國立政治大學經濟學系

碩士論文

論雙北公共運輸定期票政策之效果與影響

The Effect and Influence of the Unlimited Monthly Transit Pass Policy in Taipei Metropolitan Area

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摘要

台北都會區於 2018 年 4 月 16 日起實施了公共運輸定期票政策。本研究使用迴歸不連續法，估計此政策對於對於台北捷運系統運輸量在短期的處理效果。此外，我們也討論了這個政策是否能降低私人運輸工具所帶來的外部性。實證結果顯示此政策增加了捷運站的每日平均進出站人數，民眾受到了此政策的鼓勵，更加願意搭乘捷運。然而，並沒有任何統計上的證據表明此政策能在短期減輕交通阻塞與空氣污染。

關鍵字：公共運輸、定期票、外部性

Abstract

A policy of unlimited monthly transit pass was implemented in the Taipei metropolitan area on April 16, 2018. This research uses regression discontinuity design to estimate the short-run treatment effect of the policy on the ridership of the mass rapid transit (MRT) system. In addition, I discuss whether the policy can reduce the externality caused by private vehicles. The results show that the policy increases the average of entries and exits in MRT stations. People are encouraged to take the MRT through the policy. However, there is no evidence that the policy can mitigate traffic congestion and air pollution in the short run.

Keywords: Public Transport; Unlimited Transit Pass; Externalities

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Contents

DOI:10.6814/NCCU202100538

Tables

Figures

DOI:10.6814/NCCU202100538

1. Introduction

Recently, an increasing number of governments noticed that public transportation acts as an essential role in improving the environment of the urban area. Much previous literature shows that public transport can mitigate traffic congestion (Lo and Hall 2006; Anderson 2014; Adler and Ommeren 2016) and air pollution (Chen and Whalley 2012; Sun, Luo, and Li 2018). Taipei metropolitan area, which is composed of Taipei city and New Taipei city, is the largest metropolitan area and the political and economic center of Taiwan. However, it also has a serious problem with traffic congestion and air pollution. The number of registered cars in Taipei city has been increasing every year since 2009; it reaches a peak of 815,569 cars at the end of 2019 (Department of Transportation, Taipei city government 2020). Many cars result in considerable emission of greenhouse gases and traffic congestion in rush hours, which will generate the external costs and reduce the quality of life in urban areas. Thus, Taipei and New Taipei cities' governments try solving this problem. Public transport as a substitute for private automobiles can help decrease the externality caused by the use of private cars. Therefore, the authority of the cities tries encouraging people to take public transit instead of driving private vehicles.

To encourage people to take public transit, the Taipei and New Taipei cities' governments implement the policy of unlimited monthly transit pass in the mass rapid transit (MRT) and the bus system on April 16, 2018. The policy allows people for unlimited monthly use of the MRT and city bus without any fares after paying NT$1,280 for the transit pass. Accordingly, the Taipei city and New Taipei city governments subsidized about NT$917.15 million for this policy during the first ten months. About 182,000 tickets were sold in April 2018, and the number increased to

DOI:10.6814/NCCU202100538

about 220,000 in the following months (方炳超 2019).

The quasi-experiment provided by this exogenous policy shock can help us determine whether the unlimited transit pass will encourage people to take more public transport or not. Furthermore, if the policy increased the number of people using public transport, I also want to know whether traffic congestion and air pollution were mitigated in the urban area. Although the policy allows people for unlimited free use of the MRT and city bus after paying for the transit pass, this research mainly focuses on the treatment effect of the unlimited monthly transit pass policy on people's usage of the MRT system. Namely, the effect of policy on the bus system will not be discussed in this research. Then, it further discusses the influence of the policy on the problem of traffic congestion and air pollution.

The Taipei MRT system is the first and the largest metro system in Taiwan, which operates in the Taipei metropolitan area. Figure 1 shows the route map of the Taipei MRT system in 2018. Five lines are presented: Wenhu (brown) line, Tamsui-Xinyi (red) line, Songshan-Xindian (green) line, Zhonghe-Xinlu (yellow) line, Bannan (blue) line. The figure also shows 108 stations in the Taipei MRT system when the policy was implemented. The MRT system connects the downtown and suburbs, CBD and residential areas; thus, many salaried men commute to their works using the system. However, many people are still driving their private cars to work. After the policy of unlimited monthly transit pass was implemented, the commuting costs declined. The people who drive their private cars may be attracted by the policy and decide to take MRT to work because they can save money. As a result, the Taipei government claimed

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that the policy increased the total volume [1](旅運量) of the Taipei MRT system and encouraged people to take MRT.

Figure 1. The route map of the Taipei MRT system in 2018

Source: Retrieved from https://cloud.taipei/web_mrt_getList on November 3, 2020

Figure 2 shows the volume of the Taipei MRT system in 2017 and 2018. The blue line represents the volume from May 2017 to October 2017 before the policy was implemented. Meanwhile, the red line represents the volume from May 2018 to October

[1] A passenger travels from one station to another station will be counted as one travel volume.

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2018 after the policy was implemented. As shown in Figure 2, the red line is always above the blue line. Apparently, the volumes of these 6 months in 2018 surpass their counterparts in 2017. However, determining whether the policy caused the increase in volume is difficult. In this study, I use a regression discontinuity (RD) design to estimate the treatment effect of the unlimited monthly transit pass policy on people's usage of the MRT system. Besides, I use the same method to estimate the policy's effect on mitigating traffic congestion and air pollution.

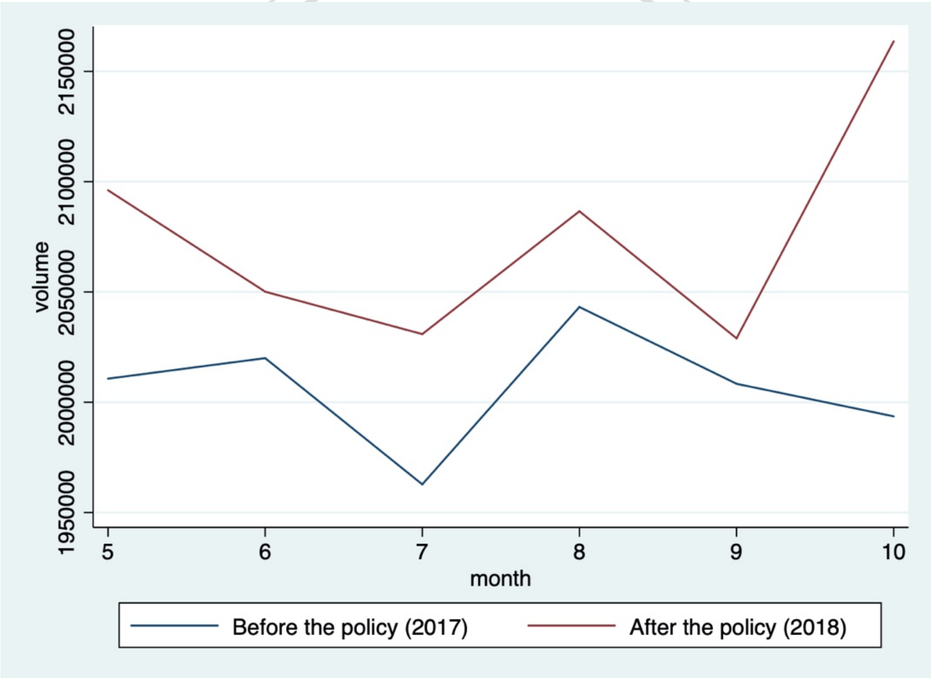

Figure 2. The total volume of the Taipei MRT System in 2017 and 2018

The remainder of this paper is structured as follows. Section 2 reviews the previous literature. Section 3 introduces a theoretical model of the unlimited transit pass. Section 4 illustrates the empirical design. Section 5 presents the estimation results. Section 6 conducts the falsification tests of estimations. Section 7 discusses the influence of the policy on the problem of traffic congestion and air pollution. Section 8 concludes.

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2. Literature Review

This section briefly reviews the literature related to transit pass and public transport. Much literature discussed the economic theory of transit pass. For instance, Carbajo (1988) used the two-part tariff model to explain the non-uniform pricing structure of transit pass. The transit pass can be regarded as a two-part tariff with a positive fixed fee and zero marginal cost. Theoretically, the non-uniform pricing strategy can increase the profit made by the public transport supplier. However, Doxsey (1984) focused on the transit pass's demand side and provided different results. His study showed that people who buy transit pass tend to expect a huge economic gain from the transit pass. This behavior will cause net loss on the part of the public transport supplier. Besides, FitzRoy and Smith (1998) proposed a simple economic model to explain that transit pass will increase public transport ridership and even improve social welfare in a certain condition. A detailed introduction of this model is provided in the next section.

For the effect of transit pass, White (1981) indicated that transit pass has advantages for both public transport's operators and passengers. For operators, the transit pass can improve the cash flow and save operating cost. For passengers, the transit pass increases convenience. Habib and Hasnine (2019) also found that transit pass is a mobility tool and provides extra utility by owning it. Meanwhile, Brown, Hess, and Shoup (2001) studied the transit pass offered by universities. The empirical results showed that transit passes can help reduce the parking demand on campus, decrease transit operating costs, and increase transit ridership. Besides, the transit pass can also be a substitute for automobiles. Scott and Axhausen (2006) used bivariate ordered probit models to show a strong substitution effect between transit pass and car use. Moreover, Thøgersen

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(2009) showed that people's choice between public transport and private vehicles could be altered. A free month transit pass was given away randomly to some car owners in Copenhagen. The results show that people who received free transit pass still commute by public transport several months after the free transit pass expired, which means that the promotion of transit pass encourages people to take public transport. Although much previous literature related to transit pass exists, none of them use a quasi-experimental design to estimate the treatment effect of transit pass policy like this research.

Public transport is commonly recognized as an efficient way to reduce the external costs generated by private car use, especially for mitigating traffic congestion and air pollution. Lo and Hall (2006), Anderson (2014), and Adler and Ommeren (2016) found that the problem of traffic congestion becomes dreadful when public transport is on strike. In terms of the air pollution problem, Sun, Luo, and Li (2018) used a dynamic panel data model to conduct the empirical study. The results illustrate improvement of the air quality after urban traffic infrastructures are invested in several cities in China. Moreover, Chen and Whalley (2012) showed that air pollution was reduced after the Taipei MRT system opened. However, public transport compared with private vehicles still has some disadvantages. Ellaway, Macintyre, Hiscock, and Kearns (2003) used survey data to show that people can gain many psychological benefits such as self-esteem from car access compared to public transit. The advantages and disadvantages of public transport are still in debate.

DOI:10.6814/NCCU202100538

3. Theoretical Model

FitzRoy and Smith (1998) proposed a simple model to explain the effect of unlimited transit pass on public transport ridership. They assumed that the total travel distance per period measured by kilometers (K) can be completed by driving a private vehicle (V) and taking public transport (P):

$$V + P = K \tag{1}$$

The total income (I) can be spent on transport and other expenditures (E). C_V and C_P represent the costs per km by driving a private vehicle and taking public transport, respectively. Therefore, the budget constraint can be written as

$$C_V V + C_P P + E = I \tag{2}$$

They further assumed a quasi-linear utility function. The total utility equals the expenditure of other goods minus the time cost and discomfort in transport. t_V denotes the money-equivalent constant marginal time cost per km caused by private vehicles. D(P) is an increasing and strictly convex disutility function that contains the money-equivalent time costs and any inconvenience by taking public transport. The utility function can be written as

$$U = E - t_V V - D(P) \tag{3}$$

DOI:10.6814/NCCU202100538

To choose an optimal level of public transport, we can write the maximization problem as

$$Max \quad U = E - t_V V - D(P)$$

$$s.t. \qquad C_V V + C_P P + E = I$$

$$V + P = K$$

After substituting the constraints, equations (1) and (2), into the objective function equation (3), the maximization problem becomes

$$Max \quad U = I - C_V(K - P) - C_p P - t_V(K - P) - D(P)$$

The first-order condition: $\frac{dU}{dP} = 0$ can derive the following equation:

$$\frac{dD(P)}{dP} = C_V + t_V - C_p \tag{4}$$

The economic implication of the first-order condition given by equation (4) is that the difference in the total marginal cost between car use and public transport should be the same as the marginal disutility by taking public transport. If the functional form of $D(P)$ is known, the optimal demand for public transport $P^*(C_p)$ can be solved. In practice, linear and exponential disutility functions are mostly used in transportation (Cheu and Kreinovich 2007). The D(P) is increasing and strictly convex in this model; therefore, we can assume that D(P) is a risk-averse exponential disutility function:

$$D(P) = a\exp(cP) + b \tag{5}$$

DOI:10.6814/NCCU202100538

Then, the derivative of the disutility function D(P) becomes

$$\frac{dD(P)}{dP} = ac\exp(cP) \tag{6}$$

In Figure 3, the blue line plots equation (6), and the purple line plots $C_V + t_V - C_p$. By finding the intersection of the blue line and the purple line, we can solve the optimal demand of public transport: $P^*(C_p)$. After determining the $P^*(C_p)$, the revenue can be calculated. The optimal revenue generated from public transport is

$$R^* = C_p\, P^*(C_p) \tag{7}$$

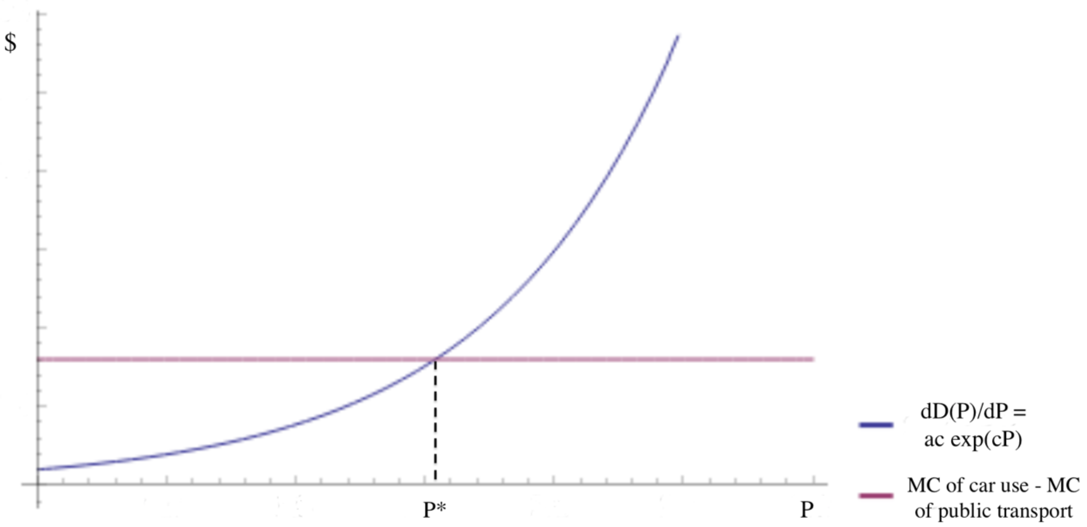

Figure 3. The solution of the first-order condition

The unlimited transit pass or season ticket allows people to take public transport for free after paying a lump sum fee for the ticket. In other words, people who buy the ticket can take public transport at zero marginal cost (Sherman, 1967). According to the law of demand, $P(0)$ is greater than $P(C_p)$ for all $C_p > 0$. If the season ticket is

DOI:10.6814/NCCU202100538

priced at R^* in equation (7), the demand for public transport will increase from $P^*(C_p)$ to $P^*(0)$, and the supplier can still earn the optimal revenue R^*. Besides, if public transport does not incur extra supply cost, social welfare is improved.

4. Empirical Design

The Taipei city and New Taipei city's government implemented an unlimited monthly transit pass policy in the MRT and the bus system on April 16, 2018. To know the effect of this policy on people's usage of the MRT system, I conduct a regression discontinuity (RD) estimation with the date as the running variable and April 16 as the cutoff. This research follows Auffhammer and Kellogg (2011), Chen and Whalley (2012), Bento, Kaffine, Roth and, Zaragoza-Watkins (2014), and Anderson (2014), using time as a running variable to do the RD estimation.

Recently, an increasing number of researchers use time as a running variable for the RD estimation, especially in Environmental Economics and Transport Economics. Such RD design is also known as regression discontinuity in time (RDit). Unlike traditional cross-sectional RD design, RDit design assumes that many observable/unobservable time-varying confounders are continuous or remain unchanged around the cutoff. The widely cited studies using RDit design have the following features (Hausman and Rapson 2018): (a) They open a relatively short time window (bandwidth) around the cutoff; hence, the assumption that many time-varying confounders are continuous or remain unchanged around the cutoff may have higher chance to be satisfied. (b) They use high-frequency data such as hourly data or daily data to obtain sufficient observations in the relatively short time windows. (c) They use panel data instead of single time series data. (d) They control for the day-of-week effect

DOI:10.6814/NCCU202100538

and other potential time-varying covariates such as weather and other policy changes.

Hausman and Rapson (2018) also indicated that RDit design may have some potential bias. The first potential bias is the time-varying treatment effect. If we open a short time window for the RDit estimation, the estimated treatment effect is the short-run effect. The treatment effect may change over time. In other words, the long-run effect may be different from the short-run effect. Because of this problem, some studies assume that the treatment effect remains constant. The other studies conducted the difference in differences (DID) estimation to test the possibility of time-varying treatment effect if the cross-sectional control group is available. The second potential bias is the autoregression problem. We may face some serially correlated problems because the running variable is time. Most RDit literature used clustered standard errors to solve this problem.

4.1 Regression Discontinuity Model

This research follows the RD estimation guideline proposed by Imbens and Lemieux (2008). Moreover, I consider the features of widely cited RDit literature and the potential bias problems of the RDit. The continuity assumption of RD or RDit design posits that observations on the left side of the cutoff are similar to observations on the right side except for the treatment assignment. In this research, I use nonparametric RD strategies to conduct a local linear estimation to estimate the treatment effect of the unlimited monthly transit pass policy. The estimation equation is demonstrated as follows:

DOI:10.6814/NCCU202100538

$$y_{it} = \beta_0 + \beta_1 policy_{it} + \beta_2 date_{it} + \beta_3 policy_{it} \times date_{it} + \beta_4 X_{it} + \varepsilon_{it}$$

In this equation, outcome y_{it} is the average entries and exits of each MRT station. Meanwhile, the variable $policy_{it}$ denotes whether the policy is implemented or not. The running variable $date_{it}$ is centered at the cutoff, which means the variable $date_{it}$ should be zero on April 16. The controls X_{it} include the day-of-week indicator, holiday indicator,[2] MRT station fixed effect, and the rainfall.

In terms of the control variables X_{it}, I control for the day-of-week effect and holiday effect just like the previous literature. I also control for an important covariate: rainfall. In this local linear specification with a short time window, many key factors that can influence MRT ridership, such as population, income, and car ownership (Taylor and Fink 2009), remain unchanged or do not change abruptly. However, the weather is volatile, and it may change abruptly to influence MRT ridership. Arana, Cabezudo, and Peñalba (2014) found that rain will decrease the number of trips served by public transport. Meanwhile, Najafabadi, Hamidi, Allahviranloo, and Devineni (2019) found a negative relationship between rainfall and daily MRT ridership in Manhattan. Therefore, I control for rainfall. Another potential covariate that may change abruptly is the gasoline price. I thought about controlling for it, but whether gasoline price will influence MRT ridership is controversial. McLeod, Flannelly, Flannelly, and Behnke (1991) showed no statistically significant relationship between gasoline price and transit ridership, whereas Chen, Varley, and Chen (2011) found that the rise in gasoline price has a significant influence on transit ridership. All the existing literature focused on transit ridership, but not purely on MRT ridership. Besides, the

[2] The national holidays in the time window of this research include Tomb Sweeping Day and Labor Day.

DOI:10.6814/NCCU202100538

retail gasoline price in Taiwan did not change at the cutoff. In the end, I decide not to control for gasoline price.

Choosing the bandwidth in RDit design is complicated. If we choose a larger bandwidth, we will use several observations far away from the date that treatment happened. Consequently, the potential time-varying confounders may change significantly or abruptly, which will violate the basic assumption of RDit. Several previous studies have conducted the local linear RDit estimation with daily data using about 30 days on each side of the cutoff as the bandwidth. For instance, Anderson (2014) used 28 days and Bento et al. (2014) used 30 days. Thus, I follow them to use the bandwidth of 30 days on each side of the cutoff. Besides, I specify the rectangular kernel in this local linear estimation, which means every observation in the bandwidth receives the same weight. Finally, to solve the serially correlated problem within day and station, I use the two-way clustering method (Cameron, Gelbach, and Miller 2011) to adjust the standard errors. All the standard errors are double clustered at the dimensions of day and station.

4.2 Data

This part introduces the data source of variables and how I construct them by the original data. The descriptive statistics of the variables are presented in Table 1.

The outcome variable y_{it} is the average of entries and exits in each MRT station, representing people's usage of MRT. The data of the entries and exits in each MRT station can be extracted from the website of Taipei MRT company.[3] The Taipei MRT

[3] The data are acquired on https://www.metro.taipei/cp.aspx?n=FF31501BEBDD0136

DOI:10.6814/NCCU202100538

system has 108 stations. I take the average number of entries and exits in each station every day to construct y_{it}. The data are from March 17, 2018, to May 16, 2018, because I use a bandwidth of 30 days on each side of the cutoff.

Table 1. Descriptive statistics

	Mean	*SD*	*Max*	*Min*	*Frequency*	*percent*
Average entries and exits	19161.3	18172.3	186537	1454.5	-	-
Rainfall	1.73	5.27	59.5	0	-	-
Holiday	-	-	1	0	648	9.84%
Day-of-week indicator						
Monday	-	-	-	-	972	14.75%
Tuesday	-	-	-	-	972	14.75%
Wednesday	-	-	-	-	972	14.75%
Thursday	-	-	-	-	864	13.11%
Friday	-	-	-	-	864	13.11%
Saturday	-	-	-	-	972	14.75%
Sunday	-	-	-	-	972	14.75%

Note: SD = Standard deviation. Total observations = 6588

One of the control variables is rainfall, which represents the precipitation observed by the weather station near each MRT station. The rainfall (precipitation) is measured in millimeter. I obtain the precipitation data from the observation data inquiry system of Central Weather Bureau (Taiwan)[4]. The Taipei metropolitan area has several weather stations. For each MRT station, I use the precipitation observed by the weather station that has the shortest distance to each MRT station, except for those weather stations in the mountain area or those that lack data. The following are the 14 weather stations that

[4] The data are acquired on https://e-service.cwb.gov.tw/HistoryDataQuery/index.jsp

DOI:10.6814/NCCU202100538

provided precipitation data used to construct the variable rainfall: Wenshan (文山), Songshan (松山), Xinyi (信義), Neihu (內湖), Shihlin (士林), Shezih (社子), Taipei (台北), Banqiao (板橋), Tucheng (土城), Xinzhuang(新莊), Lujhou (蘆洲), Zhonghe (中和), Yonghe (永和), and Tamsui(淡水). Again, the data are from March 17, 2018, to May 16, 2018.

5. Estimation Results

5.1 RD estimation results

In this specification, the RD estimates, which is the coefficient of $policy_{it}$, represent the average treatment effect of unlimited monthly transit pass policy on the outcome variable: the average entries and exits of MRT stations at the date of the cutoff. The short time window is opened in the local linear estimation; thus, the estimated treatment effect is a short-run effect.

Figure 4 plots the outcome variable, the average of entries and exits in MRT stations, across the timeline in the bandwidth of local linear estimation. To see the pure effect caused by the policy, I plot the residuals from the regression of outcome variable on control variables instead of plotting the raw data. From the graphical evidence provided by Figure 4, the observations jump up at the cutoff, which means that the average number of entries and exits in MRT stations increased after the policy was implemented.

DOI:10.6814/NCCU202100538

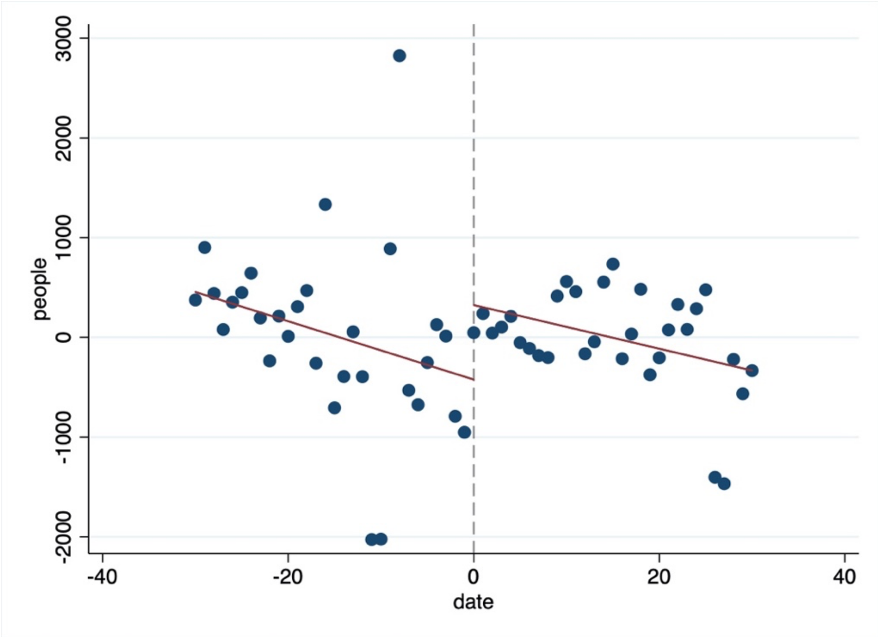

Figure 4. The average of entries and exits (Taipei MRT), 3/17/2018 to 5/16/2018

Table 2. The effect of policy on the average of entries and exits

	Local linear RD estimation	
	Mean	*Clustered standard error*
Policy	850.033***	(158.889)
Date	-35.932***	(7.304)
Policy x date	16.072*	(9.394)
Holiday	-3826.216***	(187.525)
Rainfall	-17.479**	(8.049)
Baseline mean	18833.6	
Observations	6588	

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
Standard errors are double clustered at the dimensions of day and MRT station.

Table 2 present the estimation result. The average number of entries and exits in MRT stations increased by about 850 people after the policy was implemented. This result indicates that the policy of unlimited monthly transit pass encouraged people to

DOI:10.6814/NCCU202100538

take MRT. The result is statistically significant and identical to the result in the theoretical model. Besides, the control variable rainfall negatively affects the outcome variable, which is similar to the results in previous studies. The estimation result corresponds to the graphical evidence provided in Figure 4.

5.2 Subgroup Analysis

In this part, the RD results of the different subgroups are estimated. First, I divide the sample set into observations of Taipei city and observations of New Taipei city. Taipei city is often considered the Taipei metropolitan area center and is surrounded by the outer New Taipei city. By dividing the samples into two groups, we can estimate the effect of the policy on downtown and suburban area. The estimation results in Table 3 show that the entries and exits of MRT stations all increased significantly in Taipei city and new Taipei city. However, the increase in entries or exits in Taipei city's MRT stations is greater than the increase in New Taipei city's MRT stations. This result shows that the increase in entries and exits of MRT stations in the downtown area is more pronounced than that in suburban areas after the policy implementation.

Second, I divide the sample set into observations of different MRT lines. The Taipei MRT system has five MRT lines when the policy was implemented. The brown, blue, red, orange, and green lines have 24, 23, 29, 26, and 20 stations, respectively. To determine the effect of the policy on each MRT line, I run five separate regressions with observations in different MRT line. In other words, when estimating the effect of the policy on the brown line, only observations of the stations in the brown line are used. Table 4 presents the estimation result.

DOI:10.6814/NCCU202100538

Table 3. RD estimation results: Taipei city and New Taipei city

	Taipei city		New Taipei city	
	Entries	Exits	Entries	Exits
Policy	884.499***	875.616***	778.938***	804.045***
	(214.990)	(232.624)	(159.198)	(159.311)
Date	-39.013***	-39.045***	-29.104***	-29.396***
	(9.940)	(10.527)	(7.477)	(7.667)
Policy x date	17.330	16.965	12.825	14.050
	(12.755)	(13.719)	(9.607)	(9.692)
Holiday	-4202.992***	-4260.360***	-3046.977***	-2922.662***
	(267.393)	(259.076)	(227.394)	(232.603)
Rainfall	-22.876*	-26.511**	-10.429	-2.296
	(11.740)	(12.814)	(8.854)	(8.773)
Baseline mean	20301.8	20390.5	15571.3	15586.2
Observations	4453	4453	2135	2135

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Two-way clustered standard errors in parentheses.

Table 4. RD estimation results: different MRT lines

	Brown	Blue	Red	Orange	Green
Policy	389.604	1388.954***	1359.321***	685.545***	1015.598**
	(299.364)	(531.332)	(424.329)	(220.061)	(460.104)
Date	-15.879	-60.823**	-68.349***	-25.471***	-35.763*
	(13.136)	(24.198)	(19.992)	(9.851)	(20.653)
Policy x date	1.866	36.027	42.355	7.293	5.297
	(17.121)	(31.297)	(25.904)	(12.811)	(26.198)
Holiday	-3769.848***	-4613.930***	-2835.749***	-4570.806***	-5577.773***
	(437.638)	(507.826)	(424.811)	(334.893)	(544.778)
Rainfall	-15.553	-23.453	-49.035*	-2.721	-18.459
	(14.103)	(32.744)	(25.081)	(7.871)	(16.211)
Baseline mean	12157.3	32778.7	24059.1	16359.5	22639.5
Observations	1464	1403	1708	1586	1220

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Two-way clustered standard errors in parentheses

DOI:10.6814/NCCU202100538

In Table 4, each column shows the results of different MRT lines. The results demonstrate that the blue, red, orange, and green lines show a statistically significant increase in the average number of entries and exits after the policy was implemented. However, the brown line estimation is small and statistically insignificant, implying no evidence of the policy's influence on the brown line. The brown line is noticeably the only MRT line where all the MRT stations are in Taipei city. All the other four MRT lines pass through Taipei city and New Taipei city. Hence, the impact of the policy on the four MRT lines but not on the brown line is probably due to people's behavior on using the unlimited monthly transit pass. If several people buy the unlimited monthly transit pass for commuting between Taipei city and New Taipei city, the average of entries and exits will increase significantly on the MRT lines, which pass through both cities. Meanwhile, for the brown line, the MRT line only passes through the Taipei city; hence, it received a tiny impact of the policy. Besides, the policy not only allows people for unlimited free use of the MRT but also the city bus. If people who buy the unlimited monthly transit pass need to take the brown line of the MRT to someplace, he or she can take city bus instead. This phenomenon may be another potential reason that the brown line estimation is statistically insignificant.

5.3 Sorting behavior and donut RD estimation

In RD design, people may have incentives to manipulate the running variable, which can help them obtain their desired outcome. Such behavior is called sorting behavior. In a cross-sectional RD, density test (McCrary 2008) can be used to test whether sorting behavior exists or not. If the density distribution of the running variable discontinues at the cutoff, the problem of sorting behavior might exist. In RDit design, the running variable is time. If the number of observations is identical in every time

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unit, the density test cannot be implemented. However, the RDit design may still have the problem of sorting behavior at the cutoff. In this research, the observations in each time unit are identical, so the sorting behavior is untestable by density test. Furthermore, people cannot manipulate the date the policy was implemented. The sorting behavior may not happen in this research. Although the sorting behaviors do not exist in this research, the other effect may still influence the observations close to the cutoff. For instance, people might know that the policy will be implemented, but they did not know or forgot the date of the policy's first implementation. Some people might go to MRT stations on the date before the policy was implemented and found that they could not use the unlimited transit pass, but they still chose to buy a one-way ticket to take the MRT. The other people did not know the policy until it was implemented a few days, so they did not use the unlimited transit pass in the first few days. Such situations also influence the RD estimation results when we use the observations close to the cutoff.

The RD estimation results may be sensitive to the choice of bandwidth. When using excessive small bandwidth, the observations close to the cutoff account for a large proportion of observations in the estimation. Table 5 presents the RD estimation results using 10 days, 20 days, and 30 days on each side of the cutoff as the bandwidth. As shown in Table 5, the policy has statistically significant effects on the average entries and exits of MRT stations when the bandwidth is 20 days or 30 days on each side of the cutoff. However, when it comes to 10 days, several observations close to cutoff are used in the estimation, then the effect becomes minimal and not statistically significant. This phenomenon is probably caused by the situations mentioned in the previous paragraph.

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Table 5. RD estimation results: different bandwidths

	10 days	20 days	30 days
Policy	42.458	709.397***	850.033***
	(473.388)	(196.551)	(158.889)
Date	119.880	-34.003**	-35.932***
	(89.514)	(11.604)	(7.304)
Policy x date	-132.631	28.161*	16.072*
	(91.441)	(16.414)	(9.394)
Holiday	-2228.413***	-3866.247***	-3826.216***
	(600.462)	(183.89)	(187.525)
Rainfall	-39.821***	-23.463**	-17.479**
	(10.598)	(9.758)	(8.049)
Baseline mean	18074.7	18451.3	18833.6
Observations	2268	4428	6588

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
Two-way clustered standard errors in parentheses.

Although the sorting behavior may not exist, Hausman and Rapson (2018) still suggested conducting a donut RD estimation (Barreca, Guldi, Lindo, and Waddell 2011) in RDit design. The donut RD estimation drops the observations which are close to the cutoff and creates a 'donut hole' when doing the estimation. After dropping the observations which are extremely close to the cutoff, the estimation results are not seriously affected by sorting behaviors or other effects around the cutoff. In this research, I conduct a donut RD estimation as well. I drop the observations that occurred five days before and after policy implementation to estimate the policy's effect. By conducting the donut RD estimation, we can determine the effect of the policy after considering the complicated effects around the cutoff. Besides, conducting a donut RD estimation can also prevent the potential sorting problem even though the problem may not exist in this research.

DOI:10.6814/NCCU202100538

Table 6 presents the donut RD estimation results, the policy's effect on the average of entries and exits in MRT stations increased to about 1,114 people. The effect is larger than the previous normal RD estimation. Figure 5 also shows a larger discontinuity of outcome when the observations near the cutoff are removed.

Table 6. Donut RD estimation results

	Donut RD estimation	
	Mean	*Clustered standard error*
Policy	1114.304***	(263.1787)
Date	-37.673***	(10.615)
Policy x date	7.805	(13.567)
Holiday	-3803.873***	(190.154)
Rainfall	-20.378*	(11.772)
Baseline mean	18739.8	
Observations	5400	

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are double clustered at the dimensions of day and MRT station.

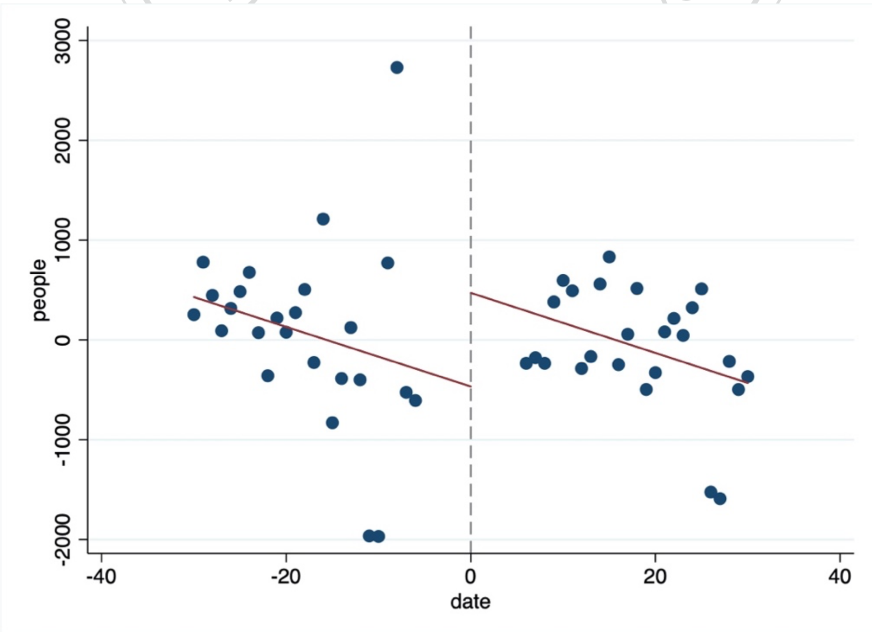

Figure 5. The average of entries and exits (Donut hole), 3/17/2018 to 5/16/2018

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6. Falsification Test

The continuity assumption is one of the most important identification in RD design. The continuity assumption assumed that the potential confounders do not change abruptly around the cutoff. In this research, if the continuity assumption is valid, the values of $E[\varepsilon_{it}|date_{it}]$ should be continuous at the left side and right of the cutoff. Nevertheless, determining whether the continuity assumption is satisfied is difficult because of several unobservable confounders. In practice, some feasible falsification tests still exist. Here, I conduct two falsification tests to check the robustness of the estimation in the previous section. One is balance test, the other is placebo cutoff.

6.1 Balance test

Due to the continuity assumption in RD design, the covariates should be balanced on both sides of the cutoff. In other words, the covariates should not jump at the cutoff. If the covariates jump at the cutoff, the jump of the outcome variable at the cutoff is caused by the covariates. In this research, I conduct a balance test using the only covariate rainfall. I run the same local linear regression as done in the previous section, but I replace the outcome variable with rainfall and control for weather station fixed effects to estimate whether rainfall will jump at the cutoff.

Table 7 presents the estimation results. The first row shows that the coefficient of the policy is not statistically significant, which means that the covariate rainfall does not jump at the cutoff. As a result, the increase in average entries and exits is not caused by the covariate rainfall. Figure 6 plots the residuals from the regression of rainfall on weather station fixed effect. The graph also shows that the rainfall smoothly changed

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across the cutoff providing the same result as the balance test.

Table 7. Balance test

	Local linear RD estimation	
	Mean	*Clustered standard error*
Policy	-0.271	(0.288)
Date	0.127***	(0.011)
Policy x date	-0.199***	(0.015)

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
Standard errors are double clustered at the dimensions of day and weather station.

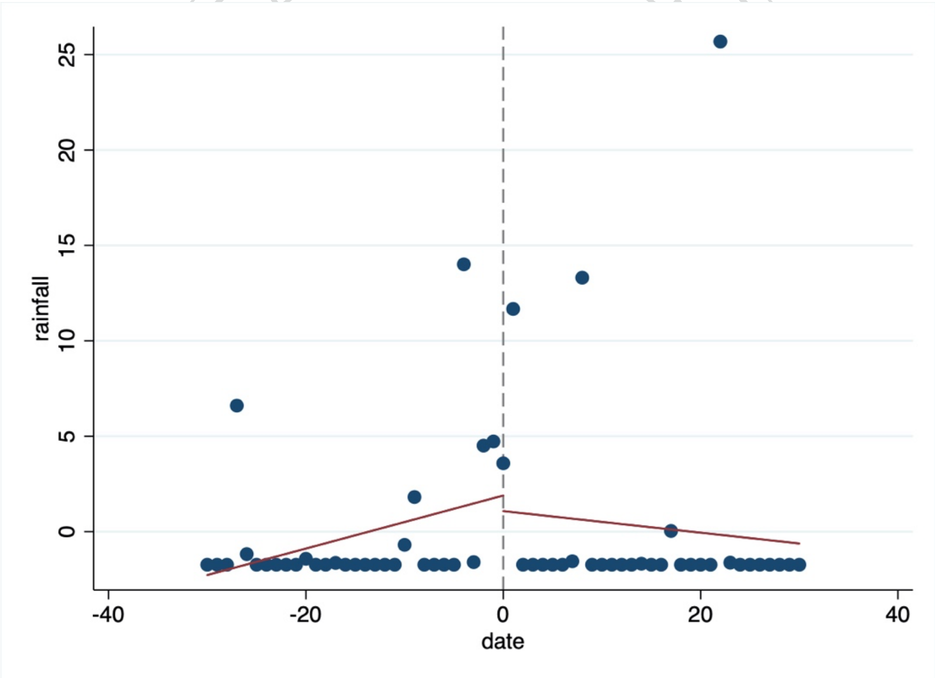

Figure 6. Rainfall (balance test), 3/17/2017 to 5/16/2017

6.2 Placebo cutoffs

Another common falsification test in RD design is the placebo cutoff. An artificial cutoff where treatment does not happen is created to test the existence of the treatment

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effect. The expected result is the absence of statistically significant treatment effect when using the placebo cutoff. Following Anderson (2014), I conduct two placebo tests. First, I create an artificial cutoff on April 16, 2017, one year before the policy was implemented in the Taipei metropolitan area. I run the same local linear regression as I do in the previous section but using the 2017 data. Second, I create an artificial cutoff on April 16, 2018 in Kaohsiung city. Kaohsiung is a city in southern Taiwan that also has an MRT system in operation but did not implement the unlimited monthly transit pass policy. The entries and exits data of each MRT station are not available in the Kaohsiung MRT system, so I use total volume as an outcome variable and use single time-series data to do the local linear RD estimation. As for the control variable rainfall in this estimation, I use the precipitation observed by the Kaohsiung weather station.

Table 8 presents the estimation result. The first column demonstrates the estimation results of the Taipei MRT system using April 16, 2017 as the cutoff and the second column demonstrates the estimation results of the Kaohsiung MRT system using April 16, 2018 as the cutoff. The estimated treatment effects at two placebo cutoffs are both statistically insignificant.

Figures 7 and 8 plot the residuals from the regression of outcome variable on control variables. Figure 7 shows that the average of entries and exits did not jump up in Taipei MRT system when using April 16, 2017 as the cutoff. Figure 8 also shows that the total volume did not change abruptly at the cutoff on April 16, 2018 in Kaohsiung MRT system. The strong graphical evidence provided by Figures 7 and 8 shows the same results as the placebo tests.

DOI:10.6814/NCCU202100538

Table 8. RD estimation results: placebo cutoffs

	2017 Taipei	2018 Kaohsiung
Policy	62.837	3639.531
	(161.251)	(9327.572)
Date	-8.222	-270.963
	(6.739)	(200.455)
Policy x date	-5.757	227.532
	(9.104)	(276.582)
Holiday	-2753.377***	35018.71**
	(216.221)	(15613.29)
Rainfall	-0.690	-322.774
	(3.879)	(488.364)
Baseline mean	19121.2	176345
Observations	6588	61

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Two-way clustered standard errors in parentheses.

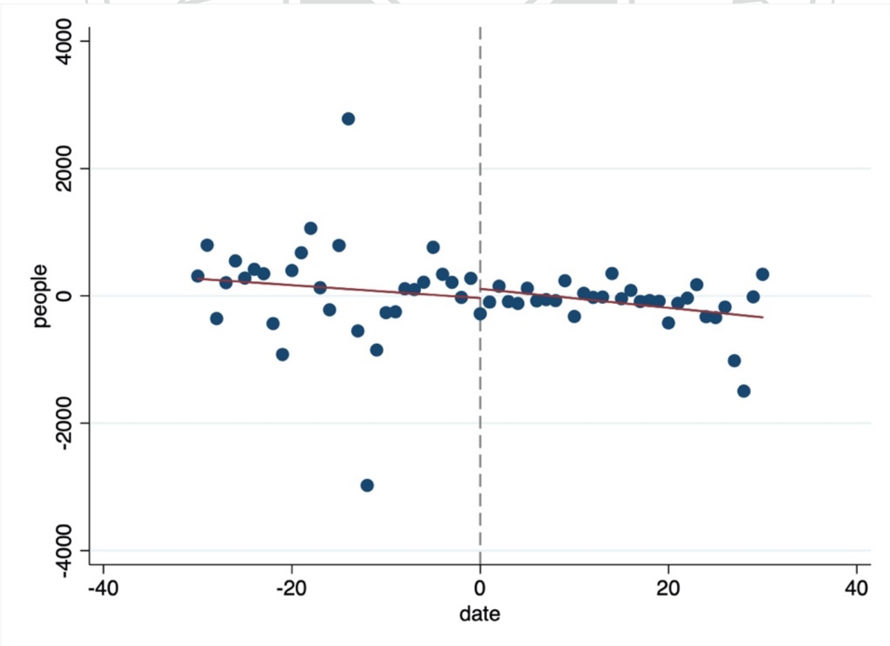

Figure 7. The average of entries and exits (Taipei MRT), 3/17/2017 to 5/16/2017

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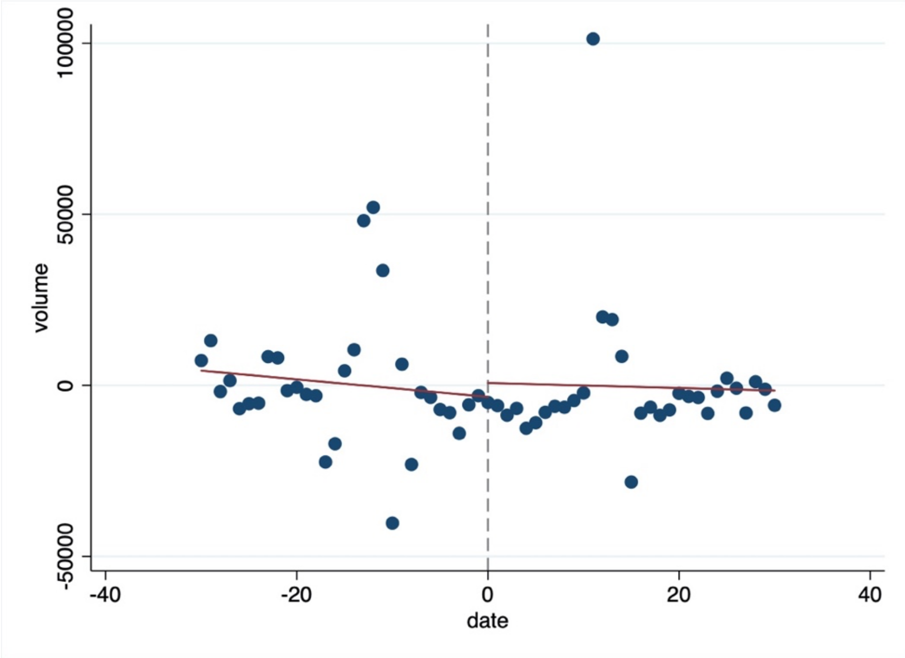

Figure 8. Total volume (Kaohsiung MRT), 3/17/2018 to 5/16/2018

7. Discussion about Externality

This section discusses whether the policy of unlimited monthly transit pass can decrease the external costs caused by private car use. I conduct a regression discontinuity (RD) design with date as the running variable and April 16 as the cutoff to estimate the effect of the policy on the outcome variables: the traffic flow on highway and the air quality index. By doing so, we can know whether the policy can mitigate the problem of traffic congestion and air pollution.

7.1 Traffic congestion

In this part, I focus on the effect of the policy on traffic congestion. The result in Section 5 demonstrates that the policy increases the ridership of Taipei MRT. The transit passes can be thought of as a substitute for private cars (Scott and Axhausen 2006);

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hence, traffic flows on the road are expected to decrease. National freeway 1 and national freeway 3 are the two main freeways that pass through the Taipei metropolitan area. The people who dwell on the outer New Taipei city usually use these two freeways to drive to the center of the metropolitan area, Taipei city. If the policy can mitigate the problem of traffic congestion, the traffic flow on highways will decrease.

The two freeways have many detectors that capture the car flow on freeways every five minutes. I collect the data of car flow observed by detectors from the database of Freeway Bureau, Ministry of Transportation and Communications (Taiwan)[5]. The observations of the two detectors are used in this research. One detector lies between the Taipei (台北) interchange and the Yuanshan (圓山) interchange on national freeway 1. The other detector lies between the Wanfang (萬芳) interchange and the Taipei (台北) interchange on national freeway 3. The number of cars observed by the detectors every five minutes are added up from 7:30 a.m. to 8:30 a.m. to create the outcome variable which represents the car flow in the morning rush hours. I do a local linear estimation of RD design to estimate the treatment effect of the policy on the car flow of highways in morning rush hours. The estimation equation is demonstrated below:

$$Car\ flow_{it} = \beta_0 + \beta_1 policy_{it} + \beta_2 date_{it} + \beta_3 policy_{it} \times date_{it} + \beta_4 X_{it} + \varepsilon_{it}$$

In this equation, the outcome $Car\ flow_{it}$ is the observed car flow from 7:30 a.m. to 8:30 a.m. in each detector. The variable $policy_{it}$ is whether the policy was implemented or not. The running variable $date_{it}$ is centered at the cutoff, which

[5] The data are acquired on https://tisvcloud.freeway.gov.tw/

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means the variable $date_{it}$ should be zero on April 16. The controls X_{it} include the day-of-week indicator, 95 unleaded gasoline price and, detector fixed effect. I focus on the car flow in morning rush hours, and thus, I only use the observations of weekdays. Moreover, I use the bandwidth of 30 weekdays on each side of the cutoff. All the standard errors are double clustered at the dimensions of day and detector in this estimation.

Table 9 presents the estimated short-run results in this part. Although the coefficient of the variable $policy_{it}$ is negative, it is statistically insignificant. There is no evidence that the policy of unlimited monthly transit pass can decrease the car flow on freeways and solve traffic congestion in morning rush hours.

Table 9. The effect of policy on traffic congestion

	Local linear RD estimation	
	Mean	*Clustered standard error*
Policy	-8.024	(59.937)
Date	-4.189	(2.709)
Policy x date	-2.496	(3.809)
Oil price	63.055	(78.641)
Baseline mean	3680.3	
Observations	122	

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
Two-way clustered standard errors in parentheses.

7.2 Air pollution

Here, I discuss the effect of the policy on air pollution. The estimation results reported in Section 5 illustrate that the unlimited monthly transit pass policy encourages

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people to take the MRT. If an increasing number of people take the MRT instead of driving their cars, the air quality in the city will be improved. Air quality index, which can also be abbreviated as AQI, is an index used by government agencies for measuring air quality. The AQI is evaluated by the concentration of sulfur dioxide, nitrogen dioxide, ozone, carbon monoxide, PM 2.5, and PM 10. The higher the value of AQI, the more serious the problem of air pollution. I use the AQI as the outcome variable to determine whether the air quality is improved after the policy was implemented. The data of AQI are acquired from the environmental resource database of the Environmental Protection Administration (Taiwan)[6]. Taipei city has the following five air quality observation stations: Daan (大安) station, Zhongshan (中山) station, Shillin (士林) station, Songshan (松山) station, and Wanhua (萬華) station. I collect the observations of all five air quality observation stations constructing panel data from March 16, 2018 to May 16, 2018. Afterward, I do a local linear estimation of RD design to estimate the treatment effect of the policy on the air quality in Taipei city. The estimation equation is demonstrated below:

$$AQI_{it} = \beta_0 + \beta_1 policy_{it} + \beta_2 date_{it} + \beta_3 policy_{it} \times date_{it} + \beta_4 X_{it} + \varepsilon_{it}$$

In this equation, the outcome AQI_{it} is the air quality index observed by the air quality observation stations. The variable $policy_{it}$ is whether the policy was implemented or not. The running variable $date_{it}$ is centered at the cutoff, which means the variable $date_{it}$ should be zero on April 16. The controls X_{it} include the day-of-week indicator, holiday indicator, station fixed effect, and other factors that can

[6] The data are acquired on https://erdb.epa.gov.tw/FileDownload/FileDownload.aspx

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influence the air quality: wind speed and relative humidity[7]. I use the bandwidth of 30 days on each side of the cutoff. In the bandwidth, no data for March 29 are available; hence, I extend the left border for one day to keep the 30 observations on the left side of the cutoff. The observations from March 16, 2018 to May 16, 2018 are used for this estimation. All the standard errors are double clustered at the dimensions of day and detector in this estimation.

Table 10 presents the estimation results in the short run. The coefficient of variable $policy_{it}$ is the treatment effect of the policy on air quality, which is statistically insignificant. There is no evidence that the policy can improve air quality and mitigate air pollution caused by private vehicles.

Table 10. The effect of policy on air pollution

	Local linear RD estimation	
	Mean	*Clustered standard error*
Policy	-3.241	(5.227)
Date	0.722***	(0.201)
Policy x date	-0.704***	(0.262)
Wind speed	-12.988***	(2.215)
Relative humidity	-0.610***	(0.171)
Baseline mean	65.98	
Observations	305	

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
Two-way clustered standard errors in parentheses.

[7] Li, Qian, Ou, Zhou, Guo, and Guo (2014) indicated that wind speed and relative humidity will influence air quality.

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8. Conclusion

This research sheds light on how unlimited transit pass influences the ridership of public transport. The unlimited monthly transit pass policy was implemented on April 16, 2018, in the Taipei metropolitan area. A quasi-experiment was conducted to determine the effect of unlimited transit pass on the ridership of the MRT system. This research uses RD in time design with the date as the running variable and April 16 as the cutoff to estimate the treatment effect of the unlimited monthly transit pass policy. The empirical results show that the average of entries and exits in MRT stations increased at the cutoff date after the policy was implemented. The estimated treatment effect is the short-run effect because the relatively short time window is opened for the estimation. This empirical result is consistent with the results of the theoretical model in previous literature. Moreover, I conduct subgroup analysis by dividing the samples into different subgroups: Taipei city, New Taipei city, and five MRT lines. The results show that the increase in Taipei city is greater than that in New Taipei city after the policy was implemented, indicating the policy's larger impact on the downtown area than the suburb. For the effect of the policy on different MRT lines, the brown line located in Taipei city is the only MRT line that did not show a significant increase in the average number of entries and exits. The other four MRT lines that pass through the Taipei city and New Taipei city exhibit a significant increase in the average number of entries and exits, implying that people probably use the transit pass to commute between Taipei city and New Taipei city.

After determining that the policy indeed increase the ridership of the MRT system, I want to know whether the policy can mitigate traffic congestion and air pollution. Results of this study reveal that the policy did not statistically decrease the car flow on

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freeways and the air quality index. There is no evidence that the unlimited transit pass policy can mitigate traffic congestion and air pollution in the short run. This research contributes to studies on the unlimited transit pass policy and externality of public transportation. The government can refer to the results of this research. However, despite its contribution, this research has some limitations. One limitation is that this research only identifies the policy's effect on the MRT system. The other limitation is that the estimated treatment effects are short-run effects. Hence, further research is needed to evaluate the long-run effect of unlimited transit pass policy.

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References

方炳超（2019 年 4 月 23 日）。 1280 月票滿周年》雙北共砸 9 億到底成效如何？3 張「成績單」帶你看定期票政策。取自 https://www.storm.mg/article/1202145

Anderson, M. L. (2014). Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion. American Economic Review, 104(9), 2763–2796

Arana, P., Cabezudo, S., & Peñalba, M. (2014). Influence of weather conditions on. transit ridership: A statistical study using data from Smartcards. Transportation Research Part A, 59, 1-12

Auffhammer, M. & Kellogg, R. (2011). Clearing the Air? The Effects of Gasoline Content Regulation on Air Quality. American Economic Review, 101(6), 2687-2722

Adler, M. W. & Ommeren, J. N. (2016). Does public transit reduce car travel externalities? Quasi-natural experiments' evidence from transit strikes. Journal of Urban Economics, 92, 106–119

Barreca, A. I., Guldi, M., Lindo, J. M., & Waddell, G. R. (2011). Saving babies? Revisiting the effect of very low birth weight classification. The Quarterly Journal of Economics, 126(4), 2117-2123

Brown, J., Hess, D. B., & Shoup D. (2001). Unlimited Access. Transportation, 28, 233-Regulation in the Presence of Multiple Unpriced Externalities: Evidence from the Transportation Sector. American Economic Journal: Economic Policy, 6(3), 1-29

Carbajo, J. C. (1988). The Economics of Travel Passes: Non-Uniform Pricing in Transport. Journal of Transport Economics and Policy, 22(2), 153-173

Cameron, A. C., Gelbach, J. B., & Miller, D.L. (2011). Robust Inference with Multiway Clustering. Journal of Business & Economic Statistics, 29 (2), 238-49.

Cheu, R. L. and Kreinovich, V. (2007). Exponential Disutility Functions in Transportation Problems: A New Theoretical Justification. Departmental Technical Reports (CS). Paper 98.

DOI:10.6814/NCCU202100538

Chen, C., Varley, D., and Chen, J (2011). What Affects Transit Ridership? A Dynamic Analysis involving Multiple Factors, Lags and Asymmetric Behaviour. Urban Studies, 48(9), 1893-1908

Chen, Y. H. & Whalley, A. (2012). Green Infrastructure: The Effects of Urban Rail Transit on Air Quality. American Economic Journal: Economic Policy, 4 (1), 58–97.

Doxsey, L. B. (1984). Demand for Unlimited Use Transit Passes. Journal of Transport Economics and Policy, 18(1), 7-22

Ellaway, A., Macintyre, S., Hiscock, R., & Kearns, A. (2003). In the driving seat: psychosocial benefits from private motor vehicle transport compared to public transport. Transportation Research Part F, 6, 217-231

FitzRoy, F. & Smith, I. (1998). Public transport demand in Freiburg: why did. patronage double in a decade? Transport Policy, 5, 163–173

Habib, K. N. & Hasnine, S. (2019). An econometric investigation of the influence of t ransit passes on transit users' behavior in Toronto. Public Transport, 11, 111-133

Hausman, C. & Rapson D. S. (2018). Regression Discontinuity in Time: Considerations practice. Journal of Econometrics, 142, 615-635

Lo, S. C. & Hall, R. W. (2006). Effects of the Los Angeles transit strike on highway congestion. Transportation Research Part A, 40, 903–917

Li, L., Qian, J., Ou, C. Q., Zhou, Y. X. Guo, C., & Guo, Y. (2014). Spatial and temporal analysis of Air Pollution Index and its timescale-dependent relationship with meteorological factors in Guangzhou, China, 2001-2011. Environmental Pollution, 190, 75-81

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. Journal of Econometrics ,142, 698–714

McLeod, M. S., Flannelly, K. J., Flannelly, L., & Behnke, R. W. (1991). Multivariate Time-Series Model of Transit Ridership Based on Historical, Aggregate Data: The Past, Present, and Future of Honolulu. Transportation Research Record, 1297, 76-84

DOI:10.6814/NCCU202100538

Najafabadi, S., Hamidi, A., Allahviranloo, M., & Devineni N. (2019). Does demand for subway ridership in Manhattan depend on the rainfall events? Transport Policy, 74, 201-213

Sherman, R. (1967). Club Subscriptions for Public Transport Passengers. Journal of Transport Economics and Policy, 1(3), 237-242

Scott, D. M. & Axhausen, K.W. (2006). Household mobility tool ownership: modeling. interactions between cars and season tickets. Transportation, 33, 311-328

Sun, C. W., Luo, Y., & Li J. L. (2018). Urban traffic infrastructure investment and air pollution: Evidence from the 83 cities in China. Journal of Cleaner Production, 172, 488-496

Taipei city government, Department of Transportation. (2020). 2019 Statistical year book of transportation, Taipei city. Retrieved from https://www.dot.gov.taipei/News.aspx?n=902EA6821196B316&sms=BE0EFDE1C72BF608

Thøgersen, J. (2009). Promoting public transport as a subscription service: Effects of a free month travel card. Transport Policy, 16, 335–343

Taylor, B.D. & Fink, F.N.Y. (2003). The Factors Influencing Transit Ridership: A. Review and Analysis of the Ridership Literature. UCLA, Los Angeles Transit Administration.

White, P. R. (1981). "Travelcard" Tickets in Urban Public Transport. Journal of. Transport Economics and Policy, 15(1), 17-34

DOI:10.6814/NCCU202100538