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Influence of a new rail transit line on travel behavior: Evidence from repeated cross-sectional surveys in Hong Kong

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A B S T R A C T

It has been well established that the infrastructural development for rail transit stimulates rail transit use. However, there is little agreement about the source of the increased rail transit use. Using data from two repeated cross-sectional surveys, we examine changes in individual travel behavior resulting from the introduction of a rail transit line in Hong Kong. To address some methodological limitations inherent to repeated cross-sectional research design (e.g., selection bias and longitudinal incomparability), a two-dimensional propensity score matching method (2DPSM) is adopted to pair samples between the treatment and control groups in both cross-sectional and longitudinal dimensions. Paired *t*-tests are used to compare the longitudinal changes in travel behavior between the treatment and control groups of the matched samples. To get a more comprehensive understanding of the net treatment effects of the new rail line on travel behavior, we examined its impacts on both home-based trips (trips originating or terminating at home) and all trips for both treatment and control group. For home-based trips, the opening of the new rail line increased the rail mode share by 10.4%, and rail trip number by 0.126 (in terms of net effect, i.e., difference in the change between treatment and control group). It reduced the bus mode share by 17.1% and bus trip number by 0.208, showing a significant bus-to-rail modal shift. For all trips, the new rail line increased rail mode share by 9.5% and total trip number by 0.189. It also decreased bus mode share by 13.2%, and bus trip number by 0.191. Hence, the source of the increased rail transit use came from both the modal shift from bus and the increased travel demand induced by the new transit infrastructure. For both home-based trip and all trips, there was no significant influence on car use and total trip distance. Our findings provide new evidence that the development of rail transit in a high-density urban setting encourages a modal shift from bus to rail transit and stimulates flexible travel behaviors, but fails to control private vehicle use.

1. Introduction

Over the last several decades, traffic congestion and the air and noise pollution associated with the use of private vehicles have degraded the urban environment and reduced urban residents' quality of life. This problem has attracted the attention of many governments and organizations. To cope with increased travel demand and reduce reliance on private vehicles, many governments have invested in rail transit (Loo et al., 2010; Nasri and Zhang, 2014). Rail transit has several advantages. Its rapid speed, massive carrying capacity, comfortable ride experience, and punctuality are attractive to urban residents and have the potential to meet the increasing demand for travel and convert motorized users into rail transit customers (Litman, 2005).

A large body of literature have focused on the link between rapid

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transit, or transit-oriented development (TOD), and individuals' travel behavior choice. Although most studies have found a positive linkage between rail transit and rail transit use (Dill, 2008; Lund et al., 2006; Renne, 2005), the source for higher rail transit use is not yet clear. It may be a switch from other travel modes such as private cars and buses, the change in the surrounding built environment resulting from the TOD program, or even residential self-selection (i.e., residents who prefer rail transit will move to areas with new rail transit) (Cao et al., 2009; Chatman, 2013).

Scholars have attributed such inconsistency to cross-sectional analysis, which cannot disentangle confounding effects such as surrounding built environment, residential self-selection and other unobserved factors to determine how individuals change their travel behavior after the introduction of new transit infrastructure (Salon et al., 2012; Spears et al., 2017). Longitudinal studies that can detect changes in the outcomes of sampled participants at individual levels, have been recommended strongly to mitigate confounding effects and provide rigorous evidence about the linkage between rail transit and individuals' travel behavior (Curtis and Olaru, 2010; Sun et al., 2020). However, due to privacy issues or high costs, panel data that needed by longitudinal studies remain rare in urban planning or transportation research (Zhong et al., 2021).

In recent years, some researchers have turned to data from repeated cross-sectional travel surveys (Wu and Hong, 2017; Xie, 2016), which are frequently conducted by local governments and institutes. Although such surveys provide a cost-effective way to obtain a large sample size with time-related change, the inability to track and compare changes in specific individual behaviors before and after the intervention makes them less statistically powerful (Yee and Niemeier, 1996). Besides, as with cross-sectional data, there remains bias that is related to residential self-selection (Zhong et al., 2021).

In order to address these methodological limitations, Zhong et al. (2021) developed a two-dimensional propensity score matching (2DPSM) approach that extended conventional one-dimensional propensity score matching (PSM) to pair observations on both cross-sectional and longitudinal dimensions. By simulating a random assignment between the treatment and control groups and matching statistically identical observations over time, this method can overcome the confounding effects that result from temporal changes and spatial heterogeneity among repeated cross-sectional data. Despite the theoretical advantage, there is little empirical evidence estimating the effect of transport infrastructure on travel behavior with 2DPSM.

In this study, we apply this new method to two repeated cross-sectional travel surveys. By comparing the longitudinal changes in travel behavior between the treatment and control groups of the paired samples, we can better understand the impact of the new rail transit line, and the source for increased rail transit use.

2. Literature review

2.1. Empirical evidence

Over the past decades, rail transit systems have become increasingly popular due to their potential to improve mobility and address transport challenges (Loo et al., 2010; Nasri and Zhang, 2014). On account of enormous expenses for the construction and maintenance of such systems, it is important to accurately assess their impact (Jeihani et al., 2013). Academics has thus paid more attention to the relationship between rail transit and individuals' travel behavior.

Appendix A summarizes studies in this area, including their sample characteristics, study design, data type, sample size, outcomes, and findings. These studies have unanimously found a positive association between the introduction of new rail infrastructure and rail transit ridership. For example, a study conducted in California showed that residents in TOD neighborhoods are five times more inclined to choose rail as their major travel mode than non-TOD residents (Lund et al., 2006). In an investigation of 103 TODs in the U.S., Renne (2005) found that the number of rail transit trips by TOD residents is approximately 3.5 times that of non-TOD residents.

However, results regarding the sources of increases in rail transit ridership are inconsistent. Most studies have shown that the launch of new rail lines can attract private car customer s to turn to use rail. For instance, in a retrospective study of people who relocated in Minneapolis, Cao and Ermagun (2016) found that residents who were movers to the Hiawatha Light Rail Transit corridor increased rail transit use and reduced car use. Pan et al. (2013) found that a high percentage of suburban residents living near new rail stations in Shanghai, China, intended to commute by metro instead of by car.

However, several studies have reported contradictory findings, showing a positive relationship between rail transit and car use. For example, Chatman (2008) showed that residents who lived near rail stations took longer driving trips, after controlling for neighborhood built environment variables. A few studies have concluded that the increase in rail ridership comes from reduced bus and non-motorized trips rather than reduced car use. For instance, Lee and Senior (2013) found that the growth of rail transit use in the new light rail corridors in the U.K. came mostly from buses. Wu and Hong (2017) found that the expansion of subway systems in Beijing was accompanied by a reduction in non-motorized trips and bus trips.

Some researchers have argued that some other factors, including residential self-selection and the built environment of the station-area neighborhoods and supportive transportation and land use policies, may influence the link between rail transit and travel behavior. Based on a survey in New Jersey, Chatman (2013) found that housing type, bus service, neighborhood density, and especially parking availability have a greater influence on changes in residents' travel behavior than does rail transit infrastructure. Huang et al. (2019) found that aside from the launch of the new metro line in Xi'an, China, neighborhood characteristics and land use policies, such as pedestrian-friendly environment, dense road network, good transit accessibility and service, could lead to reduction in driving.

2.2. Methodological challenge

Some methodological challenges in current empirical studies have yet to be resolved. As shown in Table A1, there are two major research design. The first design applies cross-sectional analysis with case-control. In these studies, the sample is divided into two groups: a treatment group that experienced an active intervention of newly opened rail infrastructure, and a control group that did not. Researchers then compare the travel behavior of individuals in the treatment group with those in the control group and the difference in outcomes can be attributed to the treatment effects of rail transit. As cross-sectional surveys are often conducted at a single point in time, the lack of temporal dimension makes it difficult to reveal changes in travel behavior, which makes it difficult to infer causal effects (Spears et al., 2017). Furthermore, it is challenging to select treatment and control zones with highly similar characteristics apart from the availability of rail transit service (Khattak and Rodriguez, 2005). Inappropriate selection of control zones can yield misleading results. For example, selecting control zones at the city, county, or region scale may lead to the overestimation of the influence of rail transit on travel behavior, because new rail lines are primarily located in areas with higher demand for transit service (Cao and Cao, 2014; Huang et al., 2019).

The second design applies a longitudinal design based on panel or repeated cross-sectional data. Panel studies are collected for a targeted population group both before and after the opening of rail stations or lines, which can provide robust evidence to infer a causal effect (Yee and Niemeier, 1996). As mentioned above, panel studies in transport research are often difficult to implement, or have small sample size due to privacy or cost issues.

Since repeated cross-sectional data sets can be collected more easily through travel surveys, they are often used as an alternative in longitudinal studies. Such data sets observe different sets of individuals over time, so they can only reveal the aggregate-level effects of travel behavior change (Zhong et al., 2021). The temporal heterogeneity of the samples may lead to bias in effect estimation, because the observed differences in travel behavior may be due to changes in demographic structure and relocation of residential area over time (Cao and Cao, 2014). In addition, as with cross-sectional case-control analysis, there is still the problem of spatial heterogeneity between treatment and control zones resulted from residential self-selection of individuals, which may confound the treatment effect.

The propensity score matching (PSM) method is usually applied to mitigate the influence of bias in treatment-selection from observed covariates when evaluating causal effects (Chang et al., 2017; MacDonald et al., 2010). PSM involves creating comparable groups by matching observations in the treatment group with those in the control group according to their demographic characteristics (Austin, 2008). This method can help assign pairs of very similar observations into the treatment group and control group. However, the conventional one-dimensional PSM method cannot address bias in longitudinal incomparability, which is due to the fact that the estimated samples in repeated cross-sectional data may not be identical before and after the intervention (Zhong et al., 2021). Therefore, a 2DPSM method has been developed to pair observations between the treatment and control groups in both the cross-sectional and longitudinal dimensions. The new method can address the methodological limitations inherent to repeated cross-sectional research design (e.g., selection bias and longitudinal incomparability). Despite the methodological advantage, few empirical studies have used this 2DPSM. To our knowledge, only one study applied 2DPSM to explore the impact of Singapore Circle Line on individuals' travel mode shares (Dai et al., 2020). Besides, most studies used difference-in-difference (DID) analysis on matched data to identify the different treatment effect on the treatment and control groups. However, DID model is usually used in the situation that there are two groups with different individuals but have the common trends over time, which may not fit the matched data structure of 2DPSM. Hence, some analysis for matched pairs (such as paired *t*-tests and the Wilcoxon signed-rank test) are better choice to estimate the group difference (treatment group versus control group) in the 2DPSM (Austin, 2008).

2.3. Research gap and our contribution

Despite the large body of literature on the development of rail transit and individual travel behavior, several research gaps have yet to be resolved. First, although most studies have concluded that constructing new rail transit system may lead to significant increase in rail use, the source of the increased rail use remains unclear. Second, few studies used 2DPSM in estimating treatment effect of rail transit, despite its advantages over conventional methods. Furthermore, the analysis method used on 2DPSM matched data needs future fine-tuning.

In this study, we attempt to fill these research gaps by (1) applying 2DPSM combined with paired t-tests to identify the true impact of a new rail line on travel behavior in Hong Kong, and (2) providing new evidence to the debate about the source of the increased rail transit use after the constructing of new rail transit. Besides, to get a more comprehensive understanding of the treatment effects of the new rail line on travel behavior, we examined its impacts on both home-based trips (trips originating or terminating at home) and all trips.

3. Materials and methods

3.1. Study area

Hong Kong is a high-density city in the southeastern tip of China, with a population of more than seven million and an area of only 1105 km^2. As Hong Kong's hilly topography limits the road capacity for vehicles in built-up districts, Hong Kong has a well-developed public transport system that contains rails, buses, trams, and ferries. Rail transit is the backbone of Hong Kong's public transport system, accounting for approximately 39% of all trips made on public transport each day (Hong Kong Transport Department, 2021).

The Ma On Shan Line was a rapid Mass Transit Railway (MTR) line in Hong Kong (which was integrated with Tuen Ma Line in 2020). The line opened in December 2004 and served as a branch of the East Rail Line, connecting Sha Tin town and Ma On Shan district. The line spans 11.4 km across nine stations. In this study, we take the launch of the Ma On Shan Line as the intervention to examine the changes in individuals' travel behavior.

Individuals who lived within 500 m of the rail stations of the Ma On Shan Line were assigned to the treatment group, while those who lived in the same Tertiary Planning Units (TPUs) but further away from the stations (up to 1500 m) were assigned to the control group (Fig. 1). We used the 500-m threshold because Hong Kong's transit-oriented development (TOD) is usually planned within a 500-m radius of the rail stations, with most residential, office and commercial buildings in Hong Kong located in this catchment (Cervero and Murakami, 2009; Xue and Sun, 2021). Besides, according to 2002 and 2011 Hong Kong Travel Characteristics Surveys (TCSs), the 500-m buffers surrounding rail stations correspond to the majority of the walking leg of home-based rail trips. 1500-m has been widely used as a maximum distance threshold in the research on the influence range of urban rail transit area (Gutiérrez et al., 2011; Yang et al., 2021). Fig. 1 illustrates the study area of the treatment group (areas enclosed in dark yellow circles) and the control group (the area beyond the circles, extending to the boundary of TPUs, a spatial unit demarcated by Hong Kong Planning Department).

3.2. Data

The dataset of this study is the 2002 and 2011 Hong Kong Travel Characteristics Surveys (TCSs), collecting the comprehensive information about the travel characteristics of Hong Kong residents by Hong Kong government. These two TCSs were carried out before and after the launch of the Ma On Shan Line, providing an ideal repeated cross-sectional dataset from which we can examine individuals' travel behavioral changes after the rail transit intervention. TCS 2002 covers 6,756,100 individuals from 2,152,900 households, and TCS 2011 covers 6,881,900 individuals from 2,363,300 households. In the surveys, trained interviewers conducted face-to-face interviews to obtain individual sociodemographic characteristics, including age, gender, family income, household size and car ownership. Travel behavior information was reported based on survey respondents' detailed travel logs from one day's activities; these included the total number of trips taken, travel distance, and the trip number of different motorized modes.

3.3. Statistical analysis

In this study, we employ 2DPSM combined with paired *t*-tests (Fig. 2) to evaluate the treatment effect of the Ma On Shan Line on individual travel behavior, including both home-based trips and all trips. First, 2DPSM approach is used to create four groups of matched individuals, including BT (the treatment group before the launch of the new rail line), BC (the control group before the launch), AT (the treatment group after the launch), and AC (the control group after the launch). Individuals in each BT, BC, AT and AC group, are sequentially paired until each group has the same number of matched individuals. Both demographic and neighborhood-level built environment variables were used for matching participants in treatment groups and control groups. The demographic variables include age group, gender, monthly family income level, household size, and car ownership. The neighborhood-level built environment attributes, including population density, land use mix, street connectivity, and density of bus stops. Each matching is implemented with the command 'psmatch2' in STATA 14, with the

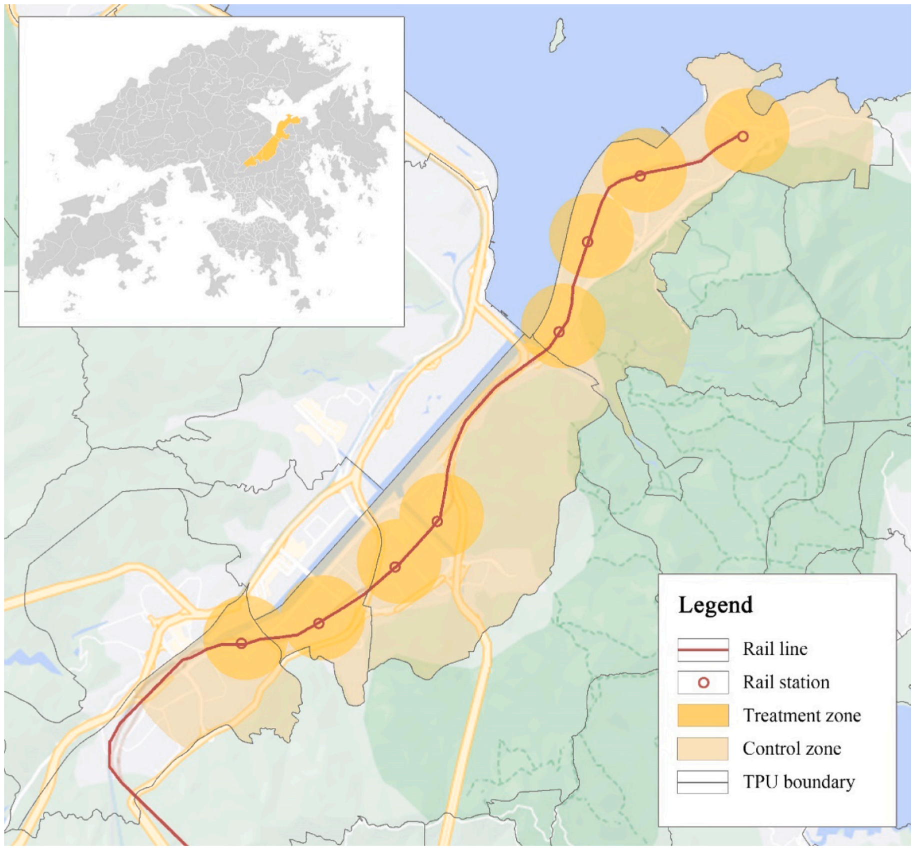

Fig. 1. Study area for the treatment and control groups.

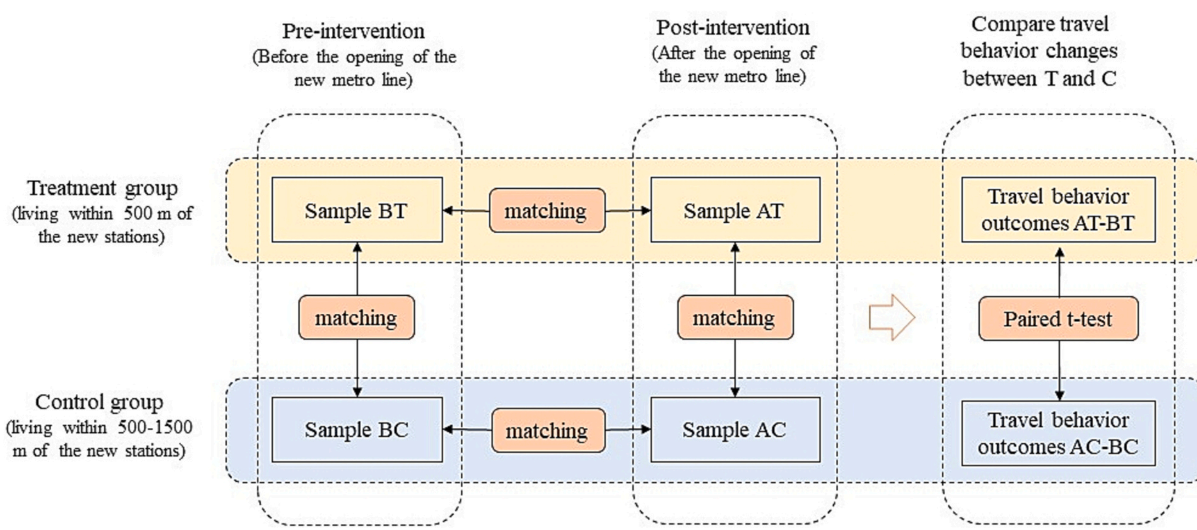

Fig. 2. Conceptual diagram of analysis. T indicates the treatment group; C indicates the control group; BT indicates the treatment group before the launch of the new rail line; BC indicates the control group before the launch; AT indicates the treatment group after the launch; AC indicates the control group after the launch.

options 'noreplacement', 'common', and 'caliper (0.02)'. Then, the command "PSTEST" is used to examine the balance among the matched samples of their sociodemographic covariates. In this way, we acquire four groups of matched individuals with statistically similar characteristics that can be used for analysis.

Then, we use paired *t*-tests to compare the before and after changes between the treatment and control groups of matched samples to estimate their statistical significance and the difference in response can be attributed to the treatment of the intervention (Austin, 2008). Paired t-tests are done in SPSS 25.

4. Results

4.1. Sample characteristics

Table 1 shows the summary statistics of the sociodemographic and neighborhood-level built environment characteristics of the treatment and control samples before and after the launch of the Ma On Shan Line.

Table 1
Descriptive statistics of participants after matching.

	Treatment group		Control group		*P*-value of paired t-test	
	Baseline (BT) (N = 524)	Follow-up (AT) (N = 524)	Baseline (BC) (*N* = 524)	Follow-up (AC) (N = 524)	Baseline	Follow-up
Individual level					0.101	0.407
Age group (years) [Count (%)]						
<18	89 (17.0)	100 (19.1)	97 (18.5)	90 (17.2)		
18–44	262 (50.0)	244 (46.6)	254 (48.5)	243 (46.4)		
45–64	139 (26.5)	143 (27.3)	141 (26.9)	153 (29.2)		
≥65	34 (6.5)	37 (7.0)	32 (6.1)	38 (7.2)		
Female [Count (%)]	266 (50.8)	267 (51.0)	264 (50.4)	267 (50.8)	0.180	0.231
Monthly family income (HKD) [Count (%)]					0.104	0.106
≤10,000	230 (43.9)	227 (43.3)	224 (42.7)	242 (46.1)		
10,001–20,000	132 (25.2)	133 (25.4)	127 (24.3)	131 (25.0)		
20,001–30,000	84 (16.1)	86 (16.4)	91 (17.4)	79 (15.1)		
30,001–50,000	61 (11.6)	60 (11.5)	64 (12.2)	56 (10.7)		
>50,001	17 (3.2)	18 (3.4)	18 (3.4)	16 (3.1)		
Number of household members [Mean (SD)]	3.5 (1.3)	3.6 (1.4)	3.6 (1.3)	3.5 (1.3)	0.377	0.462
Car ownership [Mean (SD)]	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)	0.112	0.313
Neighborhood level						
Population density (persons/km^2) [Mean (SD)]	20,534.5 (8523.5)	21,080.2 (8790.5)	20,358.6 (8302.2)	20,544.2 (8575.6)	0.124	0.130
Land use mix (ratio) [Mean (SD)]	0.47 (0.30)	0.44 (0.28)	0.48 (0.31)	0.44 (0.25)	0.173	0.111
Street connectivity (count/km^2) [Mean (SD)]	65.96 (20.33)	67.00 (21.76)	70.24 (21.09)	69.98 (18.59)	0.148	0.107
Bus stops (count/km^2) [Mean (SD)]	28.45 (13.79)	27.25 (14.87)	29.99 (14.35)	27.53 (14.33)	0.176	0.396

Note: Paired t-tests were used to examine whether there are any significant differences in travel sociodemographic and built environment characteristics between the treatment and control groups. The *p*-values in the column with heading baseline indicate the significant level of the differences between two groups at baseline; and those with heading follow-up indicate the differences at follow-up.

After matching five sociodemographic variables (age, gender, income, household size, and car ownership) and four neighborhood-level built environment variables (population density, land use mix, street connectivity, and density of bus stops), the four groups are more statistically comparable.

4.2. Changes in travel behavior

Table 2 shows the descriptive outcomes for the mode share, number, and distance of home-based trips for each group. There was an increase in rail mode share for both the treatment group (from 2.5% to 33.1%) and the control group (from 1.8% to 22.0%). For the bus mode share, the treatment group decreased from 52.3% to 50.1%, while the control group increased from 48.3% to 63.2%. For the car mode share, the treatment group increased from 5.4% to 8.6%, while the control group remained unchanged (7.4%). The outcomes for the number of each trips showed a similar pattern as that of travel mode share. For the number of rail trips, there was a larger increase in the treatment group than in the control group (from 0.055 times to 0.408 times vs. from 0.042 times to 0.269 times). There was a decrease in bus mode share for the treatment group (from 0.697 times to 0.619 times) and an increase for the control group (from 0.656 times to 0.786 times). For the number of car trips, the treatment group increased from 0.055 times to 0.085 times, while the control group decreased slightly from 0.076 times to 0.074 times. The total number and distance of trips increased for both the treatment group (from 1.082 times to 1.221 times, and from 7300.6 m to 9802.5 m) and the control group (from 1.053 times to 1.215 times, and from 7012.1 m to 10,455.1 m).

Table 3 shows the descriptive outcomes for the mode share, number, and distance of all trips for each group. There was an increase in rail mode share for both the treatment group (from 15.6% to 42.7%) and the control group (from 14.5% to 32.1%). For the bus mode share, the treatment group decreased from 47.5% to 41.4%, while the control group increased from 46.2% to 53.3%. The car mode share decreased for both the treatment group (from 6.1% to 5.8%) and the control group (from 7.5% to 6.3%). For the number of rail trips, there was a larger

Table 2
Descriptive statistics of travel behavior for home-based trips. Mean (SD) is reported at each cell.

	Treatment group		Control group		P-value of paired t-test	
	Baseline (BT) (N = 524)	Follow-up (AT) (*N* = 524)	Baseline (BC) (N = 524)	Follow-up (AC) (N = 524)	Baseline	Follow-up
Mode share (ratio)						
Rail	0.025 (0.105)	0.331 (0.432)	0.018 (0.088)	0.220 (0.384)	0.251	<0.001***
Bus	0.523 (0.461)	0.501 (0.469)	0.483 (0.466)	0.632 (0.456)	0.172	<0.001***
Car	0.054 (0.225)	0.086 (0.280)	0.074 (0.261)	0.074 (0.262)	0.178	0.503
Trip number (count)						
Rail	0.055 (0.229)	0.408 (0.492)	0.042 (0.201)	0.269 (0.443)	0.318	<0.001***
Bus	0.697 (0.640)	0.619 (0.595)	0.656 (0.668)	0.786 (0.621)	0.339	<0.001***
Car	0.055 (0.229)	0.085 (0.280)	0.076 (0.266)	0.074 (0.262)	0.166	0.503
Total	1.082 (0.988)	1.221 (0.051)	1.053 (0.825)	1.215 (0.443)	0.612	0.844
Total trip distance (m)	7300.6(6311.9)	9802.5(5822.5)	7012.1 (5987.7)	10,455.1(7348.2)	0.450	0.105

Note: (a) The number and distance of trips denotes motorized travel, including rail, bus, car and other motorized travel modes (such as ferry and taxi) which accounted for a relatively small share and thus were not analyzed in this study. (b) Paired *t*-tests were used to examine whether there are any significant differences in travel behavior outcomes between the treatment and control groups. *: p < 0.1, **: p < 0.05, ***: *p* < 0.001.

Table 3
Descriptive statistics of travel behavior for all trips. Mean (SD) is reported.

	Treatment group		Control group		P-value of paired *t*-test	
	Baseline (BT) (N = 524)	Follow-up (AT) (*N* = 524)	Baseline (BC) (N = 524)	Follow-up (AC) (N = 524)	Baseline	Follow-up
Mode share (ratio)						
Rail	0.156 (0.314)	0.427 (0.475)	0.145 (0.300)	0.321(0.438)	0.544	<0.001***
Bus	0.475 (0.440)	0.414 (0.471)	0.462 (0.425)	0.533 (0.468)	0.586	<0.001***
Car	0.061 (0.218)	0.058 (0.224)	0.075 (0.235)	0.063 (0.237)	0.299	0.693
Trip number (count)						
Rail	0.410 (0.795)	0.922 (1.086)	0.378 (0.735)	0.692 (0.956)	0.489	<0.001***
Bus	1.200 (1.126)	0.894 (1.066)	1.242 (1.138)	1.127 (1.024)	0.538	<0.001***
Car	0.210 (0.765)	0.139 (0.587)	0.231 (0.745)	0.164 (0.674)	0.645	0.537
Total	2.750 (1.219)	2.168 (0.644)	2.933 (1.376)	2.162 (0.725)	0.894	0.027**
Total trip distance (m)	17,281.4(14,587.9)	19,019.0(12,501.8)	16,370.8(13,435.8)	19,324.2(12,730.0)	0.313	0.756

Note: (a) The number and distance of trips denotes motorized travel, including rail, bus, car and other motorized travel modes (such as ferry and taxi) which accounted for a relatively small share and thus were not analyzed in this study. (b) Paired t-tests were used to examine whether there are any significant differences in travel behavior outcomes between the treatment and control groups. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.001$.

increase in the treatment group than in the control group (from 0.410 times to 0.922 times vs from 0.378 times to 0.692 times). The bus and car trips decreased for both groups. For the treatment group, the number of bus trips decreased from 1.200 times to 0.894 times and the number of car trips decreased from 0.210 times to 0.139 times. For the control groups, the number of bus trips decreased from 1.242 times to 1.127 times and the number of car trips decreased from 0.231 times to 0.164 times. The total number of trips decreased for both the treatment group (from 2.750 times to 2.168 times) and the control group (from 2.933 times to 2.162 times). The total trip distance increased from 17,281.4 m to 19,019.0 m in the treatment group and from 16,370.8 m to 19,324.2 m in the control group.

4.3. Paired t-test for measuring travel behavior changes

Table 4 presents the travel behavior changes of home-based trips for both groups. The increase in the mode share and trip number of rail for the treatment group was significantly higher than that in the control group (+30.6% vs. +20.2%, $p < 0.001$; +0.353 times vs. +0.227 times, $p < 0.001$). There were significant differences on both the mode share and trip number of bus among two groups, with a decrease in the treatment group and an increase in the control group (−2.2% vs. +14.9%, $p < 0.001$; −0.078 times vs. +0.130 times, $p < 0.001$). The differences in the mode share and trip number of car, and the total trip number and distance between two groups were nonsignificant.

Table 5 presents the travel behavior changes of all trips for both groups. The changes in the mode share and trip number of rail were the same as that of home-based trips, with the treatment group significantly higher than that in the control group (+27.1% vs. +17.6%, $p < 0.05$; +0.512 times vs. +0.314 times, $p <$ 0. 1). There were significant differences on both the mode share and trip number of bus among two groups. There was a decrease in the treatment group and an increase in the control group for bus mode share (−6.1% vs. +7.1%, $p < 0.001$). For the number of bus trips, the decrease in treatment group was significantly lower than that in the control group (−0.316 times vs. -0.115 times, $p <$ 0. 1). The differences in the mode share and trip number of car, and the total trip distance between two groups were nonsignificant. There was a margin significant difference on the total number of trips (−0.582 times vs. -0.771 times, $p < 0.1$).

Fig. 3 and Fig. 4 visualize the changes for home-based trips and all trips respectively in terms of mode share and trip number of rail, bus, and car, and the total trip number and distance before and after the intervention; it shows different slopes for the treatment and control groups.

5. Discussion

5.1. Major finding

Based on matched data from repeated cross-sectional travel surveys, we examine the influence of the Ma On Shan Line on individual travel behavior in Hong Kong, including both home-based trips and all trips. For home-based trips, the opening of the new rail line increased the rail transit use and reduced the bus use, showing a significant bus-to-rail modal shift. For all trips, the new rail line had a positive effect on both rail transit use and total trip number, and had a negative influence on bus use, showing that the source of the increased rail transit use came from both the modal shift from bus and the increased travel demand created by the new transit infrastructure. For both home-based trip and all trips, there was no significant influence on car use and total trip distance.

Our findings contribute to critical discourse in the field. Previous empirical studies have unanimously found a positive linkage between rail transit development and its ridership, but the sources of the increase

Table 4
Changes in travel behavior outcomes for home-based trips. Mean (SD) is reported.

	Mode share			Trip number				Total trip distance
	Rail	Bus	Car	Rail	Bus	Car	Total	
Treatment group change (T_2-T_1)	0.306 (0.446)	−0.022 (0.662)	0.032 (0.345)	0.353 (0.549)	−0.078 (0.874)	0.030 (0.348)	0.140 (1.103)	2501.9 (8742.0)
Control group change (T_2-T_1)	0.202 (0.397)	0.149 (0.638)	0.000 (0.375)	0.227 (0.491)	0.130 (0.895)	−0.002 (0.379)	0.162 (0.918)	3443.0 (9677.0)
Difference in changes (Treatment group change - Control group change)	0.104 (0.576) ***	−0.171 (0.884)***	0.032 (0.502)	0.126 (0.721) ***	−0.208 (1.20) ***	0.032 (0.507)	−0.022 (1.405)	−941.1 (13,314.1)

Note: Positive signs indicate positive change (T_2-T_1) in a variable; negative signs represent negative change (T_2-T_1). Paired *t*-tests are performed to compare the changes in travel behavior of the samples between the treatment and control groups; the results are labeled with asterisks in the last row: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.001$.

Table 5
Changes in travel behavior outcomes for all trips. Mean (SD) is reported.

	Mode share			Trip number				Total trip distance
	Rail	Bus	Car	Rail	Bus	Car	Total	
Treatment group change (T_2-T_1)	0.271 (0.570)	−0.061 (0.658)	−0.003 (0.317)	0.512 (1.341)	−0.316 (1.568)	−0.071 (0.968)	−0.582 (1.422)	1737.6 (19,225.5)
Control group change (T_2-T_1)	0.176 (0.529)	0.071 (0.619)	−0.012 (0.336)	0.314 (1.212)	−0.115 (1.514)	−0.067 (1.015)	−0.771 (1.559)	2953.4 (18,474.1)
Difference in changes (Treatment group change - Control group change)	0.095 (0.731) **	−0.132 (0.843)***	0.009 (0.463)	0.198 (1.752) *	−0.191 (2.117) *	−0.004 (1.380)	0.189 (2.157) *	−1215.8 (27,434.0)

Note: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.001$.

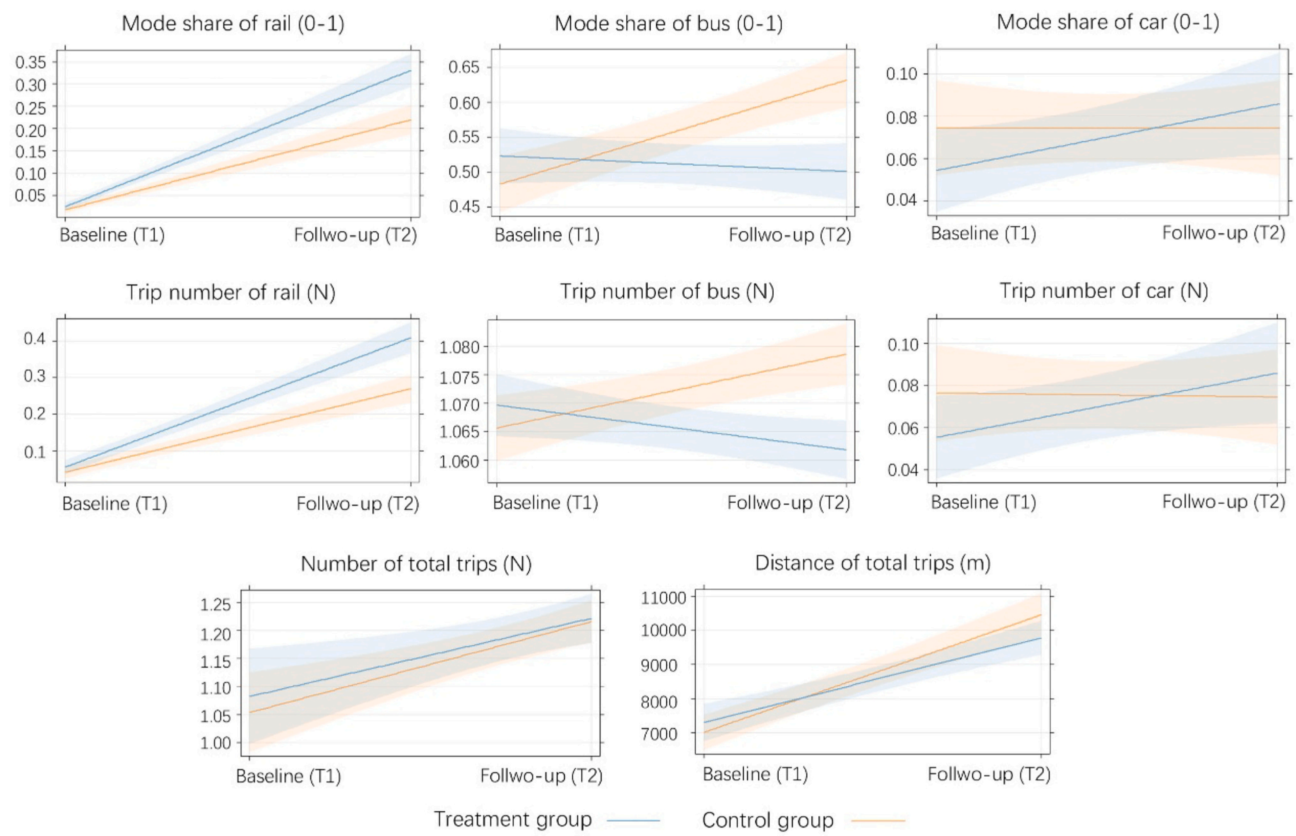

Fig. 3. Changes for home-based trips in the mode share and trip number of rail, bus, and car, and the total trip number and distance.

remain unclear. Some researchers have argued that increased rail mode share comes from reduced car use, while others have posited rail substituting for bus transit as the source. Our findings mostly support the second explanation.

It is well documented that when people consider the travel choice among different modes, various factors such as travel time, travel cost, and availability of different mode have a significant impact (Scherer and Zurich, 2012). Compared with bus transit, rail has the advantages of comfort, convenience and speed, showing a higher attraction for passengers (Ben-Akiva and Morikawa, 2002; Ingvardson and Nielsen, 2018). For instance, rail transit can save travel time as it runs on a fully segregated right of way compared with bus systems, which are constructed at the street level and must negotiate numerous traffic lights and intersections (Ingvardson and Nielsen, 2018). Indeed, Hong Kong government's transport strategy initiates a competitive public transport market that provides the freedom of choice between modes for residents (Tang and Lo, 2008). Through market-oriented competition, the overall quality of public transport services has been improved and has achieved a well-coordinated transport network (Luk and Olszewski, 2003; Tang and Lo, 2008). Along the MTR corridors, bus service automatically serves as a feeder and supplementary role.

As for the car-to-rail modal switch, many researchers have argued that rail transit attracts riders who otherwise would use cars, due to the fact that rail transit service can provide a good alternative to driving especially in areas with heavy traffic congestion (Jeihani et al., 2013). However, the performance of rail transit on controlling private vehicle use depends on local transportation contexts, such as individual socio-economic level, long-established travel preferences, and accompanying land use polices (Chatman, 2013; Ibraeva et al., 2020). High development density, high fuel costs and strict parking polices can also induce residents to reduce their driving, regardless of rail access. Moreover, individuals who rely heavily on driving may not use public transit even if transportation facilities are improved. Though Hong Kong's car ownership and usage is very low, a survey of residents who had car in Hong Kong indicated that once people owned a car, they perceived it to be a necessary part of their daily life (Cullinane and Cullinane, 2003). Indeed, 90% of all trips in Hong Kong already relied on public transport services, leaving little room to convert private car use to public transit

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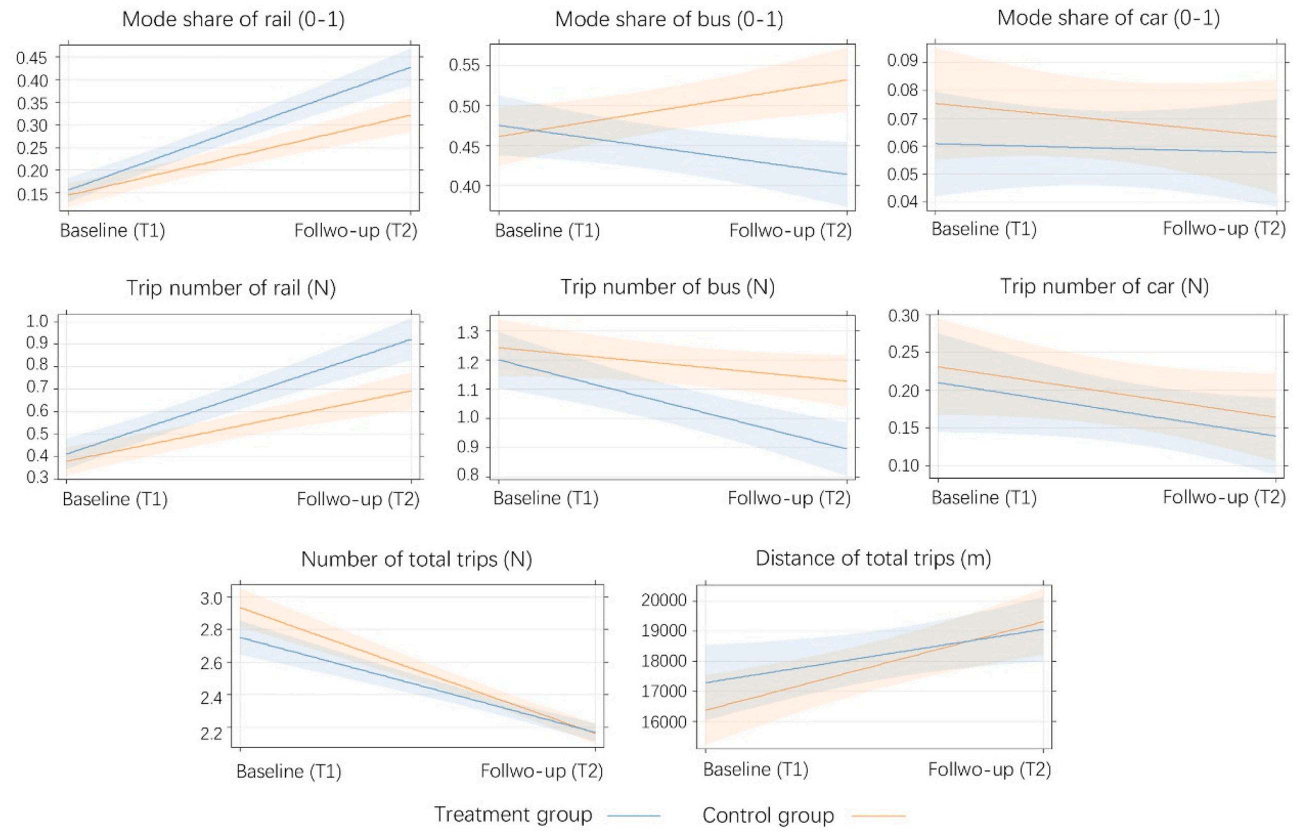

Fig. 4. Changes for all trips in the mode share and trip number of rail, bus, and car, and the total trip number and distance.

use (Tang and Lo, 2008). Therefore, the increase in rail transit usage after the construction of the new rail line may not necessarily come at the expense of car use.

Lastly, we argue that the increase in rail transit ridership may partly come from travel demand created by the new rail line, because the new rail transit shows a positive impact on trip numbers for all trips, but an insignificant effect for home-based trips. This finding indicated that the new rail line could only stimulate non-home-based trips, which are trips that don't involve home as an origin or destination. In particular, non-home-based trips are likely to occur around the workplaces, usually in the urban centers with excellent rail service and dense and diverse destinations. The advantage of rail service (e.g., high frequency, flexibility, and punctuation) may stimulate urban residents to go to other destinations rather go home directly after work, because they can always rely on rail to go home after conducting various social or leisure activities after work.

Few studies have paid attention to trip distance. Our finding showed that the new rail line had no significant influence on trip distance. Although rail service provides convenient conditions for long-distance trips, especially in travel cost and travel time, it does not necessarily lead to the increase in people's demand for long-distance travel. Indeed, before the opening of the Ma On Shan line, the residents of our study area already had high travel demand for long commutes because most jobs are outside such areas. Instead, the trip length for daily activities (e.g., shopping and dining) may be shorter after the introduction of rail transit, because there are more daily destinations near transit (Zamir et al., 2014).

5.2. Planning implication

In sum, we find that the launch of a new rail line led people living in the station area to be more likely to use rail transportation and take more flexible trips, but failed to control auto use. The findings can be generalized to other similar areas, especially those high-dense Asian cities. In areas like Hong Kong, where public transport already accounts for a high mode share, investments in urban rail transit needs to be more prudent as the performance of urban rail transit on reducing car dependency may be overestimated. On the other hand, the substitution effect between rail and bus calls for the rationalization and consolidation of public services, to avoid inefficient competition and waste of resources. Moreover, from the urban planning perspective, there is a strong argument for diversifying and intensifying rail transit hubs, to enhance the vitality of the city.

5.3. Strength and limitation

This study adds new evidence to the current debate on the source of the increased rail use after the rail transit intervention, as well as verifying the performance of 2DPSM – a new method in evaluating the treatment effect of newly built rail transit. Using repeated cross-sectional data from official travel surveys, this method reduces the selection bias nearly inevitable in case-control studies and avoids longitudinal incomparability arising from a lack of panel data. Future studies may also use the 2DPSM approach as a cost-effective way to mimic a natural experimental design, which may overcome the limitations of cross-sectional and panel research design.

This study has several limitations. First, TCS (2011) focused primarily on motorized transport, lacking in information about active travel behavior such as walking and cycling. The association between rail transit and active travel behavior needs further exploration. Second, the matched data are not true panel data, as there are still unobserved differences between the samples (Ho et al., 2007). Third, we did not consider other confounding factors, such as residential self-selection and individual travel attitudes, which may influence the relationship between urban rail transit and travel behavior. Besides, for all trips, this study did not control the samples' access to rail transit outside of the study area, which may also affect the results. Lastly, as the influence of urban rail transit on individuals' travel behavior may weaken with the distance from their residence to the rail station, the single distance threshold cannot examine the distance-decay effects of rail transit interventions.

6. Conclusion

We use the 2004 opening of the Ma On Shan Line, a new Hong Kong rail transit line, as an intervention to observe its treatment effect on individuals' travel behavior. The travel behavior data are collected from Hong Kong Travel Characteristics Surveys conducted separately in 2002 and 2011. To account for the spatial heterogeneity between the treatment and control groups and temporal changes over time, we adopt a 2DPSM approach to pair matched samples and compare the changes in travel behavior of the almost "identical" set of individuals in both longitudinal and cross-sectional dimensions, thus identifying the true impact of the new rail transit infrastructure.

Our study findings indicate that the launch of the Ma On Shan Line produce a bus-to-rail mode switching effect, while the new rail line had a nonsignificant impact on car use. Furthermore, the Ma On Shan Line showed a positive relationship with the total number of all trips, but non-significant association with that of home-base trips, which indicated that the increase in rail transit ridership may partly come from increased non-home-based travel demand created by the new rail line. Our findings provide new evidence that newly built rail transit infrastructure in a high-density urban setting encourages a modal shift from bus to rail transit and stimulates flexible travel behaviors, but fails to control private vehicle use. The evidence suggests that proper transport strategies and land use policies are essential for the efficiency of the rail transit investments.

Declarations of Competing Interest

None.

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CRediT authorship contribution statement

Jingjing Wang: Writing – original draft, Writing – review & editing, Methodology. **Yi Lu:** Writing – review & editing, Methodology, Conceptualization. **Yiyang Yang:** Data curation, Writing – review & editing. **Jiandong Peng:** Writing – review & editing, Conceptualization. **Ye Liu:** Supervision. **Linchuan Yang:** Supervision.

Data availability

Data will be made available on request.

Appendix A. Appendix

Table A1
Summary of related studies.

Author (year)	Region	Study design	Sample size	Treatment group vs. Control group	Mode considered in the study				The sources (reasons) for increase in rail transit ridership
					Rail	Bus	Car	Active	
1. Lund et al. (2006)	California, US	Longitudinal (Repeated cross-sectional study)	1501	TOD vs. not TOD	√	√	√	√	Residential self-selection, transit-friendly built environment and supportive policy
2. Cervero (2007)	San Francisco, US	Cross-sectional	10,968	TOD vs. not TOD			√		Residential self-selection
3. Renne (2005)	Australia	Cross-sectional	848	TOD vs. average of the city	√	√	√	√	Reduced car use
4. Brown and Werner (2008)	Salt Lake City, US	Longitudinal (Panel study)	51	New riders vs. non-riders and riders			√	√	Travel attitude
5. Chatman (2008)	California, US	Cross-sectional	1113	Rail neighborhoods vs. similar demographic and built environment neighborhoods	√	√	√	√	Transit-friendly built environment
6. Dill (2008)	Portland, US	Longitudinal (Panel study)	323	–	√	√	√	√	Supportive policy
7. Senior (2009)	Greater Manchester, UK	Longitudinal (Panel study)	614	Rail corridor vs. heavy rail and non-rail corridors	√	√	√	√	Reduced bus use
8. Chatman (2013)	New Jersey, US	Cross-sectional	5193	Rail neighborhoods vs. similar demographic and built environment neighborhoods	√				Transit-friendly built environment
9. Pan et al. (2013)	Shanghai, China	Cross-sectional	606	Within 1.0 km of stations vs. 1.0 km away from stations	√	√	√	√	Reduced car use
10. Lee and Senior (2013)	4 English cities	Cross-sectional	–	Rail corridor vs. no rail corridor	√	√	√	√	Reduced bus use
11. Nixon et al. (2015)	Los Angeles, US	Longitudinal (Panel study)	73	Within 0.8 km of stations vs. 0.8 km away from stations	√	√	√	√	Reduced car use
12. Kwoka et al. (2015)	Denver, US	Cross-sectional	3439	Work near stations vs. work far away from stations	√		√		Reduced car use
13. Shen et al. (2016)	Shanghai, China	Cross-sectional	1436	Rail neighborhoods vs. no rail neighborhoods	√	√	√	√	Travel attitude
14. Xie (2016)	Beijing, China	Longitudinal (Repeated cross-sectional study)	7547	New rail neighborhoods vs. no new rail neighborhoods	√	√	√	√	Reduced car use
15. Wu and Hong (2017)	Beijing, China	Longitudinal (Repeated cross-sectional study)	3022	–	√	√	√	√	Reduced bus use and active travel

(continued on next page)

Table A1 (*continued*)

Author (year)	Region	Study design	Sample size	Treatment group vs. Control group	Mode considered in the study				The sources (reasons) for increase in rail transit ridership
					Rail	Bus	Car	Active	
16. Cao and Ermagun (2016)	Minneapolis, US	Longitudinal (Panel study)	597	Movers into rail corridors vs. movers into non-rail corridors	√	√	√		Reduced car use
17. Huang et al. (2019)	Xi'an, China	Longitudinal (Panel study)	593	Movers vs. non-movers			√		Reduced car use
18. Luan et al. (2020)	Nanjing, China	Cross-sectional	4080	Rail neighborhoods vs. no rail neighborhoods	√	√	√	√	Reduced car use
19. Dai et al. (2020)	Singapore	Longitudinal (Repeated cross-sectional study)	2244	Within 0.5 km of stations vs. between 500 m and 1000 m of stations	√	√	√		Reduced car use
20. Sun et al. (2020)	Nanchang, China	Longitudinal (Panel study)	1770	Within 0.8 km of stations vs. 1.6 km and 5 km away from the stations	√	√	√	√	Reduced bus use and active travel

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