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How a new metro line influences local traffic safety: A natural experiment in China

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ABSTRACT

The introduction of a new rail transit system is expected to transform the travel behaviours of nearby residents and alleviate traffic congestion. However, the causal impacts of the rail transit system on traffic safety remain theoretically debatable, and the empirical evidence is limited. Leveraging the opening of a new metro line in a large Chinese city and longitudinal data on injurious traffic crashes covering both pre- and post-operation periods, this study provided causal evidence on how a new metro system affects traffic crashes in the vicinity of metro stations, including overall, pedestrian-involved, automobile-involved, and electric bicycle-involved injurious crashes. Treatment groups were defined as those experiencing a new metro service recently, while control groups were areas with a planned metro line and similar built environment attributes. Difference-in-differences (DID) models showed that the new metro line increases overall crash numbers by 14.0% and pedestrian-involved crash numbers by 13.8%, respectively, compared with the control groups after the metro operation. In addition, the treatment effects of the metro intervention on traffic crashes varied with the station location and the pre-intervention safety risk level. Our findings contribute causal evidence to ongoing debates regarding rail transit access and local traffic safety, and highlight the need for developing transport and land use planning integration for pedestrian safety in high-density cities.

1. Introduction

Traffic crashes remain a persistent global health threat for vulnerable road users, such as pedestrians and cyclists (Hu et al., 2024). Annually, traffic-related fatalities amount to 1.19 million globally, with over 3200 deaths per day (World Health Organisation, 2023). Notably, 90% of these deaths occur in low- and middle-income developing countries where rapid motorisation has significantly heightened traffic safety challenges. In China, for example, road injuries have become a leading cause of death, with traffic crashes resulting in over 200,000 deaths and 500,000 injuries annually (Jiang et al., 2017). However, the traffic crash threats are escalating (Loo and Tsoi, 2022). Much of this has occurred alongside significant transformations of the built environment, such as the proliferation of road networks and the expansion of urban public transport systems. However, these transport interventions are primarily driven by economic and travel demands, often sidelining traffic safety considerations. It is therefore crucial to understand how transformations of the built environment influence traffic safety outcomes (Ewing and Dumbaugh, 2009).

Urban rail transit has expanded globally to meet growing travel demands and reduce dependence on automobiles. The most common forms of urban rail transit are light rail transit and underground metro systems. The former generally consists of ground-level dedicated tracks or rights-of-way, separated from other traffic, and the latter uses separate tracks operated in underground spaces (Naznin et al., 2016). Rail transit systems may exert positive externalities, such as environmental and economic benefits (He et al., 2024). However, our understanding of its potential negative impacts remains limited. These may include gentrification (Liu and Bardaka, 2023), and increased congestion due to induced travel demand (Tao et al., 2021).

Urban rail transit access directly shapes nearby traffic volumes and speeds, and further influences the distribution of traffic crashes. However, the net effects of rail transit proximity on traffic crashes remain theoretically debatable, and the underlying mechanisms are still

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inconclusive (Pulugurtha and Srirangam, 2022). On the one hand, residents living near rail transit stations often walk or cycle to access transit services (He et al., 2022), resulting in conflicts between pedestrians, cyclists, and motorists. With increasing interactions between road users in the vicinity of rail transit stations, the surrounding traffic environment may become more hazardous (Ashraf et al., 2022). Another possible mechanism is that, as an effective public transit mode, the rail transit system substitutes automobile use and decreases vehicle volumes on the streets (Ewing et al., 2014; Tao et al., 2021). Consequently, there are safer traffic environments with reduced motor vehicles and lower probabilities of traffic crashes. However, we still know little about how rail transit systems influence traffic safety outcomes (González et al., 2019; Kim et al., 2024).

Several studies provided empirical evidence regarding rail transit and traffic crash occurrence. Pulugurtha and Srirangam (2022) showed that the total number of pedestrian crashes at the intersections near light rail transit stations in Charlotte, U.S., increased after the introduction of transit service. However, previous studies predominantly relied on cross-sectional research designs or simple before-and-after comparisons of identical station areas, lacking rigorous designs (e.g., treatment-control comparison) to investigate the impact of rail transit on traffic crashes (Kim et al., 2024). The existence of time-invariant factors undermined the validity of the before-and-after comparison without a control group. Secondly, previous studies have primarily focused on light rail transit, where crashes are mainly associated with tram-involved collisions (Currie and Reynolds, 2010; Pulugurtha and Srirangam, 2022). In contrast, underground metro carriages do not directly pose a threat to the safety of road users. Instead, metro stations connect to the surface through multiple entrances and exits, which can indirectly influence the probability of traffic crashes by affecting local traffic volumes and speeds. For example, a study in Seoul, South Korea found that a higher density of underground metro stations was positively associated with the area-level severe and fatal traffic crash counts (Rhee et al., 2016). Thirdly, previous studies predominantly investigated pedestrian-involved crashes, while the metro system can influence the safety of different road users (Kim et al., 2024). In China, significant changes in the share of motor vehicles, electric bicycles, and pedestrians have been observed following metro interventions (Sun et al., 2020). Therefore, it is necessary to provide evidence regarding the effects of metro construction on the changes in domain-specific traffic crashes.

This study provided solid evidence on how metro lines influence the occurrence of injurious traffic crashes. It will contribute to the current literature threefold. First, it employed a rigorous natural experiment research design, using as-if random treatment-control groups and four years of traffic crash data, to assess the causal impacts of underground metro systems on local traffic safety. Second, this study differentiated between overall, pedestrian-involved, automobile-involved, and electric bicycle-involved injurious crashes, acknowledging that road users may respond differently to such interventions and may face varying levels of crash risk changes. Third, this study offered insights into the heterogeneous treatment effects of metro interventions. As metro lines in China typically extend from city centres to suburban areas (Yang et al., 2016), planning in suburban regions may stimulate both population and vehicle growth. Therefore, this study examined the varying effects of metro interventions by station location and pre-intervention traffic risk levels.

2. Literature review

2.1. Rail transit system and traffic crash

An increasing number of studies in the transport field have paid attention to how urban rail transit systems affect traffic safety (Kim et al., 2024). However, two debatable assumptions remain unsettled in regard to the magnitude. One stream of literature believed that rail transit systems shape nearby areas into vibrant venues with increased vehicles and pedestrians. Consequently, there is a higher probability of vehicle-to-vehicle and vehicle-to-pedestrian crashes in the vicinity of rail transit stations (Ashraf et al., 2022). Several studies indicated that pedestrian-involved crashes in station areas increased after rail transit operations (Pulugurtha and Srirangam, 2022). A possible reason is that rail transit stations encourage higher levels of pedestrian activity, leading to increased traffic exposure and a rise in crashes. Furthermore, rail transit stations often serve as common venues for travellers switching between different modes of transport, and these complex environments and intermodal connections may increase the risk of pedestrian-involved crashes (Ashraf et al., 2022). For instance, light rail transit primarily operates on shared right-of-way with other road users, which influences different road users and induces pedestrian crash probability (Ziedan and Brakewood, 2020). A study found that the pedestrian crash counts at the intersections around light rail transit stations increased 4.6 times on average after operation compared to the pre-operation period (Pulugurtha and Srirangam, 2022).

Alternatively, rail transit service may encourage the development of more walkable environments around station areas. Since rail transit service can substitute for vehicular trips (Ewing et al., 2014; Tao et al., 2021), the probability of traffic crashes may reduce accordingly as fewer motor vehicles are present on the streets. The “safety in numbers” hypothesis also argues that higher numbers of pedestrians in an area modify the hazardous behaviours of drivers, thus creating a safer environment (Bhatia and Wier, 2011). In addition, the introduction of metro service may stimulate the installation of walking-friendly facilities (e.g., signalised crossings, footbridges, and underground pathways) around the rail transit stations (Kim et al., 2024). These facilities can separate pedestrians from motor vehicles, thereby reducing both exposure risk and the likelihood of crashes (Zhu et al., 2024).

Several cross-sectional studies provided mixed results regarding transit access and injurious traffic crashes (Rhee et al., 2016). However, the cross-sectional nature of the research design cannot provide any causal evidence. The presence of time-invariant factors may distort the results of the analysis. For instance, rail transit systems are often intentionally located in transport corridors with high-speed, high-traffic volume, and mixed land use, possibly driven by higher travel needs in the areas. In that case, the observed statistical results were determined by unobserved confounders rather than rail transit and traffic interactions. In addition, previous studies primarily focused on the impact of rail transit on pedestrian-involved crashes (Pulugurtha and Srirangam, 2022), highlighting the need to pay more attention to other road users, such as cyclists and micromobility users.

2.2. Causal inference of transport intervention on traffic safety

Longitudinal research design has been advocated to provide rigorous evidence in the transport safety field. Natural experiments are referred to as naturally occurring interventions, where treatment-control group assignments are considered randomised (He et al., 2024). By contrast, those endogenous interventions are categorised as quasi-experiments. In transport interventions, researchers typically have limited control over implementation, making randomised treatment assignments rare in real-world settings (Sun et al., 2023). As a result, quasi-experimental approaches are commonly employed, while remaining susceptible to both observed and unobserved confounders that may distort the statistical relationships.

Despite ongoing theoretical debates and empirical challenges in establishing causal inference, it has attracted significant interest due to its relevance to empirical issues and policy-making in transport planning (Graham, 2025). Several studies have assessed the causal effects of transport interventions on traffic safety using a quasi-experimental research design. Based on interrupted time-series (ITS) approaches, these studies compared changes in safety outcomes between areas with and without policy implementation to assess the treatment effects. They investigated the causal effects of transport policy implementation on traffic safety, such as 20 mph zone scheme in London, UK (Li and

Graham, 2016), and citywide speed limit reduction policies in New York, U.S. (Zhai et al., 2022). There are also studies investigating the impacts of transport facility interventions on traffic safety, such as the installation of signals and increasing pedestrian crossing time (Chen et al., 2013), platform tram stops (Naznin et al., 2016), and streetcar right-of-way intervention (Richmond et al., 2014).

Nonetheless, current studies have largely neglected how transport infrastructure construction influences traffic crashes. Though the priority of infrastructure creation was not on traffic safety, it can still alter traffic crash probability indirectly by modifying traffic volumes and speed (Pulugurtha and Srirangam, 2022). Using a quasi-experiment design, one study found that the introduction of a light rail transit system led to a significant decrease in total, injurious (by 9% – 41%), and pedestrian-involved (by 25% – 43%) traffic crash rates (Kim et al., 2024). However, further efforts are needed to use a robust research design to understand the causal effects of another form of rail transit, underground metro systems, on traffic safety.

3. Research design and method

3.1. Research area and context

3.1.1. Study area

This study focused on FH, a large city located in eastern China. As the provincial capital, FH had a population of 10 million and 2.88 million automobiles in 2022. Due to the rising number of motor vehicles, traffic crashes have become a concern in FH city, posing threats to the transport system and public health. According to the latest *National Road Traffic Accident Statistics Annual Report*, the number of severe traffic crashes in FH city increased from 1589 in 2011 to 2065 in 2016, increasing by 30%. In 2016, there were 437 fatalities resulting from traffic crashes in FH city, with a direct asset loss of 15 million CNY.

The FH municipal government had an ambitious plan to expand the public transit system, including the metro line, since the 2000s. There were five lines in service over 100 km of metro tracks in 2022, and nine metro lines were being planned or built. The metro system has become the transport backbone in FH, with an annual ridership exceeding 265 million in 2022. Although traffic safety outcomes were not explicit goals of metro development, the probability of traffic crash occurance can be altered following the construction of metro lines. The rapid metro expansion in FH city provided an ideal case for investigating the effects of rail transit on traffic safety.

3.1.2. Traffic crash data and categorisation

There are three potential crash data sources in China, including insurance company-reported (Qiao et al., 2020), police-based (Wu et al., 2023), and injurious crash data by medical centre (Xie et al., 2019). Injurious crashes result in high medical costs and health risks, making their prevention particularly meaningful. Meanwhile, injurious traffic crash data are the most available source for traffic safety research in China (An et al., 2022; Jiang et al., 2017), offering broad geographical coverage and detailed information on the individual crashes. The comparison of three data sources is shown in Table S1. Furthermore, we extracted aggregated police-based data in FH City and validated it against injurious crash data from the medical centre. Police-based data on fatal crashes showed higher coverage compared to medical centre records, whereas police-reported injurious crashes were significantly underrepresented (Fig. S2). Therefore, injurious crash data from the medical centre, which demonstrated high validity and representativeness, was used in this study.

The traffic crash data used in this study were obtained from the FH Municipal Emergency Medical Centre. This emergency medical centre granted our research team access to this dataset, and we referred to the name of this city as "FH" in this article because of the contract request. This centre is in charge of receiving information on all emergencies and coordinating the delivery of injured individuals to appropriate hospitals, depending on the severity of the injury and the location within the municipality. Therefore, the FH Municipal Emergency Medical Centre collected and documented records of emergency services involving the transportation of injured persons to hospitals, including all traffic crashes that required medical services.

The original datasets encompassed approximately 400,000 records of emergency medical services during the study period. From these, we selected a subset containing all injurious traffic crashes. This dataset recorded detailed information, including time, location, injury severity, and emergency service information. In addition, the records included demographic information of the injured, such as gender and age. Notably, the raw dataset was organised by individual injured persons requiring medical services, rather than by the number of traffic crashes. Therefore, we identified cases involving multiple injured individuals from a single crash and removed duplicate records to ensure each crash was counted only once.

The primary road users include automobiles and pedestrians. Notably, electric bicycles have a much higher mode share than traditional bicycles in the Chinese context, as they typically lack pedals and offer greater efficiency. It accounts for 17.4% of the injurious crashes in China (World Health Organisation, 2021). We thus considered three domain-specific types of crashes: pedestrian-involved, automobile-involved, and electric bicycle-involved crashes. For instance, we identified cycling-involved crashes by filtering for keywords such as "cycling" and "bicycle" (in their corresponding Chinese characters) and then manually verified these cases. The crash subcategorisation is presented in Table 1. Vehicle-vehicle crashes accounted for 48.91% of all injurious crashes, while the remainder were vehicle-pedestrian crashes. Pedestrian-involved, electric bicycle-involved, and automobile-involved crashes accounted for 48.91%, 37.32%, and 31.42% of all crashes, respectively. Notably, the latter categorisation was not mutually exclusive. For example, a crash involving both an electric bicyclist and a pedestrian would be classified as both a pedestrian-involved and an electric bicycle-involved crash.

Furthermore, since the addresses in the original dataset were in text format, geocoding was necessary for analysis. Because automated geocoding was not reliable for identifying precise locations due to the data frame, we recruited research assistants to manually geocode the data using Baidu Map (an online map provider in China) to ensure accuracy and credibility. The detailed process is shown in Table S2.

3.2. Research design

3.2.1. Treatment and control group assignment

Previous studies investigating the causal effects of rail transit intervention generally compared changes in outcomes between areas that experienced intervention and their counterparts without interventions (He et al., 2024). The analysis relied on the assumption that outcomes of the treatment (with intervention) and control groups (without intervention) would evolve along a parallel trend in the absence of intervention. Therefore, proper treatment-control group assignment is needed to infer causality. In previous studies, it was common to designate areas on the periphery of treated areas as control groups. However, the validity of this approach has been increasingly questioned (Liu and

Table 1
Categorisation of injurious traffic crashes in this study.

Category of traffic crash	Number of crashes	Percentage (%)
Classification based on collision type (mutually exclusive from other categories)		
Vehicle-vehicle crash	3211	48.91
Vehicle-pedestrian crash	3074	51.09
Classification based on the involved objects (not mutually exclusive from other categories)		
Pedestrian-involved crash	3074	48.91
Electric bicycle-involved crash	2346	37.32
Automobile-involved crash	1975	31.42
Overall injurious crash numbers	6285	

Bardaka, 2023), highlighting the need to assign more comparable control groups.

Local metro planning knowledge can help justify the rationales of this treatment-control group assignment (Sun et al., 2023). For instance, recent studies proposed using unconstructed rail transit lines (Billings, 2011), or already constructed projects as a control group (He et al., 2022). Since rail transit is generally planned or built along transport corridors, the merit of this approach was that both treatment and control areas were located in highly built and mixed-use urban environments (Billings, 2011). Therefore, such treatment-control group assignments had better validity in ensuring similarities between the two groups (He et al., 2022). In addition, the priority of the construction sequence between different lines was determined by urban development strategy and the preferences of key policymakers, which were irrelevant to the pre-intervention traffic crash levels. In other words, the metro line construction sequence and treatment-control assignment showed a degree of randomness, and such treatment and control groups alleviated (un)observable confounders to infer causality (He et al., 2024).

FH city planned five metro lines in its first metro master plan in 2008, and each line was approved by the State Council and built stepwise. This study selected the second last metro line in this package operated at the end of December 2019, as the intervention, and the treatment groups were located around the new metro line (Fig. 1). Meanwhile, the control group was the last (planned but not constructed) metro line of this package during the study period. Different metro lines in the same planning package were comparable in terms of the built environment and travel demand technically. We tested the effects of new metro lines by comparing the change in traffic crash numbers between treatment and control groups pre- and post-metro intervention periods. Furthermore, by integrating local planning knowledge into treatment-control group assignments, (un)observable confounders were alleviated. The descriptive analysis between the two groups also showed the overall built and traffic environment similarities between the two groups (Table 2).

3.2.2. Data processing

The traffic crash dataset in this study covered a span of 16 quarters, from early 2018 to the end of 2021. The metro service in the treatment group began operation at the end of December 2019 (2019 Q4). Therefore, the quarters in which the metro lines opened (2019 Q4) were used to distinguish the pre- and post-intervention periods. However, a severe COVID-19 pandemic in China started in January 2020, leading to strict national-level lockdown policies to prevent virus transmission. As a result, there was limited daily mobility for urban residents and a significant decrease in traffic crash occurrences in February and March 2020. With the implementation of the zero-COVID policy, people's daily

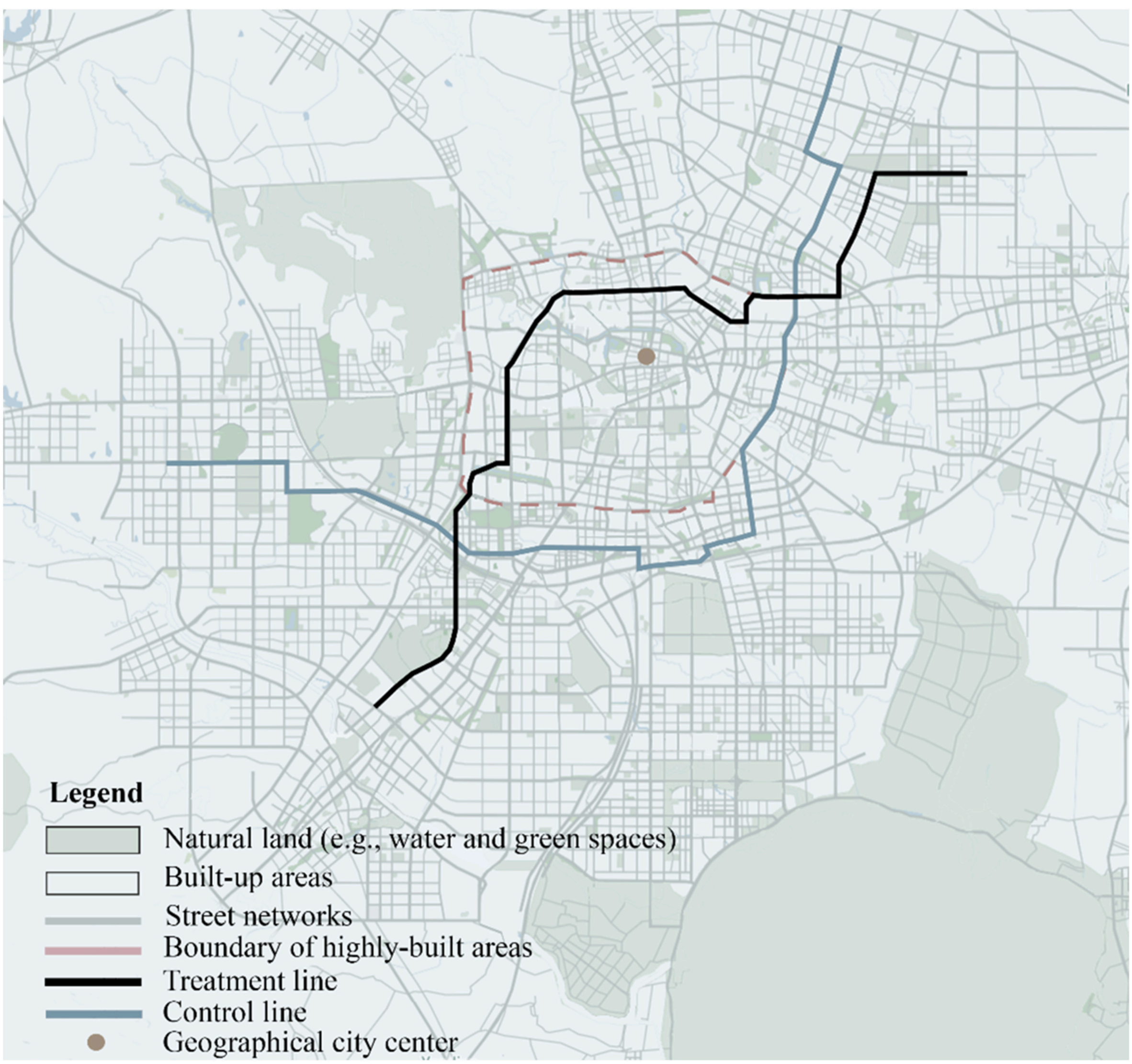

Fig. 1. Treatment and control group assignment of this study.

Table 2
Descriptive statistical results of traffic crashes and station-level environment in the study areas.

	Full samples	Treatment group (newly built metro line)	Control group (planned metro line)
	Mean (standard deviation)/ percentage	Mean (standard deviation)/ percentage	Mean (standard deviation)/ percentage
Outcomes (quarterly PCA-level)			
Overall injurious traffic crashes before intervention	6.78 (5.29)	7.50 (5.40)	6.12 (5.10)
Overall injurious traffic crashes after intervention	8.81 (6.47)***	10.23 (7.12)	7.49 (5.49)
Pedestrian-involved traffic crashes before intervention	3.46 (3.13)	3.90 (3.35)	3.04 (2.85)
Pedestrian-involved traffic crashes after intervention	4.54 (4.09)	5.40 (4.79)	3.75 (3.12)
Automobile-involved traffic crashes before intervention	2.22 (2.19)	2.35 (2.29)	2.10 (2.10)
Automobile-involved traffic crashes after intervention	2.69 (2.71)	2.76 (2.91)	2.61 (2.52)
Electric bicycle-involved crashes before intervention	2.42 (2.49)	2.65 (2.69)	2.21 (2.27)
Electric bicycle-involved crashes after intervention	3.44 (3.60)	3.88 (3.92)	3.02 (3.24)
Traffic environment			
Average speed of vehicles (km/h)	33.63 (8.63)	34.15 (8.52)	33.28 (7.85)
Daily population density (visit/ sample point)	1208.79 (858.79)***	1444.63 (969.19)	989.79 (672.35)
Locational covariate			
Distance to the city centre	10.22 (5.36)	9.83 (6.31)	10.50 (4.22)
Built environment covariates			
Floor area ratio	0.23 (0.20)	0.25 (0.20)	0.21 (0.19)
Number of street intersections	198.52 (115.79)***	218.42 (128.59)	177.69 (98.18)
Secondary road (km)	2.32 (1.42)	2.22 (0.98)	2.42 (1.73)
Tertiary road (km)	3.30 (1.64)	3.18 (1.65)	3.41 (1.63)
Alleyway (km)	17.14 (7.83)	19.51 (7.11)	14.93 (7.84)
Average housing price (thousand CNY/m^2)	18.31 (7.40)	17.78 (6.71)	18.59 (7.91)
Land use entropy	0.79 (0.10)	0.79 (0.08)	0.80 (0.11)
Number of bus stops	4.59 (3.64)	4.35 (4.31)	4.90 (2.84)
Number of parking sites	29.11 (25.36)***	22.58 (22.79)	30.54 (30.79)
Transfer station (%)	3.7	7.6	0
Number of metro station areas (PCA)	54	26	28
Number of observations	810	390	420

life in FH gradually returned to normal from April, without large lockdowns in the remaining study period. Most of the monthly infection cases in FH city were zero between 2020 and 2021 (Fig. S1). Fig. 2 shows the monthly metro ridership and injurious traffic crash counts in FH. The metro ridership and traffic crashes have recovered to the pre-pandemic level since April, indicating limited impacts of COVID-19 on travel behaviours afterwards. Considering the extremely low mobility and traffic crash immediately after the metro operation, the first quarter of 2020 (2020 Q1) was excluded. The second quarter of 2020 (2020 Q2) was considered the start of the post-intervention period, and the final dataset in this study consisted of 15 valid quarters.

Previous studies used aggregated geographical units, including traffic analysis zones (TAZs) and census tracts, for traffic crash analyses. In this study, we chose pedestrian catchment areas (PCAs) surrounding different stations as the basic units for analysis. The number of crashes that occurred in different street segments was aggregated at the station catchment area level based on the location. Following the transit-oriented development (TOD) concept in China, an 800-m distance from the station was the guide to encourage pedestrians to use the metro system as their daily travel mode (Sun et al., 2020). However, since 800-m PCA overlapped between nearby stations, especially in the city centre, we used 600-m circular PCA instead in this study. Notably, there are transfer stations between two metro lines, and we allocated the transfer stations to the lines that they initially served.

When cleaning the dataset, the following procedures were followed. First, since highways are separated transport systems serving automobiles in China, traffic crashes occurring there are unlikely to be affected by nearby urban built environments, including metro proximity. Therefore, we excluded all crashes that occurred on highways in the analysis. Second, we identified the collision type by checking the crash descriptions and differentiating them as overall, pedestrian-involved, automobile-involved, and electric bicycle-involved crashes. Third, the treated and control lines intersected and several PCAs overlapped, as shown in Fig. 1. Therefore, we removed three PCAs from the treatment group since their PCAs were largely severed by control line before the treated line operation.

3.2.3. *Covariates*

Traffic and built environments around rail transit stations were highly associated with traffic crashes (Pulugurtha and Srirangam, 2022; Zhu et al., 2024). We incorporated two traffic environment covariates into our analysis to account for confounding effects. Pedestrian exposure refers to the level of pedestrian activity exposed to vehicles and is commonly measured with population density or collective active travel trips (Sze et al., 2019). Fine-scale population distribution and mobility data were lacking in China, while recently emerged mobile cellular signalling data offered a new potential. Mobile terminals connect to cell towers periodically, and the cell tower records these connections and summarises aggregated daily user location data. This paper used ambient population data from mobile data from China Unicom (China's second-largest mobile communication operator with 300 million active users daily). The data was collected in August 2022, with a spatial resolution of 150-m and 150-m units. We estimated the average population density within each PCA and used it as a proxy for mobility. In addition, the Gaode location-based service (LBS) open platform provided traffic speed information. We thus got hourly speed and congestion data with high spatiotemporal coverage, collecting street-level average speed information for 2,559 street segments between July and August 2022. Station-level speed information was calculated by aggregating the hourly average speeds of all street segments within each respective area.

In addition, built environment attributes were determinants of traffic crashes (An et al., 2023; Choi and Ewing, 2021). Regarding the street networks, we obtained the dataset provided by Open Street Map (OSM) in 2020. After deleting redundant street typologies (e.g., paralleled lanes within a segment), we calculated the number of road intersections within each station's catchment area. The dataset contained road classes, and we calculated the aggregated length of secondary (regional) roads, tertiary (local) roads, and alleyways within each PCA. The building dataset was acquired from Gaode Map (Amap), a large map provider in China. It contained detailed information on building footprints, coordinates, and the number of floors in a building. We measured the floor area ratio (FAR) as the ratio of the total floor area of all buildings within each PCA. Point of interest (POI) data was adopted to measure the mix of neighbourhood land use using the Shannon entropy index (Frank and Pivo, 1994). We used 15 categories of POI (e.g., retail and wholesale, catering, and transport facilities) from Gaode to determine the land use mix operationalised as the Shannon index. In addition, we calculated the

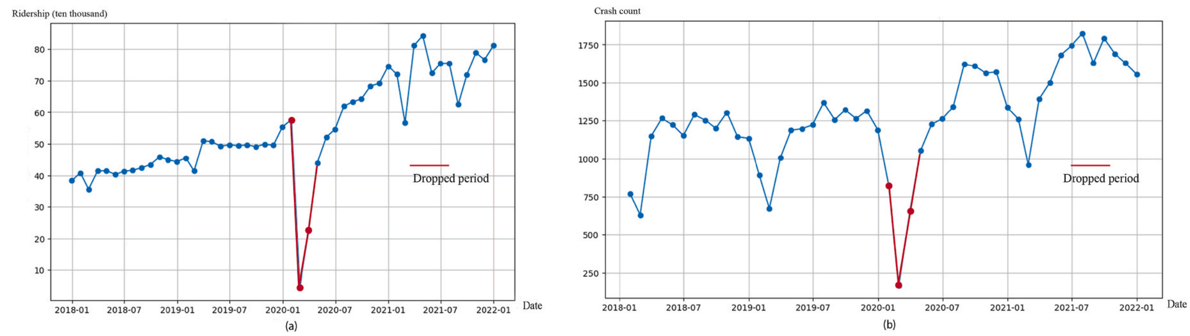

Fig. 2. Monthly mobility and crash change during the COVID-19 pandemic in FH city: (a) City-level metro ridership; (b) City-level injurious traffic crash numbers.

number of bus stops and parking sites at the PCA level to represent the transport facilities based on the POI dataset. We also used the average transacted housing prices between 2018 and 2021 within PCAs as a proxy of the station socio-economic environment.

3.3. Analysis method

3.3.1. Difference-in-differences (DID) models

We applied a difference-in-differences (DID) specification in a random effect negative binomial model to estimate the average treatment effects of the metro intervention by comparing crashes at different stages based on panel data at station areas. DID models are common tools to provide causal inference that can overcome omitted variable bias and time-invariant effects, and the outcome change in the treatment group was unlikely to be affected by unmeasured confounders (Wing et al., 2018). DID analysis generally involves estimating a linear model, while it can also be incorporated into non-linear settings (Alemi et al., 2018; Liu and Bardaka, 2023). Specifically, we observed 54 station areas over 15 quarters among 810 panel observations, and the outcome variables reflect the number of overall or domain-specific crashes in a station area for a given time. The baseline model estimated the average treatment effects with the DID model specified as follows:

$$E(Y_{it}) = \lambda_{it} = \exp\left(\beta_0 + \beta_1\ (Treat_i{*}Post_t) + \beta_2\ Post_t + \beta_3\ Treat_i + \beta_4\theta_t + \rho Individual_i + \gamma_{it} + \varepsilon_{it}\right) \tag{1}$$

Where Y_{it} represents the crash counts (overall, pedestrian-involved, automobile-involved, and electric bicycle-involved) aggregated at station areas i in time t; and λ_{it} represents the expectation of Y_{it}; $Treat_i$ is an indicator equalling one if the station area is the treatment group and zero otherwise; $Post_t$ is a time indicator that equals one for the quarters after the operation of the metro system and zero otherwise; $Individual_i$ is a set of station area level covariates that control time-invariant effects. $Treat_i{*}Post_t$ is an interaction term that captures the average treatment effect of the opening of metro lines on the change in the traffic crash occurrence. θ_t is a quarterly fixed effect controlling for the seasonal influence. β and ρ are the parameters to be estimated. γ_{it} is the unknown intercept term, which varies with the station area and time, and ε_{it} is an error term.

For the random-effects negative binomial model, we allow the dispersion parameter δ_i to vary randomly across station areas, and assume that $\frac{1}{1+\delta_i} \sim Beta(r,s)$. The joint probability of the counts for the i th station area is:

$$\begin{aligned}\Pr\left(Y_{i1} = y_{i1}, \ldots, Y_{in_i} = y_{in_i} \middle| X_i\right) &= \int_0^{\infty} \prod_{t=1}^{n_i} \Pr(Y_{it} = y_{it} | x_{it}, \delta_i) f(\delta_i) d\delta_i \\ &= \frac{\Gamma(r+s)\Gamma\left(r + \sum_{t=1}^{n_i}\lambda_{it}\right)\Gamma\left(s + \sum_{t=1}^{n_i} y_{it}\right)}{\Gamma(r)\Gamma(s)\Gamma\left(r + s + \sum_{t=1}^{n_i}\lambda_{it} + \sum_{t=1}^{n_i} y_{it}\right)} \prod_{t=1}^{n_i} \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)}\end{aligned} \tag{2}$$

where f is the probability density function for δ_i; r and s are the parameters in the *Beta* distribution. Maximum likelihood (ML) estimation was commonly used for negative binomial models. Before formal analyses, we tested the VIF of the models, and there was no severe multicollinearity (VIF <5).

In addition to the primary analysis for assessing the average treatment effects, we further conducted tests to examine the heterogeneous effects on subgroups of metro stations. The stratification of the group is based on the location of the stations (city centre vs suburban areas) and traffic crash risk before intervention (high-risk areas vs low-risk areas). The cut-off distance between the city centre and suburban areas was 8 km (km). The rationale was that the average commuting distance for FH was 7.6 km in 2022. Meanwhile, the second-ring road in FH is considered a boundary for dividing the city centre, whose network distance from the geographical centre was equal to 8 km (red line in Fig. 1). In addition, the classification of risk was based on the pre-intervention PCA-level overall traffic crash counts, and the top 50% stations were considered a high-risk group. We hypothesised that suburban and previously low-risk traffic crash areas are more responsive to metro interventions.

3.3.2. Parallel trend tests

An important prerequisite assumption of the DID model is the parallel trend assumption, i.e., the similar trend in traffic crashes exists between the treatment and control groups before metro operation. We conducted the tests based on the following equation.

$$\lambda_{it} = \exp\left(\beta_0 + \alpha_k \sum_{k=-7,k\neq-1}^{k=7} Treat_{it,k} + \beta_2\ Post_t + \beta_3\ Treat_i + \beta_4\theta_t + \rho Individual_i + \gamma_{it} + \varepsilon_{it}\right) \tag{3}$$

Where $Treat_{it,k}$ is an indicator variable equal to 1 if station area i is at relative time k (i.e., k periods before or after the event) at time t, and 0 otherwise. To avoid potential bias from cointegration, we select the quarter immediately preceding the metro operation ($k = -1$) as the reference period, which is excluded from the regression ($k \neq -1$). The remaining terms are defined as in Equation (1). We expect the metro intervention to influence crash numbers, such that α_k would be positive for $k \geq 0$, reflecting an increase in crashes after the intervention. If the parallel trends assumption holds, the coefficients α_k should be close to zero for $k \leq -2$, indicating no significant differences in pre-treatment trends between treatment and control groups.

3.3.3. Falsification tests

We used falsification (placebo) tests by randomly assigning the sample observations to the treatment and control groups to test if unobservable variables may influence the estimated effects. We had 123 observations randomly assigned to the treatment group. Falsification estimation was conducted using the same specification in our baseline model. We repeated the falsification test 500 times to increase the

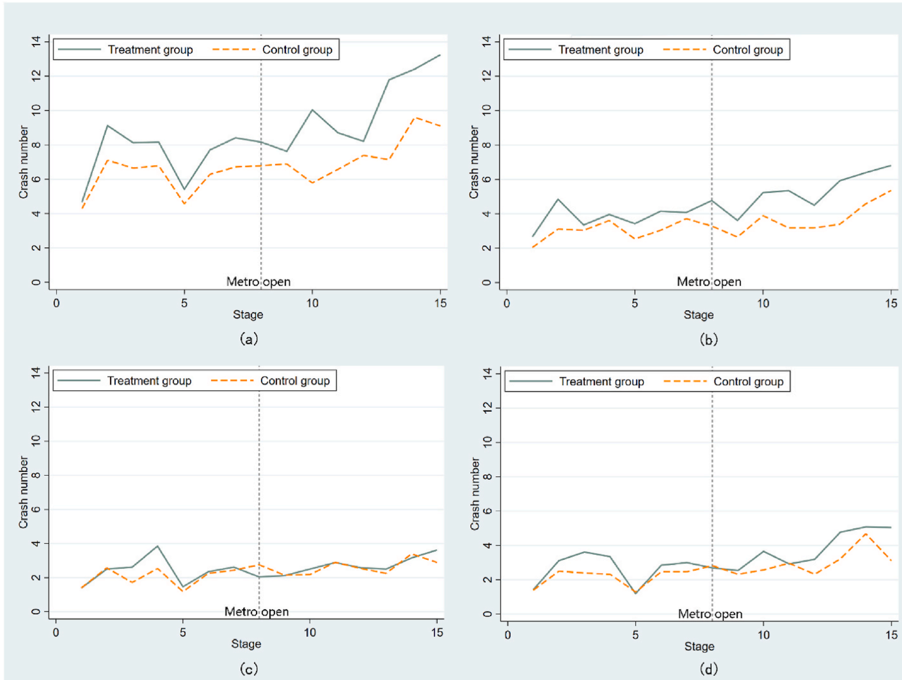

Fig. 3. Quarterly changes in the four categories of injurious traffic crashes: (a) overall crash; (b) pedestrian-involved crash; (c) automobile-involved crash; (d) and electric bicycle-involved crash numbers in PCAs.

identification power. Ideally, the false interaction item should have no statistical significance and carry a magnitude of estimate around zero.

3.3.4. Fixed-effects models

In the main models, we were not able to include station-level fixed effects because the model failed to converge, likely due to multicollinearity with $Treat_i$. To assess the robustness of our estimated average treatment effects, we conducted fixed effects models to account for the potential influence of time-invariant and omitted covariates. The fixed effects models were similar to the baseline model (Equation (1)), but the covariates $Individual_i$ and $Treat_i$ in the baseline model were replaced with a set of station-level fixed effects. By including station fixed effects in the model specification, we were able to test whether the observed average treatment effects are robust.

4. Results

4.1. Descriptive statistics

Table 2 shows the descriptive statistical results of the treatment and control groups. Regarding the traffic crash counts, the results showed that the quarterly PCA-level average crash numbers increased for all traffic crash categories after the metro intervention. Meanwhile, the increasing trend of automobile-involved crash numbers was relatively low compared to its counterparts. Regarding the built environment covariates, treatment and control groups do not differ much except for the number of street intersections and alleyway length in the PCA levels. The treatment group also shows higher visitor numbers, while it was reasonable since the data was collected after the metro operation. T-tests also show nonsignificant results between the treatment and control groups. These results ensure the similarity of treatment and control groups for further statistical analyses.

Fig. 3 compares the quarterly traffic crash numbers trend between the treatment and control groups. For four categories of crashes, both treatment and control groups experience an increasing trend. In addition, the average traffic crash level increases more for the treatment group than the control group after the intervention.

4.2. Average treatment effects

Table 3 shows the results of DID models for assessing the causal impact (average treatment effects) of the metro intervention on traffic crashes. Specifically, Model 1 illustrates the average treatment effects of the metro intervention on the overall injurious crash numbers. The interaction items showed that the metro intervention is significantly associated with the number of overall injurious crashes in treatment groups compared with control groups after the metro operation. The new metro line increased overall injurious crash numbers by 14.0 %. Regarding covariates, floor area ratio, secondary road length, tertiary road length, and number of parking sites were positively associated with overall crash occurrence. Moreover, a longer distance to the city centre was negatively associated with traffic crashes.

Model 2 illustrates the average treatment effects on the pedestrian-involved crash. Metro operation had significant effects on the number of pedestrian-involved injurious crashes in station areas, increasing crash numbers by 13.8 %. Regarding covariates, floor area ratio and average housing price were positively associated with pedestrian-involved crashes. In contrast, the number of bus stops, average speed, and distance to the city centre were negatively associated with pedestrian-involved crash numbers.

Model 3 shows the average treatment effects on the automobile-involved crashes, and there were no significant effects of the metro intervention observed. In terms of covariates, floor area ratio and average housing price were positively associated with pedestrian-involved crashes. In contrast, distance to the city centre was negatively associated with automobile-involved crash numbers.

Model 4 indicates the average treatment effects on the electric bicycle-involved crash, and there were no significant effects in station

Table 3
DID models for the average treatment effects of the metro intervention on four categories of injurious traffic crashes.

	Model 1 (DV: overall injurious crash)	Model 2 (DV: pedestrian-involved injurious crash)	Model 3 (DV: automobile-involved injurious crash)	Model 4 (DV: electric bicycle-involved injurious crash)
	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)
Intervention-related variables				
Treatment * Time	0.131** (0.062)	0.129* (0.084)	−0.034 (0.096)	0.078 (0.093)
Treatment	0.187* (0.155)	0.207 (0.170)	−0.057 (0.178)	0.078 (0.174)
Time	0.155*** (0.045)	0.174** (0.062)	0.180 (0.068)	0.254*** (0.068)
Built environment covariates				
Distance to the city centre	−0.040** (0.019)	−0.025*** (0.020)	−0.066*** (0.021)	−0.057*** (0.020)
Floor area ratio	1.549** (0.713)	2.158*** (0.768)	1.066 (0.703)	1.006 (0.695)
Daily population density	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)
Number of street intersections	−0.001 (0.001)	−0.003** (0.002)	0.001 (0.001)	0.001 (0.001)
Secondary road	0.283*** (0.076)	0.295*** (0.082)	0.123 (0.079)	0.203** (0.082)
Tertiary road	0.169*** (0.067)	0.175 (0.070)	0.038 (0.072)	0.099 (0.070)
Alleyway	0.026*** (0.007)	0.034*** (0.009)	0.030*** (0.010)	0.030 (0.010)
Average speed of vehicles	−0.020 (0.012)	−0.006** (0.012)	0.006 (0.001)	−0.011 (0.012)
Average housing price (thousand CNY/m^2)	0.000 (0.000)	0.040** (0.016)	0.001 (0.001)	−0.001*** (0.001)
Land use entropy	−1.117 (0.931)	−1.580 (0.991)	−0.403 (1.016)	1.427 (0.952)
Number of bus stops	0.008 (0.023)	0.009* (0.023)	0.054** (0.025)	0.039* (0.024)
Number of parking sites	0.009*** (0.003)	0.011*** (0.003)	−0.001 (0.001)	−0.001** (0.001)
Transfer station	−0.449 (0.412)	−0.647 (0.437)	−0.280 (0.431)	−0.098 (0.422)
Quarterly fixed effects	Yes	Yes	Yes	Yes
Constant	1.937** (0.950)	1.116 (0.938)	1.884 (1.011)	2.931*** (0.896)
Log-likelihood	−2016.649	−1676.094	−1395.013	−1471.560
N	810	810	810	810

Note: (1) ***p < 0.01, **p < 0.05, and *p < 0.10.
(2) DV represents dependent variables.

areas. In terms of covariates, alleyway length and number of bus stops were positively associated with automobile-involved crashes. By contrast, distance to the city centre, floor area ratio, the average speed of vehicles, average housing price, and the number of parking sites in PCAs were negatively associated with electric bicycle-involved crashes.

4.3. Heterogeneous tests

Fig. 4 (a) shows the heterogeneous treatment effects of the metro intervention on overall injurious crashes for metro station subgroups. The results of the interaction items showed varied treatment effects with geographical location and before-intervention traffic crash risk. Suburban areas experienced a significant overall increase in injurious traffic crashes compared to their counterparts in the control group after metro operation, while the effects were insignificant for stations in the city centre. In addition, the results illustrated that previously low-risk station areas experience an increase in overall injurious crash numbers compared with the control group.

Fig. 4 (b) illustrates the heterogeneous effects on pedestrian-involved crashes. Suburban areas experienced a significant pedestrian-involved

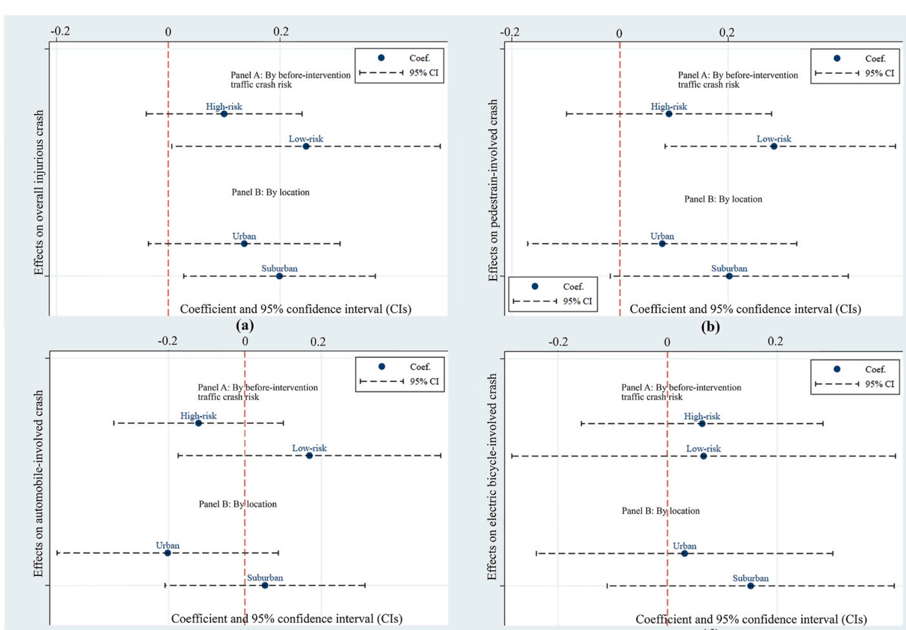

Fig. 4. Effects of metro intervention on four categories of injurious traffic crashes for metro station subgroups: (a) overall crashes; (b) pedestrian-involved crashes; (c) automobile-involved crashes; (d) electric bicycle-involved crashes. Models were adjusted for all the covariates in the main models.

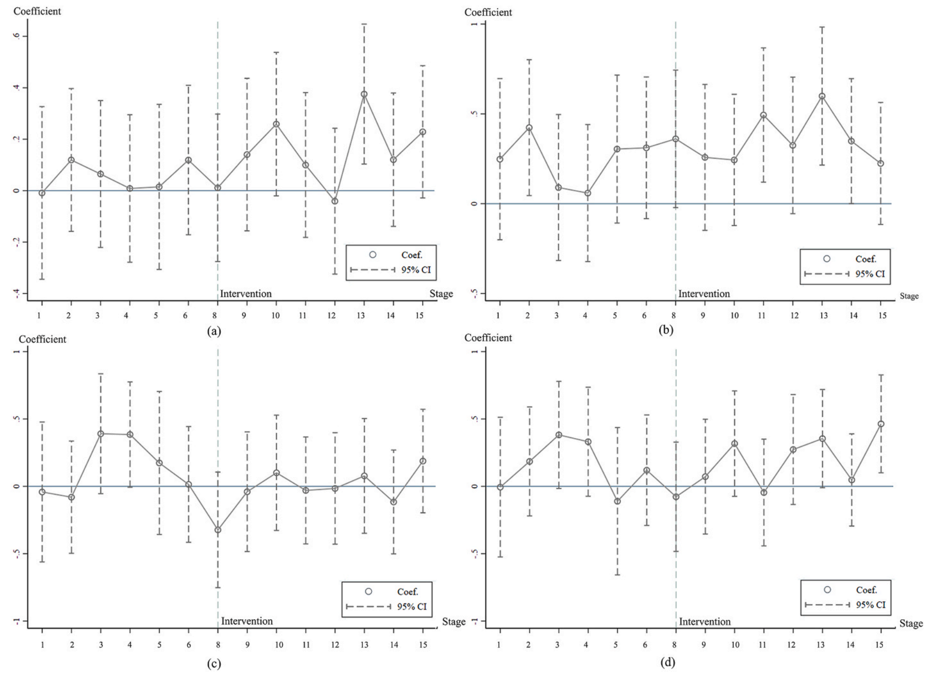

Fig. 5. Parallel trend tests for treatment and control groups across four categories of injurious traffic crashes: (a) overall crash; (b) pedestrian-involved crash; (c) automobile-involved crash; (d) electric bicycle-involved crash.

crash increase after the intervention. Nonetheless, the effects were not significant for stations in the city centre. In addition, treatment effects varied with previous traffic crash risk, and previously low-risk areas had increasing pedestrian-involved crash numbers.

Fig. 4 (c) highlights the subgroup effects on electric bicycle-involved crashes. Unexpectedly, neither urban nor suburban areas experienced a significant overall traffic crash increase after the intervention. In addition, models tested whether treatment effects on electric bicycle-involved crashes vary with before-intervention traffic crash risk, while results did not show significant effects on before-intervention high-risk and low-risk groups.

Fig. 4 (d) shows the on electric bicycle-involved crashes. The results suggested that there are no significant heterogeneous effects on bicycle-involved crashes for different stations with location and pre-intervention traffic crash risk variations.

4.4. Robust tests

4.4.1. Results of parallel trend tests

Fig. 5 shows the coefficients and 95% confidence intervals of the four models for parallel trend tests. The quarters before and after the metro operation are shown on the horizontal axis, and 1−7 and 8-15 indicate seven quarters pre- and post-the metro station operation, respectively. The key point is to observe whether α_k is significant or not before intervention. The plots in Fig. 5 (a) and (b) show that there are fluctuations in the significance of α_k after the opening of the metro station, while there is no systematic difference between the treatment and control groups in terms of overall crashes before metro intervention. The plots in Fig. 5 (c) and (d) show no significant difference between the PCAs in treatment and control groups regarding traffic crashes before metro intervention, despite the insignificant effects of the intervention. Therefore, the results indicate that the parallel trend assumption holds.

4.4.2. Results of falsification tests

Considering that only the interaction items are significant in Model 1 and Model 2 for the main analyses, we then conducted a falsification test for overall and pedestrian-involved crashes. The results of Fig. 6 (a) and (b) showed that the distribution of the estimates presented a normal distribution and was centralised to zero for the overall crash and pedestrian-involved crashes, respectively. The benchmark estimates of treatment effects (indicated by the vertical dashed line) lie outside the stimulated coefficients range. Thus, the impact of the metro intervention on traffic crashes is not likely to be affected by (un-)observable confounders. Notably, the last quarter before the intervention, i.e., 7, was dropped because of multicollinearity.

4.4.3. Results of fixed-effects models

The key results remained largely unchanged across model specifications, indicating that our findings are robust to the inclusion of more stringent station-level fixed effects. This suggested that the estimated average treatment effects are not affected much by omitted variable bias or unobserved time-invariant confounders (see Table S3).

5. Discussion

Using a natural experimental research design over a four-year period encompassing both pre- and post-metro operation phases in China, this study provided causal evidence on the impacts of a new metro line on traffic crash occurrences. Results from DID analyses showed that the new metro line significantly increases the overall and pedestrian-involved injurious crash counts in the vicinity of metro stations. This may be attributed to the metro service attracting more pedestrians, thereby increasing their exposure to vehicles and the likelihood of being involved in injurious collisions.

We examined the impacts of metro interventions on the traffic safety of different road users and found that, among the three subcategories of crashes, only pedestrian-involved crashes showed a statistically significant increase following metro interventions, with a 13.8% rise. The observed net effects were consistent with one study from the American context regarding pedestrian-involved crashes at street intersections around light rail transit systems (Pulugurtha and Srirangam, 2022), while contrary to another study showing a reduction of

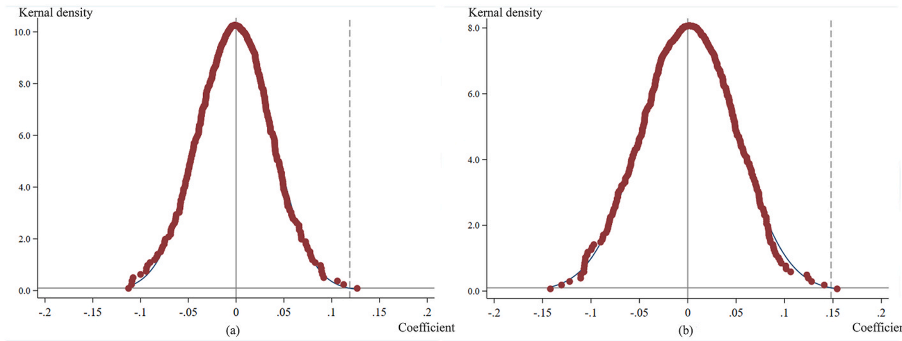

Fig. 6. Distribution of estimated coefficients of falsification test for injurious traffic crashes: (a) overall crashes; (b) pedestrian-involved crashes.

pedestrian-involved and injurious crashes around well-designed station areas in the same context (Kim et al., 2024). The plausible explanation for the increase lies in two-fold. First, metro systems in China, renowned for their punctuality, reliability, and efficiency, attract substantial ridership, with more than one million daily passengers in FH city in 2021. Walking is the most common mode for accessing or egressing at transit stations (Sun et al., 2020), and metro service might have increased the conflicts between pedestrians and vehicles. Second, local streetscapes and signal improvements around transit stations may help mitigate traffic crashes (Kim et al., 2024), which may explain the varied net effects of rail transit interventions. The success or failure of land use and transit integration may result in inconsistent effects across different cities. Nonetheless, the underlying mechanisms leading to increases in traffic crashes remain unclear due to data limitations. Specifically, it is uncertain whether the rise in crash counts reflects an escalated risk per individual pedestrian (i.e., a higher probability of being involved in a crash) or is simply a consequence of increased pedestrian volumes near transit stations. In contrast, we did not observe significant effects on automobile-involved and electric bicycle-involved injurious crashes, possibly because walking has offset motorised mode share following the introduction of metro services (Sun et al., 2020).

Moreover, our findings contribute to ongoing debates about the relationship between geographical proximity to rail transit stations and overall traffic safety. It suggests that this association may be primarily driven by pedestrian-involved crashes for underground metro systems. Results are partially consistent with cross-sectional evidence that a higher density of metro stations is positively associated with fatal and severe crash counts in Seoul, South Korea (Rhee et al., 2016). However, it contrasted with the results from light rail transit interventions that showed a decrease in total and injurious traffic crash rates in Salt Lake City, U.S (Kim et al., 2024). This study contributes solid evidence to debates on the adverse effects of metro systems on traffic safety in high-density contexts. Though the form of rail transit system and the street design improvement may lead to varying results, our robust research design provides new insights regarding underground metro systems.

Our findings also showed that new metro lines exert varying impacts on traffic crash across locations. The operation of a new metro line increased overall traffic crash counts around metro stations in suburban areas, whereas traffic safety conditions for stations in urban areas remained relatively stable to this change. After the metro operation, stations in suburban areas potentially act as transport nodes for nearby areas. Despite the fact that the number of overall crashes in suburban areas was lower (Qiao et al., 2020), metro systems stimulated the influx of population (Shen and Wu, 2020), and induced travel demand. Regarding the increased overall injurious and pedestrian-involved crash counts, we speculated that suburban residents are more likely to use metro systems for both commuting and utilitarian trips. By contrast, residents living in the city centre had more travel options and shorter commuting distances. Therefore, the impacts of the metro operation on individuals' travel behaviour and exposure to traffic risks in the city centre may not be pronounced. Also, previously low-risk areas experienced increased traffic crash risks following the operation of metro lines. In contrast to already high-risk areas, where travellers were familiar with hazardous traffic conditions and tend to self-organise to mitigate crash risks, low-risk areas experience a rapid increase in traffic volumes shortly after the introduction of new metro stations. This sudden influx of pedestrians and vehicles might increase traffic risks, resulting in a higher incidence of crashes.

Going beyond empirical evidence, our research makes methodological contributions to transport intervention literature. Assigning appropriate treatment-control groups is crucial for investigating causal inference (Sun et al., 2023), as comparable groups are more likely to account for (un)observable confounders (Billings, 2011). Leveraging local planning knowledge, our study selected areas with planned but not yet constructed metro lines as control groups, thereby reducing unobserved confounders and enhancing the validity of causal inferences. This approach demonstrates how researchers can utilise local (e.g., planning and historical) information to tailor the design of natural experimental studies and strengthen causal inference.

We can draw several transport planning implications from the findings. Our research indicates that new metro lines increase pedestrian-involved injurious crashes in the vicinity of transit stations. Pedestrians were the most vulnerable road users in the transport system, and their road safety requires more scrutiny and attention. Policymakers need to carefully weigh the trade-offs and implement strategies that balance the benefits of transit systems with the imperative to address pedestrian safety concerns. Metro expansions increase the mobility of people without private vehicle access, but it leads to more pedestrian crash counts around metro stations, even impeding potential modal shifts away from automobiles. The safety issues may discourage the use of metro systems. These results underscore the urgent need for engineering interventions under synergised TOD planning, like the installation of speed bumps, pedestrian footbridges and islands around the stations, and improvement of traffic signals to mitigate the potential traffic safety challenges, thereby ensuring safer and more equitable traffic environments. Furthermore, the varying impacts of metro expansions across different locations can also exacerbate inequalities in traffic safety. Policymakers need to make extra efforts in suburban and previously low-traffic-crash-risk areas where road users lack risk awareness and pedestrian-friendly facilities. Considering that rail transit stations are generally planned separately from nearby land use in China, and FH is a representative large city, findings and implications of this study can be generalised to more Chinese cities.

Despite the contributions, this research has several limitations. First, the COVID-19 pandemic inevitably influenced people's travel behaviour and traffic crash occurrence between 2020 and 2021. However, the stringent zero-COVID policy and rapid rebound of travel behaviours in

FH city (Fig. 2) largely alleviated the impacts. Meanwhile, given that the pandemic impacted both groups, the relative changes between the treatment and control groups mitigated potential biases. Second, our data were based on records of injurious traffic crashes, thereby the scope of our research does not encompass all traffic crashes. However, injurious crash data have been widely used in existing studies (Kim et al., 2024; Rhee et al., 2016), supporting the comparability of our findings. Third, the covariates were not updated annually, despite dynamic changes in the built environment and traffic conditions. We also neglected traffic environment features (e.g., traffic volumes) due to data limitations. However, the use of fixed-effects models confirmed the robustness of our estimates under these circumstances. Future studies could incorporate longitudinal environmental data to obtain more reliable results.

6. Conclusion

Leveraging a new metro line and longitudinal traffic crash datasets covering pre- and post-metro operation stages, this study provided causal evidence regarding how the new metro system affects traffic crash counts. DID models showed that the new metro line increased overall and pedestrian-involved injurious crash numbers compared with the control groups after the metro intervention. Furthermore, the treatment effects of the metro intervention on traffic crashes depend on the station location and the pre-intervention safety risks. This indicates the potential for traffic safety inequalities among vulnerable road users and in urban peripheries resulting from transport infrastructure interventions. Therefore, more integrated transport and land use planning is required to tackle increasing traffic crash risks in metro station areas in high-density cities.

CRediT authorship contribution statement

Dongsheng He: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Zihao An:** Writing – original draft, Methodology. **Yijia Hu:** Writing – review & editing, Resources, Methodology, Conceptualization.

Declarations of interests

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2026.104115.

Data availability

The data that has been used is confidential.

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