Public Bicycle Usage and Access to Rail Transit Stations in Nanjing, China

Journal:	*International Journal of Sustainable Transportation*
Manuscript ID:	Draft
Manuscript Type:	Full Paper
Date Submitted by the Author:	n/a

Complete List of Authors:	Ji, Yanjie; Southeast University, School of Transportation Cao, Xuening; Southeast University, School of Transportation Wang, Wei; Southeast University, School of Transportation Fan, Yingling; University of Minnesota, Hubert H. Humphrey School of Public Affairs Ermagun, Alireza; University of Minnesota, Hubert H. Humphrey School of Public Affairs Das, Kirti; University of Minnesota, Hubert H. Humphrey School of Public Affairs

Keywords:	Public bicycle, Rail transit, Modal integration, Nested logit, China

Public Bicycle Usage and Access to Rail Transit Stations in Nanjing, China

ABSTRACT

A marriage between public bicycles and rail transit presents a particularly interesting opportunity for sustainable transportation in Chinese cities. Promoting the integration of public bicycles and rail transit require a deep understanding of mode choice factors for accessing rail transit. Using data from an intercept survey conducted at fifteen urban rail transit stations in Nanjing, China, this paper examines determinants of public bicycle usage among rail transit users. Both a multinomial logit (ML) model and a nested logit (NL) model are estimated. Results from both models reveal low public bicycle usage among female, older, and low-income rail transit commuters. Rail commuters with bicycle theft experience and making school- or work-related trips are inclined to use public bicycles to access rail transit stations. Policy implications of these results are discussed for Chinese cities to boost public bicycle integration with rail transit.

KEYWORDS: Public bicycle; Rail transit; Modal integration; Nested logit; China.

INTRODUCTION

Bicycling has been widely accepted as a transportation mode that is healthy and environmentally friendly (Dill, 2009). It has also been seen as a flexible transportation mode with good adaptability to narrow and congested urban roads (Buehler and Handy, 2008). With initiatives to increase bicycle usage, bicycle sharing—the shared use of a bicycle fleet—has recently received increased attention across the globe (Demaio and Gifford, 2004). Bicycle sharing allows commuters to use bicycles on an as-needed basis without the costs and responsibilities associated with owning a bicycle (Shaheen et al., 2010). According to the Bike-Sharing World Map, there were approximately 1.1 million shared bicycles in operation across 909 cities worldwide as of June 2015 (Bike-Sharing World Map, 2015). Despite being a late adopter of bicycle sharing (the first information technology-based bicycle sharing program in mainland China was launched on May 1, 2008 in the city of Hangzhou), China now has almost 300 bicycle sharing programs and has surpassed Italy and Spain to become the country with the largest number of programs (Earth Policy Institute, 2015).

Of the many transportation modes, a marriage between public bicycles and rail transit presents a particularly interesting opportunity for sustainable transportation in Chinese cities. First, in conjunction of an unprecedented expansion in bicycle sharing programs, China is in an unprecedented stage of developing urban trail transit systems. Between 2011 and 2015, the number of cities with urban rail transit systems more than doubled from 17 to 38 cities in China (NDRC, 2012). Second, because of high construction and operating costs, urban trail transit network cannot be dense when it comes to the peripheral area of a city (Pan et al., 2010). Given that transferring generally is regarded as stressful and time-consuming, the success of urban rail systems depends on an effective multimodal transfer system to increase service coverage of rail stations and avoid long walking and waiting times. Bike-rail integration offers a unique opportunity to address this issue because bicycling offers a larger catchment area than walking and reducing the needs to use feeder bus services for access and egress. Third, although China was named the Kingdom of Bicycles in the 1970s, over the past decades, bicycle use in China has steadily declined due to economic growth, rapid motorization, longer trip distances, and a gradually detreating cycling environment (Shaheen et al., 2011; Zhang et al., 2014). Integrating rail transit with bicycle sharing programs allows for more flexibility and travel options for bicycle commuters, which may further increase the overall demand for bicycling.

Past literature has identified general measures that can facilitate bicycle and transit integration; however, so far the main focus has been on measures that encourage riding one's own bicycle to (or from) a public transport stop (Krizek & Stonebraker, 2010; Bachand-Marleau et al., 2011; Martens, 2004; Martens, 2007). Integration between public bicycles and transit has not received sufficient attention from transportation researchers. We know little whether and why public bicycle usage among rail transit users differs substantially across demographic groups and locations. Using the city of Nanjing, China as a case study, this study examines the effects of personal and locational factors on the use of public bicycle for assessing urban rail transit stations in China. Data used in the study come from a 2014 intercept survey of 780 urban commuters at locations near 15 rail transit stations in Nanjing, China. Disaggregate mode choice models, including a multinomial logit (MNL) model and a nested logit (NL) model, are estimated to quantify the effects of various personal and location variables on the rail transit user's access mode choice. Results from the two mode choice models are compared and implications of the results are discussed.

LITERATURE REVIEW

When looking at the integration of bicycles with transit, the primary focus of existing research has been on the use of private bicycles and its integration with buses with limited focus on trains or public/shared bicycles (Krizek & Stonebraker, 2010; Bachand-Marleau et al., 2011; Martens, 2004; Martens, 2007). These studies have identified multiple areas for improving integration between private bicycles and transit, including enabling bicycles to be brought on transit vehicles, improving the availability of parking near transit stops, and connecting transit stations to an existing network of bicycle paths and lanes.

Empirical evidence on how to improve integration between public bicycles and rail transit has been limited and fragmentary. Bachand-Marleau et al. (2011) studied cycle-transit integration in Montreal, Canada. Using survey data and factor analysis, they categorized respondents into three groups, including integrators, potential integrators, and non-integrators. Although the study focused on general bicycle users and did not focus on public bicycle users in particular, the study included Bixi riders (a bike share program). Bixi riders with a yearly membership were found to be most likely to integrate cycling with transit. Chen et al. (2012) examined determinants of bicycle transfer demand at metro stations in Nanjing, China by conducting a survey at two metro stations. In their survey, only 4.4 percent of the respondents reported using public bicycles to access/egress rail transit, 40 percent reported being interested but unaware about it, the remaining 55.6% reported a lack of interest in using public bicycles. Respondents reported the convenience of biking, nearby rental locations, and inexpensive costs as top reasons for choosing public bicycles to access/egress rail transit. Respondents reported high deposit fees, complex rental process, and poor bicycle quality as top deterrents to public bicycle usage.

Neither of the two studies above used a disaggregate mode choice model to examine determinants of public bicycle usage among rail transit users. This represents a significant knowledge gap: we do not know the effects of various personal and locational factors on public bicycle usage among rail transit users. Nonetheless, empirical evidence on the determinants of private bicycle usage or bicycle usage in general among rail transit users is summarized below to guide the development of the mode choice models in this study.

Land use patterns near rail transit stations have been found to be important determinants of general bicycle usage among rail transit users. Specifically, bicycle usage in general are more popular when accessing rail transit stations in residential zones than in non-residential zones (Chen et al., 2012; Heinen & Bohte, 2014). European studies found that the use of bicycles for both access and egress decreased with the level of urbanization: bicycle usage was highest in the suburbs, followed by medium-sized cities and towns, and lowest in main cities (Martens, 2004; Wang & Liu, 2013; Martens, 2007). This may be in part due to central cities being more compact with better feeder bus services which makes walking and bus more viable options for access/egress (Krizek & Stonebraker, 2010).

In addition, strong evidence suggests that distance and trip purpose affect the use of bicycles with rail transit. Studies have found that the bicycle-train combination is more popular among trips with work- and education-related purposes than other purposes (Chen et al., 2012; Givoni & Rietveld, 2007; Hagelin, 2005; Martens, 2004). Studies have also found that bicycle usage is optimal for access/egress trips with medium distances (Giovani and Rietveld, 2007; Pan et al., 2010; Keijer & Rietveld, 2000; Martens, 2004). Using a survey of rail transit users in Shanghai, China, Pan et al., (2010) found that bicycles were dominant for distances between 0.8-1.5 km (0.49-0.93 miles) with walking dominating shorter distances and buses dominating longer distances. Keijer & Rietveld (2000) found different optimal distance thresholds that people living 1.5-3.5 km (0.93-2.17 miles) from a rail station used bicycles for access most often. Martens (2004) found that most bicycles access commuters live between 2 and 5 km (1.24 – 3.1 miles) from rail transit stations. In addition, Chen et al. (2012) found that longer distances between bicycle parking and rail transit stations were associated with lower bicycle use.

Evidence on demographic factors of bicycle usage among rail transit users have been inconsistent. Giovani & Rietveld (2007) found age to be a significant factor and young adults tend to use bicycles for access/egress more frequently than old adults. However, Chen et al., (2012) found age, gender and income to be insignificant when estimating bicycle usage among rail transit users. Studies in the U.S. show bicycle usage to be negatively associated with income levels and vehicle ownership, indicating higher usage among people with limited transportation options (Hagelin, 2005; Krizek & Stonebraker, 2010). In contrast, studies in the Netherlands show opposite results that people with high income levels are more likely to use bicycles and rail transit in combination. (Krygsman & Dijst, 2001; Bachand-Marleau et al., 2011).

None of the evidence above on the effects of land use, distance, trip purpose, and demographics on bicycle usage and rail transit is specifically about the use of public bicycles. The lack of studies on public bicycle usage among rail transit users demonstrate the importance of our study. Nonetheless, the evidence above provides guidance for developing mode choice models in this study.

METHODOLOGY

Study Area

The city of Nanjing comprises 11 urban districts, with a total area of 6,597km^2. As one of the wealthiest cities in China, Nanjing's economic development has led to rapid motorization and aggravated transportation problems such as traffic congestion, air pollution, and greenhouse gas emissions. In response to the serious transportation challenges, the city of Nanjing recently initiated bicycle sharing programs targeting locations near rail transit stations in three urban districts (Xianlin, Jiangning, and Hexi as shown in Figure 1) to promote the use of and to draw in new users to the two green modes, i.e., bicycling and rail transit.

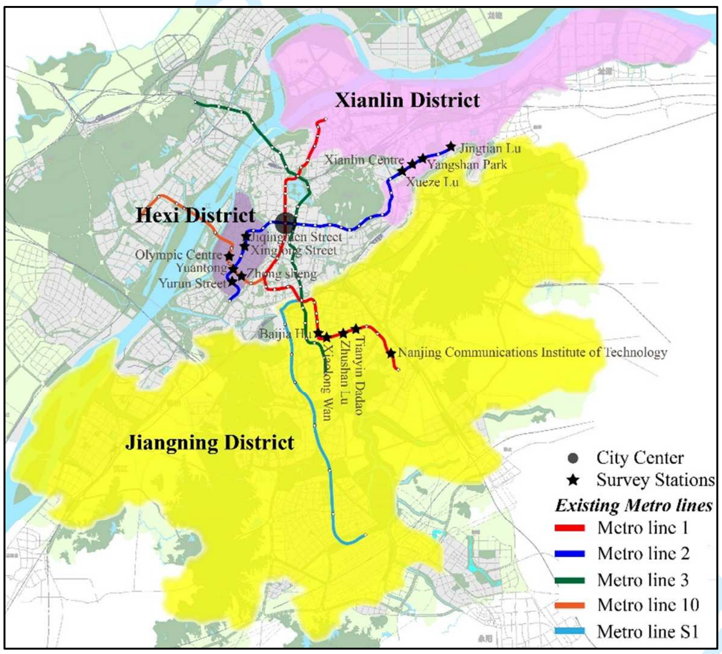

Figure 1. Locations of the City Center, the Survey Stations, the Existing Metro Lines, and the Three Districts with Public Bicycle Programs in Nanjing, China

The Nanjing public bicycle service is classified as a third generation bicycle sharing program, because it uses advanced technologies and management strategies such as smart cards for automated check-in and check-out and radio frequency identification to track bicycle information (Shaheen et al., 2011). Other characteristics of the Nanjing public bicycle system include the use of distinguishable bicycles and docking stations: as shown in Table1, public bicycles and docking stations were painted in different colours in different districts. The implementation of the Nanjing public bicycle system is in its initial stage and needs further improvement. For example, although the smart cards in the Hexi and Jiangning districts can be used interchangeably, the smart cards in the Xianlin district cannot be used in other districts. In addition, most districts in Nanjing do not allow public bicycle smart cards to be used for transit trips. In the future, the municipal government is interested in combining all bicycle sharing programs in the city and allow smart cards to be used interchangeably between public bicycles and public transit.

Table 1. Characteristics of the three district-based bicycle sharing programs in Nanjing, China

The Xianlin District	The Jiangning District	The Hexi District
		
Launched in Sep 2010	Launched in Sep 2010	Launched in Dec 2012
60 docking stations	181 docking stations	250 docking stations
1,140 bikes	2,000 bikes	10,500 bikes
230 daily trips	2,500 daily trips	60,000 daily trips
$ 35 deposit	$ 35 deposit	$40 deposit

Hourly Costs: Free for the first 2 hours;
$0.16 per hour for the third hour; $0.48 per hour after the third hour.

Table 1 briefly presents the operating conditions of the three district-based bicycle sharing programs in Nanjing, China. As of December 2014, there were a total of 491 docking stations with about 14,000 bicycles in the three urban districts in Nanjing, China. The average total daily usage of the three bicycle sharing programs are about 63,000 trips per day, with over 95% of the trips made in the Hexi district. It is clear that the average daily usage of public bicycles in Hexi is significantly higher than in Jiangning and Xianlin. In addition, the Hexi program requires a slightly larger initial deposit of $40 (250 yuan RMB) for bicycle use, compared to $35 (220 yuan RMB) in Jiangning and Xianlin. The variation in deposit values corresponds to the newer bikes in Hexi than Jiangning and Xianlin. The hourly costs of bicycle usage are the same across programs. The first two hours of use is free, followed by incremental pricing in which users pay an additional $0.16 (1 yuan RMB) per hour for the third hour, and $0.48 (3 yuan RMB) per hour after the third hour.

Survey and Data Collection

This study aims to understand the mode choice behavior of rail transit users when it comes to accessing rail transit stations, especially understanding factors that prompt commuters to use or not to use public bicycles. Given that the focus of the study population are rail transit users, researchers designed and conducted an intercept survey at locations near 15 rail transit stations (survey stations were shown in Figure 1) in the three districts with public bicycle programs in Nanjing.

The survey was conducted on weekdays in October, 2014. Five interviewers were deployed during morning and evening peak hours to randomly intercept passengers at the rail transit station waiting rooms and public bicycle rental stations. Quota sampling was used to ensure that the sample includes equal proportion of age and gender groups. The revealed preference survey technique was used to collect the mode choice information as well as other personal variables. The following data were collected from each respondent:

- The transportation mode used by the respondent to access the rail transit station, categorized into five options including walk, bus, car, private bicycle, and public bicycle.
- The respondent's socio-demographic background, including age, gender, occupation, household income, and the respondent's bicycle theft experience.
- Characteristics of the trip being made by the respondent, including trip purpose, the cost of bus fare if bus was used for accessing rail transit, travel time from the trip origin to the rail transit station, and travel time from the rail transit station to the trip destination.

A total of 780 rail commuters responded to the survey. After removing the incomplete surveys and respondents who used modes other than the five listed access modes, the final sample used in the study included 709 respondents. Table 2 presents the descriptive statistics of the variables used in the study. As show in Table 2, in addition to the personal variables that describing socio-demographics of the respondent and characteristics of the trip made by the respondent, we included variables describing station attributes and surrounding land uses in our study. The station-level variables include passenger volume at the station, whether the station connects multiple rail transit lines, the amount of parking and feeder bus services at the station, and land use characteristics within 3km of the station (Ding, 2010).

Table 2. Descriptive statistics of variables

Variable	Description	Mean	Std.Dev.	Min.	Max.
Mode choice to access the rail transit station					
WALK	Dummy variable: 1 if access mode is walk	0.44	0.50	0	1
BUS	Dummy variable: 1 if access mode is bus	0.29	0.45	0	1
CAR	Dummy variable: 1 if access mode is car	0.09	0.28	0	1
PRBIKE	Dummy variable: 1 if access mode is private bike	0.09	0.29	0	1
PUBIKE	Dummy variable: 1 if access mode is public bike	0.09	0.29	0	1
Characteristics of the transit station and surrounding land use					
RESI	# of residential communities within 3 km	10.14	1.17	9	12
EDU	# of educational institutions within 3 km	16.29	2.76	12	20
MEDI	# of medical Institutions within 3 km	7.71	1.73	4	10
COM	# of commercial centers within 3 km	5.50	1.35	4	8
FEEDER	# of feeder bus lines stopping at the station	6.71	2.13	4	10
PARK	# of parking lots at the station	3.29	1.59	1	6
TRANSFER	Dummy variable: 1 if two or more rail lines passing at the station	0.71	0.27	0	1
PASSENGER	Passenger volume at the station	545.64	295.41	293	1186
Socio-demographic variables					
FEMALE	Dummy variable: 1 if the respondent is female	0.52	0.50	0	1
STUDENT	Dummy variable: 1 if occupation is student	0.18	0.39	0	1
OFFICER	Dummy variable: 1 if occupation is officer	0.67	0.47	0	1
OTHER	Dummy variable: 1 if occupation is other	0.15	0.36	0	1
AGE	Age of the respondent	30.27	10.34	15	60
INCOME	Monthly income (US dollars)	634.20	414.94	161	1612
BIKE THEFT	# of bicycles being stolen	0.75	0.93	0	5
Trip characteristics					
SCHOOLWORK	Dummy variable: 1 if trip purpose is school or work	0.60	0.49	0	1
BUSINESS	Dummy variable: 1 if trip purpose is business-related	0.16	0.37	0	1
ENTERTAIN	Dummy variable: 1 if trip purpose is entertainment	0.11	0.31	0	1
FAMILYFRIEND	Dummy variable: 1 if trip purpose is visiting family or friend	0.06	0.23	0	1
RETURN	Dummy variable: 1 if trip purpose is return home	0.04	0.19	0	1
OTHERPUR	Dummy variable: 1 if trip purpose is other	0.03	0.18	0	1
ACCESSTIME	Travel time from the trip origin to the rail transit station (minutes)	12.29	8.81	1	60
EGRESSTIME	Travel time from the rail transit station to the trip destination (minutes)	10.65	7.13	1	50
BUS FARE	Bus fare in case of bus usage during the trip (yuan RMB)	1.46	0.58	0	4

Multinomial and Nested Logit Models

Given the ease of computation, closed-form formulation, and consistency with random utility maximization, multinomial logit (MNL) models have been widely employed in discrete choice analysis (Greene, 2008). The ease of computation, however, comes at a price of the restrictive independence of irrelevant alternatives (IIA) assumption (Train, 2009). In discrete choice theory, the IIA assumption says that when people are asked to choose among a set of alternatives, their odds of choosing A over B should not depend on the presence or absence of the other alternatives in the choice set (Train, 2009). Following the IIA assumption and in the case of travel mode choice, if the car mode is unavailable for some reason, the odds of the commuter choosing bus over walking should not be affected. Such assumption is unrealistic because the commuters who prefer car are more likely to choose other motorized modes (such as bus) over walking when car is unavailable.

The nested logit (NL) model, an extension of MNL, was introduced by Ben-Akiva and Lerman (1985) to capture interdependence among alternatives to some extent. NL relaxes the restrictive IIA assumption from alternatives to nests (e.g., bus and car could form a nest so that IIA is maintained within this nest but not with alternatives outside this nest). This allows variance of errors to differ across the nests, and yet the choice probabilities still have a closed-form formula and relatively straightforward estimation (Greene, 2008).

A three level NL model was developed in this study to explain choice of access mode to rail transit stations among walk, bus, car, private bike, and public bike. As shown in Figure 2 below, the choice set is structured in a way that the highest level represents choice of travel pattern—namely, active or non-active travel. At the second level, the nest of active travel divides into walk and bike branches, and the bike branch further divides into public and private alternatives at the lowest level. The nest of non-active travel, however, without breaking at the second level, accommodates car and bus alternatives at the lowest level.

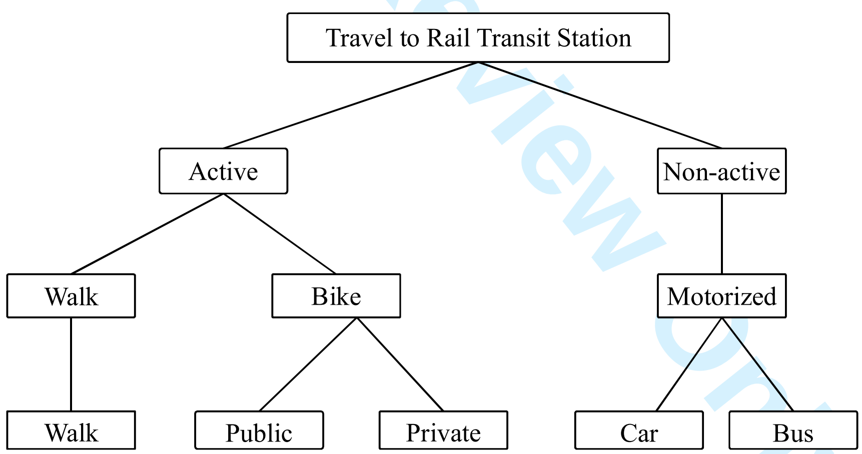

Figure 2. Tree Structure of the Three-level NL Model

Following the three-level tree structure above, the probability of choosing mode alternative i is as follows:

$$P_i = P_m * P_{n|m} * P_{i|n} = \frac{\exp(\frac{1}{\lambda_m}\tau_m)}{\sum_{m' \in M} \exp(\frac{1}{\lambda_{m'}}\tau_{m'})} \times \frac{\exp(\frac{\lambda_m}{\lambda_n}\tau_n)}{\sum_{n' \in N} \exp(\frac{\lambda_m}{\lambda_{n'}}\tau_{n'})} \times \frac{\exp(\lambda_n V_i)}{\sum_{i' \in n} \exp(\lambda_n V_{i'})}$$

Where, P_m is the probability of choosing from the highest level of nest alternatives (i.e., active vs. non-active); $P_{n|m}$ is the conditional probability of choosing a second-level branch of n given the upper nest of m (e.g., the conditional probability of choosing walk, given the upper nest of active travel); $P_{i|n}$ is the conditional probability of choosing an mode alterative of i given the second-level branch of n; λ is the inverse logsum parameter, also known as the coefficient of inclusive value (IV). Further, τ_n and τ_m are, respectively, given by $\tau_n = \ln(\sum_{i' \in N_j} \exp(\lambda_n v_{i'}))$ and $\tau_m = \ln(\sum_{n' \in N_m} \exp(\frac{\lambda_m}{\lambda_{n'}} \tau_{n'}))$.

For consistency with random utility maximization, λ in a well-calibrated NL model must lie between 0 and 1, and the λ value of the lower level must be smaller than that of the upper level. If λ is equal to 1, there is no correlation within nests and the NL model collapses to a MNL model. Hence, the value of λ can serve as a check to the NL model and the validity of the tree structure. Wald tests are often applied to test whether λ is significantly different from 1 (Hensher et al., 2005). Additional details of the logit models employed in this study can be found in textbooks introducing discrete choice analysis, such as Ben-Akiva and Lerman (1985).

RESULTS

The LIMDEP 10 package with the NLOGIT 5 module was used for model calibration and estimation. Table 3 presents results from the calibrated MNL and NL models. To make MNL and NL results comparable, we first finalized the NL model, and for each choice alternative, we applied the NL model's influential factors in the MNL model. Factors in NL models are often considered as influential with a p-value lower than 0.2 (Laura and Frank, 2011).

The finalization of the NL model is largely depended upon the estimated inclusive value parameters (the λ values). Following the tree structure in Figure 2, the second-level walk branch has only one alternative in its lower level, and thus, the λ parameter is fixed to one. The remaining λ parameters are estimated in the calibration process. As shown in Table 3, the λ parameters of theactive and non-active nests in the final model are respectively 0.82 and 0.87, and both are statistically positive and less than one, according to Wald tests. This suggests that the MNL model has misspecification issues, and results from the NL model are more reliable for discussion of policy implications.

As shown in Table 3, most of the variables included in the MNL and NL model are significant at above the 90 percent confidence interval. In the following text, we first discuss the empirical findings from the NL model. We then compare MNL and NL results to illustrate the importance of using the NL results for discussion of policy implications.

Table 3. Results of the calibrated MNL and NL Models

Variables	Alternatives	Multinomial logit (MNL)		Nested logit (NL)	
		Coefficient	t-statistic	Coefficient	t-statistic
RESI	Walk	0.191**	1.99	0.208**	2.12
OFFICER		0.785***	3.45	0.761***	2.98
ACCESSTIME		-0.208***	-7.53	-0.207***	-6.95
RETURN		2.461***	3.21	2.672	1.50
Constant	Bus	-3.885***	-3.53	-4.745**	-2.13
ACCESSTIME		0.129***	4.30	0.173*	1.78
FARE		4.493***	10.48	5.558**	2.54
Constant	Car	-2.139**	-2.05	-2.900	-1.53
INCOME		0.0003***	6.50	0.0004***	2.59
EGRESSTIME		-0.059***	-2.61	-0.060**	-1.99
ACCESSTIME		0.066**	2.50	0.111	1.40
VOLUME		-0.001**	-2.41	-0.001*	-1.86
FARE		1.190**	2.39	2.012	1.94
Constant	Private Bike	-0.914	-0.87	-0.742	-0.52
FEMALE		0.594**	2.09	0.654*	1.77
EGRESSTIME		-0.035	-1.60	-0.047	-1.43
Constant	Public Bike	-3.006***	-2.59	-3.175**	-1.98
INCOME		0.0002***	4.36	0.0003***	3.87
SCHOOLWORK		0.651**	1.97	0.680*	1.66
BIKE THEFT		1.178***	7.65	1.390***	5.74
AGE		-0.030*	-1.67	-0.034	-1.43
Inclusive value parameters:					
Active				0.823***	4.26
Non Active				0.872***	6.70
Walk				1.0(fixed)	-
Bike				0.742	6.44
Motorized				0.872***	6.70
McFadden Pseudo R-squared		0.45		0.50	
Sample size		709		709	

Note: *p<0.10; **p<0.05, ***p<0.01.

Empirical Findings on Influential Factors

Table 3 shows that influential factors differ by choice alternatives. For example, the amount of residential communities near the rail transit station is a significant factor predicting the walk mode, but not the other modes. The results show that the walk mode is more likely to be used to access rail transit stations in situations of return home trips, by commuters with a officer occupation, when assessing rail transit stations with residential communities nearby, and when the travel time from the trip origin to the rail transit station is short. Urban commuters are more likely to use bus to access rail transit stations when the trip segment from the trip origin to the rail transit station is long and involves bus fares. Commuters are more likely to use car to access rail transit stations when commuters have higher income, the rail transit station has lower passenger volume, when the trip segment from the trip origin to the rail transit station is long and involves bus fares, and when yet the trip segment from the rail transit station to the trip destination is short.

Results on private and public bicycle usages reveal interesting behavior patterns when it comes to using bicycles to access rail transit stations. Female commuters tend to use private bicycles instead of public bicycles for rail access. Similar to the car mode, private bike has a negative association with the length of the egress trip segment, indicating that people tend to use private modes (e.g., private bike, private car) in rail transit trips with short egress segments (i.e., short length between the exit rail transit station and the trip destination). The use of public bicycles is directly and positively associated with income levels, which is reasonable because the use of public bicycles still requires a relatively sizable deposit for low-income commuters. Younger commuters tend to use public bicycles more often than older commuters, which is also reasonable because public bicycle use in Nanjing requires familiarity with information technology such as smart cards and touch screen kiosks. In addition, public bicycles are more likely to be used in rail transit trips that are school- or work-related. And not surprisingly, the more bicycle theft experience people have, the more likely they use public bicycles to access rail transit stations.

Elasticity Analysis Comparing MNL and NL Models

To make the impact of influential factors more understandable, we calculated the elasticities of continuous variables. The elasticity values, listed in Table 4, include both direct and cross elasticities. Direct elasticities (shown in bold font in Table 4) show the percentage changes in the probability of choosing a travel mode alternative driven by a one-percent increase in an attribute of that same alternative. For instance, as per Table 4, a direct elasticity of **-**1.88 for the *ACCESSTIME* variable implies that the willingness to walk of people who previously chose the walk mode to access rail transit station diminishes by 1.88 percent for every percent increase in the travel time from the trip origin to the rail transit station. Cross elasticities show the percentage changes of choosing a travel mode alternative driven by a one-percent increase in the attribute of a competing alternative. For instance, an cross elasticity of 0.67 for the *ACCESSTIME* variable implies that the willingness to use private bike of people who previously chose the walk mode to access rail transit station increases by 0.67 percent for every percent increase in the travel time from the trip origin to the rail transit station.

As shown in Table 4, limited by the IIA assumption, MNL does not allow cross elastictics to vary. NL allows cross elastitics to vary across nests but not within nests. In addition, NL and MNL elasticities have the same sign but different magnitudes. In most cases, MNL underestimate the effects. In some extreme cases, for example, when estmimating the effect of travel cost on mode choice, the NL esimation is about 70% higher than the MNL estimation (a elasticity of 0.88 compared to 0.52 when it comes to the effect of BUSFARE on the CAR alternative as shown in Table 4). Such differences are consequences of model misspecifications, which may lead to distorted policy implications.

Table 4 Direct and cross elasticities of continuous factors in MNL and NL models

Attribute	Alter-native	MNL					NL				
		WALK	PRBIKE	PUBIKE	BUS	CAR	WALK	PRBIKE	PUBIKE	BUS	CAR
ACCESSTIME	WALK	**-1.88**	0.67	0.67	0.67	0.67	**-1.80**	0.73	0.73	0.55	0.55
	BUS	-0.75	-0.75	-0.75	**0.82**	-0.75	-0.77	-0.77	-0.77	**1.04**	-1.08
	CAR	-0.07	-0.07	-0.07	-0.07	**0.74**	-0.10	-0.10	-0.10	-0.22	**1.14**
EGRESSTIME	PRBIKE	0.03	**-0.34**	0.03	0.03	0.03	0.04	**-0.39**	0.11	0.02	0.02
	CAR	0.04	0.04	0.03	0.04	**-0.58**	0.03	0.03	0.03	0.11	**-0.53**
RESI	WALK	**1.10**	-0.87	-0.87	-0.87	-0.87	**1.13**	-1.00	-1.00	-0.78	-0.78
BUSFARE	BUS	-1.89	-1.89	-1.89	**0.13**	-1.89	-1.79	-1.79	-1.79	**0.13**	-2.37
	CAR	-0.01	-0.01	-0.01	-0.01	**0.52**	-0.01	-0.01	-0.01	-0.02	**0.88**
INCOME	PUBIKE	-0.13	-0.13	**0.96**	-0.13	-0.13	-0.13	-0.29	**1.00**	-0.09	-0.09
	CAR	-0.18	-0.18	-0.18	-0.18	**1.26**	-0.15	-0.15	-0.15	-0.39	**1.21**
VOLUME	CAR	0.05	0.05	0.05	0.05	**-0.72**	0.05	0.05	0.05	0.16	**-0.74**
AGE	PUBIKE	0.08	0.08	**-0.82**	0.08	0.08	0.08	0.18	**-0.86**	0.06	0.06
BIKE THEFT	PUBIKE	-0.21	-0.21	**0.65**	-0.21	-0.21	-0.20	-0.38	**0.65**	-0.15	-0.15

Note: Bold font indicates direct elasticities. Regular font indicates cross elasticities.

The notion of elasticity could not be applied to dummy variables, such as *FEMALE* and *OFFICER*, since one percent change in a dummy variable is meaningless. To illustrate the effects of a dummy variable, we calculate pseudo-elasticities in two steps. First, we set all the continuous variables at their average values and set all the dummy variables except the dummy variable of interest at their statistical mode values for a hypothetical person. Then, we calculate the amount of change in the probability of the decision variable when the magnitude of the dummy variable of interest is changed from 0 to 1. The pseudo-elasticities of dummy variables are presented in Table 5, which should be interpreted differently from the elasticities in Table 4. For example, the magnitude of -6.72 for FEMALE variable in Table 5 means that the probability of choosing the walk mode for females who previously chose private bikes is lower than males who previously chose private bikes by 6.72 percent. Similar to Table 4, NL and MNL pseudo-elasticities have the same sign but different magnitudes. The NL estimates are more accurate estimates than MNL estimates.

Table 5 Direct and cross pseudo-elasticities of dummy factors in MNL and NL models

Attribute	Alter-native	MNL					NL				
		WALK	PRBIKE	PUBIKE	BUS	CAR	WALK	PRBIKE	PUBIKE	BUS	CAR
FEMALE	PRBIKE	-6.72	**61.86**	-6.72	-6.72	-6.72	-5.82	**55.45**	-13.52	-4.39	-4.39
OFFICER	WALK	**68.61**	-20.47	-20.47	-20.47	-20.47	**61.18**	-22.13	-22.13	-16.87	-16.87
RETURN	WALK	**128.36**	-81.23	-81.23	-81.23	-81.23	**130.23**	-84.85	-84.85	-77.65	-77.65
STUDENT	PUBIKE	-4.07	-4.07	**73.45**	-4.07	-4.07	-3.28	-7.59	**68.71**	-2.47	-2.47

Note: Bold font indicates direct pseudo-elasticities. Regular font indicates cross pseudo-elasticities.

CONCLUSIONS AND DISCUSSION

This study examines factors influencing commuters' mode choice when it comes to accessing rail transit stations. By separating the public bicycle mode from the private bicycle mode, the study discovers unique factors that either encourage or discourage public bicycle integration with rail transit. The findings have important policy implications, especially in the context of Chinese cities where government agencies are heavily invested in rail transit and public bicycle infrastructure.

Specifically, the study reveals important demographic differences when it comes to private vs. public bicycle use for accessing rail transit stations. Female commuters are more likely to use private bicycles for rail transit access, while younger commuters and commuters with higher income are more likely to use public cycles. These demographic differences call for improvements to draw in lower-income, female, and older users to bicycle sharing programs. For example, female's preference toward private bicycles may be due to the inconvenience of public bicycles for women who travel with children: all the public bicycles in Nanjing are inexpensive, one-speed bicycles without any back seating. Further, women may have additional safety concerns when it comes to walking to the bicycle docking stations and/or additional comfort-related concerns because all the public bicycles in Nanjing use solid rubber tires with which any bumps or irregularities in the road may cause discomfort (People.cn, 2014). Making public bicycles friendlier to women who travel with children, installing safety measures at the bicycle docking stations, and making bicycle-riding experiences more comfortable may help to reduce the gender gap in public bicycle use. In addition, Chinese cities may consider reducing the amount of required deposit for low income users to use public bicycles. As of 2014, about 18% of the population lived on less than $2 a day in China (World Bank, 2015). A required deposit of $35 - $40 could make public bicycles not affordable to one fifth of the population in China. Finally, the limited use of public bicycles among elderly commuters is somewhat expected because the Nanjing bicycle sharing system is a third-generation, information technology-based system that may not be usable by elderly commuters who tend to have fear of high-tech. Social marketing campaigns and public education efforts that target the elderly might help them to overcome the fear and learn the technology to use public bicycles.

Levels of public bicycle use also differ by trip purpose and commuters are more likely to use public bicycles as the access mode to complete school- and work-related rail transit trips. This finding points to the importance to ensure sufficient public bicycles in morning-peak hours at docking stations that near residence communities so that people have the opportunities to use public bicycles as the access mode to complete their morning school or work commute trips. People, however, are more likely to walk to rail transit stations for their return-home trips, which is reasonable because return-home trips tend to have less strict time constraints compared to trips to other destinations. This finding further indicates that public bicycles are less important in afternoon-peak commutes, which is consistent with researchers' field observations, feedback from public bicycle users in Nanjing, China, and observations in other cities (Zhang et al., 2014). Nanjing residents have repeatedly complained about the lack of public bicycles at bicycle stations near residential communities and the lack of docking spaces for returning bicycles near metro stations during morning peak hours (China Bicycle Association, 2014). These issues are further illustrated in the three photos in Figure 3. These issues indicate poor management and ineffective redistribution mechanisms of Nanjing bicycle sharing programs. Local government agencies may address these issues by real-time information tracking of public bicycle usage to improve redistribution strategies to ensure all bicycle docking stations meet proper demand.

		
No bicycles available during morning commute time at a bicycle station near residential communities in the Hexi district.	No docking spaces available during morning commute time at a bicyle station near a metro station in the Hexi district.	Motorcycles occupying docking spaces at a bicyle station near a metro station which detoriates the shortage of docking spaces.

Figure 3. Photos taken by researchers illustrating the lack of bicycles issue vs. the lack of docking spaces issue

There is also strong evidence that commuters with bicycle theft experiences are more inclined to choose public bicycles for accessing rail transit stations. To promote public bicycle usage, cities in China may highlight the costs and responsibilities associated with owning a bicycle, including the financial loss associated with bicycle thefts. Land use characteristics around the rail transit station appear to have limited effects on the access mode choice. The limited effects of land use variables might be due to data imperfection. Due to the lack of land use data, land use measures in this study were generated by counting the number of major residential communities, educational institutions, commercial centers, and medical institutions within a large 3-km distance of the rail transit stations. The measures cannot fully capture land use variations, and as a result, all land use measures in the study have very low standard deviations. Future research may collect high-quality land use data and analyze the connection between land use and the access mode choice of rail commuters more closely.

Last but not the least, a comparison between MNL and NL results indicates clear differences between MNL and NL estimations. For any complex choice set that involves multiple levels of classification (e.g., active vs. non-active travel and public vs. private modes), NL models produce more accurate estimates for identifying factors of policy significance than MNL models. Overall, this study offer insights into factors that encourage or discourage combinations of public bicycles and rail transit, which help to increase public bicycle usage and rail transit ridership in Nanjing and other Chinese cities.

ACKNOWLEDGEMENT

This research is supported by the National Natural Science Foundation of China (Grant No.51338003), the NSFC-RCUK_EPSRC Program (Grant No.5151101143), and the National Key Basic Research Program of China (Grant No. 2012CB725402).

REFERENCES

Bachand-Marleau, J., Larsen, J., & El-Geneidy, A. (2011). Much-Anticipated Marriage of Cycling and Transit: How Will It Work?. Transportation Research Record: Journal of the Transportation Research Board, (2247), 109-117.

Ben-Akiva, M., & Lerman, R. S. (1985) *Discrete Analysis: Theory and Application to Travel Demand*, Cambridge, MA: The MIT Press.

Bike-Sharing World Map, *bikesharingmap.com,* Accessed June 30 ,2015.

Buehler, T., & Handy, S. (2008). Fifty years of bicycle policy in davis, California. *Transportation Research Record: Journal of the Transportation Research Board*, (2074), 52-57.

Chen, L., Pel, A., Chen, X., Sparing, D., & Hansen, I. (2012). Determinants of Bicycle Transfer Demand at Metro Stations: Analysis of Stations in Nanjing, China. *Transportation Research Record: Journal of the Transportation Research Board*, (2276), 131-137.

China Bicycle Association (2014). available at http://china-bicycle.com/News/View/57658aa5-dc01-414e-bb96-8d6e18c9c60d. access on 7/25/2015.

Dill, J. (2009). Bicycling for transportation and health: the role of infrastructure. *Journal of Public Health Policy*, 30(2),95-110.

Ding, D. (2010). Study on the problems about Bike transfer rail transit mode. *Thesis for the master degree of Chang'an University*.

DeMaio, P., &Gifford, J.,(2004). Will smart bikes succeed as public transportation in the United States?. *Journal of Public Transportation*,7(2),1-15.

Earth Policy Institute. *http://www.earth-policy.org/?/data_center/C23/,* Accessed June 30, 2015.

Givoni, M., & Rietveld, P. (2007). The access journey to the railway station and its role in passengers' satisfaction with rail travel. *Transport Policy*, *14*(5), 357-365.

Greene, W. H. (2008). *Econometric analysis*. Granite Hill Publishers.

Hagelin, C. (2005). A Return on Investment Analysis of Bicycles-on-Bus Programs. *National Center for Transit Research, Center for Urban Transportation Research. University of South Florida*, 576-05.

Heinen, E., & Bohte, W. (2014). Multimodal Commuting to Work by Public Transport and Bicycle: Attitudes Toward Mode Choice. *Transportation Research Record: Journal of the Transportation Research Board*, (2468), 111-122.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis: a primer*. Cambridge University Press.

Keijer, M. J. N., & Rietveld, P. (2000). How do people get to the railway station? The Dutch experience. *Transportation Planning and Technology,* 23(3), 215-235.

Krizek,K.,& Stoebraker,E.(2010). Bicycling and transit: A marriage unrealized. *Transportation Research Record: Journal of the Transportation Research Board,* (2144), 161-167.

Krygsman, S., & Dijst, M. (2001). Multimodal trips in the Netherlands: microlevel individual attributes and residential context. *Transportation Research Record: Journal of the Transportation Research Board*, (1753), 11-19.

Laura, G. & Frank, V. (2011). Nested logit or random coefficients logit? A comparison of alternative discrete choice models of product differentiation. Econoetrics. Center for Economic Studies.

Martens, K, (2004). THE BICYCLE AS A FEEDERING MODE: EXPERIENCES FROM THREE EUROPEAN COUNTRIES. *Transportation Research Part D: Transport and Environment, Volume* 9(4), 281-294.

Martens, K. (2007). Promoting bike-and-ride: The Dutch experience. *Transportation Research Part A: Policy and Practice*, *41*(4), 326-338.

National Development and Reform Commission (NDRC),(2012).*Implementation suggestions of ten key energy-conservation projects during the Eleventh Five-Year Plan*, NDRC Department of Resource Conservation and Environmental Protection Document.

Pan, H., Shen, Q., & Xue, S. (2010). Intermodal transfer between bicycles and rail transit in Shanghai, China. *Transportation Research Record: Journal of the Transportation Research Board*, (2144), 181-188.

People.cn. (2014). available at http://js.people.com.cn/n/2014/0624/c360302-21495424.html, access on 7/25/2015.

Shaheen, S., Guzman, S., & Zhang, H. (2010). Bikesharing in Europe, the Americas, and Asia: past, present, and future. *Transportation Research Record: Journal of the Transportation Research Board*,13(2143), 159-167.

Shaheen, S. A., Zhang, H., Martin, E., & Guzman, S. (2011). China's Hangzhou Public Bicycle. *Transportation Research Record: Journal of the Transportation Research Board*, *2247*(1), 33-41.Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Wang, R., & Liu, C. (2013). Bicycle-Transit Integration in the United States, 2001–2009. *Journal of Public Transportation*, *16*(3), 6.

World Bank. (2015). China - New Global Poverty Estimates, available at http://povertydata.worldbank.org/poverty/country/CHN, access on 7/23/2015.

Zhang, H., Shaheen, S. A., & Chen, X. (2014). Bicycle evolution in China: From the 1900s to the present. *International Journal of Sustainable Transportation*, 8(5), 317-335.