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Does metro expansion matter? Metro network enhances metro mode share of commuters living away from stations, but not those near stations

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ABSTRACT

As the metro system grows from a single line to a network of multiple lines, how does the expansion affect metro mode share of commuters residing near and away from stations? This study attempted to uncover the mechanism of commuters' mode choice after the expansion. We employed two waves of household travel survey data, before and after the formation of the metro network in Xi'an, to develop a difference-in-difference model. We found that after the metro network formed, the average metro mode share of residents within 1 km of metro stations increased slightly but the change was statistically insignificant. This is because the average share was smaller around the stations of newer metro lines. By contrast, the average metro mode share of residents living beyond 1 km from metro stations grew substantially, likely because of the increase of workplaces within station areas and the improvement in first-/last-mile connection services. To achieve low-carbon transport, this study underscores using metro lines to connect key destinations, densifying employment around metro stations, and promoting access to metro stations through convenient feeder buses, shared micro-mobility, and pedestrian-friendly design.

1. Introduction

Rail transit deployment and expansion have become a prevalent strategy for mitigating congestion and achieving carbon neutrality in global cities. In the U.S., the Capital Investment Grant program, formerly known as New Starts created as part of the Intermodal Surface Transportation Efficiency Act, has been used to support the development of fixed-guideway transit projects, mostly rail transit, for more than three decades. China Urban Rail Transit Association (2021) reported that the operation mileage of metro transit in mainland China has increased from about 1,700 km in 2010 to almost 8,000 km in 2020. Shanghai, Beijing, and Guangzhou have established an extensive network of metro lines. By contrast, many other large cities (such as Fuzhou, Harbin, and Taiyuan) have only one or a few lines and are eager to expand their metro network. As the metro system grows from a single line to multiple lines, an interesting question emerges: how does the metro network contribute to the market share of rail transit and other modes of transport?

The relationships between rail transit and travel behavior have been a key focus in the debate of sustainable transportation. Many scholars have explored the impact of a single rail transit line (Cervero, 2007; Shen et al., 2016; Spears et al., 2017a; Huang et al., 2019; Boarnet et al., 2020a). However, few have examined the network impact of rail transit on travel behavior.

Scholars believed that network effects matter, but there is little empirical evidence. In his discussion about rail transit impacts on land use changes in global cities, Cervero (2009) stated that urban development patterns in London, Paris, and Tokyo are largely attributable to their large-scale metro networks, which provide comparable coverage and accessibility to limited-access highways. Similarly, if the goal of rail transit investment is to compete with driving, a larger network of rail transit lines should be more advantageous. First, adding new lines benefits residents living within the newly served corridors because they

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gain convenient access to the destinations within the corridors and those along existing rail corridors (a spillover effect through transfers). Residents served by existing rail transit lines can also experience an increase in access to the destinations along the newly served corridors. Second, residents living outside of station areas may enjoy rail transit service through connection services because the new lines make some of their destinations within the catchment areas of rail transit. Although the conceptual analyses appear plausible, they have yet to be corroborated in empirical studies. This study aims to fill the gap.

By pooling two cross-sectional data collected from Xi'an in 2012 and 2021, we examine the network impact of metro lines on individuals' commuting mode choice of metro transit. Xi'an deployed its first metro line in the transit system in 2011 and had eight lines in operation by 2021. In this study, we address the following research questions: (1) How does the formation of a metro network influence metro mode choice of station-area residents? (2) How do those residing outside of station areas take advantage of the expanded coverage of metro lines? The answers shed light on the mechanisms under which the metro network contributes to mode share and ridership growth.

The remainder of this paper is organized as follows. Section 2 reviews the research methods used to examine the influence of rail transit on travel behavior. Section 3 describes the data and the modeling approach. Section 4 presents and discusses model results. The final section replicates the key findings.

2. Literature review

Many disaggregate studies have examined the relationships between access to rail transit and travel behavior. Generally, researchers have employed cross-sectional design, (quasi-) longitudinal design, and repeated cross-sectional design. Some studies use cross-sectional data of travel diaries or their variants. Access to rail transit is often measured through distance to the nearest station or a dummy variable indicating whether respondents live within station areas (e.g., a buffer of half a mile or 1 km) (Zhang et al., 2017; Yang et al., 2022a). Most of them offer supportive evidence for the desirable travel impacts of rail transit investment. For example, access to rail transit is positively associated with commuting by rail transit (Cervero, 2007; Shen et al., 2016) and transit use (Huang et al., 2016; Boarnet et al., 2020b). However, the results are not always consistent. The literature also shows that access to rail transit does not have significant influences on transit use of recent movers (Cao and Schoner, 2014) and commuting by auto (Chatman, 2013). Cross-sectional design has a few benefits. First, data are widely available. Many regions release their travel survey data for research use. Even if researchers choose to collect their own data, the effort is much lower than collecting longitudinal data. Second, the wide availability of data enables researchers to explore the issue in different regions. Accordingly, some scholars have tried to generalize the results through *meta*-analysis (Ewing and Cervero, 2010; Aston et al., 2021). However, cross-sectional studies are weak in causal inference. Although they can illustrate an association between variables, they are incapable to establish evidence for time precedence of the association: causes must precede effects (Royce and Straits, 2005). For a more robust causal inference, it is desirable to analyze data collected at two or more time points (waves).

Using longitudinal data, some studies show that rail transit investment is conducive to transit use and physical activity and helps mitigate driving (Brown et al., 2015; Spears et al., 2017b). Using a before-after treatment–control design, Brown, Werner et al. (2015) analyzed accelerometer data of residents living within 2 km of the TRAX LRT extension in Salt Lake City. They found that compared with those who have never used transit, new riders increased their physical activity; former riders reduced their physical activity; and continuing riders did not change their behavior. Longitudinal studies can offer a more robust causal inference than cross-sectional studies (Royce and Straits, 2005). They can establish the evidence for time precedence of an association. Moreover, they can automatically control for time-invariant confounding factors. However, the collection of longitudinal data is often costly and time-consuming. Furthermore, attrition is a major concern of longitudinal data (Yee and Niemeier, 1996). This is particularly salient in transit studies because many residents around station areas are home renters, who are more likely to relocate than owners. The attrition will reduce statistical power. It may also make the sample unrepresentative to the population after the opening of rail transit. The influx and outflux of residents with different travel behavior responses to the transit deployment (such as those observed by) may render the conclusions of a longitudinal study invalid (Yee and Niemeier, 1996).

Alternatively, some scholars opt to quasi-longitudinal studies. Instead of capturing travel behavior at two or more time points, they ask respondents to recall their travel behavior (or changes) before and after the commencement of rail transit. Cao and Ermagun (2017) found that compared with those moving into similar urban neighborhoods, the residents moving into the Light Rail Transit (LRT) neighborhoods in Minneapolis increased their transit use and reduced their driving, but they did not change auto ownership. Quasi-longitudinal studies enable researchers to control for time-invariant factors, besides the evidence for time precedence. Therefore, they offer a more robust inference for the impacts of rail transit deployment than cross-sectional studies. However, because the changes in travel behavior are often measured either through an ordinal scale or based on respondents' recall of past behavior, these studies can only shed lights on the direction of the influences but cannot offer precise estimates for their magnitude (Cao et al., 2007).

Some researchers have examined the before-after impacts of rail transit on travel behavior using repeated cross-sectional data. Different from longitudinal data, repeated cross-sectional data measure different respondents at a few time points. Dai et al. (2020) employed difference-in-difference models to analyze two (propensity score) matched datasets collected before and after the commencement of the Circle Line in Singapore. They found that the opening promoted rail transit use and discouraged auto use but did not have a significant relationship with bus use. Repeated cross-sectional data are superior to longitudinal data because they involve less collection effort and sample attribution is not a concern. Moreover, repeated cross-sectional data include residents moving into station areas after the commencement of rail transit and hence are more representative to the population being studied than longitudinal data (Yee and Niemeier, 1996). On the other hand, because the data may not include any common respondents, some modeling techniques (such as propensity score and statistical control) are needed to account for the influences of confounding factors in different samples.

The pros and cons of these research methods inform our choice of the repeated cross-sectional design. First, using data collected at multiple time points is more desirable than using cross-sectional data because the former data are conducive to causal inference. Second, repeated cross-sectional data are better than (quasi-) longitudinal data in our research context. It takes years or even decades for a metro system to evolve from a single line to a network. A large proportion of respondents recruited during the first wave would have changed their residential locations. The high attrition rate leads to inefficient data collection and makes the sample unrepresentative. Regarding quasi-longitudinal design, it is difficult for respondents to accurately recall their specific travel behavior from nine years ago.

3. Methods

3.1. Data and variables

The data used in this study came from two comparable cross-sectional surveys conducted in Xi'an. Xi'an, the capital city of Shaanxi Province and home of the Terracotta Warriors, housed approximately 10 million permanent residents in 2019 (Xi'an Bureau of Statistics, 2020). Private vehicles have proliferated from 1.17 million in 2012 to 3.08 million in 2019 (Xi'an Bureau of Statistics, 2013; Yang et al., 2017; Xi'an

Bureau of Statistics, 2020). To ease traffic congestion and mitigate climate change, the city government has accelerated the development of metro transit during the past decade (Fig. 1). Line 2, the first metro line, started revenue service in 2011; Lines 1, 3, 4, and 14 commenced in 2013, 2016, 2018, and 2019, respectively; Lines 5, 6, 9 opened in 2020. Seven additional lines (including the extensions of Lines 1 and 2) are under construction.

Household travel surveys were conducted in two time periods: November and December 2012 (when one metro line was in service) and April and May 2021 (when a network of eight metro lines was in operation). Researchers adopted a probability-based multi-stage sampling approach. First, they divided the main urban area of Xi'an into nine zones and randomly selected residential neighborhoods from each zone (Fig. 2). The number of neighborhood samples in each zone was determined according to the distribution of population in the nine zones. Second, surveyors randomly recruited 3–5 households in each of the selected neighborhoods through intercept surveys. After training, the surveyors administered the structured surveys through face-to-face interviews. The final samples included 1,952 respondents from 1,501 households in 2012 and 2,004 respondents from 1,584 households in 2021.

The questionnaires asked respondents to report commute information, housing characteristics, socio-economic characteristics of the household and household members. Table 1 presents the characteristics of the two samples. From 2012 to 2021, car ownership increased by 30%, and the percentage of higher-income households (with a monthly income of RMB 10,000 or more) grew by 50%. As the city expanded into exurban areas, a growing number of residents lived in these areas and average commuting distance also increased. Furthermore, the mode shares of driving, metro, and bicycle/shared bicycle increased substantially, whereas the bus mode share plummeted.

3.2. Hypothesis development

As the metro network grows from one line to multiple lines, the number of residents and workplaces near metro stations (i.e., within 1 km buffer from the nearest metro station in this study) increases. The residents who obtain metro access to workplaces may switch from other modes to metro for commuting. Therefore, as posited in Hypothesis I in Fig. 3, after the formation of the metro network, people residing near metro stations are more likely to commute by metro than before. In Hypothesis II, we further assume that the metro mode share of individuals whose home is not close to metro stations also increases for at least two reasons. First, although they live away from metro stations, their workplaces may be near metro stations. They may be willing to walk a longer distance to access metro stations now than previously. Second, they could use other modes (such as bicycle and bus) for first-mile and last-mile connections, particularly because shared micro-mobility has recently become a popular mode of transport. Moreover, because residents living near metro stations are more likely to commute by metro than those living away from the stations, we assume that station-area residents will experience a larger growth in metro mode share than those living away from the stations (Hypothesis III).

3.3. Estimation method

The difference-in-difference (DID) model is used to test the three hypotheses. It is a popular way to estimate the effect of an intervention. In a DID model (Fig. 4), the samples are separated into two groups based on their exposure status, namely treatment group and control group. The treatment group refers to households residing within 1 km straight-line distance from the nearest metro station, and the control group refers to households living beyond the distance. The model assumes a common trend between the two groups if there is no treatment. The counterfactual value is estimated based on the trend of the control group. The intervention effect is the variation between the observed value and the counterfactual value when there is no treatment.

We use a binary logit model to estimate commuter's probability of choosing metro mode in the DID modeling framework:

$$\begin{aligned} \text{logit}(y_{it}) = \ln\left(\frac{p_{it}}{1-p_{it}}\right) &= \alpha_0 + \alpha_1 HomeNearMetro_i + \alpha_2 MetroNetwork_t \\ &+ \alpha_3 HomeNearMetro_i \times MetroNetwork_t + X_{it}\beta + \varepsilon_{it} \end{aligned} \tag{1}$$

where p_{it} represents the probability of choosing metro mode; $HomeNearMetro_i$ is a dummy variable, where 1 represents the treatment group and 0 represents the control group; $MetroNetwork_t$ is a dummy variable, which equals to 1 if the commuter is in the sample collected in 2021 when the eight-line metro network has formed, and equals to 0 if the commuter is in the sample collected in 2012 when there was only one metro line; X_{it} indicates the vector of control variables; and ε_{it} is the error item. In this study, we accounted for the confounding effects of some socio-economic and demographic characteristics (age, educational background, household income, the presence of cars, house ownership), commute distance, and housing location by ring road as shown in Table 1.

4. Model results and discussion

By pooling the data collected in 2012 and 2021, we developed a binary logit model to estimate respondents' probability of choosing metro transit for commuting (Table 2). We tested all the variables listed in Table 1. The model suggests that car owners are less likely to commute by metro than non-owners. This result is plausible because cars and metro are competing modes of transport. In the data, 5.25% of car owners chose metro for commuting, whereas 9.72% of non-owners used metro. Moreover, younger people are more likely to choose metro for commuting. This makes sense because younger people are generally poorer, own fewer cars, and are more likely to advocate for alternative modes of transport. The two findings are also consistent with previous studies (Yang et al., 2018; Yang and Wang, 2018; Cao, 2019; Huang et al., 2019; Liu et al., 2020; Zhang and Jiang, 2020). Commute distance is positively associated with metro mode choice. This result appears counterintuitive because a few American studies showed that commute distance has a positive relationship with car mode choice (Cervero and Kara, 1997; Ding et al., 2018). However, it is congruent with Chinese studies (Yang et al., 2018; Yang and Wang, 2018; Huang et al., 2019). Traffic congestion is notorious during peak hours in large Chinese cities. For example, the average peak-hour driving speed in the ten most congested cities (including Xi'an) ranged from 24.2 to 26.7 km per hour in the second quarter of 2021.[1] To save travel time and ensure reliability, long-distance commuters are more likely to choose metro for commuting. Compared with driving, metro enables commuters to use their travel time more productively; they may browse news, listen to the music, watch videos, or conduct other activities (Paez and Whalen, 2010; Lopatovska, 2013). By contrast, driving is onerous and stressful. Moreover, commuting by metro could save travel costs such as fuel costs and parking fees. Additionally, commuting by metro helps reduce transport-related carbon dioxide emissions and improve air quality (Yang et al., 2020; Yang et al., 2022b), a low-carbon and pro-environment culture currently encouraged and advocated by the society. After controlling for these variables, educational background, household income, house owner, and housing location were not statistically significant and hence were dropped from the final model.

Table 2 also shows that metro network, home near metro, and their interaction term are significant in the model. Again, the base term "metro network" is a dummy variable, with "1" indicating that the

[1] https://www.statista.com/statistics/975120/china-average-driving-speed-in-the-major-congested-cities-during-rush-hour/, accessed on February 25, 2023.

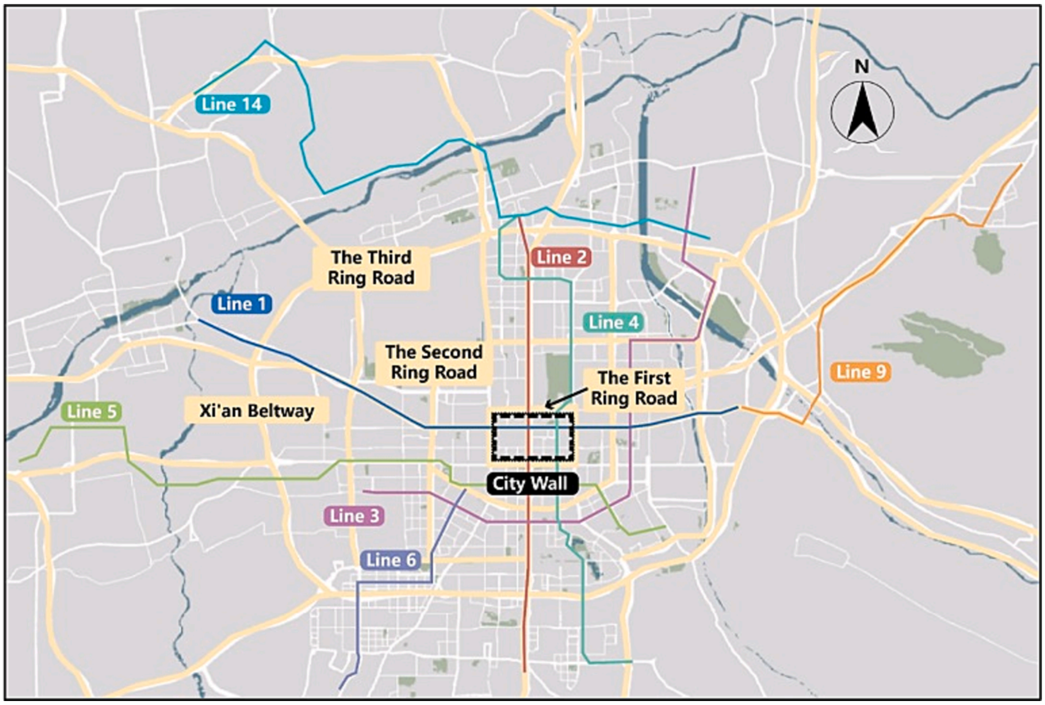


Fig. 1. Xi'an metro lines in 2021.

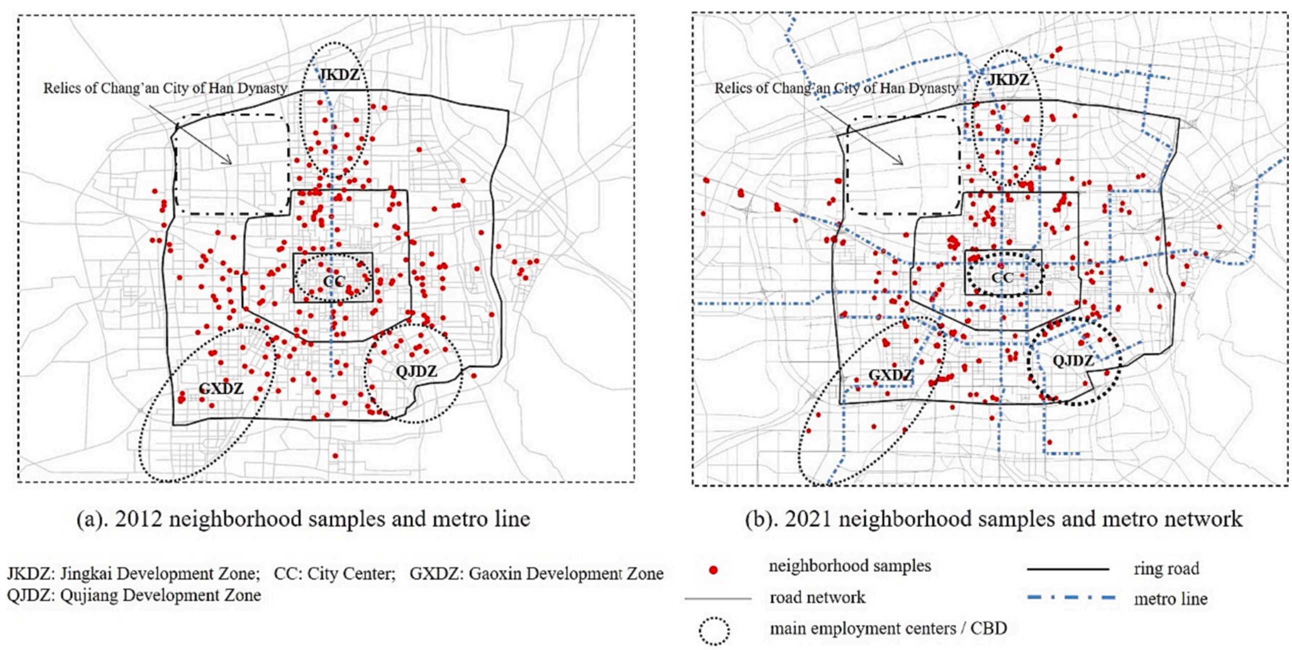


Fig. 2. Geographical locations of neighborhood samples in 2012 and 2021.

respondent is from the data collected in 2021 when there was a network of metro lines. The base term "home near metro" is also a dummy variable, with "1" indicating that the respondent resided within 1 km of a metro station. Because their interaction term is statistically significant, the impact of one base term on the probability of choosing metro for commuting depends on the value of the other base term. That is, we cannot interpret the coefficients of the based terms independently. Instead, we use predictive probabilities under four scenarios (by cross-listing the two base terms) to assess their joint effects.

Table 3 shows the predictive probabilities of the four scenarios after controlling for other variables in the model. When there is a single line, the probabilities of commuting by metro are 1.2% for those living away from metro stations and 11.7% for those residing near metro stations. When there is a network of metro lines, the probabilities of commuting by metro are 6.5% for those living away from metro stations and 12.8% for those residing near metro stations. Fig. 5 also illustrates the four probabilities. Interestingly, for those living near metro stations, the probability of commuting by metro increases slightly, whereas for those residing away from stations, the probability increases a lot. We then test whether the changes in the probabilities are statistically significant.

The second panel in Table 3 presents changes in the probabilities between scenarios. First, this study fails to provide supportive evidence

Table 1
Sample Characteristics.

		2012		2021	
	Levels	**N**	**(%)**	**N**	**(%)**
Age	18–32 years old	677	34.86%	930	46.41%
	32–55 years old	1201	61.84%	1015	50.65%
	>55 years old	64	3.30%	59	2.94%
Educational background	Middle school graduates	149	7.63%	25	1.25%
	Graduates of high school or technical secondary school	377	19.31%	100	4.99%
	Associate degree	478	24.49%	538	26.85%
	Bachelor's degree	789	40.42%	1178	58.78%
	Graduate degrees	145	7.42%	163	8.13%
Car owner	Presence of cars in the household	507	40.89%	1419	70.81%
Household monthly income	< RMBY5,000	54	4.35%	65	3.24%
	RMBY5,000–8,000	246	19.84%	233	11.63%
	RMBY8,000–10,000	778	62.74%	481	24.00%
	RMBY10,000–20,000	114	9.19%	746	37.23%
	>RMBY20,000	29	2.34%	479	23.90%
House owner	House is owned	1584	81.15%	1555	77.59%
	House is not owned	355	18.19%	449	22.41%
Housing location by ring road	Inside the 1st Ring Rd.	76	6.13%	49	2.45%
	1st – 2nd Ring Rd.	376	30.32%	473	23.60%
	2nd – 3rd Ring Rd.	734	59.19%	1281	63.92%
	Outside the 3rd Ring Rd.	54	4.35%	201	10.03%
Commute mode share	Car	554	28.85%	843	42.07%
	Bus	736	38.33%	222	11.08%
	Metro	59	3.07%	220	10.98%
	Employee shuttle	22	1.15%	23	1.15%
	E-bicycle/motorcycle	153	7.97%	198	9.88%
	Bicycle/Shared bicycle	52	2.71%	170	8.48%
	Walk	344	17.92%	328	16.37%
Average commute distance (km)		3.77		6.10	
Respondents living within 1 km from the nearest metro station		377	19.31%	1575	80.69%
Respondents living beyond 1 km from the nearest metro station		1322	65.97%	682	34.03%
Sample size		1952		2004	

for Hypothesis I. When the metro system grows from a single line to a network of multiple lines, the probability that those residing near metro stations choose metro for commuting increases by 1.1 percentage points. However, this increase is not statistically significant. This result is also plausible. The first metro line in a region is not deployed at random. It is often located in a corridor with high (if not the highest) bus ridership and bus mode share and connects major destinations (such as the downtown and employment centers) in the region. This is particularly true for Line 2 (Fig. 2). It is located along the North-South axis of the transportation network. The axis used to be the most important transit corridor with the largest number of bus lines and the highest bus ridership. After the commencement of Line 2, many residents in station areas switched their commuting modes to metro. However, as the number of metro lines in a region grows, some lines are deployed to guide future land development and some are used to connect high ridership areas through low ridership areas. We speculated that those living near newer stations may be less likely to use metro for commuting than those residing near the stations of the first line.

To test this assumption, we developed a binary logit model (Table 4). The model was based on a subsample of the 2021 data, which contained only respondents who lived within 1 km of metro stations. Table 5 presents predictive probabilities that station-area residents of different lines commute by metro. It seems that the probabilities for Lines 1–3 are larger than those for Lines 4–6. Statistically, those residing near Lines 4 and 5 are less likely to commute by metro than those near Line 2 (Table 4). This finding offers supportive evidence for the assumption. It is worth noting that although the predictive probabilities for Lines 4–6 are similar, Line 6 is insignificant. This is likely because it has fewer respondents than Lines 4 and 5. The coefficients for Lines 1 and 3 are also negative, but statistically insignificant.

Second, this study offers supportive evidence for Hypothesis II. When the metro system grows from a single line to a network, the probability that those residing away from metro stations choose metro for commuting increases by 5.3 percentage points and the increase is statistically significant. Again, it makes sense for a couple reasons. To begin with, after the formation of a metro network, more workplaces are likely to be within the catchment areas of metro stations. We calculated some statistics using the two waves of household travel survey data. We found that about 19% of the respondents in 2012 worked in the areas within 1 km of metro stations, and that the proportion in 2021 increased to 56%. Moreover, although many respondents resided in the areas beyond 1 km of metro stations, they could access the stations by shared bike, bus, or being dropped off by a driver. Fig. 6a illustrates the first-mile connections of those living beyond 1 km of metro stations in the 2021 data. About 45% of them walked to metro stations; 20% rode buses; 18% used shared bikes; 14% used both buses and shared bikes; and others used cars or taxies. Moreover, even if their workplaces are not within station areas, some may use other modes to make connections to the attraction end of the metro trip. In the 2021 data, among those working in the areas beyond 1 km of metro stations and commuting by metro, 22% rode buses for the last-mile connection; 3% used shared bikes; 16% used both buses and shared bikes, and 59% walked to stations (Fig. 6b). However, in the 2012 data, few respondents made first-/last-mile connections by mode other than walking. This comparison shows the important role of feeder buses and shared bikes in facilitating metro use for commuting.

Third, in both years, those residing near metro stations are more likely to use metro for commuting than those living outside of the 1 km buffers. However, the mode share gap in 2021 is smaller than that in 2012. This result is contrary to Hypothesis III. The aforementioned reasons are instrumental to explaining the discrepancy.

The findings above manifest that the performance of the metro

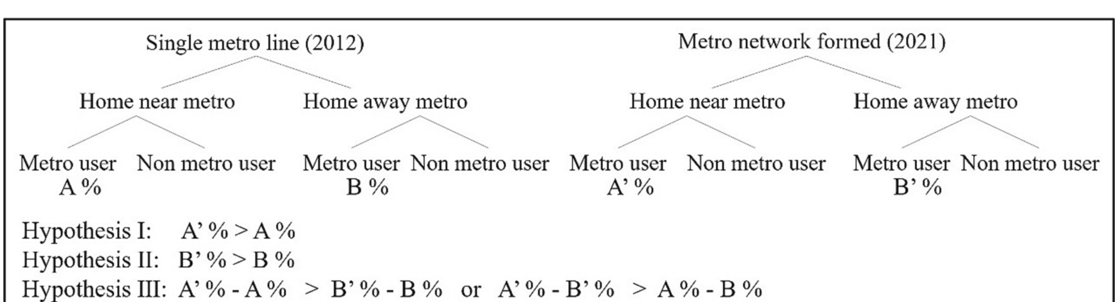


Fig. 3. Hypothesized effects of forming the metro network on metro mode share of residents living near and away from metro stations.

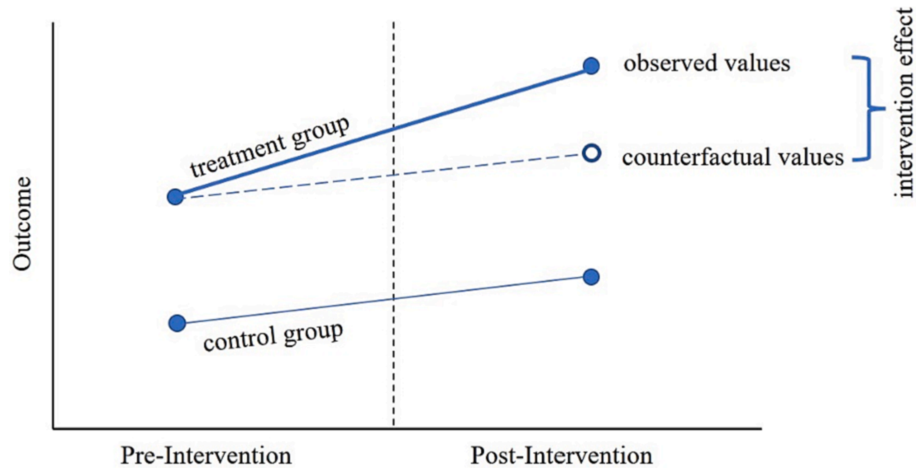


Fig. 4. Graphical illustration of the DID method.

Table 2
Model results of metro mode choice.

Variables	Coefficients
Metro network	1.823*** (6.07)
Home near metro	2.511*** (8.44)
Metro network × Home near metro	−1.705*** (-4.89)
Car owner	−1.231*** (-8.37)
Age 18–32 years old	0.549*** (3.88)
Commute distance	0.115*** (9.97)
Constant	−4.883*** (-18.51)
Log-likelihood at market share	−1007.9
Log-likelihood at convergence	−809.4
McFadden R^2	0.197
N	3944

Notes: (1). t statistics in parentheses; (2). * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

system in Xi'an has been strengthened after its expansion from a single line to a network of multiple lines. First, the coverage area of the metro system has greatly increased and many people have gained convenient access to metro stations. In 2012, the 1 km catchment areas of metro stations were 45.6 km^2, and the size has increased to about 382 km^2 by 2021. Although we did not find that the average metro mode share in the catchment areas has significantly increased over time, metro ridership has grown substantially because of the expanded coverage area. Second, the expansion of the metro system enables more workplaces to be accessible by metro transit. Although some commuters may need to make transfers to reach their workplace, the transfer penalty tends to be small within the metro system (Hua et al., 2021; Cheng et al., 2022). Furthermore, the improvement in workplace access by metro facilitates residents living beyond metro catchment areas to commute by metro. Our data show that about half of the riders who were at least 1 km away from metro stations walked more than 1 km to ride metro. The restructuring of feeder bus routes and the emergence of shared micro-mobility also play an important role in the first-/last-mile connections to metro stations. Therefore, those who reside away from metro stations greatly increase their metro use.

Different people may respond to metro expansion differently. To explore the heterogeneity within the sample, we developed a supplement model by interacting socio-economic and demographic characteristics with the dummy indicating whether a household is located within 1 km of metro stations and the dummy indicating whether the metro network has formed. Table A1 in the appendix presents a parsimonious model as we dropped insignificant interaction terms with socio-economic and demographic characteristics. The results manifest that compared with other age groups, individuals who were between 18 and 32 years old and resided near metro stations would use metro for commuting more often after the metro network formed. This finding suggests that younger people are an important group that metro services can attract. However, there is no statistical evidence for heterogenous effects resulting from car ownership, educational background, household income, house owner, and housing location.

COVID-19 may have some effects on transit use during the post-pandemic era. Although transit ridership has reduced in almost all western countries (Almlöf et al., 2021; Gkiotsalitis and Cats, 2021; Tori et al., 2023), the ridership in Chinese cities is not greatly affected by the

Table 3
Predictive probabilities and average marginal effects.

Predictive Margins							
Scenario	Metro Network	Home Near Metro	Predictive Probability	Std. Error	P-value	95% Conf. Interval	
①	0	0	0.012***	0.003	<0.001	0.007	0.018
②	0	1	0.117***	0.016	<0.001	0.085	0.149
③	1	0	0.065***	0.009	<0.001	0.047	0.084
④	1	1	0.128***	0.009	<0.001	0.110	0.146
Average Marginal Effects							
Scenario			Probability Change	Std. Error	P-value	95% Conf. Interval	
Home near stations between 2021 and 2012		④-②	0.011	0.019	0.551	−0.026	0.049
Home away from stations between 2021 and 2012		③-①	0.053***	0.010	<0.001	0.034	0.072
Home near and away from stations in 2012		②-①	0.105***	0.016	<0.001	0.072	0.137
Home near and away from stations in 2021		④-③	0.063***	0.013	<0.001	0.038	0.088

Notes: (1). * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

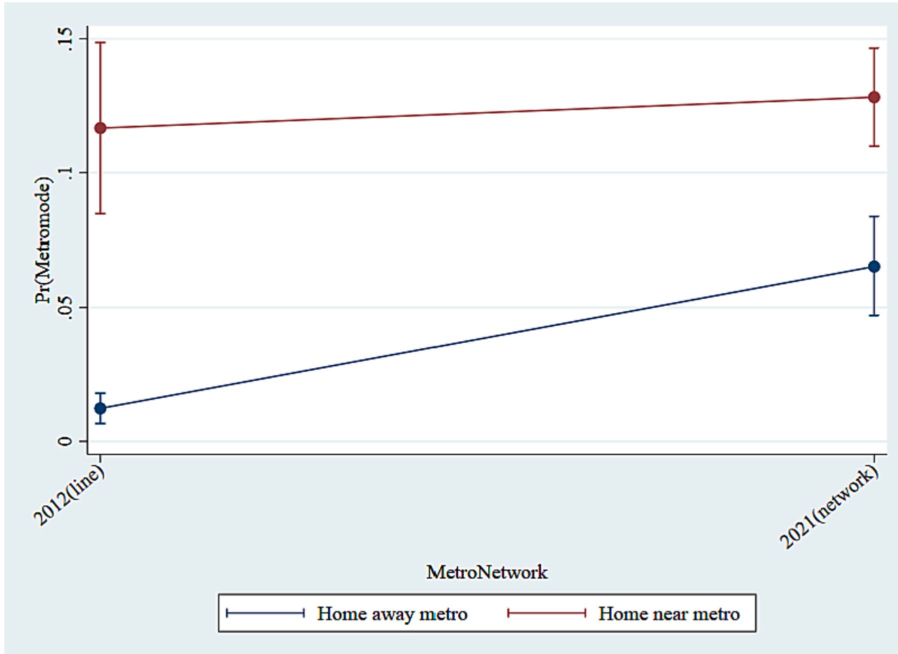


Fig. 5. Predictive probabilities under the four scenarios.

Table 4
Model results for metro mode choice of respondents residing within 1 km of metro stations in 2021.

Variables	Commencement Year	Number of respondents	Coefficients
Home Near Line 2	2011	278	The reference category
Home Near Line 1	2013	217	−0.203 (-0.79)
Home Near Line 3	2016	345	−0.056 (-0.23)
Home Near Line 4	2018	261	−0.778*** (-2.66)
Home Near Line 5	2020	146	−1.027** (-2.49)
Home Near Line 6	2020	75	−0.785 (-1.42)
Car owner			−1.127*** (-5.98)
Age 18–32 years old			0.903*** (4.61)
Commute distance			0.114*** (7.46)
Constant			−2.235*** (-8.45)
Loglikelihood at market share			−509.2
Loglikelihood at convergence			−431.0
McFadden R2			0.153
N			1322

Notes: (1). t statistics in parentheses; (2). * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 5
Predictive probability for metro mode choice of respondents residing within 1 km of metro stations in 2021.

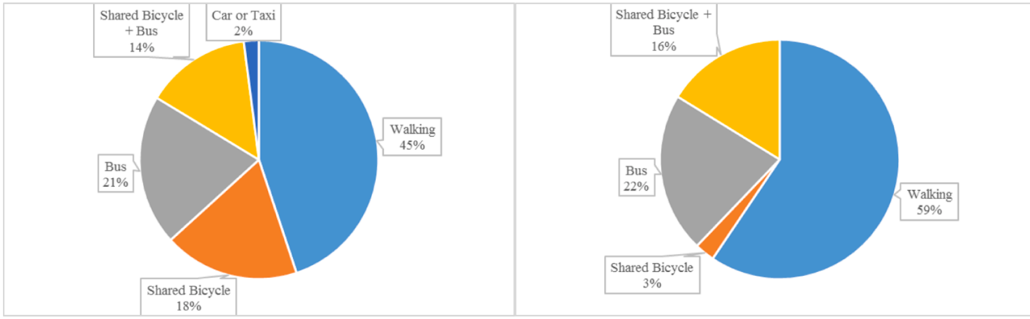
Lines	Predictive Margin	Std. Err.	z	P-value	[95% Conf. Interval]	
Home Near Line 2	0.161	0.020	7.98	<0.001	0.121	0.200
Home Near Line 1	0.138	0.020	6.97	<0.001	0.099	0.177
Home Near Line 3	0.154	0.019	8.23	<0.001	0.118	0.191
Home Near Line 4	0.088	0.017	5.15	<0.001	0.054	0.121
Home Near Line 5	0.071	0.023	3.15	0.002	0.027	0.116
Home Near Line 6	0.087	0.038	2.31	0.021	0.013	0.161

pandemic, especially for rail transit. During the survey time in April 2021, the average number of daily passenger trips by Xi'an metro was 3.465 million,[2] while in April 2019 before the pandemic, the number was 2.622 million.[3] The ridership grew for a few reasons. First, the growth was due to the addition of three new metro lines (Line 5, Line 6, and Line 9). Moreover, residents' desire for shopping, entertainment, and tourism have increased a lot, for some, as a way for making up for the lost time during the pandemic.

5. Conclusions

This study examined the influence of the metro network on rail transit commuting using repeated cross-sectional data in Xi'an. We found that after the formation of a metro network, station-area residents on average did not experience statistically significant changes in the

[2] https://weibo.com/ttarticle/p/show?id=2309404632004754014230#_loginLayer_1685933206841, accessed on June 5, 2023.
[3] https://oppo.yidianzixun.com/article/0MERFJ5E?s=oppobrowser&appid=oppobrowser&_pf_=detail&impid=_1560194014420_0JkvxXaR_n2n&_publisher_id_=RnV1KXa7Bi3Fx6EkbkWdkA, accessed on June 5, 2023.



(a). Residence beyond 1 km from metro stations (b). Workplace beyond 1 km from metro stations

Fig. 6. Metro access/egress mode shares in the travel survey data collected in 2021.

Table A1
Supplement model results of metro mode choice.

Variables	Coefficients
Metro network	2.183*** (5.13)
Home near metro	2.677*** (6.53)
Metro network × Home near metro	-2.460*** (-5.03)
Car owner	-1.212*** (-8.21)
Commute distance	0.115*** (10.00)
Age 18-32 years old	0.560 (1.14)
Age18-32 years old × Metro network	-0.690 (-1.18)
Age18-32 years old × Home near metro	-0.455 (-0.75)
Age18-32 years old × Metro network × Home near metro	1.484** (2.09)
Constant	-4.896*** (-13.61)
Log-likelihood at market share	-1007.9
Log-likelihood at convergence	-804.5
McFadden R^2	0.202
N	3944

Notes: (1). t statistics in parentheses; (2). * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

commute mode share by metro transit. However, this finding obscures the nuanced impacts of the metro network. Our further analysis showed that the mode share of residents around newer metro lines tended to be significantly smaller. Given the overall insignificant growth in mode share, the probability that residents around older lines chose metro for commuting should have increased. Therefore, this study implies that the formation of a metro network does improve metro commuting of residents living within 1 km from the stations of older lines, but newer lines have a diminishing return. In Xi'an, the mode share of three older lines almost doubled that of three newer lines. With that said, the three newer lines commenced a few years ago. It may take a few decades or longer to have all the station areas fully developed (Cervero and John, 1997) and to have residents sorted into the neighborhoods nearby (Cao and Ermagun, 2017). That is, the long-term impacts of the newer lines remain to be seen.

Respondents residing beyond 1 km of metro stations experienced a significant increase in metro commuting. Their share of metro commuting was about half of that of station-area residents in 2021. The increase is likely because the expansion of metro lines has made more workplaces within station areas and/or connection services (such as feeder buses and shared micro-mobility) have greatly improved.

These findings point to a few planning strategies for enhancing metro commuting. First, the alignment of metro transit corridors should prioritize existing activity centers, including institutions, college campuses, and commercial and service hubs. In general, rail transit that connect residential neighborhoods with multiple employment centers tends to generate high ridership (Thorne-Lyman and Wampler, 2010). Seamless transfers within metro stations will further magnify the network effect of destination connectors. Second, job opportunities around station areas should be densified. Overall, station-area density is key to transit commuting.

Furthermore, metro transit that connects destinations not only benefits station-area residents, but also attracts those living away from metro stations to commute by metro. Given a limited number of metro stations in a region and limited station-area lands for development, it is important to fully exploit the latter benefit. Our findings suggest that the catchment area of a metro station exceeds 1 km. This manifests the importance to improving feeder services to metro stations. Metro transit agencies should coordinate with bus transit agencies[4] and residential neighborhood associations to optimize first-/last-mile connections with metro stations. Specifically, planners should identify key residential neighborhoods that house transit-dependent people and work with neighborhood associations to offer conventional feeder services to the neighborhoods. If transit-dependent people are scattered, bus transit agencies could deploy paratransit (a fixed-route service that stops at the request of users) to ease users' walking access to the service. Additionally, providing free transfers between metro transit and feeder services can promote metro ridership. Facilitating biking and shared micro-mobility is another way to enhance intermodal connections. Although walking is not a feasible solution for those who live a few kilometers from metro stations, the proliferation of shared bikes and e-scooters offers metro users a viable option. Based on the geographical distribution of transit-dependent people, planners could develop bike-friendly corridors to metro stations by providing protected bike lanes, bike signal priority, and bike storage around metro stations. Within metro station areas, a bike network is desirable. Moreover, because walking accounted for about half of the mode choice by those who lived or worked beyond 1 km from metro stations (Fig. 6), a pedestrian-friendly environment is also critical to metro access/egress trips. Barrier-free sidewalks and safe road-crossing can help improve walkability.

It is well-documented that the recent COVID-19 pandemic has an adverse effect on transit ridership (e.g., Parker et al., 2021). Xi'an is not an exception. Based on the data of May 24–31, 2019 and May 24–31, 2023, the metro ridership of Lines 1–4 in Xi'an decreased by approximately 5.9%. The reduction may be attributable to a few factors. First, some previous metro users, especially the vulnerable population and

[4] In Xi'an (as well as many Chinese cities), bus transit and metro transit are operated by different agencies (Xi'an Public Transport Group Company Limited and Xi'an Rail Transit Group Company Limited). Because they have different objectives and priorities, coordinated effort between agencies is needed to maximize the utility of metro transit.

long-distance riders who expose to others for a longer duration, may worry about the lingering effect of the COVID-19 pandemic and hesitate to ride the metro. However, they are likely to come back to the metro system over time. As the COVID-19 is not regarded as a major threat to public health and transit agencies do not require masks or any other preventive measures, only a small share of metro riders wear masks. The concern will be eased in a few years. It is worth noting that we do not recommend any mandatory preventive measures unless the COVID-19 becomes a public health threat again. The measures would make the public panic and delay the recovery of the transit system and other aspects of human activities. People should take the measures at their own discretion and without discrimination. Second, some have acquired and hence switched to personal vehicles. As it has been difficult to attract car users to use transit (Vuk, 2005), this change may have a long-term impact on metro ridership. Third, some have switched to shared micro-mobility (Teixeira and Lopes, 2020). In fact, the substitution effect of shared micro-mobility for transit happened even before the pandemic (Campbell and Brakewood, 2017). Overall, the aforementioned policies and programs have become more urgent and crucial to capture the lost market resulting from the pandemic.

This study has a few limitations. First, we did not address the confounding effect of shared mobility (such as bike sharing and ride hailing). Because the emergence of shared mobility and the formation of the metro network occurred at the same time, we did not have a control group to disentangle the impact of shared mobility from the effect of the metro network on mode share. In the literature, there is no consensus on the net effect of shared mobility on transit trips (Shaheen and Cohen, 2020). Shared mobility facilitates first-/last-mile connections to transit stations and enhances ridership. A study in Minneapolis and St. Paul showed that bike sharing made more people switch travel mode toward rail transit (15%) than away from it (3%) (Shaheen et al., 2013). On the other hand, shared mobility may substitute for transit trips. In densely-developed areas, bike sharing is a viable alternative to short transit trips as it offers faster, cheaper, and more direct connections to destinations (Shaheen and Martin, 2015). For example, bike-sharing substituted for buses in the city center or secondary centers in Shenzhen, China (Tang et al., 2021). Rail transit may also enhance the use of shared mobility. After a new LRT station opened in Seattle, WA, the number of shared bikes within a 5-minute walking radius of the station grew from 0.54 to 1.30 bicycles per km^2 (Tyndall, 2022). This suggests that more people chose LRT stations as an anchor of their bike-sharing trips. Overall, the associations between shared mobility and transit could be endogenous. Second, this study did not control for built environment variables. The literature shows that commuters' mode choice is affected by built environment variables near their residences and workplaces (Sun et al., 2017; Ding et al., 2021). Here we assumed that the effect of built environment changes that occurred naturally would be captured by the before-after treatment–control design adopted in this study. The built environment changes that were associated with metro transit were the outcomes of metro investment. In other words, if there were no metro stations, the built environment around station areas would not have changed as greatly as it was. Controlling for the latter changes would underestimate the impact of the investment on mode choice. However, built environment changes that did not occurr naturally or were not induced by metro transit may confound its effect on mode share.

CRediT authorship contribution statement

Liu Yang: Conceptualization, Methodology, Software, Investigation, Writing – original draft, Funding acquisition. **Xinyu Jason Cao:** Conceptualization, Methodology, Validation, Writing – review & editing. **Yuanqing Wang:** Conceptualization, Investigation, Funding acquisition. **Yujun Lian:** Methodology, Software. **Zhongming Guo:** Software.

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.

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