How does free-floating bike-sharing integrate with urban rail transport? Exploring the nonlinear effects of the built environment

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Abstract

Bike-sharing offers a convenient feeder mode for connecting to public transport, which helps to address the last-mile problem. However, few studies have examined the nuanced relationship between the built environment and the integration of free-floating bike-sharing (FFBS) with urban rail transport (URT). Drawing on weekly records of 3.12 million trips of the FFBS system in Nanjing, China, we examined the nonlinear effects of the built environment on FFBS-URT integrated use. A quantile regression method is utilised to estimate the relationship for morning and evening peaks, respectively. The results demonstrate the existence of the nonlinearity of the relationship. The effects of the built environment show variations in the significance levels and magnitudes of coefficients, depending on the quantiles. For example, the length of minor roads in station areas is strongly related to the integrated use at low quantile stations, whereas this effect is not statistically significant at medium and high quantiles. We also find that bicycle infrastructure displays more salient nonlinear effects than land-use variables and external transport facilities. In addition, temporal differences in the relationship between the built environment and the integrated use are also unveiled. Our research results help to inform dedicated and effective built environment interventions which support the planning of seamless connections between bike-sharing and urban rail transport.

Keywords: Bike-sharing; Public transport; Bike-and-ride; Built environment; Nonlinearity; Shared mobility; Nanjing (China)

1. Introduction

A lack of connectivity has been identified as a major challenge for developing urban rail transport (URT) systems. It refers to the issue related to the first/last-mile connectivity from home and public transport to destination (Chandra et al., 2013). Bike-and-ride is an effective multimodal solution to the issue by providing convenient, flexible, affordable, and eco-friendly access to URT stations. Over the last decade, bike-sharing has witnessed exponential growth. More than 2,000 cities around the world have launched bike-sharing programs, providing a total of 9.7 million shared bikes for public use (Meddin et al., 2021). Currently, there are two main types of bike-sharing systems: station-based bike-sharing (SBBS) and free-floating bike-sharing (FFBS). In comparison with SBBS systems, the FFBS system is much more convenient as it allows users to easily locate and unlock a bike via smartphones and return it almost anywhere (as long as parking is permitted) once they have completed their trips. It offers substantial flexibility and a truly seamless journey with door-to-door services. The high flexibility of FFBS creates a stronger integration of bike-sharing with public transport than that of an SBBS system (Chen et al., 2020). Hence, achieving a better understanding of the integration process between FFBS and URT is crucial.

The integration of bike-sharing with URT provides users with a flexible travel option and has the potential to increase the overall demand for both public transport and bicycling (e.g. Fishman et al., 2015; Gu et al., 2020a; Marten, 2007). A system-level analysis from Washington DC indicates that promoting Capital Bikeshare ridership by 10% would lead to a 2.8% increment in rail transport ridership (Ma et al., 2015). In Minneapolis-St. Paul, US, and Montreal, Canada, rail usage was observed to increase by 15% and 11%, respectively, due to the bike-sharing integration (Martin and Shaheen, 2014). In addition, bike-sharing as a feeder mode to URT could substitute for passenger vehicles, thereby reducing greenhouse gas emissions. A scenario analysis conducted in New Delhi, India, shows that the integration between bike-sharing and public transport could result in CO_2 emissions savings of more than 1,000 tonnes per day (Mohanty et al., 2017). In sum, the FFBS-URT integration is bringing new opportunities for a sustainable and efficient urban multimodal transport system.

It is well documented that the built environment can significantly influence the integrated use between bike-sharing and URT (e.g. Campbell and Brakewood, 2017; Griffin and Sener, 2016; Gu et al., 2019b; Guo and He, 2020; Guo et al., 2020; Ji et al., 2017; Kong et al., 2020; Li et al., 2020; Lin et al., 2018; Ma et al., 2015; Ma et al., 2018; Martin and Shaheen, 2014; Zhao and Li, 2017). However, existing studies have not reached a consensus on the dose-response relationships between built environment characteristics and the integrated use. For example, Lin et al. (2018) found that higher population density contributes to more bike-sharing use for accessing metro stations, whereas Martin and Shaheen (2014) observed more integrated use in areas with lower population density. The effect of transport facilities is also inconclusive. The number of bus stops near a rail transport station could increase (Guo and He, 2020) or decrease (Zhao and Li, 2017) the likelihood of choosing bike-sharing as a feeder mode. Regarding possible rationales for the mixed findings, recent research has pointed out the nonlinearity of built environment effects on urban mobility (e.g. Cheng et al., 2020a; Ding et al., 2018). In fact, the impact of the built environment (such as population density) can become negligible when it reaches a certain level. There is likely an inverted U-shape relationship between transport infrastructure investments and total travel demand. Such a relationship is similar to the classic environmental Kuznets curve (1955). For example, at relatively low levels of road capacity, an increment in road capacity will induce more traffic production as the improved accessibility and connectivity for most road users. When the capacity reaches a certain critical point, it could lead to a diminishing marginal return of infrastructure investment (Loder et al., 2019). To be more specific, increased traffic volume may cause severe road congestion and more accidents, shifting some road users to alternative routes (Systematics, 2005). Ignoring this nonlinear relationship may lead to ineffective land-use policy interventions for changing urban mobility patterns. However, there is a lack of research that investigates the nonlinear effects of built environment characteristics on the integration of FFBS with URT.

Drawing on the weekly records of 3.12 million trips of the FFBS system in Nanjing, China, this paper revisits a classical econometric approach, namely the quantile regression model, for analysing bike-and-ride frequencies in relation to various built environment variables. This study addresses the following two research questions: (i) is there any nonlinear relationship between the built environment and the integrated use between FFBS and URT?, and (ii) what are the temporal differences in the nonlinear effects of the built environment on the integrated use? The novely of this study is twofold. First, it explores the nonlinear effects of the built environment on FFBS-URT integration. To the authors' knowledge, this is one of the first studies to focus on how the FFBS-URT integrated use responds to different built environment variables varies across quantiles. Second, this study complements the recent stream of the nonlinearity of land use-travel research. By making statistical inferences, it provides significance levels with confidence intervals that support land-use policy priorities.

The rest of the paper is organised as follows. The next section reviews existing literature regarding the effects of the built environment on bike-sharing integration with public transport. Section 3 introduces the case study area, data, and methods. Section 4 presents model results and a discussion of the nonlinear effects. Finally, major findings are summarised and policy implications are suggested in Section 5.

2. Literature review

The built environment has been extensively acknowledged as a determinant of bike-sharing integration with URT in the existing literature (e.g. Guo and He, 2020, 2021; Guo et al., 2020; Ji et al., 2017; Ma et al., 2015). However, how certain built environment variables play a role remains inconclusive. Below we will review the built environment correlates of bike-sharing based on three categories of variables: land use, external transport facilities, and internal transport facilities.[1]

Empirical studies in Asian cities, such as Singapore, Beijing, and Nanjing, found that URT stations close to the central business district (CBD) or in an urban area will encourage bike-sharing-URT integration (Gu et al., 2019b; Ma et al., 2018). However, the situation changes in North American cities where more integrated use is induced in suburban areas (Martin and Shaheen, 2014). This difference is partly due to the less-served public transport in these areas, and bike-sharing becomes a first- and last-mile facilitator. Chen et al. (2012) found that population density is positively related to the integrated use of bike-sharing with URT, and these bike-and-ride trips are associated with commuting travel for employees and students. Interestingly, an insignificant relationship was found between population density and bike-sharing-URT integrated use in a study by Zhao and Li (2017). They argued that overcrowded areas may cause traffic congestion and road safety concerns, which is not suitable for bicycling activity. This argument has been supported by the literature discussing the relationship between the built environment and bicycling (e.g., Salon et al., 2019). Thus, formulating policies on residential densification might not be an effective method for encouraging bike-and-ride in all contexts.

Regarding the effects of employment density, a consensus seems to have been reached that a denser job distribution leads to higher bike-sharing-URT integrated use (Chen et al., 2021; Lin et al., 2018; Ma et al., 2015), which results from high commuting demands. In addition, land use mix is positively correlated with

[1] We refer to external transport facilities as facilities related to bike-sharing and/or URT systems; otherwise as internal transport facilities.

the integration (Böcker et al., 2020; Guo and He, 2020). Mixed land use within URT station areas can produce short trips between stations and residential, employment, and recreational locations. The type of points of interest (POIs) near URT stations is thought to affect the integrated use. For instance, more green space increases the likelihood of bicycling to stations (Guo and He, 2020), because of the good environment for bicycling making it possible to avoid traffic, potential injuries, and waiting at traffic lights. However, divergent findings were reported in terms of the presence of shopping locations. Ji et al. (2017) found that locating food and retailing stores near a rail station does not substantially affect the integrated use of bike-sharing-URT. However, Zhao and Li (2017) observed that shopping malls within station catchment areas deter the use of bike-sharing. The influence of educational places (i.e. proximity of schools and university campuses) also calls for further investigations due to an unclear effect (Chen et al., 2021; Lin et al., 2018).

The density of road intersections can positively or negatively affect bike-sharing usage as a feeder mode. Increasing intersection density improves accessibility to bicyclists, but may attract more vehicles passing by and incur safety concerns. The positive relationship is observed in Beijing, China, while the negative relationship is found in Taipei, Taiwan, and Tokyo, Japan (Lin et al., 2018). Different levels of roads within station catchment areas also influence bike-and-ride trips differently. Major roads are found to be negatively related to the integrated use due to the large traffic volume and possible traffic congestions on major roads (Guo et al., 2020; Li et al., 2020). Zhao and Li (2017) noted that the total length of local roads within URT station areas is negatively associated with bike-sharing use. The reason might be that a higher density of local roads promotes motorised travel, e.g. driving. This finding differs from a study by Guo et al. (2020), which found no significant effects of the length of local roads on bike-sharing usage as a feeder mode. Empirical findings regarding the impact of public transport facilities are also mixed. For example, some studies reported that more bus routes or bus stops near a URT station decrease the likelihood of bike-and-ride use (Liu et al., 2020; Zhao and Li, 2017). This result is contrary to a case study in Shenzhen, China, where the number of bus stops is conducive to the integrated use (Guo et al., 2020).

As for internal transport facilities, bicycle infrastructure including bicycle lanes and parking facilities, is important to support bicyclists to access URT (Campbell and Brakewood, 2017; Cervero et al., 2013; Martens, 2007; Mohanty et al., 2017). Undoubtedly, safe and exclusive parking facilities near URT stations are conducive to bike-and-ride use. According to a survey in Shanghai, approximately 60% of respondents would choose a bicycle as a feeder mode if more parking facilities were provided around metro stations (Pan et al., 2010). Empirical studies in the US cities have illustrated the role of bicycle lanes on bike-sharing connectivity to public transport (e.g. Griffin and Sener, 2016). Whilst bicycle lanes can be occupied by private vehicles and for-hire vehicles (Zhao and Li, 2017). More docking stations in the catchment area also increases demand for feeder trips by bike-sharing (Gu et al., 2019b). Yet, the densification process may have a threshold effect. Liu et al. (2020) found that a very high density of stations in catchment areas decreases the likelihood of choosing bikes as a transfer mode. For the URT itself, a transfer URT station attracts more integrated use (Ji et al., 2017). More importantly, the distribution of URT stations determines the demand for bike-sharing as a feeder mode. Several studies have shown that a higher density of stations contributes more to walking as a feeder mode, thereby reducing the likelihood of using bike-sharing to access/egress URT stations (e.g. Ma et al., 2018).

Some recent studies have pointed out that the nonlinearity of built environment effects is likely to be an essential source of these inconsistent results (e.g. Guo et al., 2020; Lin et al., 2018; Liu et al., 2020). It refers to the varying effects of the built environment for different levels of integrated use at different stations. The agglomeration effect and diminishing return effect in urban economics could help to justify the potential nonlinear effect of the built environment (Galster, 2018; Melo et al., 2009). A cluster of transport facilities and services, such as the number of shared bikes, in certain regions would attract a lot more travellers than a single facility could achieve alone. The diminishing return effect means that an addition of the input yields progressively smaller, or diminishing, increases in the output. The primary idea is that the perceived benefits of travelling in a certain way are associated with multiple factors that influence endogenously as the built environment characteristics change. Empirical studies have increasingly recognised the importance of identifying and understanding the nonlinear effect of the built environment on urban mobility (Ding et al., 2018; Tao et al., 2020; Wang and Ozbilen, 2020; Xu et al., 2021). Ding et al. (2018) observed that in Oslo population density under 3,000 persons/km^2 in the neighbourhood and distance to the city centre less than 20 km have substantial impacts on reducing driving distance on weekdays. Above these thresholds, they produce trivial effects. Wang et al. (2020) found that the built environment has nonlinear effects on shared car usage in Shanghai. Distance from a car-sharing station to the nearest metro station negatively influences the hourly borrows/returns. This influence decreases remarkably in the interval of 0 to 4 km, and remains relatively stable above 4 km. In particular, van Wee and Handy (2016) and Cheng et al. (2020a) pointed out that the overlook of nonlinear relationships would result in biased estimates of built environment effects and inappropriate planning implications. However, there is a lack of studies that especially investigate the nonlinear effects of the built environment on the integrated use of free-floating bike-sharing and urban rail transport (FFBS-URT). Identifying the effective range of built environment variables is of paramount importance for implementing policy interventions and planning practices to enhance the FFBS-URT integration efficacy.

3. Methods

3.1. Study context and data

This research investigates the integration of free-floating bike-sharing (FFBS) with urban rail transport (URT) using Nanjing, China as a case study. Nanjing is located in the eastern part of China, as the capital of Jiangsu Province. As of 2018, Nanjing had a population of 8.33 million and a total area of 6,587 km^2. There are 11 administrative districts where six are urban districts (Gulou, Jianye, Yuhuatai, Qixia, Xuanwu, and Qinhuai), and the other five are suburban districts (Liuhe, Pukou, Jiangning, Lishui, and Gaochun) (Figure 1). By 2018, there were seven URT lines, covering 129 stations and a total length of 260 km, with a daily ridership of over 2.67 million. 55% of the public transport trips in Nanjing were performed by URT. Nanjing launched its first FFBS scheme in January 2017. At the end of 2017, approximately 325,000 FFBS bikes had been put into use, with around nine million registered members. This offers a great opportunity to promote FFBS-URT integration in Nanjing. According to a survey conducted in 2017, 51% of bike-sharing riders used FFBS to access/egress URT stations (Du and Cheng, 2018). It is well noted that bike-sharing-public transport integration is especially important in China given that bikes are not allowed to be taken on board.

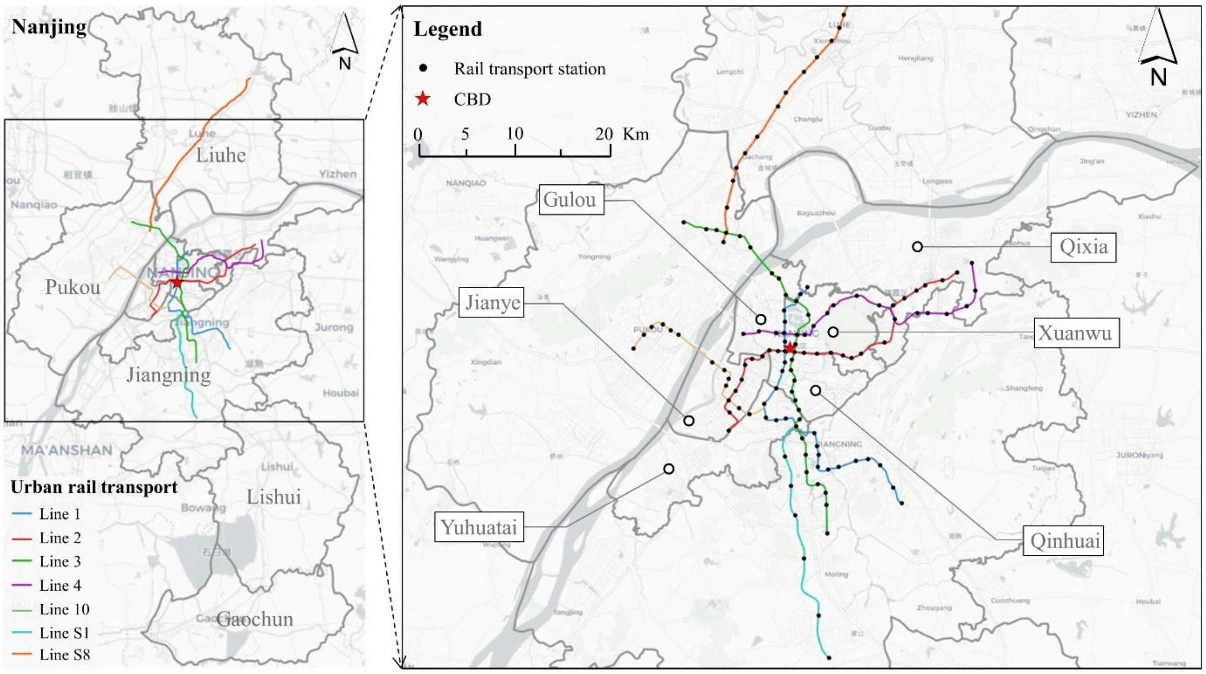


Figure 1. Urban rail transport (URT) network in Nanjing

The bike-sharing data were obtained from Mobike, the largest FFBS operator in Nanjing. The trip data contain user ID, unlock time, lock time, unlock location, and lock location (longitude and latitude). We focus on the integrated usage pattern on weekdays, from 11 (Monday) to 15 (Friday) September, 2017. The one-week raw data are composed of 3.12 million trip records. The average temperature was between 19 °C and 29 °C, and the weather was sunny or cloudy, which was suitable for bicycling. Bike-sharing trips whose origins or destinations are within a certain buffer distance around the entrance of a rail transport station are considered as an approximation to transfer trips between FFBS and URT. According to an intercept survey conducted by the Nanjing Municipal Transportation Bureau in 2021, during morning and evening peak-periods, 88% of travelers borrow/return free-floating shared bikes near metro stations' entrances/exits for their daily commute. Lin et al. (2019) and Chen et al. (2021) used 50 metres as the radius of buffer areas around URT stations for analysing bike-and-ride trips. In practice, the Nanjing government also has stipulated that bike transfer facilities shall be deployed within less than 50 metres to the entrance of URT stations. Therefore, we use a 50-metre buffer of each URT station entrance for extracting the trip volume of FFBS-URT integrated use. The built environment data were sourced from the Nanjing Urban GIS database. Variables were calculated within the 800-metre radius of each station, which is commonly used as the distance threshold for delineating the catchment area of a URT station (Guerra et al., 2012; Ji et al., 2017).

3.2. Variables

The dependent variable is the average ridership for FFBS-URT integrated use – measured by the number of shared bike rentals – over five working days. We examine the integrated use at morning peak (7:00-9:00) and evening peak (16:00-19:00), separately. Table 1 shows that morning integrated demand is overall higher than evening integrated demand. The ridership peak values in the morning and evening are 9,700 and 8,539 trips, respectively. The average ridership for morning peak integrated use per station is 51 trips per hour, while the average ridership for evening peak integrated use is 46 trips per hour.

According to the literature review in Section 2, the explanatory built environment variables considered include land use, external transport facilities, and internal transport facilities within the 800-metre radius of each station. Specifically, land-use variables include population density, employment density, and land use mix. Land use mix is calculated from six patterns of land use: residential, commercial, industrial, transport, green space, and public services. It is calculated as:

$$H = -(\sum_{i=1}^{n} p_i * ln(p_i))/ln\,(n) \quad (1)$$

where H denotes land use mix entropy, which spans from zero (complete dominance of one pattern of land use) to one (even distribution for all patterns of land use); p_i represents the areal percentage of the i^{th} pattern of land use; and n is the total number of land use patterns. External transport facilities are measured by length of major/minor roads, street connectivity, and number of feeder bus routes. In Nanjing, major roads go through the main part of a city and connect (sub-)districts, with the design speed of 40-60 km/h. Minor roads refer to collectors and local roads, with the design speed below 40 km/h. Street connectivity – calculated as the density of street intersections – is used to measure bikeability around rail transport stations (Lowry et al., 2016; Winters et al., 2013). Internal transport facilities comprise number of docking stations for SBBS and area of parking spaces for bicycles. The number of docking stations is considered because SBBS is expected to influence FFBS as a feeder mode to URT (Chen et al., 2021; Cheng et al., 2020b). In addition, we take into account another four control variables related to whether a URT station is a transfer station, whether it is located in urban areas, its distance to the central business area (CBD), and presence of a school[2]. A transfer station refers a rail transport station serves more than one rail transport lines, which usually carries more passengers than the non-transfer one. In the study area, there is a strong correlation between overall transport accessibility and distance to CBD. The performance of transport accessibility will decrease gradually as the distance to the city centre increases. Descriptive statistics of these variables are presented in Table 1.

[2] We only consider secondary schools and universities given that primary school students who are under the age of 12 are prohibited from using FFBS in Nanjing.

Table 1. Descriptive statistics for variables

Variables	Description	Mean	Std.
Dependent variables			
Morning peak integrated use	Number of FFBS rentals within URT catchment areas at the morning peak (trips/hour)	51	44
Evening peak integrated use	Number of FFBS rentals within URT catchment areas at the evening peak (trips/hour)	46	44
Built environment			
Population density	Total number of residential population divided by total built-up area (thousand persons/km^2)	10.45	10.43
Employment density	Total number of employed people divided by total built-up area (thousand persons/km^2)	7.80	15.66
Land use mix	Mixture entropy of land use patterns, calculated by Equation (1)	0.61	0.22
Length of major roads	Total length of major roads (km)	14.47	10.51
Length of minor roads	Total length of minor roads (km)	11.14	8.18
Street connectivity	Number of street intersections divided by total built-up area (per km^2)	19.75	15.45
Number of feeder bus routes	Number of feeder bus routes to/from the URT station	18.43	10.84
Number of docking stations	Number of docking stations for SBBS	6.10	4.82
Bicycle parking spaces	Area of parking spaces for bicycles (m^2)	473.86	299.07
Control variables			
Transfer station	Whether a URT station is a transfer station (1 for yes, 0 otherwise)	0.08	0.27
Urban areas	Whether a URT station is located in urban areas (1 for yes, 0 otherwise)	0.56	0.50
Distance to CBD	Distance to the central business area (km)	14.82	11.58
Presence of a school	Whether there is a secondary school or a university (1 for yes, 0 otherwise)	0.61	0.49

Notes: (1) Std. = standard deviation; (2) The skewness values for morning peak integrated use and evening peak integrated use are 1.15 and 1.89, respectively; (3) The kurtosis values for morning peak integrated use and evening peak integrated use are 4.00 and 8.89, respectively.

3.3. Quantile regression approach

This study employs a quantile regression approach to explore the factors associated with the integration of FFBS with URT. This approach extends the traditional Ordinary Least Squares (OLS) regression method. The latter focuses on the average relationship between a dependent variable and a set of explanatory variables. Quantile regression has two main advantages over OLS regression: (1) it deals with heteroscedasticity by not assuming the distribution of the residuals; (2) it tends to resist the impact of outlying observations (Koenker and Hallock, 2001 ; Yu et al., 2003). As this study explores the nonlinear relationship between the built environment and FFBS-URT integrated use (i.e., how the integrated use responds to the built environment varies across different usage levels), the quantile regression approach is adopted. In our case, the integrated FFBS-URT ridership data are right-skewed, and therefore the OLS estimates based on the condition mean function do not reflect the actual relationships across the entire distribution. From a policy perspective, planners and system operators may be particularly interested in the higher and lower quantiles. The correlates at these quantiles provide insights on improving the effectiveness of policy interventions. To the best of the authors' knowledge, this is the first study that employs a quantile regression technique to reveal the changing correlates of the integrated FFBS-URT ridership. In the above context, quantile regression models are formulated as:

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau)x_{i1} + \beta_2(\tau)x_{i2} + \cdots + \beta_p(\tau)x_{ip} + \varepsilon_i \quad (2)$$

where $Q_\tau(y_i)$ is the τth quantile of the integrated FFBS-URT ridership; $\beta_0(\tau)$ is a constant; x_{i1} to x_{ip} are explanatory variables related to observation i; and ε_i is the error term with a mean equal to zero. $\beta_1(\tau)$ to $\beta_p(\tau)$ are the coefficients for quantile level τ that are estimated through a linear programming problem:

$$\min_{\beta \epsilon R_p} \sum_{i=1}^{n} \rho_\tau \left(y_i - \beta_0(\tau) - \sum_{j=1}^{p} \beta_j(\tau) x_{ij} \right) \quad (3)$$

where ρ is the check loss function which gives asymmetric weights to the error based on the quantile (Koenker and Hallock, 2001; Yu et al., 2003). The form of ρ is:

$$\rho_\tau(r) = \tau \max(r, 0) + (1 - \tau) \max(-r, 0) \quad (4)$$

Equation (4) returns the maximum value in the parenthesis. If the error r is positive, then the check function multiplies the error by τ; if the error r is negative, then the check function multiplies the error by $(1 - \tau)$. Minimizing Equation (3) reaches minimum median absolute deviation for the quantile regression. The solutions lead to different sets of regression coefficients at different quantile levels. In this study, we estimate a series of models using OLS and quantile regression analyses, which produce coefficients with significance levels for mean, 5th percentile, 10th percentile, 20th percentile, 30th percentile, 40th percentile, 50th percentile, 60th percentile, 70th percentile, 80th percentile, 90th percentile, and 95th percentile of the integrated FFBS-URT ridership. We also cluster the estimates' robust standard errors at the URT station level to account for repeat recorded observations from each station.

This application of quantile regression models also complements the recent stream of the nonlinearity of land use-travel research. Tree-based machine learning algorithms have been commonly used to identify nonlinear and threshold effects of the built environment (e.g., Cheng et al., 20020a; Ding et al., 2018; Wang et al., 2020; Wang and Ozbilen, 2020; Wang and Wang, 2021). These methods can offer detailed information on the effective ranges of variables of interest, thereby supporting specific policy priorities. One of the frequently mentioned limitations is that tree-based machine learning methods are not able to make statistical inferences. Producing significance levels with confidence intervals are the strengths of quantile regression models.

4. Results and discussion

4.1. Spatial and temporal dynamics in the integrated use

Figure 2 shows that the average ridership of integrated use at the morning peak (7:00-9:00) was 11.7 % more than that at the evening peak (16:00-19:00). The integrated ridership during the morning peak period was more temporally aggregated, which is expected because of less time flexibility for the morning commute. The result is also in line with previous studies (e.g., Gu et al., 2019b; Guo and He, 2020). The highest level of integrated use in the morning and evening occurred at around 8:00 and 18:00, respectively. For daily variations, Friday witnessed the largest total amount of integrated use, reaching 61,532 trips. It is presumably due to the fact that on Friday additional travel demands are generated, in particular for out-of-city journeys. On the contrary, Monday had the lowest ridership of integrated use with a quantity of 44,528 trips. Interestingly, the maximum hourly ridership of the morning peak was recorded on Thursday (9,700 trips). Regarding the evening peak, the highest recorded ridership appeared on Wednesday (8,539 trips).

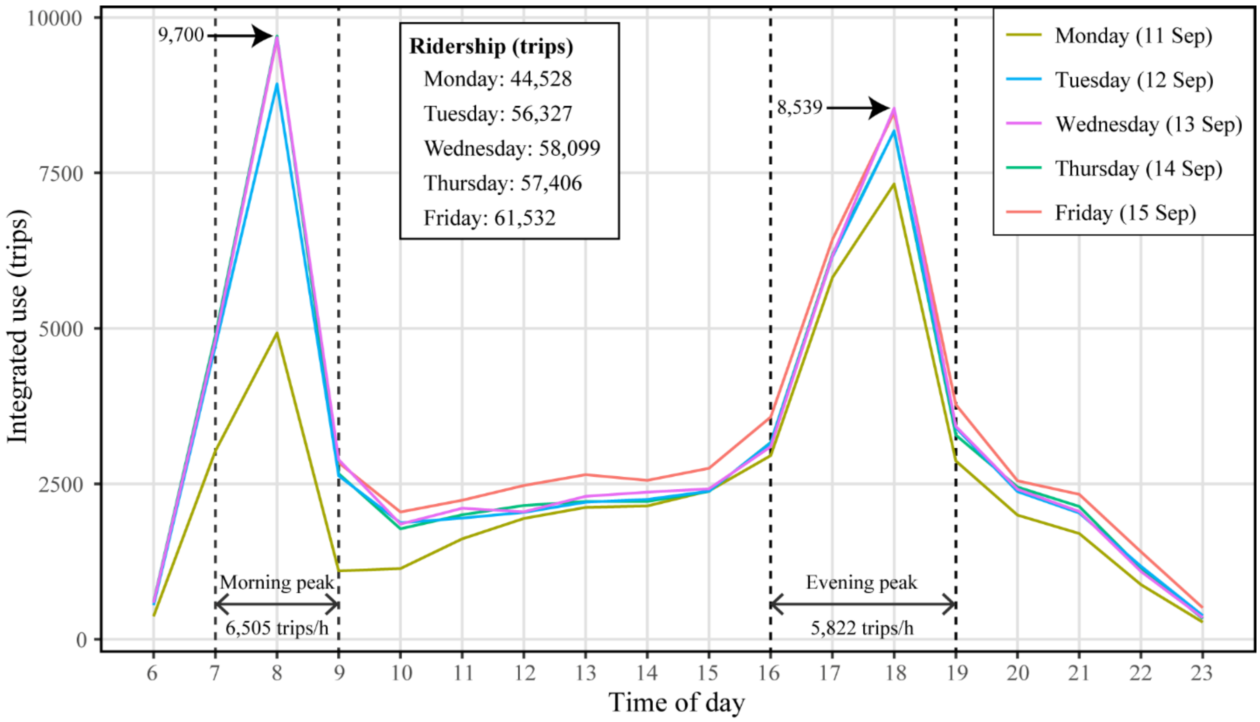
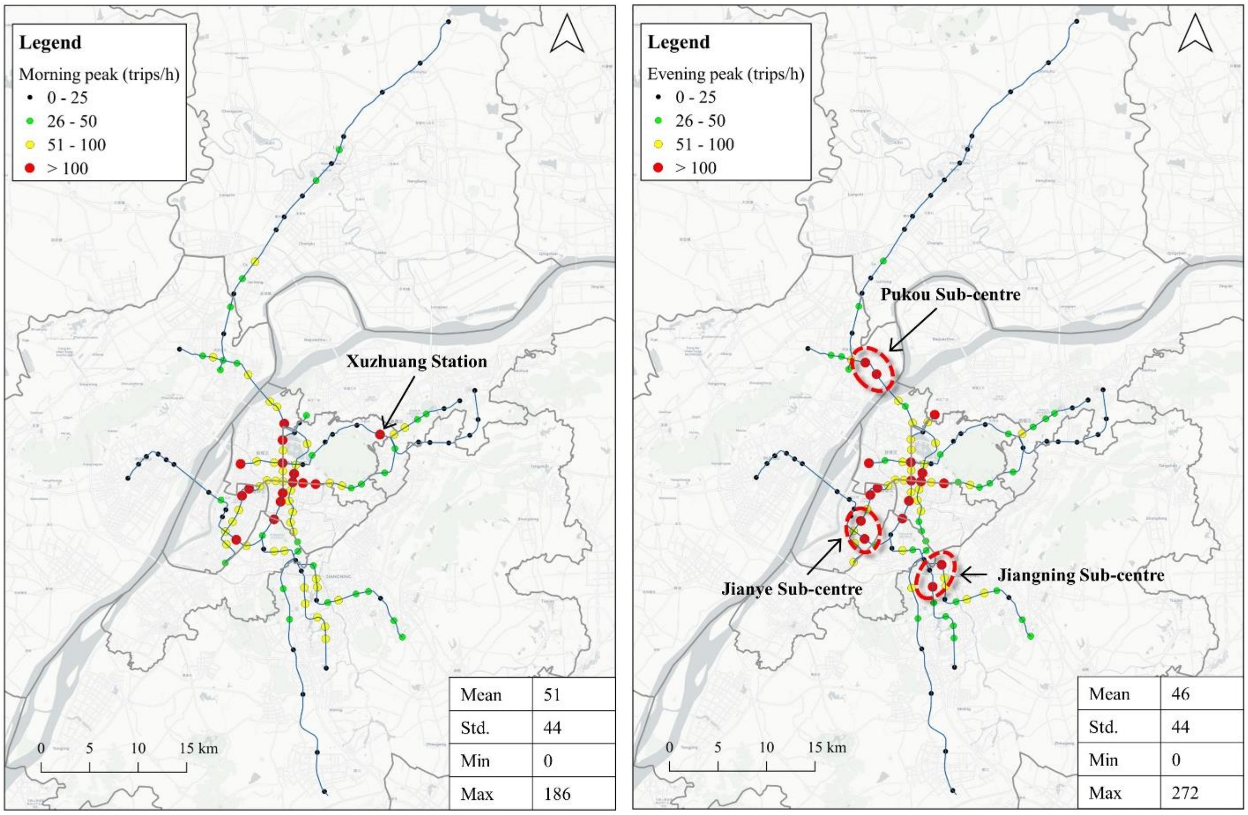


Figure 2. Temporal variations in the integrated use of FFBS with URT



(a) Morning peak integrated use (b) Evening peak integrated use

Figure 3. Spatial distribution of the integrated use (left = morning peak, right = evening peak)

Figure 3 displays spatially aggregated integrated use by rail transport stations during the two peak periods. From the descriptive result, we can see that the average number of bike-and-ride trips at the morning peak is 10.9% larger than the evening peak. It again demonstrates that travel demand in the morning is more intensively concentrated. In general, stations in central areas have a higher level of integrated use while peripheral stations have a minimal quantity of feeder trips. The spatial pattern indicates a spatial mismatch in job-housing distributions in Nanjing. An interesting example is Xuzhuang Station (Figure 3a). The station is surrounded by a large number of companies, thereby becoming a hotspot for morning commuting (132 trips/hour). People would ride shared bikes to arrive at their workplaces after getting off rail transport. However, in the evening this station has much fewer last-mile trips by bike-sharing (46 trips/hour). In addition, there is an increased integrated FFBS-URT ridership at some stations in Pukou, Jianye, and Jiangning sub-centres during the evening peak period. These stations are adjacent to large residential neighbourhoods and as a result, witness more last-mile bike-and-ride trips to homes in the evening.

4.2. Built environment effects on the integrated use

Before building statistical models, we detected the correlation patterns among all explanatory variables listed in Table 1, and found no strong correlations. Figure 4 displays the distribution of the integrated use of FFBS with URT at morning and evening peaks. In order to make a comparison with quantile regressions, OLS regressions for the integrated FFBS-URT ridership were also performed. OLS regressions are estimated based on the sample mean values (morning peak = 51 trips; evening peak = 46 trips). In Table 2, OLS regression reports that only three built environment variables are significant for the morning peak integrated use: population density, street connectivity, and bicycle parking space. Quantile regressions uncover some additional built environment variables that are significantly associated with the morning peak integrated use, such as length of minor roads at the 5th and 20th quantiles and number of docking stations at the 40th, 50th, and 60th quantiles. Similarly, compared to OLS regression results for the evening peak, Table 3 reveals that quantile regressions produce a more nuanced relationship between the integrated use and built environment variables. Although some variables are statistically significant in the OLS regression, their coefficients (i.e. significance levels and magnitudes) vary greatly across different quantiles. For example, population density is a significant predictor of the sample mean (OLS), but the coefficients of quantile regressions are not statistically significant at the 20th and 95th quantiles (Table 3). Moreover, the magnitude of coefficients for population density appears to increase with quantiles. In sum, employing a quantile regression approach not only shows ranges within which built environment variables become significant, but also unveils the varying sizes of their effects on FFBS-URT integrated use. For a better representation of the quantile regression results, built environment variables that are significant for at least four consecutive quantiles are plotted in Figures 5 and 6. The following model interpretation mainly focuses on these significant variables.

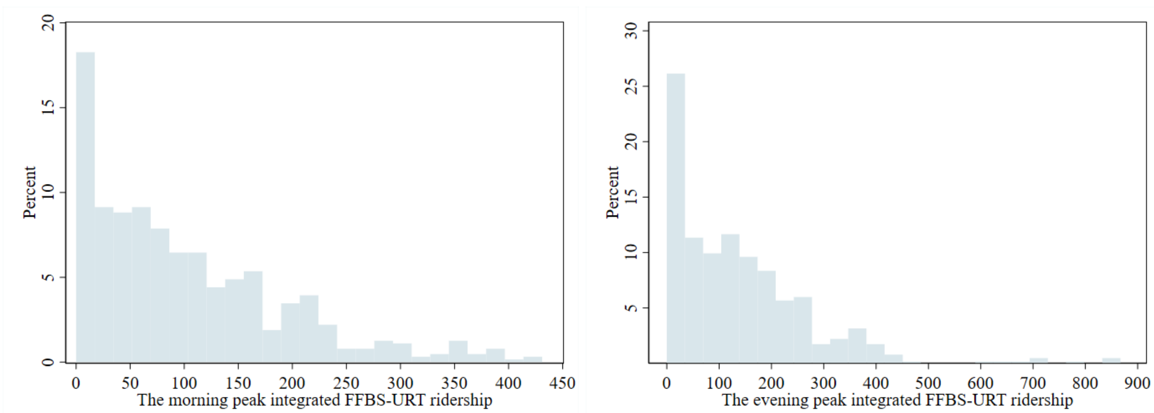


Figure 4. The distribution of the integrated use of FFBS with URT at morning and evening peaks

Table 2. Quantile regression of the morning peak integrated FFBS-URT ridership

Dependent variable: Morning peak integrated use	OLS	10^{th}	20^{th}	40^{th}	50^{th}	60^{th}	80^{th}	90^{th}
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Built environment								
Population density	1.297**	0.734	0.988*	1.320*	1.829*	2.045*	2.149	2.806**
Employment density	0.146	0.160	0.571	0.110	0.019	-0.309	-0.243	-0.779**
Land use mix	-1.818	-2.453	-16.839	6.561	9.148	-4.970	-13.484	2.945
Length of major roads	-0.699	0.249	0.252	0.008	-0.633	-0.222	-1.534	-2.038
Length of minor roads	-0.974	-1.714***	-1.567*	-1.095	-1.225	-0.338	-1.100	-0.110
Street connectivity	1.714***	1.759***	1.766***	1.210	1.553***	1.699**	2.459***	1.991
Number of feeder bus routes	-0.479	-0.009	0.380	-0.522	-0.759	-0.369	-0.261	-0.719
Number of docking stations	3.713	-0.443	-0.575	4.765**	4.847**	3.330**	3.358	3.132
Bicycle parking space	0.081***	0.073***	0.068***	0.057**	0.080***	0.084***	0.087***	0.106***
Control variables								
Transfer station	-11.762	-11.072	-19.728	-20.300	-13.463	-11.389	10.698	30.266
Urban areas	36.086**	29.924***	24.781**	22.779	28.196	22.128	49.345***	73.850
Distance to CBD	-1.451**	0.013	-0.173	-1.147	-1.313	-1.523	-1.312**	-0.955
Presence of a school	-3.350	-0.039	5.953	-8.494	-16.729	-14.611	-7.355	19.489
Date (ref.: 11 Sep)								
12 Sep	44.780***	14.846***	20.985***	33.509***	39.602***	45.550***	42.875***	35.918***
13 Sep	51.339***	16.846***	23.385***	34.227***	42.602***	50.933***	46.875***	40.918***
14 Sep	52.165***	18.507***	24.005***	31.942***	41.904***	48.933***	47.620***	37.918***
15 Sep	51.236***	17.000***	21.903***	33.227***	45.904***	49.078***	44.620***	44.918***
Constant	-12.559	-51.103***	-41.326***	-11.329	-7.923	-4.106	19.761	10.727
Adj. R-squared	0.595	0.539	0.535	0.578	0.582	0.579	0.581	0.542

Notes: (1) This study does not report the estimates for 5%, 30%, 70%, and 95% quantiles due to space constraints; these are available from the authors upon request. (2) * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level; (3) Number of observations = 635.

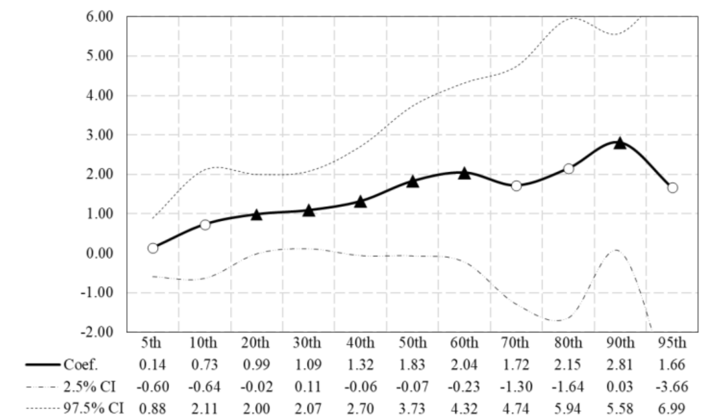
Table 3. Quantile regression of the evening peak integrated FFBS-URT ridership

Dependent variable: Evening peak integrated use	OLS	10^{th}	20^{th}	40^{th}	50^{th}	60^{th}	80^{th}	90^{th}
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Built environment								
Population density	2.667***	0.377	1.184	2.228**	2.407*	2.778*	2.736**	2.639
Employment density	1.101**	1.624***	1.914***	1.421***	1.314**	1.130	0.226	0.036
Land use mix	-80.410	-30.961*	-13.179	26.177	27.079	14.828	-20.713	-123.760
Length of major roads	-1.049	0.115	0.420	-0.084	0.050	0.270	-1.487	-4.127**
Length of minor roads	1.451	-1.994**	-0.829	-0.629	0.530	0.977	1.408	3.200
Street connectivity	-1.364	2.363***	0.372	-0.264	-0.393	-0.288	-0.286	0.624
Number of feeder bus routes	0.525	0.090	0.028	-0.299	0.130	0.340	2.111*	1.255
Number of docking stations	12.519***	-0.343	3.631	8.490***	8.428***	8.432**	9.559**	9.240
Bicycle parking space	0.061	0.104***	0.093***	0.069***	0.071***	0.076***	0.082	0.111
Control variables								
Transfer station	-35.927	-17.429	-66.959	-40.242	-44.089	-49.825	31.425	26.125
Urban areas	-31.650	33.003***	21.849	0.999	1.222	-1.688	-2.159	-15.968
Distance to CBD	-4.089***	-0.714	-1.545	-2.061	-0.732	-0.811	-1.760	-4.802
Presence of a school	4.563	-0.554	4.807	-0.758	12.795	18.187	20.001	-27.099
Date (ref.: 11 Sep)								
12 Sep	10.976***	5.000	0.835	5.243	5.000	5.527	15.581	19.005
13 Sep	13.480***	8.874*	7.000	9.159**	5.922	5.000	14.916*	19.000
14 Sep	11.252***	3.000	1.889	4.127	3.779	2.724	16.581*	21.005
15 Sep	18.701***	9.000*	6.114	12.127**	9.901*	7.512	21.310**	23.000**
Constant	126.957*	-35.911	-9.252	19.154	-11.511	-7.516	42.489	237.469
Adj. R-squared	0.492	0.312	0.392	0.440	0.432	0.433	0.430	0.425

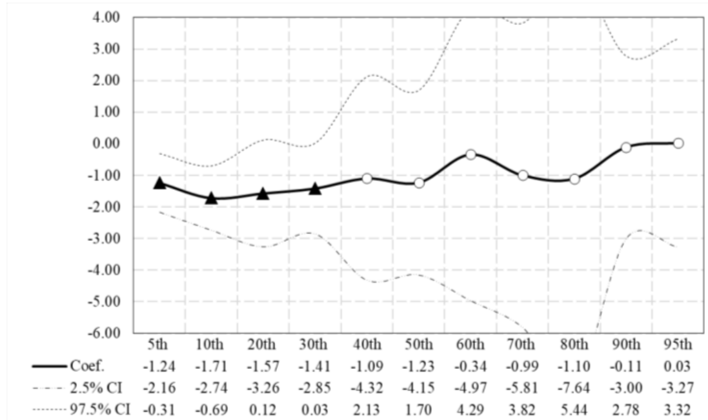
Notes: (1) This study does not report the estimates for 5%, 30%, 70%, and 95% quantiles due to space constraints; these are available from the authors upon request. (2) * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level; (3) Number of observations = 635.

Figure 5 shows the effects of the built environment on the morning peak integrated use across quantiles. As displayed in Figure 5a, population density is statistically insignificant for stations with extremely low or high ridership of integrated use, such as at the 5th, 10th, and 95th quantiles. When bike-and-ride trips range from 20th to 60th quantiles and at the 90th quantile, population density is observed to significantly positively correlate with the integrated use. It indicates that higher population density in these station areas contributes to FFBS integration with URT, which is in line with expectations. Higher population density around URT stations results in higher travel demand and thus is likely to generate more bike-and-ride trips. With respect to the length of minor roads, all the significant coefficients are negative and keep almost stable across low quantiles (Figure 5b). A denser network of minor roads in station areas facilitates driving, and greater vehicle volume brings safety concerns. Besides, Figure 4 presents that low quantile stations are mainly located on urban peripheries, where a higher density of minor roads may attract more park-and-ride travellers, rather than bike-and-ride users. For street connectivity, it plays a positive role in FFBS-URT integrated use at a greater spectrum of quantiles (Figure 5c). Improved street connectivity may provide bicyclists with more direct routes and shorter distances to access/egress URT stations. In this way, it creates a more convenient and efficient bicycling environment, which encourages bike-and-ride use. When looking at the effects of the number of docking stations, the relationship is statistically significant and positive at medium quantiles (Figure 5d). It is an interesting finding that the existence of SBBS in station areas could be beneficial to the FFBS-URT integrated use. This aligns with the work of Cheng et al. (2020b) and Chen et al. (2020) that SBBS and FFBS complement each other to foster a bicycle-friendly environment that makes bicycling become a convenient feeder mode to URT stations. Figure 5e describes that bicycle parking space is significantly associated with the integrated use for all quantiles except at the 95th quantile. Safe and exclusive parking facilities in stations areas encourage travellers to choose shared bikes as a feeder mode, which concurs with earlier empirical findings (Pan et al., 2010). As also indicated by a nationwide study in the Netherlands (Martens, 2007), 11% of railway travellers suggested that the main barrier to travel by bicycle to train stations is limited parking facilities.

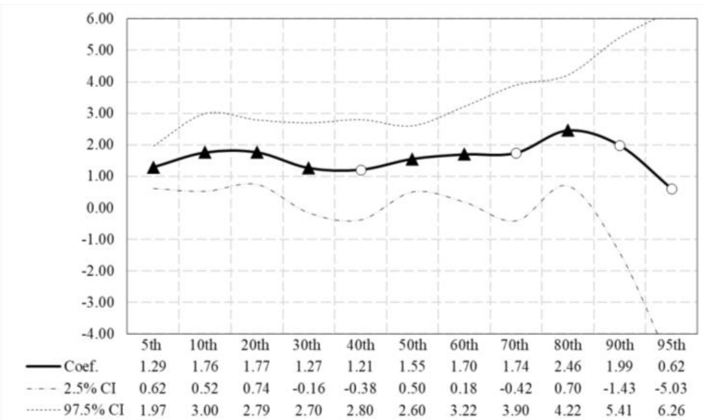
Figure 5 also demonstrates the nonlinear relationship between built environment variables and FFBS-URT integrated use. The significance level and size of built environment effects vary across quantiles. Among the considered variables, population density and bicycle parking space show pronounced nonlinear effects, which is demonstrated by the remarkable inter-quantile changes of significant coefficients. Figure 5a illustrates that population density is more valued at higher quantiles. It is presumably due to the agglomeration effects of density-related attributes. Stations with higher integrated FFBS-URT ridership are supportive to establish a good atmosphere of improved perceived bicycling safety and social norms to promote bike-and-ride. This in turn reinforces the effects of population density: residents around high quantile stations will make more bicycling feeder trips than that could be made at low quantile stations. The other variable exhibiting profound nonlinearity is bicycle parking space. Figure 5e visualises that, on the whole, the response of integrated use to bicycle parking space becomes stronger at higher quantile stations and reaches the peak at the 90th quantile. High quantile stations at the morning peak are concentrated in central urban areas, depicted in Figure 4a, where parking resources are often limited. At these stations, bicycle parking space is a major influencing factor for bike-and-ride, and therefore an increase in parking space would generate substantial benefits.



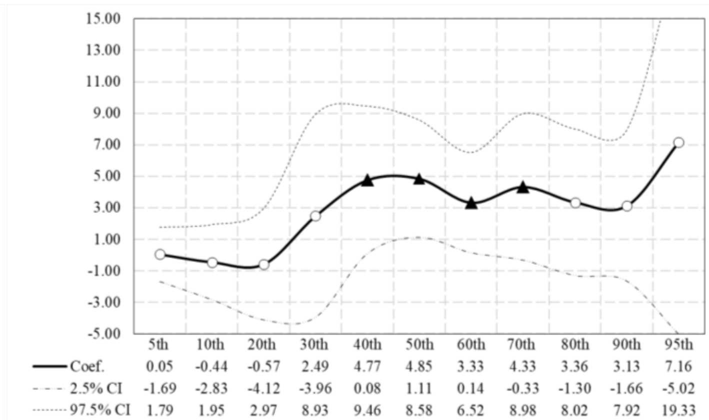
(a) Population density (1,000 person/km^2)



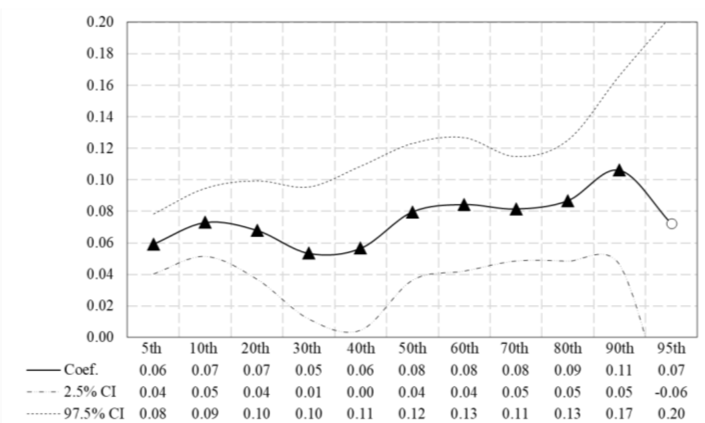
(b) Length of minor roads (km)



(c) Street connectivity (# of intersections/ km^2)

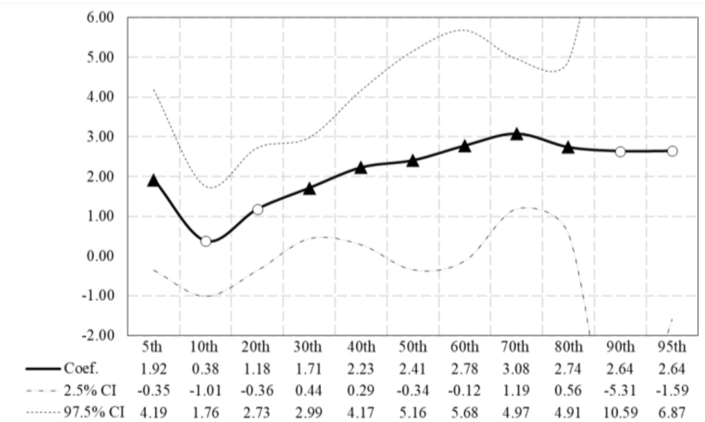


(d) Number of docking stations



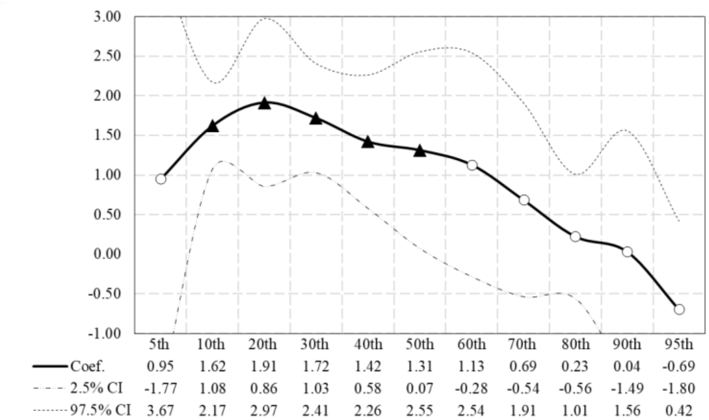
(e) Bicycle parking space (m^2)

Figure 5. Estimates for built environment variables in the morning peak models (▲ = Estimates that are statistically significant for the quantile; ○ = Estimates that are not statistically significant for the quantile)



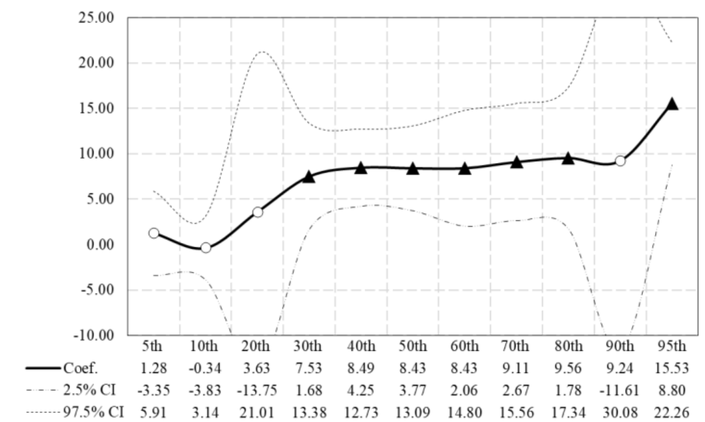
	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Coef.	1.92	0.38	1.18	1.71	2.23	2.41	2.78	3.08	2.74	2.64	2.64
2.5% CI	-0.35	-1.01	-0.36	0.44	0.29	-0.34	-0.12	1.19	0.56	-5.31	-1.59
97.5% CI	4.19	1.76	2.73	2.99	4.17	5.16	5.68	4.97	4.91	10.59	6.87

(a) Population density (1,000 person/km^2)



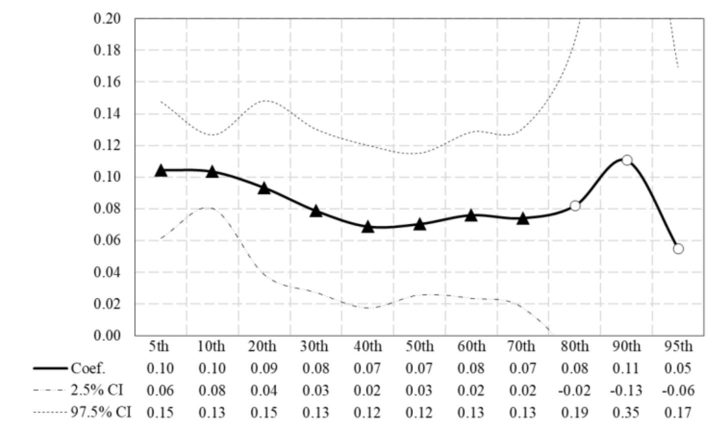
	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Coef.	0.95	1.62	1.91	1.72	1.42	1.31	1.13	0.69	0.23	0.04	-0.69
2.5% CI	-1.77	1.08	0.86	1.03	0.58	0.07	-0.28	-0.54	-0.56	-1.49	-1.80
97.5% CI	3.67	2.17	2.97	2.41	2.26	2.55	2.54	1.91	1.01	1.56	0.42

(b) Employment density (1,000 person/km^2)



	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Coef.	1.28	-0.34	3.63	7.53	8.49	8.43	8.43	9.11	9.56	9.24	15.53
2.5% CI	-3.35	-3.83	-13.75	1.68	4.25	3.77	2.06	2.67	1.78	-11.61	8.80
97.5% CI	5.91	3.14	21.01	13.38	12.73	13.09	14.80	15.56	17.34	30.08	22.26

(c) Number of docking stations



	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Coef.	0.10	0.10	0.09	0.08	0.07	0.07	0.08	0.07	0.08	0.11	0.05
2.5% CI	0.06	0.08	0.04	0.03	0.02	0.03	0.02	0.02	-0.02	-0.13	-0.06
97.5% CI	0.15	0.13	0.15	0.13	0.12	0.12	0.13	0.13	0.19	0.35	0.17

(d) Bicycle parking space (m^2)

Figure 6. Estimates for built environment variables in the evening peak models (▲ = Estimates are statistically significant for the quantile; ○ = Estimates are not statistically significant for the quantile)

Estimates for built environment correlates of the evening peak integrated use are depicted in Figure 6. Similar to the morning peak, population density, number of docking stations for SBBS, and bicycle parking space are positively associated with FFBS-URT integrated use. In addition, consistent with morning peak models, population density shows a noticeable nonlinear relationship. This variable displays an overall increasing trend with quantiles and is the most highly valued at the 70th quantile. A few dissimilarities are also identified. First, employment density is insignificant in the morning peak model but shows a significantly positive relationship with the evening peak integrated use from the 10th to 50th quantiles (Figure 6b). It may probably be accounted by the fact that in the evening, there are a certain number of people who have to work overtime and go back to workplaces after dinner. In China's megacities such as Nanjing, it is common that people work until 10 or even 11 pm, especially in the catering and entertainment sector and dot-com companies (Xiao et al., 2020). Employed people around URT stations generate evening commuting demand to workplaces. Second, the effects of number of docking stations reflect a considerable nonlinear trend of the relationship, notably at the 95th quantile (Figure 6c). This result further evidences that the SSBS complements FFBS for accessing/egressing URT stations, and the complementarity appears to be more prominent for stations with a high ridership of integrated use. Third, compared to the morning peak model, bicycle parking space has different ranges at which it exerts a significant effect. The variable does not significantly work for high quantile stations (i.e. 80th, 90th, and 95th quantiles) at the evening peak, which is shown in Figure 6d. Besides, the relationship between bicycle parking space and integrated use shows a decreasing trend moving towards higher quantile stations. This result contrasts with the morning peak model, where an increasing relationship is unveiled. Low quantile stations are more sensitive to bicycle parking space in the evening. One possible explanation is due to the peripheral locationality of these stations (Figure 4b). Urban peripheries are less-served by public transport, which stimulates bike-and-ride use (Martin and Shaheen, 2014). In the evening, people living around low quantile stations (mainly located on urban peripheries) more value larger bicycle parking spaces, where increases the likelihood of finding shared bikes to ride back homes.

5. Conclusions and policy implications

The high flexibility of free-floating bike-sharing (FFBS) systems makes them an ideal feeder mode to seamlessly integrate with urban public transport. This study uses trips records of FFBS in a China's megacity to investigate the potential use of bike-sharing as a feeder mode to urban rail transport (URT). The applications of quantile regression models produce a more nuanced relationship between the integrated use and built environment variables. As shown in Figures 5-6, population density and internal transport facilities – i.e., bicycle infrastructure including number of docking stations and bicycle parking space – show a strong nonlinear relationship with the integrated FFBS-URT ridership. It is worth noting that bicycle parking space is more valuable in the lower density and urban periphery stations for the evening last-mile commute to home. Perhaps, more bicycle parking space increases the likelihood of finding a shared bike. Overall, FFBS increases in station areas with higher population density, bike parking, availability of docked bikes, and road connectivity. It decreases in station areas with longer road lengths. Morning peak use is higher and more time-concentrated than evening peak use. The usage of travelling from the station to the destination (last-mile) is higher than that of from the origin to the station (first-mile).

The varying effects of the built environment could assist transport planners and bike-sharing operators in designing effective policies and regulations to facilitate FFBS-URT integrated use. Specifically, in urban areas bicycle infrastructure should necessarily be taken into account. An increase in bicycle parking space and number of docking stations can produce considerable benefits for both the morning and evening integrated use, particularly at high quantile stations. The marginal utility of well-equipped bicycle infrastructure is more pronounced than land-use interventions, including improving road density and street connectivity. Densification – increasing population density – in station areas also produces a significant marginal change in the integrated ridership. Nevertheless, densification strategies are often costly, no matter by building new compact residential neighbourhoods or by densifying existing residential areas (Broitman and Koomen, 2015). Therefore, from the perspective of policy effectiveness and cost-efficiency, we advocate that the provision of exclusive and spacious parking spaces is a better way to encourage the integrated use between FFBS and URT. However, in new town planning and construction, densification could be regarded as a feasible bike-and-ride facilitator. Pertaining to other built environment variables, tailored interventions may be proposed according to the range of significant quantiles. On the one hand, the length of minor roads is significantly related to the morning peak integrated use only for low quantile stations. The effects of street connectivity on the morning peak integrated use are not important for high quantile stations. On the other hand, the evening peak integrated use is significantly responsive to employment density only for low and medium quantile stations. Therefore, we conclude that policies and practices to enhance the integration between FFBS and URT should not be implemented homogeneously across the entire rail transport stations. These planning efforts should be differentiated based on the identified nonlinear effects.

The temporal variations in the built environment effects also provide meaningful policy implications. Based on Figure 4, we infer that the jobs-housing spatial mismatch can bring different bike-and-ride usage patterns at morning and evening peaks. The differences are crucial for rebalancing the FFBS fleet. For example, hotspot stations in the morning are mainly in central urban areas while more bikes need to be allocated at stations in sub-centres in the evening. It is found that employment density is insignificant in the morning peak model but shows a significantly positive relationship with the evening integrated use at low quantile stations (mainly located on urban peripheries). Thus, a certain fleet size of shared bikes should be allocated at these stations for accommodating the evening last-mile travel demand. Number of docking stations is only significantly related to medium quantile stations at the morning peak while this significant relationship expands to a wider range of stations at the evening peak. This suggests that the complementarity between FFBS and SBBS is more prevalent in the evening. Their operation and coordinating strategies, such as the synchronised distribution of FFBS and SBBS bikes and shared use of bicycle parking spaces, deserve more attention at the evening peak. Furthermore, the effects of bicycle parking space show differentiated nonlinear patterns: more valued at high quantile stations at the morning peak whereas at the evening peak low quantiles are more benefited. Geo-fenced parking spaces have gained popularity in many cities worldwide to regulate the parking of FFBS (Zhao and Ong, 2021). In order to maximise the benefits of parking spaces, transport operators could design a time-dependent size of the geo-fenced area in station areas in accordance with the varying effects of bicycle parking space.

The contribution of this study could be extended in some avenues for future research. First, the nonlinear relationship between the built environment and FFBS-URT integrated use is obtained based on empirical data collected in Nanjing, China and whether the finding is comparable to other contexts is unclear. Therefore, future work in other cities (also outside China) and regions is needed for a better generalisation of the nonlinearity of built environment effects. Second, this research concludes the findings by analysing cross-sectional data, and the causality is not able to be inferred. A (quasi-)longitudinal study or focus-group research is called for to further investigate the causal effects of the built environment on the integration of bike-sharing with public transport. To better understand the nonlinear effects of the built environment and bicycle infrastructure, future research could also compare the differences in FFBS-URT integrated use between peak and non-peak hours. Due to data limitation, this study considers bikeshare trips happened at rail stations within the 50-metre buffer as transfer trips between FFBS and URT. Although a local survey conducted in Nanjing supports this assumption to a certain extent, the destinations for some transfer trips may be misidentified. The actual destinations of these trips can be shops or restaurants surrounding rail stations. Future studies are needed to verify our assumption by analysing datasets that contain explicit origin-destination (OD) information. Nonetheless, as the first study focusing on the nonlinear relationship between the built environment and FFBS-URT integration, this study produces new insights for transport and land use policies that could promote bike-and-ride and improve the overall connectivity of urban public transport systems.

Declaration of interest

None.

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