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New metro system and active travel: A natural experiment

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ABSTRACT

Background: We used the first metro system in a developing city as a natural experiment to investigate the causal inference in the new metro's impact on modal shift and active travel.

Material and methods: The treatment group was formed by residents from neighbourhoods located within the 800-m walking distance to new metro stations. The first control group was formed by residents lived 1.6 km away from and outside of walking distance to the nearest station, and the second was 5 km away and outside of cycling distance. The groups were determined by local transit-oriented planning practice and empirical studies on active travel. Of the 5627 participants who had finished a baseline travel behaviour survey before new metro launched, 1770 returned and completed the follow-up survey a year after the metro's operation, which consists of 833 cohort participants in the treatment group and 937 in the two types of control groups. We used a difference-in-difference method to make before and after comparisons of travel behaviour changes between treatment and control groups.

Results: Our longitudinal data analyses revealed diverse travel behaviour changes. In general, people who used to take bus have adopted metro. The average metro usage was 30.9 (28.8–33.3) minutes daily for work trips and 16.6 (14.9–18.7) minutes daily for non-work trips. Walking time decreased 19.7 minutes at most ($p < 0.001$), and cycling decreased 22.1 minutes daily ($p < 0.001$). Car and e-bike usages remained largely unchanged before and after new metro, without difference between treatment and control groups.

Conclusion: The natural experiment study provided the first empirical evidence in a developing city context on causal inference in new metro's impact on active travel. A new metro does not necessarily promote active travel increase or car use reduction, calling for caution in making general assumptions about the effects of urban rail transit investments. We suggest local urban and transport planning knowledge could be useful in designing and explaining the complex natural experiments in transport and health.

1. Introduction

Transport may offer a transformative solution to achieve healthy living (Khreis et al., 2016; Nieuwenhuijsen et al., 2016). However, the difficulties lie in the lack of scientific evidence to support the expensive transport infrastructural modification, because the linkage between transport and health is largely based on cross-sectional studies (Fitzhugh et al., 2010; Ogilvie et al., 2016). There is a lack of research design to look at the before-and-after effect of a new transport infrastructure to see if it leads to meaningful behavioural changes (e.g., converting car travels), in order to advance our knowledge on what works and how it works (Aldred et al., 2019; Chatterjee and Carey, 2018). The main reason for this lagging is that transport interventions are intrinsically difficult to manipulate or amend experimentally, and its design or opening is usually out of researchers' control.

Natural experiment uses naturally occurring variations in exposure to study the impact of the transport modifications on travel behaviours. Recently, guidelines are emerging for using natural experiments to study built environment and public health (Craig et al., 2012; Humphreys et al., 2016). A few reviews included a broad range of built environment interventions such as park improvements or new walking and cycling greenways (Hirsch et al., 2018; Kärmeniemi et al., 2018; Mayne et al., 2015; Xiao et al., 2019). The heterogeneity of these interventions in the reviews makes it difficult to evaluate the actual effect of transport infrastructure on the uptake of active modes (Stappers et al., 2018). Nevertheless, a few natural experimental studies have provided some evidence that new public busway (Heinen et al., 2015; Ogilvie et al., 2016; Panter et al., 2016; Panter and Ogilvie, 2017) and light rail transit (Hong et al., 2016; Huang et al., 2017) may encourage modal shift to the new system and increase of active travel. The robust

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evidence is appealing, but the few existing studies have significant limitations such as small sampling size or constructing controlled comparisons. Moreover, these studies are in low-density cities in developed countries, which ignores a larger study context – the developing countries.

Numerous new urban rail transit projects are concentrated in developing countries. For example, in China 53 metro lines were reported under construction in 2016 (Sun et al., 2016). The primary justification of these metro developments is to solve traffic congestions by converting people from car to the new public transit. The travel speed, the way of access and the impact threshold of the metro options are different from light rail transit and bus in previous studies (Hirsch et al., 2018; Kärmeniemi et al., 2018; Mayne et al., 2015; Xiao et al., 2019). However, the impacts of the new metros on modal shift and active travel have not been investigated, nor have these transit infrastructural modification opportunities been leveraged to provide scientific evidence.

In this study, we fulfill a gap in the existing literature by presenting results from the first natural experimental study of travel behaviour change before and after a new metro system in a developing context. Our treatment and control comparisons research design and longitudinal data might allow a stronger causal inference than previous cross-sectional studies. We hypothesise that people would shift from other travel modes to metro, and the pattern would be more apparent with those living closer to metro stations. We aim to answer the following research questions:

- What is the mode shift before and after the new metro?
- What is the time spent difference for each travel mode between baseline and follow-up survey?
- How do the changes differ between treatment and control groups?

2. Materials and methods

2.1. Natural experiment research design

2.1.1. The intervention: Nanchang Metro Line 1

We considered the inception of Nanchang's first metro line as a natural experiment. The intervention was the Metro Line 1 that went into operation in late December 2015, with 24 stations, running along the west bank of the Gan River and across the river through the city core to the eastern urban fringe. Nanchang citizens did not have metro as a travel mode option before this first metro line. We conducted a longitudinal study before and after Metro Line 1′s operation to investigate how the new metro changes participants' travel behaviours.

Nanchang is the capital of Jiangxi province in China, with an urban area of 208 km^2 and an urban population of 2.4 million in 2017. As other Chinese cities, Nanchang is experiencing rapid motorisation, bringing increasingly severe congestion.

2.1.2. Defining treatment and control groups

Fig. 1 illustrates the research design. We aimed to make before-and-after comparisons in travel behaviours changes of participants between living in a group of transit-served neighbourhoods (treatment groups) and their control counterparts.

The treatment group, named as group 1, contained neighbourhoods that are within 800-m walking distance from six of the metro stations. The first control group, named as group 2, contained three study sites which are neighbourhoods with their centroids located 1.6 km away from the closest metro stations. The second control group, group 3, contained three neighbourhoods with their centroids located 5 km away from stations.

The selection of treatment and control groups was based on previous active travel studies in Chinese cities and local urban rail transit planning practices. Nanchang metro used a transit-oriented development (TOD) planning concept in which the station's catchment was designed as 800-m (Qu et al., 2014). TOD principle assumes that people who are within an 800-m distance to their nearest transit station would be likely to walk to the station and use the transit system. Empirical findings from Chinese cities found people who are beyond 1.6 km away from a transit station would be unlikely to walk but still be possible to cycle to the stations if cycling environments are supportive (Sun et al., 2020; Sun and Zacharias, 2017); however, people who live more than 5 km away, an average car travel distance, are much less likely to use the public transit (Yang and Zacharias, 2015).

Local transport planners were invited for discussion to ensure the representability of the selected stations. We also considered the comparability of the built environment (e.g., types, building ages) between the treatment and control neighbourhoods. We excluded the rich villa areas (residents may seldom use public transit) and the poor village areas (residents may have limited options in using private cars) to enhance the results generalizability. We assumed that there are no group-specific preferences to public transport since the travel mode share by public bus before the new metro line was around 19% in 2015 (Nanchang Statistics Bureau, 2015).

2.2. Questionnaire design, participant recruitment and data collection

A questionnaire was used to collect participants' detailed travel behaviours for five types of travel modes: car, bus, walking, cycling, and e-bike. For each mode, we asked participants the frequency and average minute spent per trip in a typical workday and a weekend day, for work and non-work trips respectively. Work trip was defined as the home-workplace trips that take place regularly. Non-work trips were trips for non-working purposes, such as regular grocery shopping. We also measured recreational walking by frequency and duration. The baseline survey did not contain metro mode since the metro had not been opened, while the follow-up added two question items regarding metro use.

We conducted the baseline survey in November – December 2015 (t_1), before the new metro launched. Trained interviewers were assigned to entrances of and public spaces in the neighbourhoods treatment and control sites to recruit participants who are (1) 18–65 years of age; (2) residents in the neighbourhood for at least three years (to control potential self-selection biases (Heinen et al., 2018)); (3) able to walk unassisted for at least 15 min. We used a randomised protocol to intercept residents, enquired their willingness, and got their commitment to accomplish two waves of surveys. We confirmed their provided mobile phone numbers for contacting about the follow-up survey. After the new metro went into operation for almost a year, we collected a follow-up survey in November – December 2016 (t_2). The one-year gap minimised seasonal influence and gave participants time to adapt to their new travel routines. We reminded participants for the second survey first through text messaging and followed by at least three rounds of phone calls to encourage them to return to finish the follow-up survey. Trained interviewers worked with each participant to administer both baseline and follow-up questionnaire surveys.

Of the 5,627 people who completed the baseline questionnaire (t_1), 1,804 returned and completed the follow-up survey (t_2). The response rate of the baseline survey was 38.5%, while the retention rate for the follow-up survey was 32.6%. The ethical committee of the authors' institution approved the study protocol.

2.3. Statistical analysis

2.3.1. Data cleaning, matching and reliability check

The follow-up survey dataset (t_2) was matched with the baseline survey dataset (t_1) using a unique identifier. Both baseline and follow-up datasets were cleaned by removing entries with missing group identifier, and after that baseline dataset was reduced from 5627 to 5436 participants and the follow-up from 1804 to 1770. The matched dataset (t_1&t_2) of 1,770 cohort participants was used for later analyses (Fig. 2).

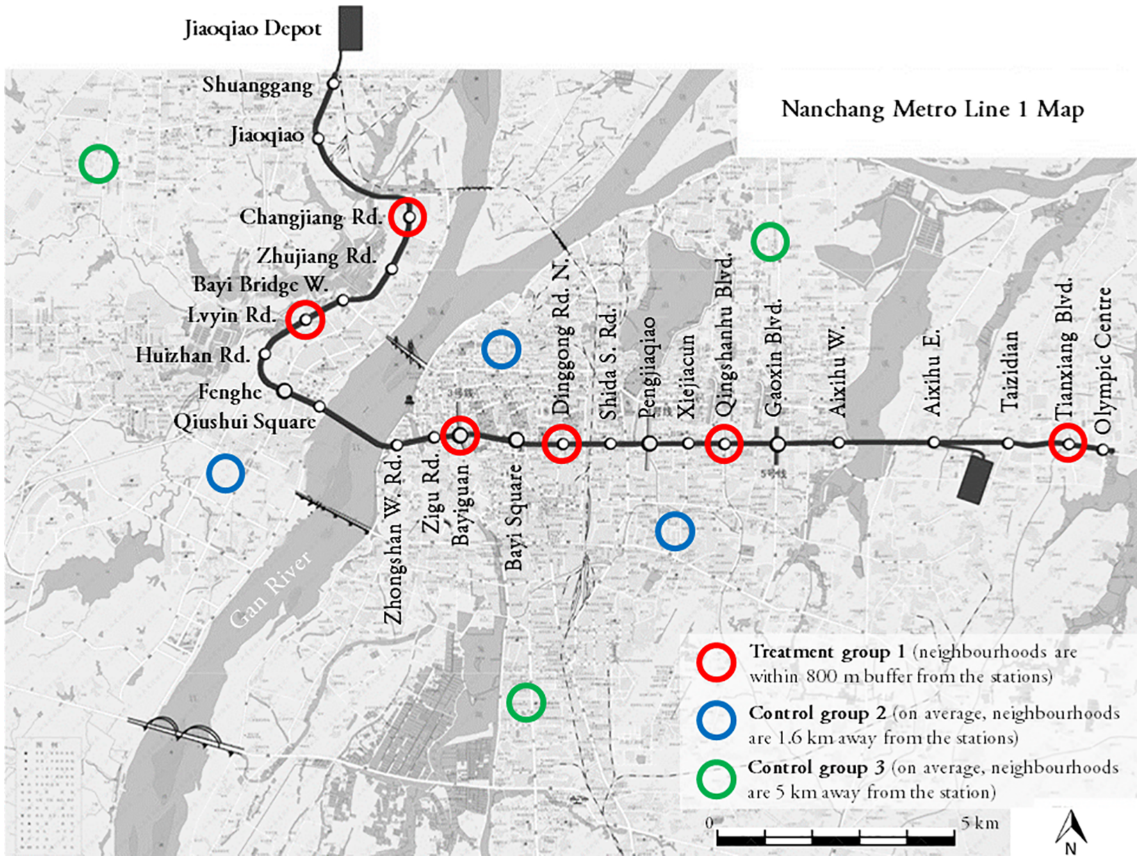

Fig. 1. Study sites for the treatment and control groups.

We further refined the dataset by removing trip pairs that contain exceptionally long or short durations. We set the longest trip as 2 h journey for bus and 1 h for car. The length was determined according to local experience that the travel time from the location of Olympic Centre station (eastern terminal) to Shuanggang station (western terminal), which is almost the longest travel distance across the city (Fig. 1), are within the maximum time threshold. Similarly, we set a minimum duration using bus or car as 5 min. Once an outlying trip was identified, this trip and its corresponding follow-up record were removed in pair. Since our analysis unit was trip-based, the pairwise deletion thus does not affect this participant's answers to other travel modes or trip purposes.

Moreover, if a person only used some of the given six mode choices, the rest of the travel modes would contain answers of "zero". We selected the applicable values for later travel behaviour change analyses using the exclusion criterion $T_{t1} = T_{t2} = 0$, where T stands for weekly time spent measured in minutes.

2.3.2. Analysis

Analysis 1: Visualise the modal shift before and after the new metro. We visualised the modal shift in two aspects: mode share and usage combination. For the mode share, we summed up the weekly time spent of primary and secondary usages for each participant (N = 1770), differentiated by trip purposes and survey waves. We presented the mode share using pie charts, categorised into four scenarios: work-primary usage, work-secondary usage, non-work-primary usage and

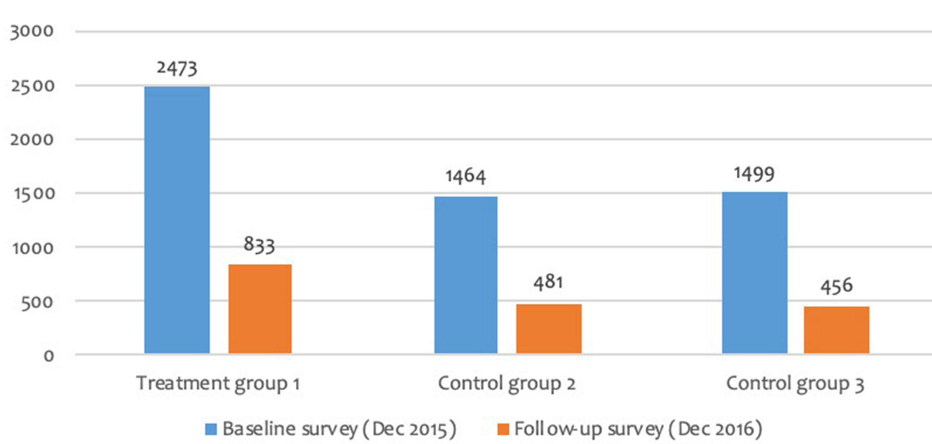

Fig. 2. Participant numbers in baseline and follow-up surveys.

non-work-secondary usage. For the usage combination, we counted the occurrence of the primary and secondary usage combinations for all participants, with regards to trip purposes and survey waves. We ranked the combinations in bar charts.

The primary and secondary usages were defined as the modes with the longest and second longest time spent by a participant. The usage was defined by the ranking of weekly time spent on each travel mode by a participant.

Analysis 2: T-tests for travel behaviour changes between baseline and follow-up survey. We used a paired *t*-test to examine whether participants' travel behaviours have changed significantly between t_1 and t_2 for each group. The null hypothesis (H_0: $\mu(T_{t2}) = \mu(T_{t1})$) for each travel mode and trip purpose was that weekly time spent at t_1 and t_2 remains the same. The difference in means was calculated as $\mu(T_{t2}) - \mu(T_{t1})$, and percent of change as $(T_{t2} - T_{t1})/T_{t1}$.

Furthermore, to better understand how individuals' travel behaviour had changed, we measured the modal weekly time spent by two types of participants: those who adopted metro and those who did not. We calculated the number of individuals and their average travel time on each mode, followed with a two-sample *t*-test to evaluate the significance of the difference between these two types. The null hypothesis is H_0: $\mu(T_{\Delta t.metro > 0}) = \mu(T_{\Delta t.metro=0})$, meaning that the mean time spent changes on each travel mode for participants who adopted metro is the same as those who did not.

Analysis 3: Difference-in-Difference among treatment and control groups. We conducted a difference-in-difference analysis to investigate group difference by comparing the change in time spent difference for each travel mode between the baseline and follow-up surveys. The strength of difference-in-difference is that it controls for unobserved as well as observed differences in the fixed characteristics of the groups and is therefore less prone to omitted variable bias caused by unmeasured confounders or measurement error (Craig et al., 2017). The method relies on the assumption that, in the absence of metro intervention, former travel behaviours would continue.

When there is only one treatment group and one control group, a two-sample *t*-test can be applied to study the significance of their difference. In our case, however, we have one treatment group and two control groups. A *T*-test would make p-value inflated and significance testing inaccurate. We thus used the *multcomp* package in R to conduct a Tukey's multiple comparison test that is more suitable for multiple group comparisons and unbalanced participants among groups (Mangiafico, 2015).

The analyses were all done in R language (v3.6.0).

3. Results

3.1. Participant characteristics in the baseline and follow-up surveys

Table 1 is the descriptive statistics of the participants in the baseline and follow-up surveys. The general image of our participants was that there were slightly more male than female, aged 31–35, have worked at their current workplace for 4–6 years, have lived at their current place for 6–7 years, did not own a car, earned 2,000 – 4,000 RMB monthly, and held a bachelor's or equivalent degree. Our participants resembled those of Nanchang with regard to income but had a slightly higher educational level (bachelor education level in Nanchang was 38%, while our sample for treatment–control groups was 41.6% on average) (Nanchang Statistics Bureau, 2015).

3.2. Modal shift: Mode share and usage combinations

Fig. 3 is the visualisation of the modal shift before and after the new metro. It summarised the total weekly time spent on each travel mode for eligible trips, and the results were categorised into work/non-work trips, baseline/follow-up surveys, and primary/secondary usages. The size of the pie chart depended on the sum of time spent on each category. Therefore, the pie was smaller for secondary usages than its primary pairs.

For work trips, the time spent share on bus, walking cycling and e-bike all decreased in different percentage and contributed to the increase in metro and car uses at follow-up. The time share on bus decreased from 31% (as primary usage) and 23% (as secondary usage) to 24% and 21%. The car time share increased slightly, from 19% (as primary usage) and 12% (as secondary usage) to 21% and 13%. There was a decrease of walking time share, from 25% (as primary usage) and 27% (as secondary usage) to 9% and 21%. Larger decrease was found in cycling time share, from 8% (as primary usage) and 16% (as secondary usage) to 2% and 3%. Similarly, e-bike time share decreased from 19% and 22% to 16% and 10%. In the follow-up survey, the metro took up 28% and 33% of the time share for primary and secondary usages.

For non-work trips, the mode share changes were less homogeneous. The decreased time share on bus, cycling and walking shifted to the increase of time spent on car, e-bike and metro as the primary usage. In contrast, all travel modes decreased to contribute to the increase in metro time share as the secondary usage. The bus time decrease was 15% more compared to its counterpart in work trips as the primary usage, while this number was 9% as the secondary usage. The car time share increased 4% as the primary usage, 2% more compared to the work trip counterpart, and decreased 5% as the secondary usage. Walking time share decreased for both usages, with 12% for primary and 6% for secondary, similar pattern compared to the work trip counterpart. Cycling time share also decreased, but the amount is 4% less than the work trip counterpart for both primary and secondary usages. The e-bike usage increased 4% as the primary mode and decreased 4% as the secondary mode. The metro time share increase was 1% (as primary usage) and 4% (as secondary usage) more than the work trip counterparts, and the proportion was higher as a secondary usage.

Fig. 4 shows results of the primary and secondary usage combinations. Three most noticeable trends were: first, in the follow-up survey, the most popular usage combination was metro-bus (as primary and secondary usages), regardless of trip purposes; second, car-only remained frequent despite the metro's opening; third, the occurrence of walking as the primary usage decreased by 6 and 7 in terms of ranking for work and non-work trips respectively. For work trips, the most popular combinations changed from walk-only, car-only, and walk-bus to metro-bus, car-only and metro-walk. For non-work trips, it changed from bus-walk, bus-only and walk-bus to metro-bus, metro-only and car-only.

3.3. Travel behaviour changes between baseline and follow-up survey

3.3.1. Paired t-test for measuring before-and-after changes within each group

Table 2 shows the results of the average changes and change percentage separated by groups. As a general trend, the average travel time spent on various travel modes except car decreased since t_1.

For bus trips, the weekly time spent on bus for work decreased around 34% for group 1 (-56.9 mintes, $p = 0.001$) and 2 (-70.5 mintes, $p = 0.006$), but remained unchanged for group 3 (7.4 mintes, $p = 0.801$). For non-work bus trips, all groups presented a significant decrease in time spent, with group 1 decreasing the greatest (-93.4 mintes, $p < 0.001$), followed by group 2 (-46.9 mintes, $p < 0.001$) then group 3 (-44.9 mintes, $p < 0.001$).

For car trips, there was no statistically significant change in mean travel time for either work or non-work purposes. This could be a result from the counteraction between the decreased driving time by the metro adopters and increased time by metro non-adopters.

For walking trips, the travel time for all trip types decreased by a large amount, except for group 3 on non-work trips (-2.4 mintes, $p = 0.876$). For work trips, group 2 on average decreased

Table 1
Descriptive statistics of participants.

	Baseline survey (N = 5436)			Follow-up survey (N = 1770)		
	Treatment group 1[a]	Control group 2[b]	Control group 3[c]	Treatment group 1[a]	Control group 2[b]	Control group 3[c]
Count (%)	2473 (45%)	1464 (27%)	1499 (28%)	833 (47%)	481 (27%)	456 (26%)
Male ratio	1.1	1.1	1.4	1.2	1.2	1.2
Age (SD)	31.9 (10)	34.7 (11)	33.0 (12)	31.5 (10)	35.0 (12)	32.0 (11)
Years working at current workplace (SD)	4.4 (6)	5.9 (7)	3.8 (6)	4.2 (6)	6.2 (7)	3.7 (5)
Years living at current place (SD)	6.8 (9)	7.3 (9)	6.6 (11)	6.3 (8)	7.4 (9)	6.3 (10)
Car ownership in count						
Own a car	804 (33%)	622 (43%)	466 (31%)	264 (32%)	200 (42%)	152 (33%)
Do not own a car	1605 (65%)	823 (56%)	1010 (67%)	549 (66%)	277 (58%)	300 (66%)
Monthly income in RMB in count						
< 2,000	308 (12%)	166 (11%)	181 (12%)	89 (11%)	60 (12%)	44 (10%)
2,000–4,000	1056 (43%)	505 (34%)	646 (43%)	346 (42%)	179 (37%)	197 (43%)
4,000–6,000	645 (26%)	482 (33%)	344 (23%)	229 (27%)	141 (29%)	96 (21%)
6,000–8,000	218 (9%)	208 (14%)	144 (10%)	79 (9%)	69 (14%)	62 (14%)
8,000–10,000	53 (2%)	54 (4%)	76 (5%)	22 (3%)	26 (5%)	23 (5%)
greater than10,000	67 (3%)	15 (1%)	75 (5%)	27 (3%)	4 (1%)	27 (6%)
Education level in count						
Middle school or below	408 (16%)	254 (17%)	447 (30%)	148 (18%)	82 (17%)	142 (31%)42
High school	514 (21%)	385 (26%)	328 (22%)	175 (21%)	133 (28%)	98 (21%)
Bachelor	1191 (48%)	578 (39%)	576 (38%)	385 (46%)	198 (41%)	175 (38%)
Master or above	108(4%)	55 (4%)	37 (2%)	29 (3%)	26 (5%)	9 (2%)

[a] Group 1: participants from neighbourhoods that are within 800-m walking distance from six of the metro stations.
[b] Group 2: participants from neighbourhoods with their centroids located 1.6 km away from their closest metro stations.
[c] Group 3: participants from neighbourhoods with their centroids located 5 km away from stations.

138.3 minutes ($p < 0.001$) per week, equivalent to 20 minutes per day. Group 2′s decrease for non-work trips was the most (-58.0 mintes, $p < 0.001$). The control group 2′s decrease was also topped among three groups for recreational walking (-115.4 mintes, $p < 0.001$), outrunning group 1 and group 2 by roughly 50 min.

For cycling trips, the mean travel time decreased more than 60% for work trips in all groups, with group 2 being the greatest (-154.8 mintes, change percentage = 83%, $p < 0.001$, N = 70 participants). The decrease for group 1 was the most in non-work trips (-79.8 mintes, change percentage = 79%, $p < 0.001$, N = 112 participants). The number of cycling users was much smaller compared to other travel modes.

For e-bike trips, the further away from metro stations there was a greater decrease in mean weekly travel time for work, with group 3 experiencing a 40% decrease (-68.6 mintes, p = < 0.001). For non-work trips, there was no significant weekly time spent change in all groups.

For metro use, the weekly time spent on work trips ranged from 201.7 minutes (s.d. = 145) to 233.4 minutes (s.d. = 191). For non-work trips, the metro usage ranged from 104.2 minutes (s.d. = 86) to 130.6 minutes (s.d. = 107).

3.3.2. Two-sample t-test for measuring the modal shift to metro

We found a significant difference between metro adopters and non-adopters in the decrease in weekly time spent among almost all travel modes. The non-work metro time spent was much less compared to the work trip counterparts. To save space we only present results of the work trips (Table 3).

Measured by weekly time spent, the decrease of bus usage ranged from 89.4 minutes (s.d. = 263) to 171.8 minutes (s.d. = 291) amongst individuals who adopted metro, with group 3 being the least and group 1 the greatest. For people who did not adopt metro, the bus time spent decreased in group 2 (-52.5 mintes, s.d. = 392) but increased in group 3 (38.8 mintes, s.d. = 383). Metro adopters' decreases of bus usage were significantly different from non-adopters in group 1 ($p < 0.001$) and group 3 ($p = 0.025$)

Car time spent for individuals who adopted metro also decreased by a great amount, whereas it for non-adopters increased up to 60.5 minutes (s.d. = 258) weekly. The metro adoption rate (group 1 = 19%, group 2 = 21%, group 3 = 18%) for car users was the lowest compared to all other travel mode users. These measurements may explain the slight decrease in car mode share in Fig. 3. Metro adopters' changes in car usage were significantly different from non-adopters ($p < 0.001$).

Walking time spent decreased regardless of the metro's usage, but metro adopters walked even less. Group 2 (-171.6, s.d. = 182) decreased the most, followed by group 1 (-133.9, s.d. = 144) and group 3 (-85.7, s.d. = 156). Cycling trips were similar to walking trips. The time spent decreased regardless of metro adoption.

E-bike trips were shortened significantly for the metro adopters compared to non-adopters, with group 3 decreasing the most (-190.1, s.d. = 222) and followed by group 2 (-115.3, s.d. = 151) and group 1 (-113.1, s.d. = 177).

3.4. Group difference among treatment and control groups

Table 4 presents the difference-in-difference analysis of intergroup behavioural change comparisons.

For bus trips, there were significant differences for the non-work trips between treatment and control groups (group pair 2–1, difference = 46.5 mintes, $p = 0.012$; and group pair 3–1, difference = 48.5 mintes, $p = 0.007$). For work trips, we observed that p-values were nearly significant for comparisons between groups 3 and 2 (difference = 77.9 mintes, $p = 0.082$) and groups 3 and 1 (difference = 64.3 mintes, $p = 0.132$).

For car trips, there was no significant intergroup difference.

For walking trips, every group was significantly different from each other for work trips. For non-work trips, the group differences were between groups 3 and 2 ($p = 0.011$) and groups 3 and 1 ($p = 0.004$), while there was no significant difference between group 1 and group 2. Since group 3 remained almost no change, it implies behavioural changes only in group 1 and 2. For recreational walking, all groups decreased their time spent, and there was group difference between group 2 and the other two groups (group pair 2–1, difference = -51.8 mintes, $p = 0.006$; group 3–2, difference = 48.1, $p = 0.035$).

For cycling trips, no intergroup difference was found on work trips. For non-work trips, there was a significant difference between group 1 and group 2 (difference = - 65.3 mintes, $p = 0.05$). Particularly, group 1 decreased their cycling time by 78.5 mintes, while the time changes for

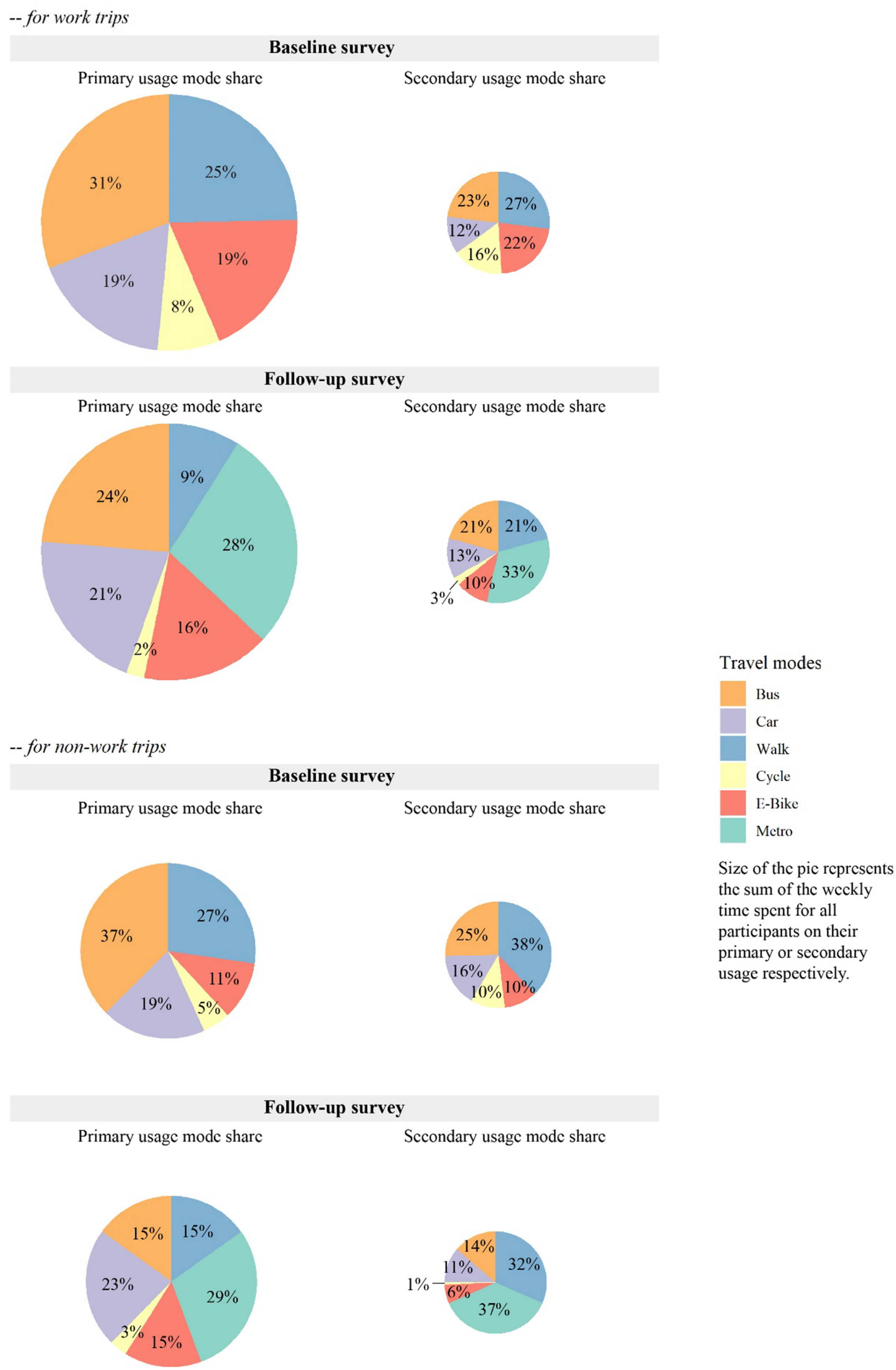

Fig. 3. Travel mode share as primary and second usages under different scenarios.

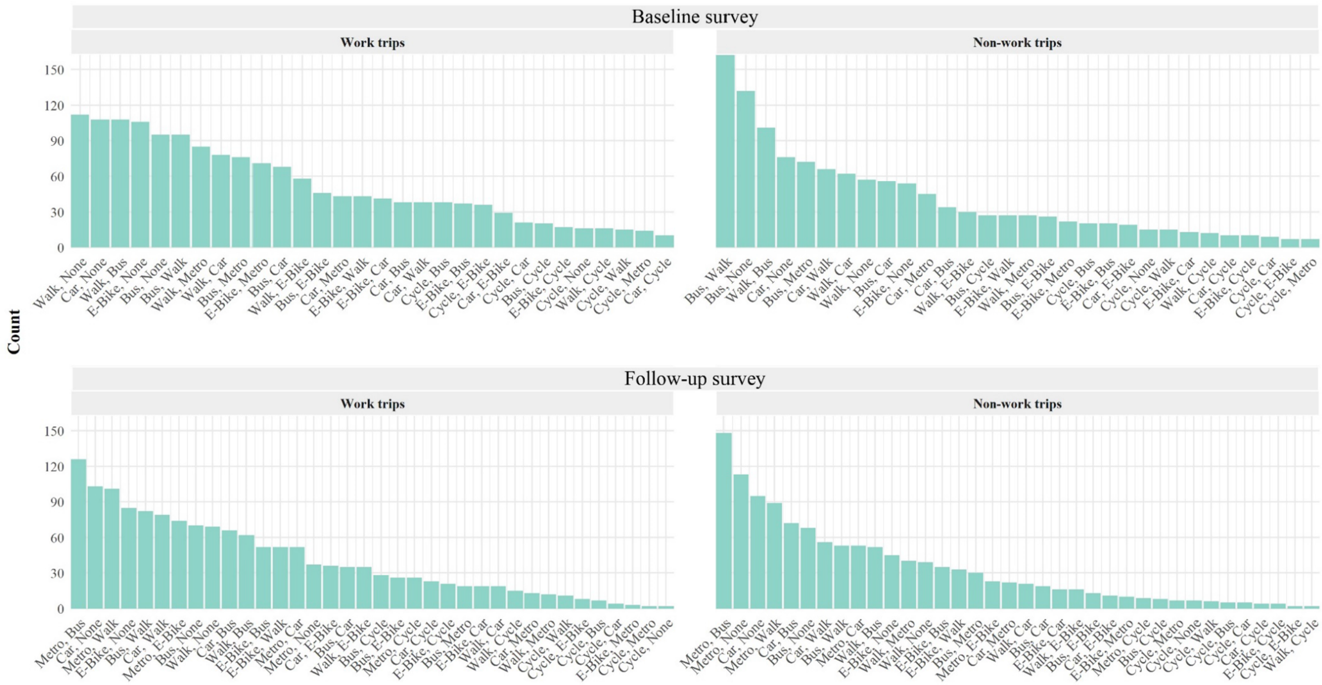

Fig. 4. The most popular primary and secondary usage combinations under different scenarios.

groups 2 and 3 were insignificant.

For e-bike trips, there was no significant intergroup difference.

For metro use, the significant intergroup difference was between group 3 and 2 in non-work trips (difference = 26.4 mintes, p = 0.04). Group 3 also showed a trend to significant difference to the treatment group 1 in non-work trips (difference = 18.6, p = 0.126).

4. Discussion

In this paper, we presented the first natural experiment study using a new metro system in the developing city context of Nanchang as an intervention to investigate the causal inference on model shift and active travel change before-and-after the new metro system. We expected there to be a modal shift to the new metro. The finding is somewhat consistent with this expectation; however, there are large variations in shift patterns for different travel modes. We also expected that accessibility to metro stations by walking and cycling are conducive to metro usage; therefore, we assigned the treatment–control groups based on distance thresholds of walking and cycling. However, the finding is unexpected as living closer does not always yield a more striking modal shift than living further away. It turns out to be a case by case situation for each travel mode.

4.1. Research design in the natural experiment

The research design in this study is unique in several aspects. First, the study subject is a medium-sized city in a developing context. Nanchang is a city with 2.4 million people and in rapid motorisation. It could be representative of a developing city, to fulfil the gap in existing natural experiment literature which is mainly focused on developed cities. According to the review on public transit and active travel by Hirsch et al. (2018), only one natural experiment out of the existing five is done in a developing context, which is a new bus rapid transit study in Mexico City. Although both cities have similarities in the rapid motorisation and reduction of physical activities, Nanchang is less developed than Mexico City as it has never had a rapid transit prior to the metro system, whereas Mexico City has had their metro for decades.

Second, our focus on metro intervention is different from previous research in terms of study subjects which are either bus rapid transit or light rail transit (Hong et al., 2016; Huang et al., 2017; Ogilvie et al., 2016). Unlike these systems, metro system is more expensive, intrinsically difficult to modify and takes longer to build. Therefore its influence to travel modal shift and active travel would be more steady and profound.

Third, the sample size of our research is considerable comparing to previous studies. Our cleaned baseline sample size is 5436 and follow-up 1770. The light rail study in Seattle worked with 214 participants (Huang et al., 2017); the Los Angeles longitudinal study involved 279 households (Hong et al., 2016). The large sample size of our study enabled us to have sufficient statistical power in detecting the changes in various travel modes along with the new metro intervention.

Fourth, we designed a control comparison assignment that is based on active travel distance backed by local urban rail transit planning knowledge. It provides a new perspective on the challenging task in defining control comparisons (Humphreys et al., 2016; Kärmeniemi et al., 2018; Kesten et al., 2015). In Hong et al. (2016)'s light rail transit natural experiment the treatment group are residents living within 800-m catchments of the stations, while the control groups are right adjacent to treatment groups but the distance is further than 800 m. However, it would be reasonable to argue that there might be transit riders in the control groups, who were willing to walk longer than 800 m to access the station. Thus this benchmark would be difficult to separate the treatment and control groups. In Heinen et al. (2017)'s new busway study, they used a continuous distance variable to explore the intensity of exposure (Heinen et al., 2017; Ogilvie et al., 2010). The use of walking and cycling access to metro station to define control comparisons can have more straightforward practical implications, as current metro developments are based on such planning concept.

4.2. A large variability in before-and-after changes on the modal shift

As a general trend found in Figs. 3 and 4, the metro became the most frequently chosen primary travel mode. There is a consistent decrease in time spent on bus, walking and cycling modes. Time spent on car increased slightly for all scenarios except for non-work trips as secondary usage. Similarly, the e-bike mode share increased by 4% for

Table 2
Descriptive statistics on modal shift for each group.

Travel Mode	Travel Purpose	Group	Baseline Survey Mean (SD[a])	Follow-up Survey Mean (SD)	Difference in Means [b] (SD)	Change(%)[c]	P-Value	N (total participants)[d]
Bus	Work	1	168.1 (210)	111.2 (199)	−56.9 (312)	–33.9	0.001**	323 (833)
		2	207.2 (282)	136.7 (227)	−70.5 (362)	−34.0	0.006**	203 (481)
		3	142.6 (174)	150.0 (276)	7.4 (361)	5.2	0.801	151 (456)
	Non-work	1	129.8 (184)	36.4 (76)	−93.4 (205)	−72.0	< 0.001***	353 (833)
		2	101.4 (125)	54.5 (107)	−46.9 (181)	−46.3	< 0.001***	199 (481)
		3	85.4 (101)	40.6 (82)	−44.9 (138)	−52.5	< 0.001***	202 (456)
Car	Work	1	117.5 (151)	138.2 (154)	20.7 (240)	17.6	0.174	250 (833)
		2	137.7 (157)	110.4 (152)	−27.2 (244)	−19.8	0.122	193 (481)
		3	106.1 (140)	138.3 (172)	32.2 (252)	30.4	0.134	139 (456)
	Non-work	1	80.6 (119)	80.9 (119)	0.3 (195)	0.4	0.980	241 (833)
		2	96.7 (133)	75.4 (123)	−21.3 (204)	–22.1	0.148	193 (481)
		3	66.6 (103)	72.4 (132)	5.8 (187)	8.8	0.700	154 (456)
Walk	Work	1	138.7 (120)	47.1 (96)	−91.6 (171)	−66.0	< 0.001***	330 (833)
		2	171.0 (162)	32.6 (61)	−138.3 (187)	−80.9	< 0.001***	201 (481)
		3	107.4 (111)	73.3 (131)	−34.1 (198)	−31.8	0.025*	173 (456)
	Non-work	1	107.0 (151)	49.2 (100)	−57.8 (197)	−54.0	< 0.001***	375 (833)
		2	99.0 (108)	40.9 (76)	−58.0 (149)	−58.6	< 0.001***	210 (481)
		3	74.8 (125)	72.4 (125)	−2.4 (194)	−3.2	0.876	160 (456)
	recreation	1	132.9 (137)	69.3 (137)	−63.6 (217)	−47.9	< 0.001***	420 (833)
		2	162.4 (143)	47.1 (111)	−115.4 (198)	−71.0	< 0.001***	256 (481)
		3	132.7 (136)	65.4 (131)	−67.3 (214)	−50.7	< 0.001***	222 (456)
Cycle	Work	1	146.3 (134)	34.0 (96)	−112.3 (175)	−76.8	< 0.001***	114 (833)
		2	185.9 (161)	31.1 (93)	−154.8 (213)	−83.3	< 0.001***	70 (481)
		3	138.0 (135)	50.9 (136)	−87.2 (224)	−63.1	0.008**	51 (456)
	Non-work	1	101.7 (112)	21.9 (69)	−79.8 (145)	−78.5	< 0.001***	112 (833)
		2	77.5 (79)	63.0 (122)	−14.5 (172)	−18.7	0.562	48 (481)
		3	84.8 (117)	39.7 (141)	−45.2 (199)	−53.3	0.233	29 (456)
E-bike	Work	1	130.0 (125)	110.3 (159)	−19.7 (230)	−15.1	0.166	264 (833)
		2	135.1 (149)	88.5 (166)	−46.6 (252)	−34.5	0.026*	149 (481)
		3	171.4 (178)	102.8 (161)	−68.6 (245)	−40.0	< 0.001***	162 (456)
	Non-work	1	83.4 (128)	79.6 (125)	−3.7 (206)	−4.5	0.808	180 (833)
		2	76.3 (98)	80.6 (160)	4.3 (195)	5.6	0.825	100 (481)
		3	73.7 (119)	72.5 (103)	−1.2 (185)	−1.6	0.950	93 (456)
Metro	Work	1	0.0 (0)	214.8 (148)	214.8 (148)	Inf	NA	244 (833)
		2	0.0 (0)	233.4 (191)	233.4 (191)	Inf	NA	132 (481)
		3	0.0 (0)	201.7 (145)	201.7 (145)	Inf	NA	122 (456)
	Non-work	1	0.0 (0)	112.0 (91)	112.0 (91)	Inf	NA	297 (833)
		2	0.0 (0)	104.2 (86)	104.2 (86)	Inf	NA	159 (481)
		3	0.0 (0)	130.6 (107)	130.6 (107)	Inf	NA	142 (456)

[a] SD = Standard Deviation
[b] Difference in Means $=\mu(T_{t2})-\mu(T_{t1})$
[c] Change (%) $=\frac{T_{t2}-T_{t1}}{T_{t1}}$
[d] N is the number of participants who has adopted a particular transit mode at either baseline or follow-up, i.e. N = $N_{(T_{t1}\neq 0 or T_{t2}\neq 0)}$; Total participants is the total number of participants in each group

non-work trips as a primary use. This finding coincides with Heinen et al. 's finding that the intervention did not result in one specific pattern of behaviour change or produce any full modal shifts (Heinen et al., 2017). Our results imply the relationships between metro and other travel modes are rather complicated.

Particularly for the former active travel modes, walking and cycling, we found a sizeable decrease after the launch of metro. Walking used to rank top three at baseline, but slid to the ninth and tenth (Fig. 4), and reduced up to 20 minutes daily. Few people cycled in the baseline survey, and in the follow-up survey, its share almost vanished (Fig. 3). Table 3 also shows an apparent trend of decreasing physical activities among participants with higher metro adoption rates. The cycling, walking, and recreational walking trips decreased regardless of the metro usage. This finding is strikingly contrasted to previous natural experiment on Cambridge new busway that shows a sizeable increase of walking and cycling, with cycling reported to be an increase of 80 min/week (Panter et al., 2016). The reason for the decline in our study may be because of the unfavourable walking and cycling environments, for example, unsupportive pedestrian facilities, absence of cycling lanes, hot weather and collision risk with cars (Sun et al., 2017). The new metro does not seem to mitigate the decline.

Overall, we see a trend that car, the effortless and flexible travel mode, remains popular amid the opening of metro. Although metro adopters reduced car travel time, the metro adoption rate for car users is lower than other travel modes. This longitudinal evidence is in line with previous cross-sectional findings on light rail transit (Copley et al., 2002; Golias, 2002; Mackett and Edwards, 1998; Vuk, 2005). We found the new metro systems would have less impact than their promoters anticipated concerning the shift from cars. On the contrary, the majority of new rail passengers would come from the pre-existing public bus.

4.3. *Causal inferences in the difference between treatment and control groups*

We found no significant time spent difference between treatment and control groups for car. This is in line with a former informative association study that finds living closer to metro station does not yield less car driving (Li and Zhao, 2017). Our result might provide scientific evidence for causal inferences that investing in the massive metro system may not be able to convert cars in order to solve traffic congestion and environmental issue in China and similar developing countries.

On the other aspect, metro's operation has led to a significant

Table 3
The mean time spent change comparisons for work trips between metro adopters and non-adopters.

Work Trips		Individuals who *adopted* metro		Individuals who did *not adopt* metro		
Travel mode	Group	Mean time spent change (SD)[a]	Number of individuals (adoption rate)[b]	Mean time spent change (SD)	Number of Individuals	P-Value[c]
Bus	1	−171.8 (291)	102 (32%)	−3.9 (308)	221	< 0.001***
	2	−121.4 (256)	53 (26%)	−52.5 (392)	150	0.150
	3	−89.4 (263)	37 (25%)	38.8 (383)	114	0.025*
Car	1	−128.1 (212)	47 (19%)	55.1 (233)	203	< 0.001***
	2	−145.7 (215)	41 (21%)	4.7 (242)	152	< 0.001***
	3	−96.8 (176)	25 (18%)	60.5 (258)	114	< 0.001***
Walk	1	−133.9 (144)	91 (28%)	−75.4 (177)	239	0.002**
	2	−171.6 (182)	50 (25%)	−127.3 (188)	151	0.143
	3	−85.7 (156)	40 (23%)	−18.6 (207)	133	0.031*
Cycle	1	−144.4 (179)	27 (24%)	−102.4 (173)	87	0.289
	2	−115.5 (301)	19 (27%)	−169.4 (170)	51	0.468
	3	−159.5 (150)	19 (37%)	−44.2 (250)	32	0.045*
E-bike	1	−113.1 (177)	56 (21%)	5.5 (237)	208	< 0.001***
	2	−115.3 (151)	33 (22%)	−27.0 (272)	116	0.017*
	3	−190.1 (222)	42 (26%)	−26.0 (240)	120	< 0.001***
Metro	1	214.8 (148)	244 (30%)	0.0 (0)	583	NA
	2	233.4 (191)	132 (28%)	0.0 (0)	348	NA
	3	201.7 (145)	122 (27%)	0.0 (0)	333	NA

[a] Mean time spent change $= \mu(T_{t2}) - \mu(T_{t1})$, where T stands for weekly time spent measured in minutes.
[b] The adoption rate is the fraction of individuals who adopted metro within those who used a particular travel mode.
[c] The p.value tests for the significance of the difference between the mean time spent change for individuals who adopted or did not adopt metro. The null hypothesis is H_0: $\mu(T_{\Delta t.metro > 0}) = \mu(T_{\Delta t.metro=0})$.

Table 4
Result of difference-in-difference analysis.

Travel mode	Trip purpose	Group pair (minuend – subtrahend)	Difference in means in minuend	Difference in means in subtrahend	Difference-indifference mean* (SD)	p-value
Bus	Work	2–1	−70.5	−56.9	−13.6 (30)	0.895
		3–1	7.4	−56.9	64.3 (33)	0.131
		3–2	7.4	−70.5	77.9 (36)	0.082.
	Non-work	2–1	−46.9	−93.4	46.5 (16)	0.012*
		3–1	−44.9	−93.4	48.5 (16)	0.007**
		3–2	−44.9	−46.9	2.1 (18)	0.993
Car	Work	2–1	−27.2	20.7	−47.9 (23)	0.101
		3–1	32.2	20.7	11.5 (26)	0.896
		3–2	32.2	−27.2	59.5 (27)	0.073.
	Non-work	2–1	−21.3	0.3	−21.6 (19)	0.487
		3–1	5.8	0.3	5.5 (20)	0.960
		3–2	5.8	−21.3	27.2 (21)	0.405
Walk	Work	2–1	−138.3	−91.6	−46.7 (16)	0.012*
		3–1	−34.1	−91.6	57.4 (17)	0.003**
		3–2	−34.1	−138.3	104.2 (19)	< 0.001***
	Non-work	2–1	−58.0	−57.8	−0.2 (16)	1.000
		3–1	−2.4	−57.8	55.4 (17)	0.004**
		3–2	−2.4	−58.0	55.6 (19)	0.011*
	Recreation	2–1	−115.4	−63.6	−51.8 (17)	0.006**
		3–1	−67.3	−63.6	−3.7 (18)	0.975
		3–2	−67.3	−115.4	48.1 (19)	0.035*
Cycle	Work	2–1	−154.8	−112.3	−42.5 (30)	0.334
		3–1	−87.2	−112.3	25.2 (33)	0.729
		3–2	−87.2	−154.8	67.6 (36)	0.152
	Non-work	2–1	−14.5	−79.8	65.3 (28)	0.050*
		3–1	−45.2	−79.8	34.6 (34)	0.553
		3–2	−45.2	−14.5	−30.7 (38)	0.693
E-bike	Work	2–1	−46.6	−19.7	−26.9 (25)	0.518
		3–1	−68.6	−19.7	−48.9 (24)	0.104
		3–2	−68.6	−46.6	–22.0 (27)	0.699
	Non-work	2–1	4.3	−3.7	8.0 (25)	0.943
		3–1	−1.2	−3.7	2.5 (25)	0.994
		3–2	−1.2	4.3	−5.5 (28)	0.979
Metro	Work	2–1	233.4	214.8	18.6 (17)	0.527
		3–1	201.7	214.8	−13.0 (18)	0.741
		3–2	201.7	233.4	−31.6 (20)	0.255
	Non-work	2–1	104.2	112.0	−7.8 (9)	0.674
		3–1	130.6	112.0	18.6 (10)	0.126
		3–2	130.6	104.2	26.4 (11)	0.040*

* Difference-in-difference mean = the group-wise subtraction of Difference in Means in table 2. For example, if the comparison group pair is 2–1, then the subtraction would be group 2 difference in means minus group 1 difference in means.

difference in walking time spent between treatment and control groups, and walking time dropped strikingly. The before and after changes on metro and walking is in line with previous studies which reveal that exposure to the new light rail transit results in a declining trend of total physical activity (Brown et al., 2007; MacDonald et al., 2010). In addition, our setting of two control groups further differentiates the impact magnitudes of the new metro. Specifically, for work trips, the result in Table 4 shows group 3 decreased the least; for non-work trips, control group 3′s decrease is also the smallest comparing to that of treatment group 1 and control group 2. The metro intervention is minimised for control group 3 due to its remote distance to stations.

In the intergroup difference analysis, we found the impact thresholds of the new metro for different travel modes or purposes are different. For example, for bus work trips the threshold could reach 1.6 km, while for the non-work trips the threshold is 800 m. For walking non-work trips, there is no significant difference between treatment group 1 and control group 2, and the threshold thus can reach 1.6 km. We found no intergroup difference for e-bike. Although there is a decline further away from the stations, there is no clear indication of a better setting of control comparisons for e-bike. These difference-in-difference analysis findings may suggest that a treatment–control assignment that specifies active modes and is backed by urban rail transit planning knowledge might be more appropriate than a unified geographic distance based method for designing future rail transit planning interventions (Humphreys et al., 2016; Kärmeniemi et al., 2018; Kesten et al., 2015).

4.4. Limitation and strength

There are several limitations to this study. We had a comparatively low retention rate, although this is common in longitudinal studies involved with public transport infrastructural interventions (Panter et al., 2016). Our data collection that is based on self-reported questionnaire makes it feasible to access a large cohort, while objective measures using accelerometer with global positioning system could accurately record the travel behaviours (Oreskovic et al., 2015). Our questionnaire focused on the main travel mode in a trip to minimise measurement error due to recall bias, but measuring the entire journey could refine the behavioural changes. Though the research design is insightful, this type of large-scale study may encounter financial and temporal constraints in other contexts due to high risk of postpones and other uncertainties in the infrastructure construction. The generalisation of our findings to other contexts needs cautious since we only researched one Chinese city; however, the natural experiment research design would be transferable to urban rail transit system studies throughout China and further afield.

Despite the above limitations, there are several strengths to this study. This natural experiment study in a developing city context might contribute scientific evidence to causal inferences in transport and health literature. The current understanding of how public transport system relates to active travel and health lies primarily on cross-sectional studies, which might be limited by the inability to investigate the causal inferences (Dunning, 2012; Mayne et al., 2015). In contrast, our natural experiment controls confounding and unobserved factors through research design rather than statistical modellings at a later stage, making the analysis straightforward and results reliable. We provide more nuanced and deeper insights into the relationship between new transit infrastructure and travel behaviour changes in a developing context, where numerous new urban rail transit projects are currently concentrated. This study can bolster the accumulation of natural experiments in transport and health by leveraging on those infrastructure changing opportunities. In addition, we complied with the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guideline to ensure the transparency and completeness of our finding reporting (Craig et al., 2012; von Elm et al., 2007).

5. Conclusion

Natural experiments are becoming an increasingly popular tool to help transport and health researchers generate better evidence when true experiments are not possible. The findings from this natural experiment study in a developing city context provide novel evidence of the new metro's impact on modal shift and active travel. In short, new urban rail transit does not necessarily promote active travel increase or car use reduction, calling for caution in making general assumptions about the effects of transit investments. Lastly, urban and transport planning knowledge can help design and elaborate on complex natural experiments in transport and health.

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CRediT authorship contribution statement

Guibo Sun: Conceptualization, Methodology, Software, Investigation, Formal analysis, Visualization, Writing - original draft, Funding acquisition. **Jianting Zhao:** Conceptualization, Methodology, Software, Investigation, Formal analysis, Visualization, Writing - original draft. **Chris Webster:** Conceptualization, Methodology, Writing - original draft, Supervision, Project administration, Resources. **Hui Lin:** Conceptualization, Methodology, Writing - original draft, Supervision, Project administration, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aldred, R., Croft, J., Goodman, A., 2019. Impacts of an active travel intervention with a cycling focus in a suburban context: one-year findings from an evaluation of London's in-progress mini-Hollands programme. Transp. Res. Part A Policy Pract. 123, 147–169. https://doi.org/10.1016/j.tra.2018.05.018.

Brown, B.B., Werner, C.M., Amburgey, J.W., Szalay, C., 2007. Walkable route perceptions and physical features: converging evidence for en route walking experiences. Environ. Behav. 39, 34–61. https://doi.org/10.1177/0013916506295569.

Chatterjee, K., Carey, R.N., 2018. Special Issue on the theory, design and evaluation of behaviour change interventions in transport. J. Transp. Heal. 10, 7–10. https://doi.org/10.1016/j.jth.2018.08.009.

Copley, G., Thomas, M., Maunsell, F., Georgeson, N., 2002. Croydon Tramlink Impact Study, in: European Transport Conference. 9–11 September, Cambridge, UK.

Craig, P., Cooper, C., Gunnell, D., Haw, S., Lawson, K., Macintyre, S., Ogilvie, D., Petticrew, M., Reeves, B., Sutton, M., Thompson, S., 2012. Using natural experiments to evaluate population health interventions: new Medical Research Council guidance. J. Epidemiol. Community Health 66, 1182–1186. https://doi.org/10.1136/jech-2011-200375.

Craig, P., Katikireddi, S.V., Leyland, A., Popham, F., 2017. Natural Experiments: An Overview of Methods, Approaches, and Contributions to Public Health Intervention Research. Annu. Rev. Public Health 39–56. https://doi.org/10.1146/annurev-publhealth-031816-044327.

Dunning, T., 2012. Natural Experiments in the Social Sciences: A Design-Based Approach. Cambridge University Press, Cambridge, UK.

Fitzhugh, E.C., Bassett, D.R., Evans, M.F., 2010. Urban trails and physical activity: a natural experiment. Am. J. Prev. Med. 39, 259–262. https://doi.org/10.1016/j.amepre.2010.05.010.

Golias, J.C., 2002. Analysis of traffic corridor impacts from the introduction of the new Athens Metro system. J. Transp. Geogr. 10, 91–97. https://doi.org/10.1016/S0966-6923(01)00033-3.

Heinen, E., Harshfield, A., Panter, J., Mackett, R., Ogilvie, D., 2017. Does exposure to new transport infrastructure result in modal shifts? Patterns of change in commute mode choices in a four-year quasi-experimental cohort study. J. Transp. Heal. 6, 396–410. https://doi.org/10.1016/j.jth.2017.07.009.

Heinen, E., Panter, J., Mackett, R., Ogilvie, D., 2015. Changes in mode of travel to work: a natural experimental study of new transport infrastructure. Int. J. Behav. Nutr. Phys. Act. 12, 81. https://doi.org/10.1186/s12966-015-0239-8.

Heinen, E., Wee, B. Van, Panter, J., Mackett, R., Ogilvie, D., 2018. Residential self-selection in quasi-experimental and natural experimental studies: an extended conceptualization of the relationship between the built environment and travel behavior. J. Transp. Land Use 11, 939–959. https://doi.org/10.5198/jtlu.2018.1165.

Hirsch, J.A., DeVries, D.N., Brauer, M., Frank, L.D., Winters, M., 2018. Impact of new rapid transit on physical activity: A meta-analysis. Prev. Med. Reports 10, 184–190. https://doi.org/10.1016/j.pmedr.2018.03.008.

Hong, A., Boarnet, M.G., Houston, D., 2016. New light rail transit and active travel: a longitudinal study. Transp. Res. Part A Policy Pract. 92, 131–144. https://doi.org/10.1016/j.tra.2016.07.005.

Huang, R., Moudon, A.V., Zhou, C., Stewart, O.T., Saelens, B.E., 2017. Light rail leads to more walking around station areas. J. Transp. Heal. 6, 201–208. https://doi.org/10.1016/j.jth.2017.02.002.

Humphreys, D.K., Panter, J., Sahlqvist, S., Goodman, A., Ogilvie, D., 2016. Changing the environment to improve population health: a framework for considering exposure in natural experimental studies. J. Epidemiol. Community Health 70, 941–946. https://doi.org/10.1136/jech-2015-206381.

Kärmeniemi, M., Lankila, T., Ikäheimo, T., Koivumaa-Honkanen, H., Korpelainen, R., 2018. The Built Environment as a Determinant of Physical Activity: A Systematic Review of Longitudinal Studies and Natural Experiments. Ann. Behav. Med. 52, 239–251. https://doi.org/10.1093/abm/kax043.

Kesten, J.M., Guell, C., Cohn, S., Ogilvie, D., 2015. From the concrete to the intangible: understanding the diverse experiences and impacts of new transport infrastructure. Int. J. Behav. Nutr. Phys. Act. 12, 72. https://doi.org/10.1186/s12966-015-0230-4.

Khreis, H., Warsow, K.M., Verlinghieri, E., Guzman, A., Pellecuer, L., Ferreira, A., Jones, I., Heinen, E., Rojas-Rueda, D., Mueller, N., Schepers, P., Lucas, K., Nieuwenhuijsen, M., 2016. The health impacts of traffic-related exposures in urban areas: understanding real effects, underlying driving forces and co-producing future directions. J. Transp. Heal. 3, 249–267. https://doi.org/10.1016/j.jth.2016.07.002.

Li, S., Zhao, P., 2017. Exploring car ownership and car use in neighborhoods near metro stations in Beijing: Does the neighborhood built environment matter? Transp. Res. Part D Transp. Environ. 56, 1–17. https://doi.org/10.1016/j.trd.2017.07.016.

MacDonald, J.M., Stokes, R.J., Cohen, D.A., Kofner, A., Ridgeway, G.K., 2010. The effect of light rail transit on body mass index and physical activity. Am. J. Prev. Med. 39, 105–112. https://doi.org/10.1016/j.amepre.2010.03.016.

Mackett, R.L., Edwards, M., 1998. The impact of new urban public transport systems: will the expectations be met? Transp. Res. Part A Policy Pract. 32, 231–245. https://doi.org/10.1016/S0965-8564(97)00041-4.

Mangiafico, S.S., 2015. An R Companion for the Handbook of Biological Statistics. Rutgers Cooperative Extension.

Mayne, S.L., Auchincloss, A.H., Michael, Y.L., 2015. Impact of policy and built environment changes on obesity-related outcomes: a systematic review of naturally occurring experiments. Obes. Rev. 16, 362–375. https://doi.org/10.1111/obr.12269.

Nanchang Statistics Bureau, 2015. Nanchang statistical yearbook. Statistics Press, China.

Nieuwenhuijsen, M.J., Khreis, H., Verlinghieri, E., Rojas-Rueda, D., 2016. Transport And Health: A Marriage Of Convenience Or An Absolute Necessity. Environ. Int. 88, 150–152. https://doi.org/10.1016/j.envint.2015.12.030.

Ogilvie, D., Griffin, S., Jones, A., Mackett, R., Guell, C., Panter, J., Jones, N., Cohn, S., Yang, L., Chapman, C., 2010. Commuting and health in Cambridge: a study of a "natural experiment" in the provision of new transport infrastructure. BMC Public Health 10, 703. https://doi.org/10.1186/1471-2458-10-703.

Ogilvie, D., Panter, J., Guell, C., Jones, A., Mackett, R., Griffin, S., 2016. Health impacts of the Cambridgeshire Guided Busway: a natural experimental study. Public Heal. Res. 4, 1–154. https://doi.org/10.3310/phr04010.

Oreskovic, N.M., Goodman, E., Park, E.R., Robinson, A.I., Winickoff, J.P., 2015. Design and implementation of a physical activity intervention to enhance children's use of the built environment (the CUBE study). Contemp. Clin. Trials 40, 172–179. https://doi.org/10.1016/j.cct.2014.12.009.

Panter, J., Heinen, E., Mackett, R., Ogilvie, D., 2016. Impact of New Transport Infrastructure on Walking, Cycling, and Physical Activity. Am. J. Prev. Med. 50, e45–e53. https://doi.org/10.1016/j.amepre.2015.09.021.

Panter, J., Ogilvie, D., 2017. Can environmental improvement change the population distribution of walking? J. Epidemiol. Community Health 71, 528–535. https://doi.org/10.1136/jech-2016-208417.

Qu, L., Gao, Y., Salzberg, A., Ollivier, G., 2014. Walkability Analysis for Chinese Transit Oriented Development: A Case Study in Nanchang. In: Transportation Research Board 93rd Annual Meeting. pp. 1–15.

Stappers, N.E.H., Van Kann, D.H.H., Ettema, D., De Vries, N.K., Kremers, S.P.J., 2018. The effect of infrastructural changes in the built environment on physical activity, active transportation and sedentary behavior – a systematic review. Heal. Place 53, 135–149. https://doi.org/10.1016/j.healthplace.2018.08.002.

Sun, G., Wallace, D., Webster, C., 2020. Unravelling the impact of street network structure and gated community layout in development-oriented transit design. Land use policy 90, 104328. https://doi.org/10.1016/J.LANDUSEPOL.2019.104328.

Sun, G., Webster, C., Chiaradia, A., 2017. Objective assessment of station approach routes: development and reliability of an audit for walking environments around metro stations in China. J. Transp. Heal. 4, 191–207. https://doi.org/10.1016/j.jth.2017.01.010.

Sun, G., Zacharias, J., 2017. Can bicycle relieve overcrowded metro? Managing short-distance travel in Beijing. Sustain. Cities Soc. 35, 323–330. https://doi.org/10.1016/j.scs.2017.08.010.

Sun, G., Zacharias, J., Ma, B., Oreskovic, N.M., 2016. How do metro stations integrate with walking environments? Results from walking access within three types of built environment in Beijing. Cities 56, 91–98. https://doi.org/10.1016/j.cities.2016.03.001.

von Elm, E., Altman, D.G., Egger, M., Pocock, S.J., Gøtzsche, P.C., Vandenbroucke, J.P., 2007. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: Guidelines for reporting observational studies. Prev. Med. (Baltim) 45, 247–251. https://doi.org/10.1016/j.ypmed.2007.08.012.

Vuk, G., 2005. Transport impacts of the Copenhagen Metro. J. Transp. Geogr. 13, 223–233. https://doi.org/10.1016/j.jtrangeo.2004.10.005.

Xiao, C., Goryakin, Y., Cecchini, M., 2019. Physical Activity Levels and New Public Transit: A Systematic Review and Meta-analysis. Am. J. Prev. Med. 56, 464–473. https://doi.org/10.1016/j.amepre.2018.10.022.

Yang, M., Zacharias, J., 2015. Potential for Revival of the Bicycle in Beijing. Int. J. Sustain. Transp. 150817130233009. https://doi.org/10.1080/15568318.2015.1012281.