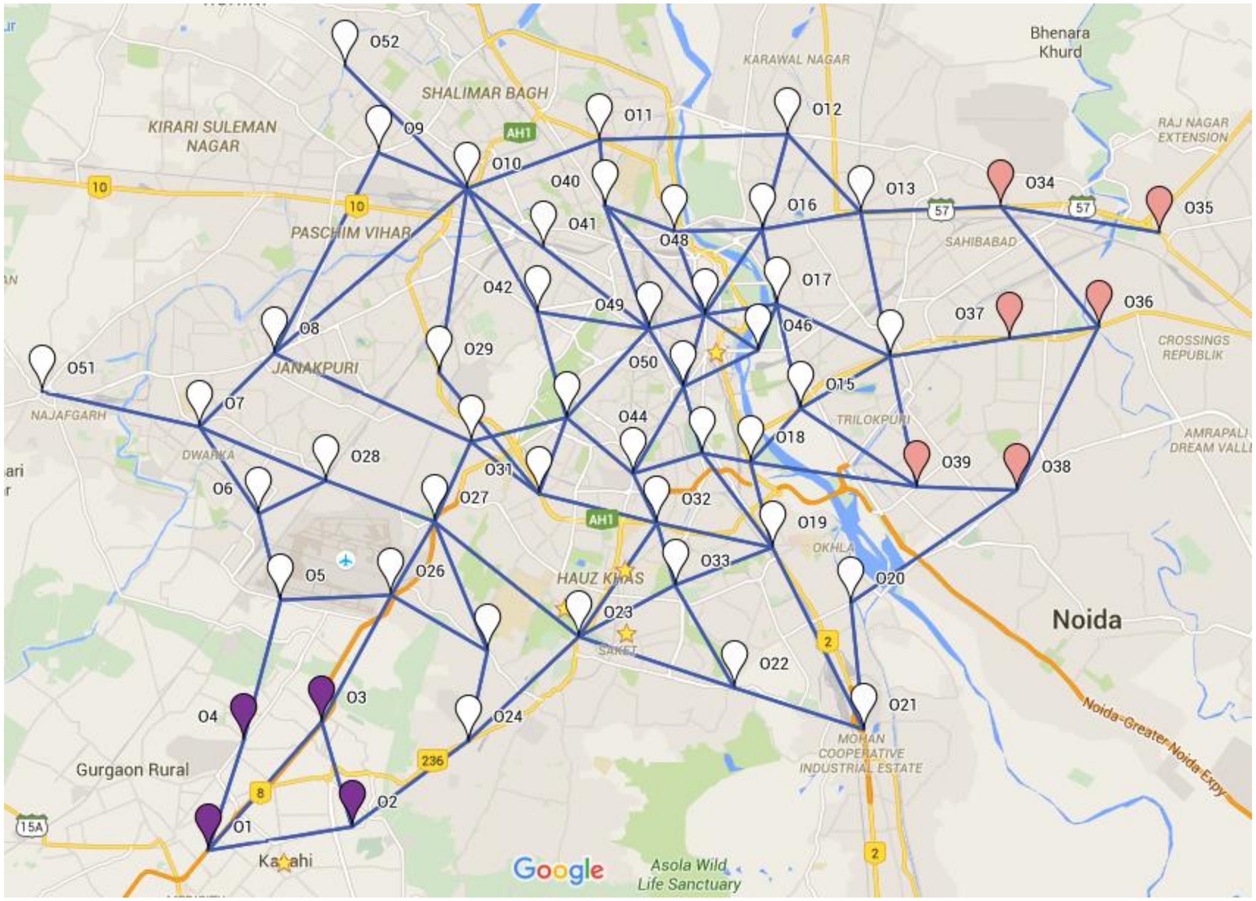


Figure notes. This figure plots the endpoints of the routes used for travel time queries. Each connected pair of points on the map represents two queries, one in each direction. In addition to 150 routes completely within the Delhi National Capital Territory, 36 routes (not used in this analysis) are between Delhi and neighbouring cities, or within neighbouring cities.

Appendix Figure 2. Google Maps traffic congestion queries routes

10 Appendix Tables

Appendix Table 1. Balance Tables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
							Household has:			Planned Response:				
Dependent Variable	Odd license plate	18-29 years old	30-49 years old	over 50 years old	College degree	Private employment	Self-employed	another car	motorcycle	Find alt'ive travel	Use car	Use motorcycle	Use auto rickshaw	Use metro
Panel A. Full Sample														
Odd plate		0.046	-0.034	-0.012	0.006	0.037	-0.039	0.026	0.029	0.044	-0.023	0.046*	0.022	0.066**
		(0.032)	(0.032)	(0.014)	(0.030)	(0.032)	(0.032)	(0.031)	(0.032)	(0.029)	(0.022)	(0.025)	(0.023)	(0.030)
Constant	0.488***	0.393***	0.552***	0.055***	0.679***	0.372***	0.438***	0.323***	0.506***	0.701***	0.139***	0.153***	0.143***	0.268***
	(0.016)	(0.022)	(0.023)	(0.010)	(0.021)	(0.022)	(0.022)	(0.021)	(0.023)	(0.020)	(0.015)	(0.017)	(0.016)	(0.021)
Observations	956	956	956	956	956	956	956	956	953	956	956	956	956	956
P-value	0.477	0.146	0.293	0.376	0.835	0.244	0.218	0.397	0.365	0.131	0.278	0.063	0.352	0.026
Joint χ^2 test of significance														0.223
Panel B. January Sample														
Odd plate		0.058	-0.051	-0.007	0.006	0.065	-0.055	0.043	0.059	0.063*	-0.011	0.076**	0.023	0.069
		(0.043)	(0.043)	(0.017)	(0.042)	(0.042)	(0.043)	(0.039)	(0.043)	(0.037)	(0.022)	(0.035)	(0.034)	(0.043)
Constant	0.499***	0.429***	0.530***	0.041***	0.609***	0.342***	0.429***	0.271***	0.530***	0.733***	0.075***	0.169***	0.177***	0.372***
	(0.022)	(0.031)	(0.031)	(0.012)	(0.030)	(0.030)	(0.030)	(0.028)	(0.030)	(0.026)	(0.016)	(0.025)	(0.024)	(0.030)
Observations	531	531	531	531	531	531	531	531	529	531	531	531	531	531
P-value	0.965	0.179	0.242	0.655	0.886	0.120	0.197	0.282	0.170	0.087	0.618	0.031	0.493	0.104
Joint χ^2 test of significance														0.271
Panel C. April Sample														
Odd plate		0.026	-0.009	-0.017	0.015	0.003	-0.018	0.010	-0.012	0.015	-0.032	0.004	0.016	0.050
		(0.047)	(0.048)	(0.024)	(0.041)	(0.048)	(0.048)	(0.047)	(0.049)	(0.046)	(0.039)	(0.033)	(0.031)	(0.036)
Constant	0.475***	0.350***	0.578***	0.072***	0.762***	0.408***	0.448***	0.386***	0.477***	0.664***	0.215***	0.135***	0.103***	0.143***
	(0.024)	(0.032)	(0.033)	(0.016)	(0.028)	(0.033)	(0.033)	(0.033)	(0.034)	(0.032)	(0.027)	(0.023)	(0.021)	(0.025)
Observations	425	425	425	425	425	425	425	425	424	425	425	425	425	425
P-value	0.309	0.572	0.849	0.467	0.717	0.953	0.714	0.827	0.803	0.751	0.410	0.903	0.608	0.172
Joint χ^2 test of significance														0.980

Table notes. This table reports a balance check on the driver sample. Panels B and C restrict to drivers recruited prior to the first and second rounds, respectively. The p value in the first column comes from a test of equality with 0.5. The joint χ^2 test covers columns 2-14, and the p-value is reported. Robust standard errors in parentheses.

Appendix Table 2. The Impact of Restrictions on Private and Public Modes of Travel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	Used primary car		Used any other private mode		Used any private mode		Used public transit		Made any trip	
Restricted Day	-0.336***	-0.336***	0.135***	0.135***	-0.201***	-0.201***	0.0958***	0.0958***	-0.101***	-0.101***
	(0.0205)	(0.0205)	(0.0211)	(0.0211)	(0.0234)	(0.0234)	(0.0147)	(0.0147)	(0.0221)	(0.0221)
Week before Odd-Even	0.0620**		-0.0451**		0.0169		-0.0139		0.0130	
	(0.0260)		(0.0200)		(0.0252)		(0.0131)		(0.0238)	
Week after Odd-Even	0.128***		-0.069***		0.0594***		-0.0244**		0.0363*	
	(0.0225)		(0.0175)		(0.0213)		(0.0103)		(0.0206)	
Not Odd-Even		0.101***		-0.059***		0.0421**		-0.0201**		0.0268
		(0.0203)		(0.0163)		(0.0197)		(0.0100)		(0.0188)
Observations	2,825	2,825	2,825	2,825	2,825	2,825	2,825	2,825	2,825	2,825
Unrestricted mean	0.495	0.495	0.167	0.167	0.662	0.662	0.0638	0.0638	0.731	0.731

Table Notes. This table repeats the analysi in Table 4 for the April (second round) sample, including data on the weeks before and after the policy. Standard errors, clustered at the driver level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3. Driver Survey Descriptive Statistics

	(1) Mean	(2) Observations that satisfy condition	(3) Total Observations
Panel A. Number of Respondents and Response Rates			
Baseline survey			
January sample		556	
April sample	46.0%	494	1074
Respondents reached during phone surveys		956	
January Sample	95.5%	531	556
April Sample	86.0%	425	494
Phone survey response rate			
in January	89.8%	502	559
in April (including before/after Odd-Even)	87.2%	916	1050
Phone surveys		4178	
in January, during Odd-Even		1353	
in April (total)		2825	
in April, during Odd-Even		1530	
in April, before Odd-Even		527	
Panel B. Demographics			
Age			
18-29 years old	41.5%	397	956
30-49 years old	53.6%	512	956
over 50 years old	4.9%	47	956
College degree	69.4%	663	956
Occupation			
Private employment	39.0%	373	956
Self-employed	41.8%	400	956
Government employee	6.0%	57	956
Student	8.3%	79	956
Other	3.9%	37	956
Panel C. Vehicle ownership			
Primary car has odd license plate	48.8%	467	956
Primary car age (years)	5.2	-	312
Household has another car	33.6%	321	956
Household has motorcycle	52.0%	496	953
Believes Odd-Even policy is good or very good for Delhi	69%	381	554

Table Notes. This table repeats the analysis in Table 1 with more information in Panel A on response rates.

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