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Does Traffic Management Matter? Evaluating Congestion Effect of Odd-Even Policy in Jakarta

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Abstract

Travel demand restriction is getting popular to disentangle traffic jams in heavily congested urban areas. The policy is easy to implement while reduction in congestion level is perceived to be substantial. We test this hypothesis by evaluating the impact of odd-even policy on congestion level in Jakarta, one of most severe congested cities in the world. Using hourly travel time data at road segment level drawn from GoogleMaps, the odd-even policy reduces the travel time by 3% on average after a month of its implementation. The effect is higher during weekend and at afternoon peak-hour window. Yet, the effect vanishes after the third week of policy introduction. Our result then sheds an indication of ineffective transport demand restriction in Jakarta.

JEL Classification: R41; R42; R48

Keywords

odd-even policy — travel time — Jakarta — traffic demand management

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1. Introduction

Traffic congestion is one of persistent threats of urbanized areas because of substantial economic costs associated with with longer travel times. On American roads, not less than US$306 billion was loss is due to congestion by 2017 (Cookson, 2018). Although later studies also attribute the cost with but associated with more pollution, mental stress, accidents, and labor supply decision[1], any policies sought to curb the congestion mainly target the economic cost reduction from longer travel times.

Policy makers reduce the congestion externalities with both public transport service expansion or travel demand management intervention. The latter has been widely used among urbanized areas in the world which may take form of financial-based incentives and command-and-control policies (Santos et al., 2010). The financial-based incentives perceives to provide more behavioral responses and are likely to be more cost effective in congestion reduction than the command-and-control policies (Luechinger & Roth, 2016). Nevertheless, the command-and-control policies remain popular as they are likely to be more easily implementable while the outcome remains tractable (Button, 1990). The policies commonly take forms as traffic demand restriction, including, but not limited to odd-even policy (Li & Guo, 2016), passengers restriction policy (Daganzo & Cassidy, 2008; Dahlgren, 1998; Hanna et al., 2017; Li & Guo, 2016), car-free day policy (Gallego et al., 2013; Wang et al., 2014), and parking restriction (Santos et al., 2010).

In this paper, we examine to what extent traffic demand restriction can curb longer travel times due to traffic externalities using the case of latest odd-even policy expansion in several main roads in Jakarta, one of most congested megacities in the world. The policy only allows cars with odd (even) plate number to drive in odd (even) days at designated road segments. We uses hourly travel time data from 1 July-31 August 2018 drawn from GoogleMaps to elicit the causal impact.

This paper contributes to the literature in two ways. First, we add empirical evidence on the growing literature on the effect of traffic demand management, especially the role of the odd-even policy. While the policy has been introduced in several cities around the world, the empirical evidence of the effects of this policy remains small. The evaluation of the policy has been done for Beijing, China (Li & Guo, 2016; Wang et al., 2014; Gu et al., 2017; Viard & Fu, 2015), Delhi, India (Kreindler, 2016), Mexico City, Mexico (Davis, 2008; Gallego et al., 2013), Santiago, Chile (Gallego et al., 2013; de Grange & Troncoso, 2011), Quito, Ecuador (Carrillo et al., 2016), Bogata and Medellin, Columbia (Ramos et al., 2017). Much of the previous studies, however, do not necessarily analyze the impact on the congestion; some of them look at whether the policy induces more pollution, or assess the role of the policy on the volume of the vehicle. We then provide results on the impact of the policy on the travel time. Our results suggest the limited effects of the introduction of the odd-even policy on the travel time by about two percent to five percent, at most. The effects of the policy vary within days and departure. We also provide the supportive argument of change in the behavior of the road users. In addition to the heterogeneous impact, we further our analysis by exploring the sustainability of the odd-even policy. Surprisingly, we find that the effect of the policy only sustains for the three weeks since its introduction. To support the results of the study, we perform several robustness checks and confirm that the results remain robust.

Second, our study provides a more robust estimate as it can control any other factors that also affect travel time

[1] Santos et al. (2010) provide a brief discussion on the cost of road transport externalities

during the odd-even policy introduction. There are several reasons as to why we can pin down the effects of the policy. First, unlike most of the abovementioned studies, we use the real-time data provided by the Google Maps API. The richness of the data allows us to quantify the traffic congestion for each road segment precisely compared to survey data used in several of the studies mentioned earlier. To our knowledge, two studies employ the same kind of data; Hanna et al. (2017) in examining the effects of the passengers' restriction policy to the congestion in Jakarta, Indonesia, and Kreindler (2016) in analyzing the behavior response towards the odd-even policy in Delhi, India. The second reason is that we also include a long list of control variables to isolate the effect and use a fixed effect approach to confine the effect further. This also explains why our estimates are likely to be much lower than other studies using survey data.

The remainder of this paper is structured as follows. Section 2 discusses the policy context of odd-even implementation in Jakarta, Indonesia. The discussion is followed by the baseline empirical strategy, as well as the nature of the data employed in this study. Section 3 provides our main result, the heterogeneity effects of the policy, and the discussion whether the policy intervention is sustainable. Section 4 gives concluding remarks and future research agenda.

2. Data and Empirical Strategy

2.1 Context: Odd-Even Policy in Jakarta

Jakarta faces serious road congestion challenges. The congestion level is on of the highest among major urban areas in the world (Waze, 2016; Cookson, 2018). The cost reaches not less than US$5 billion annually as a result from low-level of public transport provision, urbanization and fast motorization process (Jakarta Post, 2017; Burke et al., 2017). To overcome the worst traffic congestion, particularly in major road segments, the government has introduced odd-even policy since 2016. The policy only allows private passenger cars with even (odd) plate number to traverse during even (odd) date. Taxi, ambulance, public bus, motorcycle are exempted.

While the odd-even policy is relatively new, the Jakarta Provincial Government has imposed travel demand restriction since 2004 in the form of the '3-in-1' policy. The policy prohibit cars with less than three passengers to pass the designated road segments. The government first introduced the policy in 2004, and it lasted to 2016 where the government changed the policy to odd-even policy. The '3-in-1' policy is imposed on several roads, such as Jl. Sisingamangaraja, Jl. Jenderal Sudirman, Jl. MH. Thamrin, Jl. Medan Merdeka Barat, and some parts of Jl. Gatot Subroto. The motivation behind this '3-in-1' policy was the introduction of the Bus Rapid Transportation (BRT) system in the Jakarta Province with the name of *Transjakarta*. The '3-in-1' policy was enforced from 7 AM to 10 AM and 4 PM to 7.30 PM.

On late March of 2016, the Jakarta Provincial Government decided to remove the '3-in-1' policy (and entirely abolished the policy in early May 2016). The government cited three reasons which motivated the abolition of the policy; (1). The development of Mass Rapid Transportation (MRT) system, (2). Overpass construction in Bundaran Semanggi, and (3). Pedestrian path (sidewalk) construction around it. There was effectively no traffic density management policy imposed by the Jakarta Provincial Government starting from March 2016 to late July 2016. After such a hiatus of no traffic intervention, the government finally introduced the odd-even policy in late July in that same year. The road segments which was enacted by the odd-even policy was the same as in the previous '3-in-1' policy.

In August 1st, 2018, the Jakarta Provincial Government decides to enlarge the road section in the odd-even policy from five road sections to more than twenty sections, such as Jl. Metro Pondok Indah, Jl. Benjamin Sueb, the entire road section of Jl. Gatot Subroto, Jl. A. Yani, Jl. DI Panjaitan, and others. The broader road section accommodated in the latest version of the policy is to take into account the 18th Asian Games 2018 that will take place in Jakarta[2]. The difference between the new and the existing is not just on the new road sections. The time of the policy is also extended from 6 AM to 8 PM. The existing road section in the odd-even policy is depicted in blue color (since August 2016), while the red color shows different road section included in the latest version of the odd-even policy. The detail of the difference in road section between the latest version of the odd-even policy and the previous one is depicted in Figure 1.

2.2 Methods and Data

To elicit the causal impact of odd-even policy on the traffic travel time, in spirit of Hanna et al. (2017), we estimate the following equation

$$\begin{aligned}\ln(tt_{idh}) = \beta_0 + \beta_1 OE_{dh} \\ + \gamma X + \theta_{h:d} * direction_i \\ + \theta t_d + \varepsilon_{idh}\end{aligned} \quad (1)$$

tt_{idh} is our dependent variable, per kilometer travel time of road i at date d and departure time h measured in minutes[3]. The variable is presented in natural logarithm so that the effect is presented in percentage change by $100(e^{\beta_1} - 1)$.

Our main variable of interest is the policy intervention variable OE_{dh} which equals to one if the road section is part of the set of roads which is enacted by the odd-even policy at day d and time h, and zero, otherwise. The variable will be set to one from August 1st, 2018 onwards.

The primary data we use to estimate the $ttime_{idh}$ is drawn from Distance Matrix API of the Google Maps. To obtain the $ttime_{idh}$ for each road section, we first determine two coordinates to proxy each road section. The API will then extract the data hourly for each road section[4]. For each road section, the Google Maps API will extract several variables;

[2] The 18th Asian Games 2018 is conducted in two cities; Jakarta and Palembang. Most of the sports events, however, are taking place in Jakarta. The Asian Games are scheduled from August 18th, 2018 to September 2nd, 2018.

[3] The travel time can be written as an inverse of speed, $travel\_time_{idh} = \frac{duration\_of\_traffic}{distance}$

[4] Alternatively, Hanna et al. (2017) collect the data every twelve minutes. As for the case in our study, we decide to take the data hourly because the variation is not that different between hourly data and data taken for every twelve minutes.

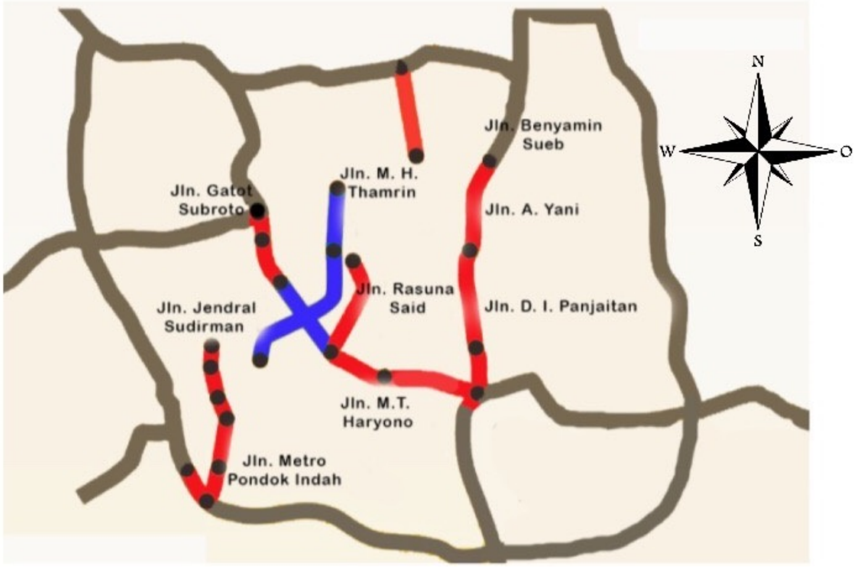


Figure 1. The Existing and New Road Section in the Odd-even Policy

- *distance_km*: Distance between one coordinate to another (unit: kilometer).
- *distance_m*: Distance between one coordinate to another (unit: meter).
- *duration_minute*: Amount of time needed to travel from one coordinate to another (unit: minute). The *duration_minute* variable captures the average time based on the historical data of the road section i at time h, at day d.
- *duration_second*: Amount of time needed to travel from one coordinate to another (unit: second). The *duration_minute* variable captures the average time based on the historical data of the road section i at time h, at day d.
- *duration_traffic_minute*: Amount of time needed to move from one coordinate to another (unit: minute). The *duration_traffic_minute* variable captures the average time based on the real-time data of the road section i at time h, at day d.
- *duration_traffic_second*: Amount of time needed to move from one coordinate to another (unit: second). The *duration_traffic_second* variable captures the average time based on the real-time data of the road section i at time h, at day d.

The difference between $duration$ and $duration\_traffic$ variables is that the $duration$ variable only captures the average time travel between one coordinate to another based on the historical data, which the Google Maps API has, for each road section i at time h, at day d. While the $duration\_traffic$ variable captures the average time travel between one coordinate to another based on a real-time data. This difference suggests that we can compare the actual real-time travel time with its past. For the benchmark analysis, we will use the $duration\_traffic$ because this variable gives a real-world change compared to the $duration$ variable which has been smoothed out. In the upcoming sections, we will also deeply discuss how we incorporate the discussion between the two variables.

The period of data collection starts from July 1st, 2018 to August 31st, 2018. The data is gleaned for every hour from 5 AM to 9 PM. We divide the collection period into two periods; (1) Before the policy enforcement, and (2) After the policy enforcement.

X_{idh} represents the control variables. We include control for precipitation rate[5]. We also control for the two national holidays (the Indonesian Independence day on August 17th and Ied Al-Adha on August 22nd), the odd days, and the 18th Asian Games controls[6]. Note that travel time also varies hourly within a day. The variable $\theta_{h:d}$ controls for hourly variation within a day. We interact the hourly variation with the segment direction dummy to or from Jakarta to control for different pattern of the variation. We further add daily trend to capture the linear trend of travel time growth.

2.3 Expected result and possible mechanisms

We expect the average impact of the odd-even policy on the travel time, denoted by β_1, to be negative and statistically significant. The mechanism as to which this negative estimate is outlined as follows; We expect that the policy introduction will push the road users to avoid the designated road segments. Therefore, the policy will induce people to travel using other alternative routes, or they can decide to switch their departure time (for instance, people decide to commute to their workplace earlier compared before the policy introduction, or they can back home late compared to their usual schedule). Other possible mechanisms include people decide to shift to other modes of transportation, and

[5]The weather data used in this research is obtained from the NASA-Giovanni (see https://giovanni.gsfc.nasa.gov/giovanni/). To proxy the weather, we use the precipitation data obtained every thirty minutes, then we aggregate the data by using a simple arithmetic average to get hourly data. We only include the precipitation data at Jakarta level. We assume that, aside from difficulties in obtaining precipitation for each segment, the variation in precipitation across segment is relatively small.

[6]As outlined in the previous section; we control for the Asian Games. We specify the opening, closing, and separate the events for three weeks to represent the qualification round, quarter and semifinal round, and the final round

even postpone their scheduled trips.

The impact is also anticipated to be small in magnitude. Various underlying reasons might explain as to why the small impact may arise (i.e., the limited impact of travel demand restriction). First, some of the road users might have at least two private cars with odd and even numbers, respectively. Thus, they will still use their cars even when the policy is enforced. Second, in contrast to the first reasoning, the policy introduction might as well promotes an adverse effect to the road users who happened to be rarely drive in the usual days to use their car more frequently after the policy is enacted[7]. Lastly, given the relatively broad coverage of road segments compared to before the policy introduction, the Jakarta Police Department and the Jakarta Transportation Department will be entitled to a higher and manual work in supervising each road segments. Given the human resources constraints, the supervision would be much strict during earlier days of the policy implementation, yet also it would be more lenient afterward.

2.4 Threats to identification

There are several identification issues needed to be addressed in order to estimate the Equation 1 correctly. From the economic modeling perspective, estimation of Equation 1 will provide an unbiased estimate of β_1 if the error term ε_{idh} is not correlated with the variable of interest OE_{dh}. The correlation can occur in various forms; (1). An incorrect functional form, (2). A reverse causality problem: that is, the expectation of the travel time influences the decision of time and place of the odd-even policy (vice verse), and (3). An omitted variable bias: that is, the other important independent variables are not included in the regression, or simply put, the error term is correlated with other potential explanatory variables. After discussing those three forms that can bias the estimation of β_1, we will discuss the needs of standard errors clustering in estimating β_1.

The first potential source of bias is from functional form miss-specification. In order to minimize the potential source of bias, we use several robustness checks. Even though the time-series of the data is quite long, the Equation 1 does not necessarily need to be estimated using the first-difference approach because of no specific time-trend for the three months of data collection

We also see there is no threat coming from the reverse causality bias. The decision of which roads' section selected in the odd-even policy is not influenced by the travel time. The odd-even policy might influence the travel time by, say, decreasing the amount of time needed to travel from one coordinate to another. Alternatively, the odd-even policy could affect the travel time; however, it is unlikely that the travel time could have an impact on the odd-even policy itself.

The real challenge in addressing the identification issues comes from the threat of omitted variable bias. We find it hard to isolate the sole impact of this policy intervention on the travel time since there is no available data on traffic management done by Jakarta Police Department or Jakarta Transportation Department (*Departemen Perhubungan* DKI Jakarta) during the policy intervention. The kind of data that we lacked are how much traffic tickets issued by the Jakarta Police Department on road section i, at day d at time h, and the plan to alternate a particular road segment i, at day d at time h usually conducted by Jakarta Transportation Department. Even if we have such detailed data, the problem left is still not thoroughly assessed since it is possible for both departments to change their plans instantaneously during the day; that is, they deviate from their original plan written in the administration data. Hence, in interpreting the parameter β_1, one must note that the concerns as mentioned earlier will also be reflected in the total impact of odd-even policy on the travel time.

Another important discussion is the appropriate way to cluster the standard errors from β_1. If we do not control the standard errors appropriately, it is possible that the standard errors that we obtained will be underestimated and the t-value will be too big (Cameron & Miller, 2015). In our case, there are forty-four road segments. Assuming that for every road there are two segments (that is, two road segments with two different directions), there will be twenty-two roads. The characteristics of each road segments i for each road g are assumed to be the same. For instance, the two road segments in road g are assumed to be built using the same kind of material and the width for each road segments is also the same. Furthermore, it makes sense to observe that the characteristics for each road g are correlated for every hour. Therefore, by considering the road's characteristics and time correlation, we argue that the appropriate way to obtain the correct measure of the standard errors of the point estimate β_1 is by employing two-way clustering on road segment and departure time (hour).

2.5 Variation before and after odd-even policy

We present daily and hourly travel time before and after odd-even policy implementation in the Figure 2a and 2b, respectively. The daily plot rather shows that the impact of the odd-even policy is limited. Furthermore, we also find a slowing daily travel time during the observation period. The slowing travel time can be observed through the time distance from the implementation of the policy.

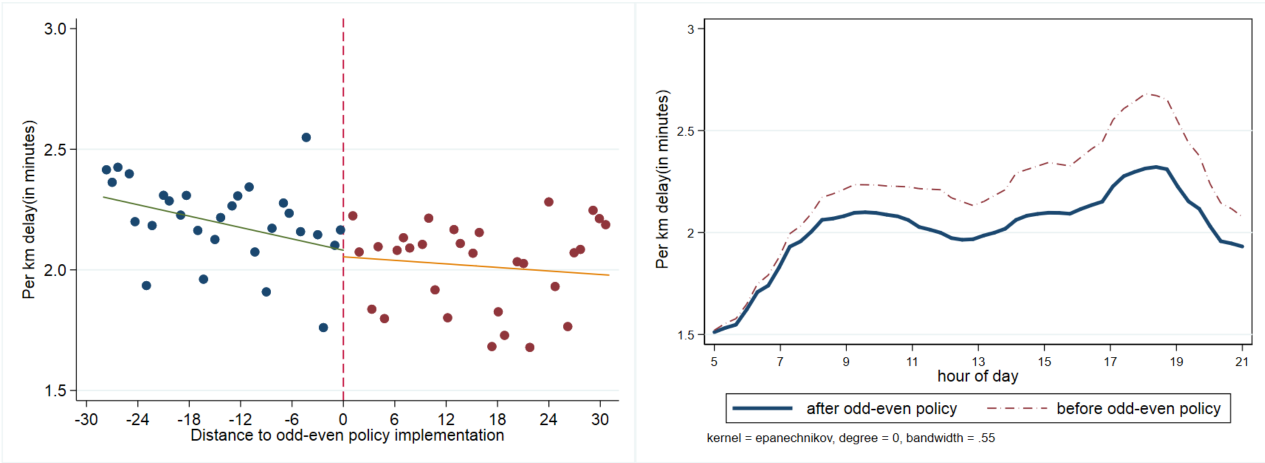
Nevertheless, Figure 2b shows that within-day variation is evident as per kilometer travel time is higher during the morning (8am–10am) and afternoon peak hour (5pm–7pm). It can be seen that travel time is lower after the odd-even policy, particularly during the afternoon peak-hour period. Different variation is also evident between weekends and weekdays as presented in the Appendix A. Nevertheless, this figure only serves as a descriptive purpose since. Our econometric result provides the quantitative measure of the extent of such impact as presented in the next section.

3. The effect of odd-even policy on travel time

3.1 Main result

The empirical work starts from Table 1 by presents the main estimate of Equation 1. Column 1 reports the average estimate of the odd-even policy impact. Column 2 adds interaction between the policy and Saturday and Sunday to distinguish the effect during weekdays and weekend.

[7]That is, before the policy intervention these kind of road users are barely driving their cars, however, after the policy was introduced, they remember what day is it, and decide to drive their car.



(a) Daily Trend **(b) Hourly Variation**

Figure 2. Per km Travel Time Before and After Odd-even Policy

Table 1. Congestion Effects of Odd-even Policy: Base result

Dependent variable: $ln(ttime_{idh})(min/km)$	(1)	(2)
Odd-even policy	-0.0265*	-0.0233*
	(0.00475)	(0.00495)
Odd-even policy *weekend		-0.0112**
		(0.00546)
R-sq within	0.363	0.363
Observations	34896	34896
Number of road	44	44

Note: Standard errors in parentheses clustered in road segment and departure hour. Additional controls include precipitation, hour of day, day of week, daily time trend, and extensive list of dummy variables presented in the Appendix. ***, **, * indicate level of significance at 10, 5, and 1 percent, respectively

The estimate suggests that odd-even policy has an adverse effect on per kilometer travel time in both specifications. The policy reduces the per kilometer travel time by 2.6% on average, and statistically different from zero at 1% level. The result supports recent empirical evidence on the limited effect of similar traffic demand restriction; that is, although theoretically the amount of vehicle is significantly reduced, the impact of the policy restriction on the travel time is not that high. Furthermore, we also find that the impact is 1.1 percentage point higher during the weekend than in the weekdays, statistically significant. The policy is likely to drive out more trips during the weekend, particularly the non-working trips as it is more sensitive toward the restriction than the working trips.

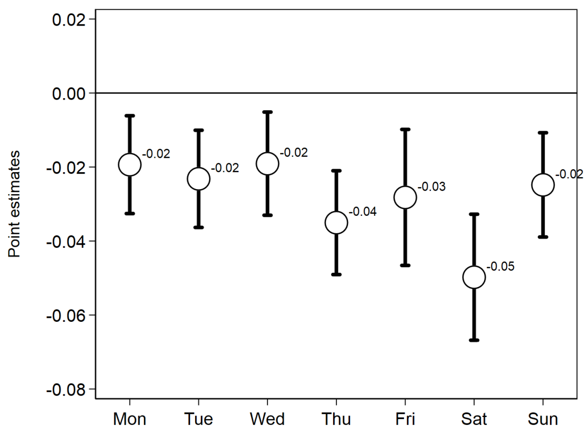
Table 1 omits the coefficients for our controls, and we provide the discussion here. A percent increase in precipitation tends to slow down road users, increasing the per kilometer travel time by 0.6%. Travel time also exhibits hourly and daily seasonality. Longest per kilometer travel time is during Friday and afternoon peak-hour. Travel time during Friday is about 10% longer than during the base day, Saturday. Meanwhile, per kilometer travel time is 40–50% higher during 4–7pm than at the 5am. We also find limited effect of Asian Games 2018 in Jakarta.

3.2 Daily effect

One might concern that the effect of odd-even may daily differ. To capture the effect, we re-estimate Equation 1 with some modifications as depicted in the following equation,

$$\ln(ttime_{idh}) = \beta_0 + \sum^{k} \beta_1^k OE_h^k + \gamma X + \theta_{h:d} * direction_i + \theta t_d + \varepsilon_{idh} \tag{2}$$

where OE_h^k equals 1 if a road segment i is restricted for odd-even policy at day-of-week k.



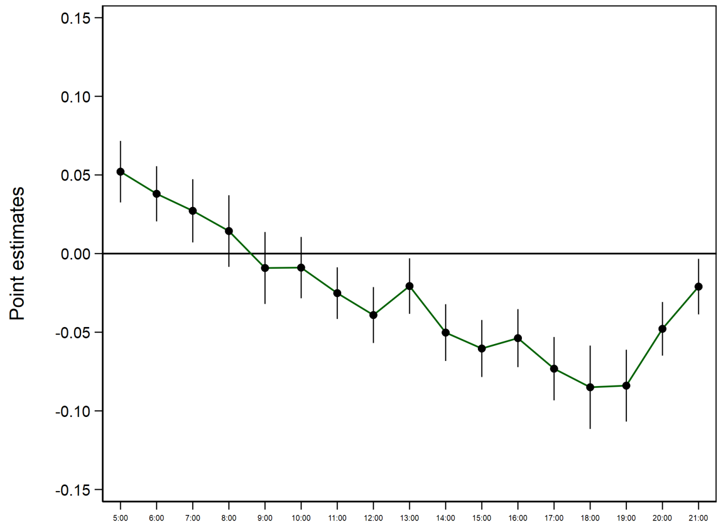
Note: The point estimates show daily impact of odd-even policy at 95% confidence interval.The interval is represented by the bars stemming from point estimates.The point estimate is statistically different from zero if the bar does not pass the horizontal line at 0.

Figure 3. Daily Impact of Odd-even Policy

Figure 3 presents the estimate of Equation 2. We find variation within day-of-week with the impact in range of -1.0% to -5.0%, statistically different from zero at 5%. From Figure 3 one can observe that the policy intervention does reduce the travel time for each day. One interesting observation is that Saturday is the day that experience the most reduction in the travel time.

3.3 Variation of hourly effect

We further look closely how the odd-even policy may affect differently across departure time. To obtain the estimate, Equation 2's framework is used except that the odd-even policy varies across departure time. Figure A2 provides



Note: The point estimates show hourly impact of odd-even policy at 95% confidence interval.The interval is represented by the bars stemming from point estimates.The point estimate is statistically different from zero if the bar does not pass the horizontal line at 0.

Figure 4. Hourly Impact of Odd-even Policy

point estimate of the policy for each departure time at 95% confidence interval. We plot the estimate from 5am to 9pm.

The figure shows that, while the policy reduces the travel time on average, the effect substantially varies over time. Highest reduction in travel time is during afternoon peak hour 5pm–7pm. 7–8% travel time reduction is associated with the odd-even policy, statistically significant at 1% level. In contrast, we find that the policy may alter road user's choice of departure time to travel earlier in the morning for policy avoidance. Travel time in morning off peak-hour (5am–7am) is higher by 3–5% after the introduction of the odd-even policy.

3.4 Is the impact sustainable?

The effect of odd-even policy may also differ over time. People may avoid the targeted road segment in the short-run, yet adjust the travel behavior with extensive margin in the long-run to keep traversing the road.

To capture the effect, several specifications are considered. Firstly, we add additional linear trend after the policy to capture the possibility of daily linear change of the impact. Secondly, we disaggregate the impact by week using similar estimation in the Equation 2. At last, we modify the Equation 1 by separating the first n-week effect and the rest of the period as follow,

$$\ln(ttime_{idh}) = \beta_0 + \beta_1 OE^1_{dh} + \beta_2 OE^2_{dh} + \gamma X + \theta_{h:d} * direction_i + \theta t_d + \varepsilon_{idh} \quad (3)$$

where OE^1_{dh} and OE^2_{dh} represent the first nth-week of odd-even policy implementation and the rest of period, respectively.

Table 2 provides all estimates of our specification. The first column presents the estimate of interaction between the policy and the linear trend. The second column gives the result for the weekly disaggregated impact. The last four columns present the estimates of the Equation 3. Since the whole month of August data available for after the policy introduction only, we estimate the Equation 2 up to first 4-week effect. Columns 3 to 6 present the result for the first week to 4-week, respectively[8].

The estimates suggest that, while the impact is on average evident during the first month of policy implementation, the impact is likely to diminish as time passes. Estimates in column 1 show that the impact is daily decreasing by 0.1%. Furthermore, the weekly estimates the impact has lasted only until the third week since the policy introduced (Column 2). The results in column 2 of Table 2 suggest that the policy intervention is only useful in reducing the travel time for the first three weeks.

Our further results in column 3 to column 6 also support this notion. Column 3 details the effect on the first week and the rest of the period (that is, from the second week to the end of the period of data collection). The average impact of the policy introduced in the first week is about 2.9%. The magnitude of the policy in the following weeks then become smaller and smaller. One can notice, starting from the third week onwards, the rest of period magnitude is not statistically significant[9]. The results lend support to the notion outlined in the previous paragraph that the impact of the odd-even policy diminishes over time. Thus, our results reinforce the supportive evidence of the limited impact of travel demand restriction, as well as confirm that the impact of the odd-even policy has dwindled throughout the policy enactment.

3.5 Robustness check

In this section, we examine the robustness of the baseline specifications. As mentioned in section 2, we perform robustness checks to inspect whether there is functional form misspecification in our model. Specifically, the test checks whether the estimate is sensitive toward different measurement of travel time, alternative functional form, time win-

[8] To read columns 3 to 6: The first, second, third, and fourth weeks correspond to August 1st–August 5th, August 6th–August 12th, August 13th–August 19th, August 20th–August 26th, respectively

[9] The rest of period in column 5 means starting from the fourth week onwards -without the previous weeks-

Table 2. First n-th Week of Travel Time Effects of Odd-even Policy

Dependent variable: $ln(ttime_{idh})(min/km)$	*Linear trend*	*Weekly*	*Average n-th week* (1st)	(2nd)	(3rd)	(4th)
Odd-even policy	-0.0312*					
	(0.00495)					
Policy*Linear trend	0.00119*					
	(0.0004)					
Odd-even policy during:						
*week 1		-0.0261*				
		(0.00555)				
*week 2		-0.0204*				
		(0.00562)				
*week 3		-0.0146*				
		(0.00708)				
*week 4		0.00667				
		(0.0119)				
*week 5		0.0208				
		(0.0129)				
Odd-even policy during:						
First n-th week			-0.0291*	-0.0267*	-0.0248*	-0.0238*
			(0.00544)	(0.00475)	(0.00480)	(0.00487)
Rest of period			-0.0242*	-0.0216*	-0.0000805	-0.00760
			(0.00537)	(0.00670)	(0.0102)	(0.00792)
R-sq within	0.364	0.365	0.364	0.364	0.364	0.364
Observations	34896	34896	34896	34896	34896	34896
Number of road	44	44	44	44	44	44

Note: Standard errors in parentheses clustered in road segment and departure hour.
The estimate includes all controls introduced as in the Table 1.
***, **, * indicate level of significance at 10, 5, and 1 percent, respectively

dow, and polynomial trend. The check is then followed by a falsification test in forms of shifting the date of policy introduction.

Table 3 provides our base specification, two alternatives and two different sample lengths, focusing on the average effect of the odd-even policy. For each specification, we change the trend up to the fifth polynomial order[10]. On the alternatives, column 2 uses the ratio of our ”live” version of travel time over its historical data of respective road segment[11]. Column 3 uses travel time at level data. Both specifications show the adverse effect of the odd-even policy, and also the estimates are statistically significant at 1% level.

The last two specifications estimate the Equation 1 but using observations during ± 2 and ± 3 weeks around the first day of policy implementation. The estimates are slightly higher, particularly for the latter specification. The reason is that we only include observations during ± 2 and ± 3 weeks. If we include observations for more weeks -that is incorporating the weeks where the impact of the policy might not be that effective- the results are quite the same. All in all, we still believe that our checks remain comparable with our baseline estimates, and they are statistically different from zero at 1% level.

The estimates are also relatively robust to changes in the polynomial order. For all alternative specifications, additional polynomial orders are likely to increase the point estimates slightly, yet remaining consistent of magnitude and statistically different from zero. For example, the estimates for the logarithmic form of $ttime_{idh}$ in the first column are in ranges of -0.027 to -0.050. However, for the reasons outlined in the previous paragraph regarding over-fitting, we will only present the results up to the fifth polynomial.

Table 4 reports the falsification test by two specifications. *Firstly*, we estimate the effect for historical travel time as we expect zero effect of the policy on past travel time. The point estimate is relatively small in magnitude and statistically insignificant. *Secondly*, we shift the timing of policy introduction 15 days backward and 15 days forward in time to 16 July 2018 and 16 August 2018, respectively. This specification also serves to check to what extent anticipation behavior may occur. As the introduction date of the policy was announced a month in advance, there is a possibility that transport demand is higher during days near implementation day to avoid the policy. Yet, we find the estimates are statistically not different from zero.

4. Conclusion

This paper identifies the effect of the odd-even policy enforced in several road segments in Jakarta, Indonesia. The contributions of this study are two folds. The first significant result is the reduction of travel time induced by the

[10]We restrict up to fifth order to avoid noisy estimates due to over-fitting model (Angrist & Rokkanen, 2015; Gelman & Imbens, 2018).

[11]As explained in section 2; the ”live” version corresponds to the $duration\_traffic$ and the historical version is depicted by $duration$. Thus, the construction of the $ttime\_livehistorical_{idh}$ variable follows the same $ttime_{idh}$, and becomes $ttime_{idh} = \frac{\frac{duration\_traffic}{duration}}{distance}$ The main difference between the two is that $duration$ has been smoothed using based on the historical data for each road segments i at time h and day d.

Table 3. Alternative Specification

	$ln(ttime_{idh})$		$ttime_{idh}$	$ln(ttime_{idh})$	
	Live	*Live/Historical*	*Level*	*±2 week*	*±3 week*
1st	-0.0268*	-0.0334*	-0.0455*	-0.0286*	-0.0320*
	(0.00475)	(0.00548)	(0.0126)	(0.00645)	(0.00549)
2nd	-0.0324*	-0.0409*	-0.0610*	-0.0287*	-0.0325*
	(0.00482)	(0.00556)	(0.0127)	(0.00645)	(0.00574)
3rd	-0.0358*	-0.0419*	-0.0782*	-0.0298*	-0.0317*
	(0.00626)	(0.00729)	(0.0165)	(0.00859)	(0.00718)
4th	-0.0351*	-0.0414*	-0.0760*	-0.0298*	-0.0277*
	(0.00626)	(0.00729)	(0.0165)	(0.00859)	(0.00741)
5th	-0.0300*	-0.0327*	-0.0647*	-0.0150	-0.0183**
	(0.00718)	(0.00834)	(0.0189)	(0.00964)	(0.00853)

Note: Standard errors in parentheses clustered in road segment and departure hour.
The estimate includes all controls introduced as in the Table 1.
***, **, * indicate level of significance at 10, 5, and 1 percent, respectively

Table 4. Falsification Test: Shifting the Beginning of Implementation Date

	Historical	(Shift in policy date (days))	
	travel time	-15	+15
Odd-even policy	0.00362	-0.0113	0.0175
	(0.00244)	(0.0165)	(0.0203)
R-sq within	0.097	0.364	0.364
Observations	34896	34896	34896
Road segment	44	44	44

Note: Standard errors in parentheses clustered in date.
The estimate includes all controls introduced as in the Table 1.
***, **, * indicate level of significance at 10, 5, and 1 percent, respectively

policy intervention. Using the traffic congestion real-time data from Google Maps API, our baseline estimates suggest a limited impact of the policy on the travel time; that is, the magnitude of the impact reduces the travel time only by 2% on average. The results, in particular, have a higher magnitude on Saturday. We observe that the impact is more apparent during afternoon peak-hour window. We also see the evidence of increasing travel time during morning off-peak-hour window. This seemingly small magnitude also re-invigorates other empirical findings of the limited effect of traffic restriction.

The second critical result assesses whether the effect will be sustainable or not. In addition to the small magnitude of the policy, we find that the policy is only effective in the short-run. We observe that the impact of the policy is more likely to be faded from the fourth week since its implementation on August 1st, 2018.

Adding to the policy discussion, given the low impact of the odd-even policy, the policymakers may reconsider more comprehensive implementation of odd-even policy in other major roads in Jakarta as the policy alone is not enough for controlling the congestion. Recent Government of Jakarta's decree on broader implementation of odd-even policy is then, likely to provide a limited effect on the effort in congestion reduction. Looking forward, complementary policy options are in need to be sought to exploit higher congestion reduction.

Our study further suggests future possible research. The effect of odd-even policy, or any other similar travel demand policies, may also affect the public transport sector or other transport alternatives. As is the Jakarta, it would be interesting to investigate the spillover effect on transJakarta, Jakarta's bus rapid transit, ridership and headway that are daily available. Similar effect might also take place on online transportation ridership that is fastly growing in major urban areas in Indonesia.

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Appendix A: Detailed variable definitions

Ln travel time: Natural log per kilometer travel time of a road segment on certain departure time and day. Source: GoogleMaps (2018)
Ln historical travel time: Natural log of historical kilometer travel time of a road segment on certain departure time and day. Source: GoogleMaps (2018)
Distance: Distance from a point origin to a point destination, measured in meters. Source: GoogleMaps (2018)
Odd-even policy: dummy variable whose value is equal one if the odd-even policy has been implemented, i.e. August 1st 2018 onwards; 0 otherwise.
Ln precipitation: Area-averaged hourly precipitation estimate. Data are for the Jakarta. Source: national Aeronautics and Space Administration (NASA, 2018), series GPM3IMERGHHE_v05
Independence day: equals one in August 17th 2018; 0 otherwise.
Idul Adha day: equals one in August 22nd 2018; 0 otherwise.

Appendix B: Daily per kilometer travel time (in minutes) before and after policy

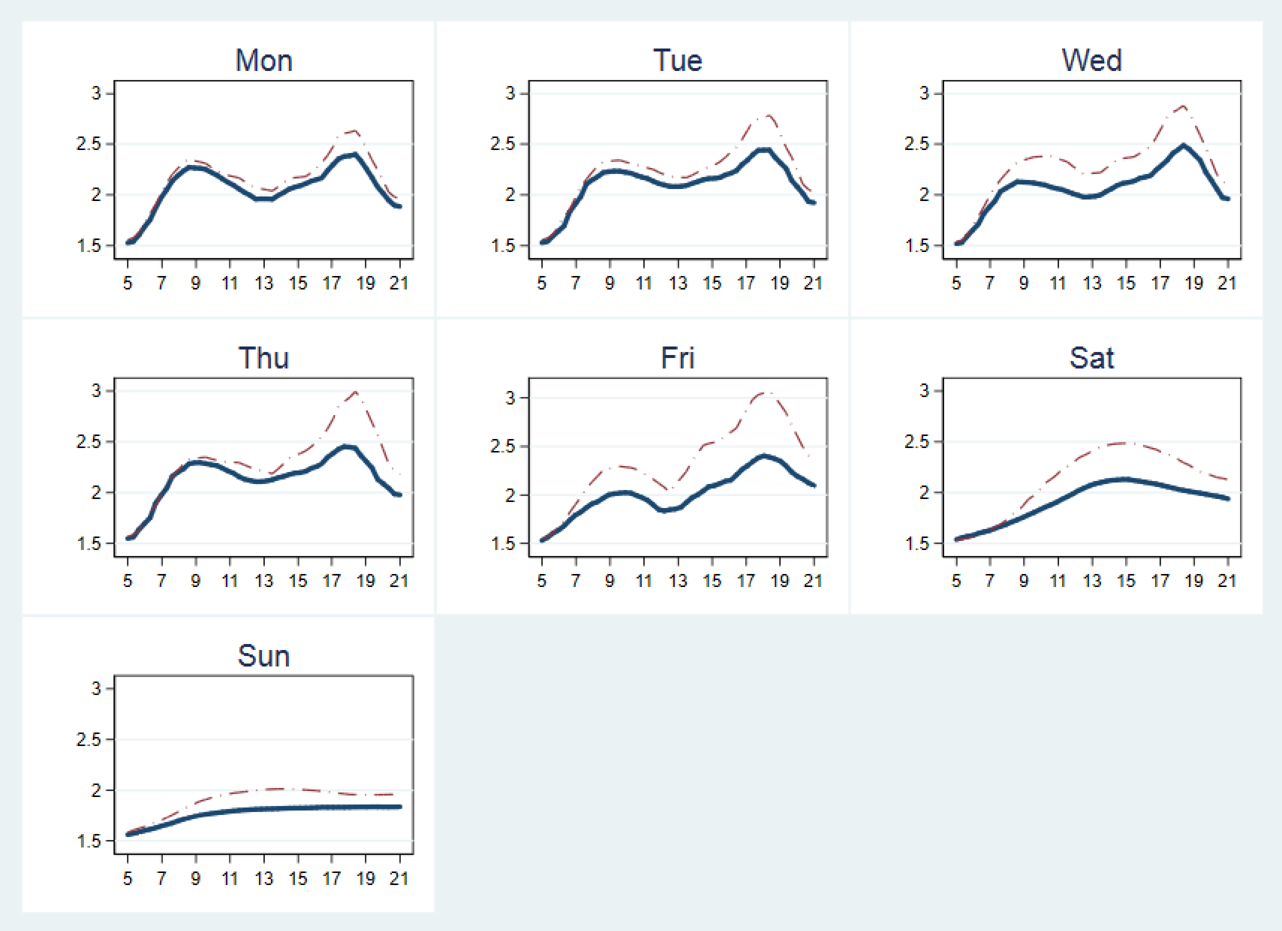
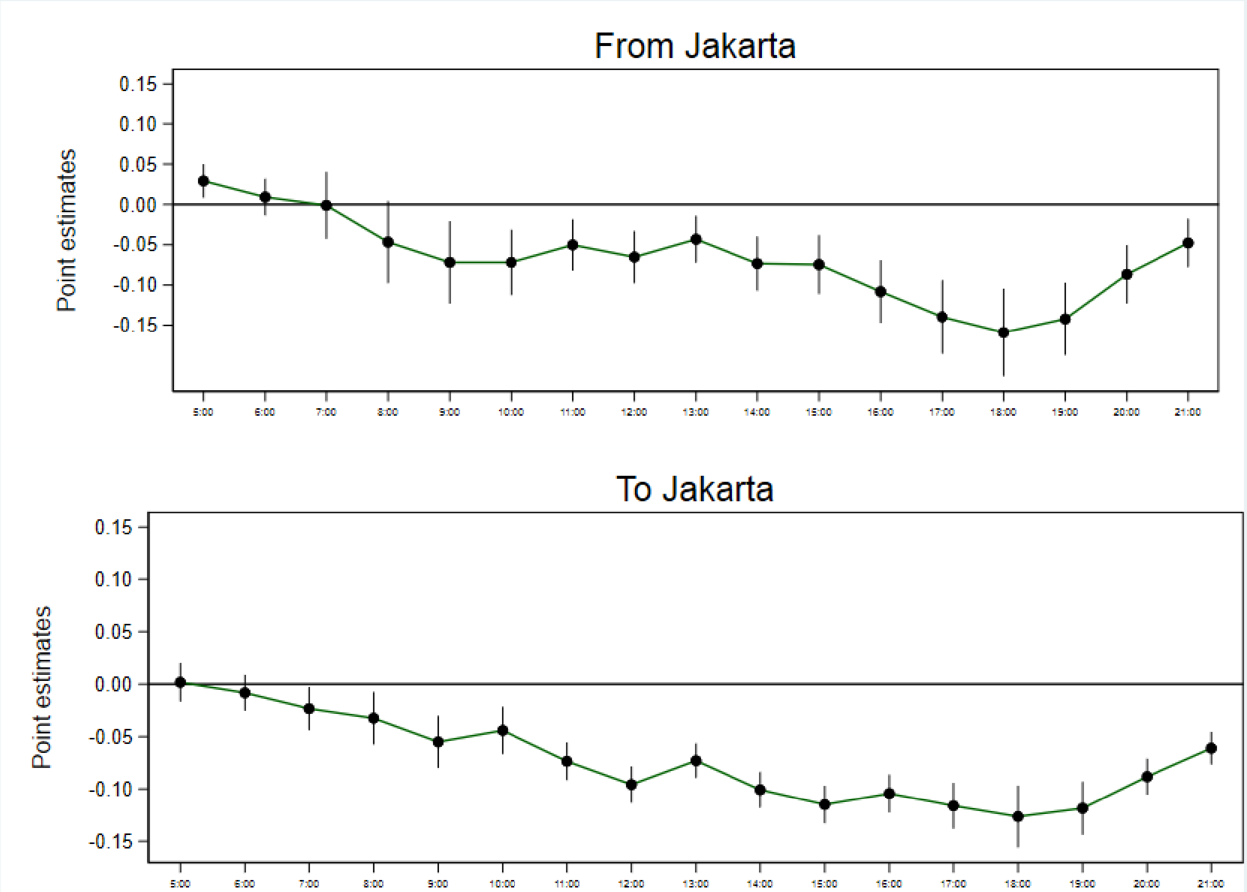


Figure A1. Daily per km travel time before and after odd-even policy
Note: x- and y-axis represent departure time and per kilometer travel time, respectively. Blue and dashed lines represent travel time before and after odd-even policy, respectively.

Appendix C: Hourly impact by road segment direction



Note: The point estimates show hourly impact of odd-even policy at 95% confidence interval for road segments from and to Jakarta, respectively.The interval is represented by the bars stemming from point estimates.The point estimate is statistically different from zero if the bar does not pass the horizontal line at 0.

Figure A2. Hourly impact of odd-even policy

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