A NATURAL EXPERIMENT APPROACH TO EVALUATING THE IMPACT OF TEMPORARY PEDESTRIANIZATION ON SURROUNDING ROADS: A CASE STUDY OF TOKYO METROPOLIS

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This study uses a natural experiment approach to evaluates the causal effect of three regular road pedestrianization schemes in Central Tokyo on traffic conditions in surrounding areas. Cross-sectional traffic flow data collected by the Metropolitan Police Department via traffic counters was used as the dependent variable and causal effect evaluation was done via a difference-in-differences (DID) approach, where the temporal pedestrianization of a street was used as the treatment of interest. We take advantage of (1) the variability in pedestrianization execution days and (2) the seasonal variability in pedestrianization time periods, to define the natural experiments. Furthermore, three different buffer areas of 500m, 750m and 1000m were used to evaluate the sensitivity of effect estimates to the definition of the impact area. Results suggest that irrespective of buffer size, the impact of temporal road pedestrianization on cross-sectional traffic flow of surrounding roads is negligible. Point estimates of treatment effect magnitudes across all models are small and estimated with high degrees of uncertainty, with most confidence intervals including zero. As such, results do not show evidence of practically important increases in traffic flow in the surrounding areas of pedestrianized roads and point to some degree of "traffic evaporation" resulting from drivers' behavioral adaptation. Ultimately, these results suggest that human-centric network design is not necessarily a zero-sum game between pedestrians and drivers.

Keywords :*Pedestrian environment, traffic evaporation, human-centric planning, road traffic, causal effect, natural experiment, Braess' paradox*

1. INTRODUCTION

In recent years, a paradigm shift in urban and transportation planning has resulted in the prioritization of people in streets and public spaces. One of the most commonly used measures is the temporary or permanent pedestrianization of roads otherwise dedicated mostly to car traffic. Against severe road space constraints, a particularly critical issue in high-density Asian cities, the introduction of pedestrianized streets (usually referred to as hokōsha-tengoku or "walker's paradise" in Japanese) affects different travel modes in different ways. Direct positive impacts include the increase of the speed and efficiency of pedestrian movement, the reduction in the number of accidents, and improved "attractiveness" of places, resulting in increases in the number of pedestrians and visitors to the area[1, 2]. This may further lead to indirect positive impacts, including environmental benefits such reductions in environmental and noise pollution, economic benefits such as increases in retail turnover, and social benefits such as increases in sociability and civic pride[3,4]. Castillo-Manzano et al.[3] empirically evaluated the impacts of street pedestrianization in Seville, Spain, and found that pedestrianization is

positively valued by citizens who are more aware of the need for environmental protection, and that it increased the frequency of visits to the area, resulting in increases in spending in the area. Such a positive reaction to pedestrianization has been reported in a number of studies. Shirgaokar et al.[5] reported that the reallocation of road space made during the COVID-19 pandemic in North America was generally positively evaluated by citizens; Pandit et al.[2] examined how people use open public space newly generated by the road closure experiment in the Mainkai riverfront in Frankfurt, Germany, and reported increases in pedestrians and cyclists, particularly among people with restricted mobility. He et al.[1] also reported that the opening of East Lake greenway in Wuhan, China, increased walking behavior, particularly of women and socio-economically disadvantaged people.

Although these various positive impacts have been confirmed, opposing views on its introduction largely stem from concerns about the worsening of traffic congestion[6], with the pedestrianization of Times Square in New York City being the most well-known case[7]. Such a potential adverse effect is often considered to be serious, but the degree would depend on to what extent "traffic evaporation" (the reduction in traffic through behavioral adaptations such as changing travel mode and route) occurs. In this regard, the phenomena of traffic evaporation after road closure have been repeatedly reported. Cairns et al.[6] examined over 70 case studies of road space reallocation from eleven countries and concluded that traffic levels would be significantly reduced in the long-run due to various behavioral adaptations people made, and thus the adverse effects of road closure were less serious than expected. Recent case studies also support this conclusion. Tennøy and Hagen[8] , taking an opportunity of a 14-month road tunnel closure in Oslo, Norway, confirmed that this road closure did not bring major negative consequences, partially thanks to adaptation behavior of citizens. Behavioral adaptations were also reported in In Seoul, South Korea, after the Cheonggyecheon expressway (a 10-lane roadway, including a 4-lane elevated highway along the Cheonggyecheon stream) removal to give way to a pedestrian green corridor. Chung et al.[9] reported that after the Cheonggyecheon stream restoration, people adapted their behavior by changing departure time and shifting to transit, thus preventing traffic congestion. They also reported that while speeds on adjacent roads deteriorated after restauration works began, these effects gradually disappeared over time and travel speeds increased to pre-restauration levels. Safitri and Chikaraishi[10] reported that considerable reductions in travel demand were observed after the massive road network disruption caused by the July 2018 heavy rain disaster in Hiroshima, Japan, largely thanks to the behavioral adaptation of citizens. Nello-Deakin[11] evaluated the impacts of the superblocks scheme in Barcelona, Spain (where each superblock consists of nine individual city blocks, of which inner streets are designed and used for non-motorized modes, and the outer edges for motor traffic) and confirmed that traffic levels have reduced substantially on the target streets without causing a substantial increase in the surrounding areas.

It should be noted that, while traffic evaporation through behavioral adaptations has been widely observed as discussed above, some behavioral adaptations may generate negative consequences. For example, canceling trips due to pedestrianization could bring negative economic benefits to the surrounding area as a result of less patronage; and changing travel destinations from urban to suburbs' facilities may result in increased environmental burdens. As such, it would be important to confirm whether sufficient road network capacity exists or not in the surrounding area of pedestrianized zones. In that regard, pedestrianization would sometimes improve the traffic conditions thanks to the (reverse) phenomena of Braess' paradox, where the removal of certain links actually improves the overall network performance[12,13]. This underscores the importance of exploring transportation supply conditions, in addition to exploring the possibility of traffic evaporation.

While the above case studies provide some empirical evidence on the impacts of pedestrianizations, further research is needed on two aspects. First, most existing studies have focused on North American and European cities, with relatively few studies on Asian cities. What characterizes Asian cities is their high density, which results in severe road space constraints. For example, The Greater Tokyo Area (the world's largest urban agglomeration and the target of this study) developed from Edo, a castle town founded in 16th century Feudal Japan that served as the de-facto capital of the Tokugawa period (Edo downtown area population density has been estimated to range from 58,000 to 67,000 persons/km^2). As such, Central Tokyo's road network is largely based on this old urban structure, and with few exceptions, such as the Great Kanto Earthquake reconstruction plan (1923), large-scale modifications to the road network have been historically difficult. However, even in the face of severe spatial constraints, high levels of transit service might also hint to different behavioral adaptation, compared to European and North American cases, as the Seoul case showed. That is, as high density allows for a higher level of service for transit over automobiles, modal shifts become much easier. Furthermore, since car ownership and use costs tend to be high (in Japan, on-street parking is essentially not allowed, and car buyers must provide proof-of-parking to be able to purchase a car) car modal share has been reducing over time in

the Tokyo central area. While these trends suggest there should be sufficient road capacity and alternative high-quality travel modes to proactively introduce pedestrianized streets without observing negative effects in traffic conditions, practical implementations are still limited, partially due to limited empirical evidence and fears of worsening congestion. Furthermore, most empirical studies in the literature have drawn conclusions without paying attention to causal inference.

Against this background, this study aims to evaluate the causal effect (or lackthereof) of temporal pedestrianization of downtown roads in Tokyo, Japan on surrounding traffic conditions.

2. METHODOLOGY

In order to evaluate the impact of temporal pedestrianization on traffic conditions in surrounding areas we use data from cross-sectional traffic flow data collected by the Metropolitan Police Department via traffic counters and published by the Japan Road Traffic Information Center (JARTIC). We focus on the three regular road pedestrianization schemes approved by the Tokyo Metropolitan Police Department (Under Japanese law, police departments are the traffic administrators) namely Shinjuku, Akihabara and Ginza. All three roads are surrounded by trunk roads and are located in commercial districts with high transit accessibility.

To evaluate traffic conditions in the area surrounding pedestrianized streets we first (1) draw a buffer of radius r around the pedestrianized street of interest, and (2) collect cross-sectional traffic flow data for all the traffic counters inside the buffer area, excluding counters on the pedestrianized street (Fig 1). Due to the irregularity of the Tokyo road network, we set three different buffer radii (500m, 750m and 1000m) to define the evaluation area. This allows us to evaluate the sensitivity of the results to changes in the buffer definition. Fig 2 shows the buffer settings along with the traffic counters that fall in each buffer area.

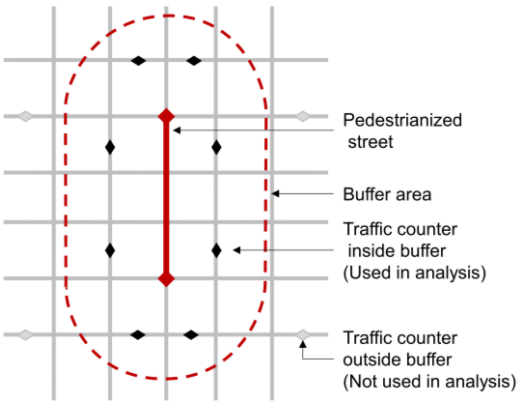


Fig 1. Definition of observational units to analyze traffic conditions in the area surrounding a pedestrianized street.

(1) Two natural experiments

Impact evaluation is done using a difference-in-differences (DID) approach. In this study, the temporal pedestrianization of a street is used as the treatment of interest. We take advantage of (1) the variability in execution days and (2) the seasonal variability in pedestrianization time periods, which essentially function as natural experiments. We explain the details below.

Case 1: Shinjuku and Akihabara

For simplicity we will refer to the days where temporal pedestrianization is held as “event days”. Traffic counters inside the buffer area during event days are assigned to the treatment group, while traffic counters inside the buffer area during non-event days are assigned to the control group. Traffic counters inside the buffer during the pedestrianization time period are defined as post-treatment observations, while counters inside the buffer and outside the pedestrianization time period are defined as pre-treatment observations. Note that for the DID parallel trend assumption to hold, non-event days must be as similar as possible to event-days in terms of the trend of outcome variable (e.g., same days of the week, no special events etc. that might affect traffic flow across treatment status), this is why the variability of execution days can be used as a natural experiment.

As shown in Table 1, for the Shinjuku and Akihabara projects, during the analysis period, there were several cancellations due to several reasons. Provided these reasons do not substantially affect car traffic flow, we can assume the parallel trend assumption holds and such days can be used as the control group (i.e., non-event days). For example, in Akihabara, for April 16 and 24, pedestrianization was cancelled because local elections were scheduled to be held April 24. April 16 was election notice day, which marks the pre-election campaign start. It is unlikely however that election notice or the elections would substantially affect car traffic, which make them an ideal natural experiment. For April 30, in both Shinjuku and Akihabara, pedestrianization was cancelled due to poor weather forecast (the Ginza event was held as scheduled). The Japan Meteorological Agency forecast was “Cloudy with occasional rain” with less than 2mm of rain in the period from 5am to 11am, and according to Japan Weather Association data, the observed precipitation was mostly in the morning from between 3am and 9am, and again at 3pm, with a total of 3mm of rain for the whole day. This is unlikely to severely affect car traffic, as such it was also used as a control group. On May 14, pedestrianization was cancelled only in Shinjuku, and while no reason was provided, the weather was actually sunny and no particular events were held that day that would have affected car traffic, and thus included in the control group.

Table 1. General characteristics of pedestrianization schemes in Tokyo

Area	Length	Schedule	Analysis period	Execution notes
❶Shinjuku	500m + other minor streets	Sundays and Holidays October-March: 12:00~17:00 April-September: 12:00~18:00	April-May 2023	Event cancellation (reason): Apr-30 (weather– realized: 3mm rain) May-7 (weather– realized: 44mm rain)* weekend after Golden Week May-14 (not specified – sunny weather)
❷Akihabara	570m	Sundays October-March: 13:00~17:00 April-September: 13:00~18:00	April-May 2023	Event cancellation (reason): Apr-16 (election) Apr-23 (election) Apr-30 (weather– realized: 3mm rain) May-7 (weather– realized: 44mm rain) * weekend after Golden Week
❸Ginza	1,110m	Saturdays, Sundays, and Holidays October-March: 12:00~17:00 April-September: 12:00~18:00	Oct.-Nov. 2022 April-May 2023	No cancellations recorded during analysis period.

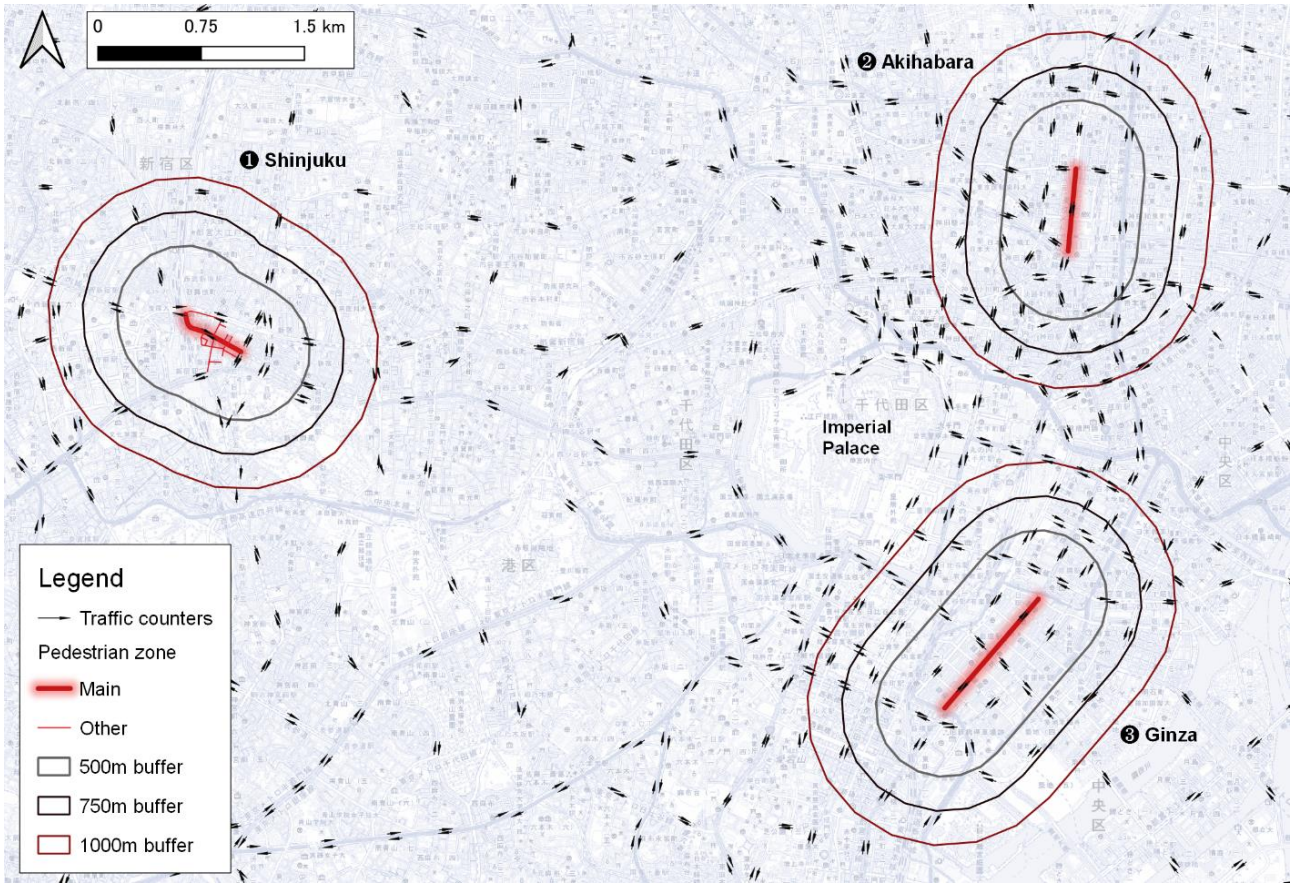


Fig 2. Buffer setting and location of traffic counters

Finally, pedestrianization was cancelled on May 7 in both Shinjuku and Akihabara due to poor weather with a “heavy rain” forecast. Observed precipitation was in fact around 44m which is likely to have affected car traffic. Furthermore, May 7 was the Sunday after Golden Week (a week-long holiday period in Japan) so it was not a regular Sunday, hence excluded from the analysis. Fig 3 illustrates the DID concept in the context of the Shinjuku and Akihabara analysis as well as a graphical interpretation of the model parameters explained next.

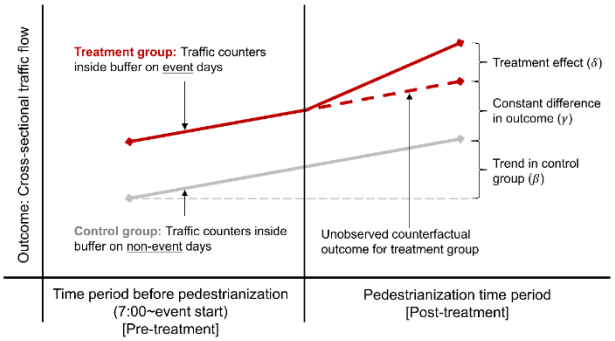


Fig 3. Difference-in-difference conceptualization used for Case 1: Shinjuku and Akihabara.

Given the panel nature of the data, we specify a fixed effects model as:

$$Y_{i,h}^{fe} = \alpha_i + \beta time_{i,h} + \gamma event_{i,h} + \delta time_{i,h} \cdot event_{i,h} + \varepsilon_{i,h} \quad (1)$$

where $Y_{i,h}^{fe}$ is the natural logarithm of cross-sectional traffic flow (vehicles per hour) for link i for hour h. α_i is a fixed effect parameter for link i and can be interpreted as the average baseline traffic flow level for link i; $time_{i,h}$ is a dummy variable that takes value 1 if hour h falls within the pedestrianization time period and zero during the pre-treatment period (7:00 until the start of the event). Since April-May data is used in the analysis, pedestrianization time corresponds to 12:00~18:00 for Shinjuku and 13:00~18:00 for Akihabara. $event_{i,h}$ is a dummy variable that takes value 1 during event days and zero otherwise. Parameter β captures the trend in the control group, that is, the average difference in traffic flow between pedestrianization and non-pedestrianization time periods for non-event days. γ captures the average difference between event and non-event days. Finally, δ captures the treatment effect, that is, the effect of pedestrianization on the surrounding links. Note that only Sunday data is used in the analysis, which makes event days and non-event days comparable. Holidays are excluded from the analysis. As an alternative formulation, and in order to account for the possibility of time-variant unobserved effects, we also define a model with a lagged dependent variable. Autoregressive models are commonly used in transportation in traffic flow prediction. The lagged dependent variable model is defined as:

$$Y_{i,h}^{lag} = \alpha + \beta time_{i,h} + \gamma event_{i,h} + \delta time_{i,h} \cdot event_{i,h} + \theta Y_{i,h-1}^{lag} + \varepsilon_{i,h} \quad (2)$$

where θ captures the effect of the lagged dependent variable.

Case 2: Ginza

While variability in execution was observed in the Shinjuku and Akihabara cases, no cancellations were observed in the Ginza case, as such, a different approach was used. For Ginza, we took advantage of the differences between execution time periods between Spring-Summer and Autumn-Winter. As shown in Table 1, the Ginza pedestrianization is conducted from 13:00 to 17:00 from October to March but is extended to 18:00 during the April-September period. This difference in execution time is used a natural experiment. As illustrated in Fig 4, for the Ginza case, we defined the temporal pedestrianization of a street for the 17:00~17:59 time period as the treatment of interest. Traffic counters inside the buffer area during event days for the April-September period are assigned to the treatment group, while traffic counters inside the buffer area during event days for the October-March period are assigned to the control group. Traffic counters inside the buffer area for the 17:00~17:59 time period are defined as post-treatment observations, while counters inside the buffer area and outside the pedestrianization time period (7:00~11:59) are defined as pre-treatment observations.

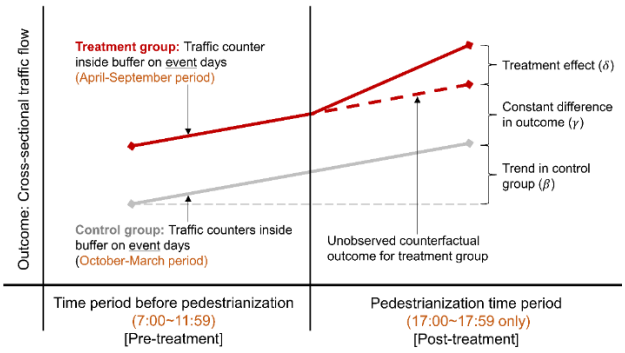


Fig 4. Difference-in-difference conceptualization used for Case 2: Ginza.

For the Ginza case, the fixed effect model is formulated as:

$$Y_{i,17h}^{fe} = \alpha_i + \beta time_{i,17h} + \gamma event_{i,17h}^{apr-oct} + \delta time_{i,17h} \cdot event_{i,h}^{apr-oct} + \varepsilon_{i,17h} \quad (3)$$

where $Y_{i,h}^{lag}$ is the natural logarithm of cross-sectional traffic flow (vehicles per hour) for link i for the Ginza case. $time_{i,17h}$ is a dummy variable that takes value 1 during the 17:00~17:59 time period, and zero during the pre-treatment period (7:00~11:59). $event_{i,17h}^{apr-oct}$ is a dummy variable that takes value 1 during event days for April-September period and zero otherwise. Parameter β captures the average difference in traffic flow between pedestrianization and non-pedestrianization time periods for the October-March period, that is, the trend in the control group. γ captures the average traffic flow difference between the April-September period and the October-March period, and δ captures the treatment effect, that is, effect of pedestrianization on the surrounding links. The lagged dependent variable model is defined as:

$$Y_{i,h}^{lag} = \alpha + \beta time_{i,17h} + \gamma event_{i,17h}^{apr-oct} + \delta time_{i,17h} \cdot event_{i,17h}^{apr-oct} + \theta Y_{i,h-1}^{lag} + \varepsilon_{i,17h} \quad (4)$$

3. RESULTS

Table 2 and 3 summarize the estimation results for the fixed effect and lagged dependent variable models, respectively. Since the dependent variable enters the model in log-form, model parameters of dummy variables can be interpreted as semi-elasticities, that is, the percentage change in the dependent variable when the dummy variables take value 1. The first thing to point out is that irrespective of buffer size, the impact of temporal road pedestrianization on cross-sectional traffic flow of surrounding roads, as captured by the interaction terms, is negligible. Even when ignoring the large degree of uncertainty in the estimates (almost all confidence intervals include zero) point estimates of effect magnitudes across all models are small. The largest observed effect is 5.7% (95% C.I.: -0.2% – 11.6%) increase in cross-sectional traffic in the Ginza area inside the 500m buffer for the lag-variable model, an effect that diminishes as the buffer size increases. Note that this effect is specific for the 17:00~17:59 time period. It is also worth noting that in some cases, a reduction traffic was also observed. The Shinjuku fixed effect model suggest an average reduction in traffic flow of 5.6% for the 750m buffer and 3.55 for the 1000m buffer.

While the Ginza model estimates the effect for the 17:00~17:59 time period, the estimates in the Shinjuku and Akihabara models correspond to average changes across the whole pedestrianization time period and do not capture the effect variability over the hours. To account for this, we estimated a new set of models where the term $\beta_1 time_{i,h}$ and its respective interactions are segmented by the hour. For the fixed effect case the fixed effect and lagged models are defined as:

$$Y_{i,h}^{fe} = \alpha_i + \sum_k^K \beta_k time_{i,h=k} + \gamma event_{i,h} + \sum_k^K \delta_k time_{i,h=k} \cdot event_{i,h} + \varepsilon_{i,h} \quad (5)$$

$$Y_{i,h}^{lag} = \alpha + \sum_k^K \beta_k time_{i,h=k} + \gamma event_{i,h} + \sum_k^K \delta_k time_{i,h=k} \cdot event_{i,h} + \theta Y_{i,h-1}^{lag} + \varepsilon_{i,h} \quad (6)$$

Estimation results are summarized in Fig. 5. Estimates suggest there are some differences in both effect direction and magnitude over time. For example, both models suggest reductions of more than 15% in traffic in Shinjuku during the 12h period for the 750m and 1000m buffer, while increases in traffic are observed for Ginza and Akihabara for the 17h period, albeit with some considerable uncertainty in some estimates. That being said, the biggest takeaway from Fig 5 is the lack of evidence in support of the hypothesis that pedestrianization increases traffic flow in surrounding areas. The most plausible explanation for these results is the occurrence of some degree of "traffic evaporation" stemming from drivers' behavioral adaptation.

Several adaptation mechanisms can explain the observed behavior. The simplest one would be that drivers would adapt to the road closure by modifying their route. Provided there is enough road capacity, this would provide alternative routes to drivers without imposing any burden on the network. Given the observed effect magnitudes, and assuming that no other behavioral adaptation is a play, it is likely that the flow is diffused in the network to an ignorable degree. Another hypothesis is that drivers visiting these areas as their final destination (as opposed to through traffic) would choose to visit the area using alternative modes such as transit, a plausible scenario given the high transit accessibility of the three areas (the railway modal share is around 72% in this area). Both of these mechanisms were observed in Seoul, after the Cheonggyecheon stream restoration. Given that these pedestrianization schemes have been conducted regularly for decades (with the notable exception of the COVID-19 pandemic), it is likely that drivers have already adapted to these regular changes in the network.

Table 2. Model estimation results (fixed effects)

Shinjuku	**500m buffer**			**750m buffer**			**1000m buffer**		
Variable	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**
Time	0.348	0.289 - 0.407	<0.01	0.371	0.32 - 0.422	<0.01	0.358	0.315 - 0.401	<0.01
Event	0.055	0.005 - 0.105	0.033	0.052	0.009 - 0.095	0.019	0.06	0.023 - 0.097	0.001
Time x Event	0.009	-0.059 - 0.077	0.8	-0.056	-0.115 - 0.003	0.065	-0.035	-0.085 - 0.015	0.168
R-square	0.22			0.18			0.18		
Akihabara	**500m buffer**			**750m buffer**			**1000m buffer**		
Variable	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**
Time	0.336	0.293 - 0.38	<0.01	0.35	0.315 - 0.386	<0.01	0.356	0.326 - 0.385	<0.01
Event	0.02	-0.017 - 0.057	0.285	0.014	-0.016 - 0.044	0.366	0.032	0.007 - 0.057	0.012
Time x Event	0	-0.055 - 0.055	0.998	0.005	-0.04 - 0.05	0.825	-0.001	-0.038 - 0.036	0.956
R-square	0.16			0.15			0.14		
Ginza	**500m buffer**			**750m buffer**			**1000m buffer**		
Variable	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**
Time	0.038	-0.002 - 0.078	0.064	0.042	0.011 - 0.073	0.008	0.049	0.018 - 0.079	0.002
Event	-0.034	-0.076 - 0.008	0.111	-0.039	-0.071 - -0.007	0.018	-0.037	-0.069 - -0.006	0.02
Time x Event	0.057	-0.002 - 0.116	0.058	0.022	-0.023 - 0.067	0.337	0.018	-0.026 - 0.062	0.431
R-square	0.02			0.01			0.01		

Table 3. Model estimation results (lagged dependent variable)

Shinjuku	**500m buffer**			**750m buffer**			**1000m buffer**		
Variable	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**
Intercept	0.837	0.733 - 0.941	<0.01	0.737	0.636 - 0.839	<0.01	0.801	0.722 - 0.88	<0.01
Time	-0.104	-0.151 - -0.057	<0.01	-0.119	-0.162 - -0.075	<0.01	-0.118	-0.158 - -0.079	<0.01
Event	0.006	-0.036 - 0.047	0.785	-0.002	-0.041 - 0.037	0.931	0.005	-0.03 - 0.04	0.769
Lag of ln(flow)	0.882	0.865 - 0.899	<0.01	0.901	0.885 - 0.918	<0.01	0.89	0.876 - 0.903	<0.01
Time x Event	0.001	-0.052 - 0.055	0.963	-0.017	-0.067 - 0.034	0.516	-0.021	-0.067 - 0.024	0.352
R-square	0.85			0.82			0.83		
Akihabara	**500m buffer**			**750m buffer**			**1000m buffer**		
Variable	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**
Intercept	1.078	0.986 - 1.17	<0.01	1.144	1.072 - 1.216	<0.01	1.148	1.093 - 1.203	<0.01
Time	-0.097	-0.132 - -0.062	<0.01	-0.105	-0.135 - -0.074	<0.01	-0.12	-0.145 - -0.095	<0.01
Event	-0.005	-0.036 - 0.027	0.769	-0.01	-0.037 - 0.017	0.479	-0.007	-0.029 - 0.015	0.52
Lag of ln(flow)	0.836	0.82 - 0.852	<0.01	0.824	0.811 - 0.836	<0.01	0.822	0.812 - 0.831	<0.01
Time x Event	0.012	-0.033 - 0.056	0.608	0.027	-0.011 - 0.064	0.17	0.027	-0.004 - 0.058	0.083
R-square	0.78			0.76			0.77		
Ginza	**500m buffer**			**750m buffer**			**1000m buffer**		
Variable	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**	**Coef.**	**95% C.I.**	**p-value**
Intercept	1.142	1.004 - 1.28	<0.01	1.104	0.997 - 1.211	<0.01	0.902	0.81 - 0.994	<0.01
Time	-0.187	-0.229 - -0.145	<0.01	-0.188	-0.219 - -0.158	<0.01	-0.171	-0.199 - -0.143	<0.01
Event	-0.004	-0.047 - 0.038	0.838	-0.03	-0.061 - 0.001	0.056	-0.025	-0.054 - 0.004	0.086
Lag of ln(flow)	0.835	0.813 - 0.857	<0.01	0.841	0.823 - 0.858	<0.01	0.87	0.855 - 0.886	<0.01
Time x Event	0.055	-0.005 - 0.115	0.075	0.053	0.009 - 0.097	0.017	0.03	-0.011 - 0.07	0.147
R-square	0.81			0.81			0.80		

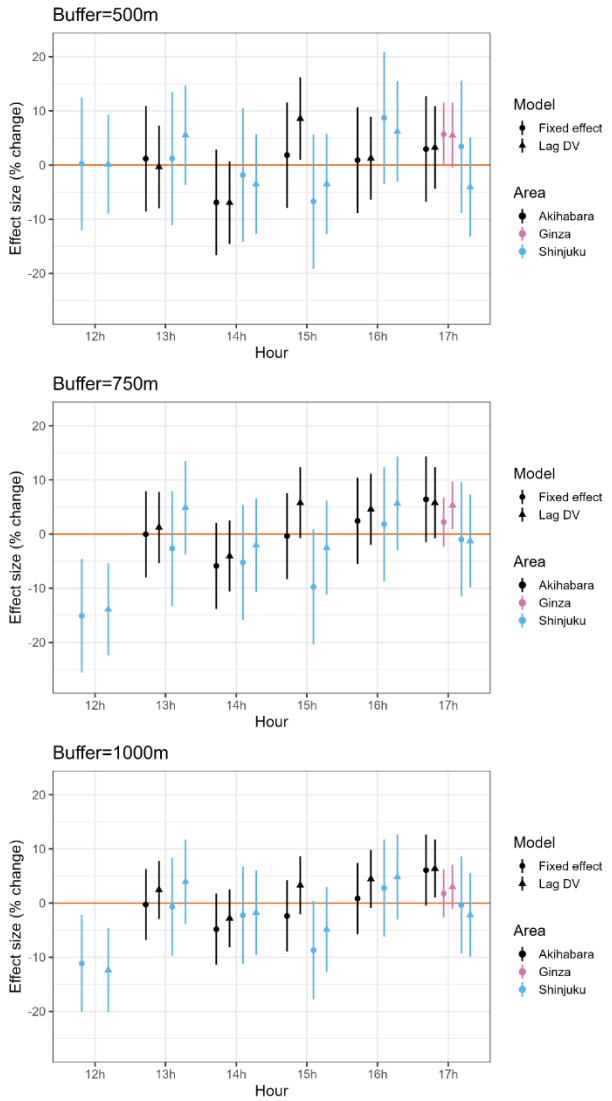


Fig 5. Comparison of effect size across time, areas, and model specifications

An alternative hypothesis would be that drivers visiting these areas as their final destination would choose to cancel the trip altogether or choose a different location, an undesirable outcome from an economic perspective, but a rather unlikely scenario given the high access level by alternative modes. Although the data at hand does not allow us to observe the actual behavioral changes undertaken by drivers, it is likely that the observed results are a mix of different degrees of different types of behavioral adaptation. However, further research is needed to clarify this point.

4. CONCLUSIONS

In this study we used a natural experiment approach to evaluates the causal effect of three regular road pedestrianization schemes in Central Tokyo on traffic conditions in surrounding areas. Model results do not show evidence of severe increases in traffic flow in the surrounding areas of pedestrianized road. It is important to note that all schemes are located in highly central commercial districts in Tokyo, and all pedestrianized links have a certain degree of betweenness centrality. Our results suggest that even in such contexts, pedestrianization can be implemented without severe adverse effects to car traffic. In other words, human-centric network design is not necessarily a zero-sum game between pedestrians and drivers. This study adds another point of quantitative evidence in support of more human-centric network designs.

There are some limitations to our study. First, while we estimated a time-lagged model, our models did not consider spatial dependence among links. Incorporating spatial autocorrelation in our model remains a further task. Second, we did not evaluate congestion effects, however, the fact that traffic flow does not change drastically suggest that congestion is most likely not worsening. Finally, since our study was limited to Sundays, where congestion is less of a concern, these results cannot be generalized to weekday conditions. However, the methodology is directly applicable, provided there is data available. One promising case study is the pedestrianization project of Midōsuji street in Osaka. This project aims to fully pedestrianize a 6-lane arterial road in central Osaka. Since the project is being conducted over different phases, it provides a great opportunity to evaluate effects on traffic flow over time.

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