行政院國家科學委員會補助專題研究計畫成果報告

建成環境對公共自行車使用之影響：東亞四城市實證分析

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壹、綜合說明

近年來由於汽機車數量逐年攀升，增加石化能源使用與廢氣排放，造成交通壅塞問題，影響生活品質與個人健康。由於上述問題，各國開始大力提倡永續運輸（sustainable transportation），永續運輸係指在環境保護、經濟發展和社會公平的基礎上進行整體的運輸系統規劃以及發展。自行車是城市內重要的綠色運具，由於體力的限制，日常旅次多為短程使用，若要進行長程運輸則需要整合大眾運輸才能夠有系統的發展成都市綠色運輸路網。自行車與大眾運輸系統的整合，若空間允許可直接以大眾運輸搭載自行車的方式，或是在大眾運輸場站周遭增設自行車停放設施，供自行車使用者轉乘大眾運輸系統使用。但並非每個大眾運輸場站都開放自行車進出，大眾運輸若過於擁擠也無法搭載自行車。部分場站的周遭空間礙於資金不足、土地徵收困難，難以增設自行車停放設施。面對這些問題，歐洲城市發展出短時間停放、周轉率高的「公共自行車系統(public bike system, PBS)」。公共自行車的目的是增加民眾使用綠色運具的比率、取代私人運具的使用，其設置與推廣需要掌握影響使用的因素與關係，才能據以設計軟硬體系統，以及形塑良好使用環境，鼓勵民眾選擇使用。「建成環境(built environment)」是指為滿足人類活動需要而由人為形成的實質環境，包括土地使用、運輸系統、設施/設備等綜合形成的空間特徵，是影響旅運行為的重要環境因素之一。然而，過去探討建成環境對運具使用的影響，侷限於汽機車的私人運具、公車捷運的大眾運具以及步行自行車的非機動運具，尚未有探討公共自行車此種新型態運具的實證經驗，另公共自行車兼具大眾運具與非機動運具的特徵，其受建成環境的影響關係應該跟傳統的公車、捷運以及自有自行車有所不同，因此，建成環境對公共自行車使用的影響關係，有待進行探索。

本研究計畫原擬以三年時間探討建成環境對公共自行車使用的影響，並以位置及文化基礎相近的東亞城市(臺北、北京、東京、首爾)為研究對象，探討該影響關係在四個城市間的相似性與相異性，及其跟城市發展背景脈絡間的關係與意義。但因只通過二年期計畫經費，在重新評估研究計畫，並經實地訪查發現首爾的公共自行車營運狀況不佳，故在時間與經費限制下，調整為探討台北、北京與東京三個城市間的異同性。同時因為跨國調查之溝通協調較費時間，本計畫報經科技部同意後，在原通過經費下，展延一年研究時間。本計畫共進行兩階段調查，在第一年度進行台北調查，完成兩個主題研究：「建成環境對公共自行車使用之影響：台北市YouBike之實證研究」、「公共自行車費率對使用之影響：台北市YouBike之實證研究」。第二年度及展延第三年度進行北京與東京調查，並進行三城市的比較分析，完成一個主題研究：「建成環境對公共自行車使用之影響：台北、北京與東京之比較」。因此本報告包括以下三個研究成果。

第一個研究主題為「建成環境對公共自行車使用之影響：台北市YouBike之實證研究」，該研究首先針對「建成環境與私人自行車使用」與「公共自行車使用影響因素」兩個主題進行文獻回顧，之後再進一步透過個案訪談佐證因果關係以提出理論假說。繼

而挑選臺北市信義區捷運101/世貿站、捷運象山站、捷運永春站和捷運市政府站之公共自行車租賃站為調查空間範疇，以問卷調查資料做為樣本，了解實際公共自行車使用的旅運行為。再以主成份分析、二項羅吉特模式和潛在類別模式進行分析。此主題研究成果已發表於*The 2016 Association of American Geographers Annual Meeting* 如下：

Cheng, Y. T. and Lin, J. J. (2016), "The influences of built environment on public bike usage," presented in the *2016 Association of American Geographers Annual Meeting*, San Francisco, CA, US.

上文已再作改寫後投稿國際期刊，目前正在*Transport Policy* 審查中。

第二個研究主題為「公共自行車費率對使用之影響：台北市YouBike之實證研究」，本研究係併同第一個研究主題的調查工作一起進行，該研究首先透過文獻回顧歸納影響運具選擇之費率因素，繼而以台北捷運之市政府、台北101/世貿、永春與象山等四個車站出入乘客為樣本，應用個體選擇理論構建捷運乘客使用公共自行車轉乘之選擇模式，進而探討民眾使用行為之費率彈性，以瞭解民眾選擇使用YouBike的機率分別與費率結構中之『基本使用費率』、『基本使用費率時段』、『超過基本時段後之累進費率』間之關係，建立更貼近現實的使用者選擇行為模式。並應用潛在類別模式針對使用者進行市場區隔，探討不同族群的行為模式與選擇偏好，幫助瞭解台北市公共自行車使用者之特性，對應提出不同族群的經營策略方向，作為未來營運者訂定費率結構及研擬相關優惠措施之參考依據。此主題研究成果已發表於SSCI收錄期刊 *International Journal of Sustainable Transportation* 如下：

Lin, J. J., Wang, N. L., Feng, C. M. (2017), "Public bike system pricing and usage in Taipei", *International Journal of Sustainable Transportation*, Vol. 11, No. 9, pp. 633-641.

第三個研究主題為「建成環境對公共自行車使用之影響：台北、北京與東京之比較」，該研究立基於第一個研究主題的研究設計，進行北京與東京的問卷調查與變數資料蒐集，由北京大學城市與環境學院Pengjun Zhao 教授以及東京電機大學建築與都市環境學系Kazuyuki Takada 教授協助進行調查與蒐集工作。北京調查地點為朝陽門與亮馬橋兩個捷運站，東京調查地點為Toyosu捷運站。並應用主成份分析、二項羅吉特模式和潛在類別模式進行分析。此主題研究成果已撰寫為論文，預計投稿*Transportation Research Part A*，目前正進行英文編修中，如下：

Lin, J. J., Zhao, P., Takada, K., Li, S., Yai, T., and Chen, C. H. (2017), "Built environment and public bike usage for metro access: A comparison of Beijing, Taipei and Tokyo", an article prepared for submission of *Transportation Research Part A*.

本報告為上述三個主題的研究成果，為避免混淆，每個主題採獨立文章方式呈現於後續三個段落內容中。

貳、建成環境對公共自行車使用之影響：台北市 YouBike 之實證研究

Built Environments and Public Bike Usage: A Disaggregate Analysis

Abstract

To broaden understanding of how built environments influence public bike usage for metro access, this research addresses two issues: how the effects of built environment differ between public bike usage and private bike usage; and what population is affected the most by built environments. The study sampled passengers entering or leaving the four metro stations in Xinyi District, Taipei, Taiwan. Their mode choices of connecting travels between trip endpoints and metro stations were analyzed using logit and latent class models. The empirical evidence reveals that not only the 5Ds attributes raised by Cervero *et al*. (2009) but also the distribution of rental stations (the 6^{th} D) mattered public bike uses. Among the 5Ds attributes, the effects of commercial floor space and connecting travel distance on public bike usage are different from that on private bike usage. Furthermore, younger males who did not have driving licenses of car and owned private bikes cared about built environments more significant than other metro passengers. The empirical results not only contribute novel evidence to the study issue but also benefit developing a bike-friendly built environment in urban areas.

Keywords: built environment, public bike, metro access, logit model, latent class model.

Introduction

Since a third generation of public bike system (PBS) launched in Lyon in 2005, PBSs are increasingly included in urban public transport systems and been widely set to all over the world (DeMaio, 2009; Shaheen *et al*., 2010). A PBS is not only a non-motorized transport system that negatively affects pollution production, energy consumption and traffic congestion caused by motorized vehicles, it is also an active transport mode enhancing users' physical health. (de Hartog *et al*., 2010; Maizlish *et al*., 2013; Rojas-Rueda *et al*., 2011; Shaheen *et al*., 2010; Woodcock *et al*., 2013). Furthermore, PBSs are usually used for short-distance travels and provide a solution to the "last mile problem" of public transportation systems (DeMaio, 2009; Shaheen *et al*., 2010; Shaheen *et al*., 2011; Fishman *et al*., 2013; Tran *et al*., 2015; O'Brien, *et al*., 2014; Wood *et al*., 2011). According to The Bike-sharing Blog (http://bike-sharing.blogspot.tw/), 1,055 cities worldwide operated over 1.35 million public bikes in June, 2016.

In response to the sharp increase of PBS programs worldwide, more and more PBS research contributes understanding the system in the past decade. The existing research covers general reviews of history and implementations (DeMaio, 2009; Fishman *et al*., 2013; O'Brien *et al*., 2014; Shaheen *et al*., 2010), user behaviors and perceptions (Corcoran *et al*., 2014; Efthymious *et al*., 2013; Etienne and Latifa, 2014; Goodman and Cheshire, 2014;

Kraemer *et al*., 2012; Nakamura and Abe, 2014; Shaheen *et al*., 2011; Vogel *et al*., 2011; Vogel *et al*., 2014), repositioning bikes among rental stations (Caggiani and Ottomanelli, 2013; Chemla *et al*., 2013; Dell'Amico, 2014; Raviv and Kolka, 2013; Raviv *et al*., 2013; Sayarshad *et al*., 2012), optimizing spatial distributions of rental stations (Garcia-Palomares *et al*., 2012; Hu and Liu, 2014; Lin and Yang, 2011; Lin *et al*., 2013; Romero *et al*., 2012) and determinants of PBS usage (Noland and Ishaque, 2006; Rixey, 2013; Corcoran *et al*., 2014; Fishman *et al*., 2014; Faghih-Imani *et al*., 2014; Tran *et al*., 2015).

Despite the recognized need to understand the relationships between built environment and PBS usage benefits developing a PBS-friendly environment, few studies have explored these relationships. Faghih-Imani *et al*. (2014), Rixey (2013) and Tran *et al*. (2015) applied regression methods to analyze the influences of built environments on arrivals and departures of a rental station and discovered that residential density, job density, retailers, roadway network design, travel distance and distribution of rental stations are significant determinants of PBS uses. So far, studies of these relationships have only provided aggregate analyses of regional average data and have only measured built environments around rental stations. Such aggregate analyses are unable to know well an individual's travel behaviors and experiences along a journey. In contrast, disaggregate approaches can be used to investigate individual travelers in terms of origins, destinations, mode choices and travel routes, which provide further complete information to identify determinants of PBS usage. A few existing disaggregate studies such as Cervero and Duncan (2003), Cervero *et al*. (2009), Moudon *et al*, (2005) and Zhao (2014) have explored how built environment influences on private bike usage, but their empirical findings are not necessarily consistent with actual public bike usage.

The current study explores influences of built environments on public bike usage by using a disaggregate approach. The study sample comprises 311 metro passengers entering or leaving the metro stations in Xinyi District, Taipei; and, the transportation modes used by the respondents to travel between metro stations and trip endpoints were analyzed. In addition to comprehensively analyzing built environment attributes around origins and destinations and along travel routes, this research further addresses two questions. The first question is how the effects of built environment differ between public bike usage and private bike usage. Based on a comparison of discrete choice analysis results of this research to the previous private bike studies, this research argues that not only the 5Ds attributes (i.e., density, diversity, design, distance to transit, and destination accessibility) proposed in Cervero *et al*. (2009) but also the distribution of rental stations (the 6th D) mattered public bike uses. Among the 5Ds influences on public bike usage, some are similar to, while some are different from that on private bike usage. The second question is who concern built environments the most. Latent class models were applied to answer this question and the results reveal that younger males who did not have driving license of car while owned private bikes concerned built environments more significant than other metro passengers. The empirical results not only contribute novel evidence to the study issue but also benefit developing a bike-friendly built environment in urban areas

Method

Survey

The Taipei PBS (also named YouBike) is a major metro transfer mode, and work-commuting is one of the major rental purposes. Therefore, the survey target in this research was metro passengers leaving or entering metro stations for home-based work trips. Based on the survey of Thi Consultants Inc. (2015) in October, 2013, among the top 20 origin-destination (O-D) pairs of YouBike rental stations in terms of the daily average rentals, 19 O-D pairs contained rental stations located near metro stations; approximately one quarter of the rentals was for work-commuting purpose.

This study had a binary outcome, i.e., whether or not a metro passenger uses PBS as a connecting travel mode between a metro station and a trip endpoint (destination for leaving station trip or origin for entering station trip). In addition to built environment attributes, PBS pricing, trip attributes and individual socio-economic attributes were also selected as explanatory variables to explain the study outcome. The variable data were obtained from a stated preference survey and existing databases.

The first part of the survey collected information about the decision by a metro passenger to choose the PBS as a connecting travel mode given different PBS pricing scenarios. Because pricing is a critical determinant of transportation mode choice and since the YouBike pricing system is the same for all users, varying price attributes were necessary to reveal their effects on PBS usage. The pricing system has three attributes: the basic fee is a constant charge for a rental, the basic period is the maximum rental period charging the basic fee, and the variable fee is a variable charge for a rental after the basic period. The YouBike does not charge membership fees. Pricing included four levels for the basic fee, four levels for the basic period, and two categories of the variable fee; therefore, 32 total combinations were used as pricing scenarios. To simplify the survey for interviewees, each questionnaire provided four diverse scenarios for interviewee responses. Thus, eight versions of questionnaire sheet were used in the survey.

The second part of the survey recorded information about socio-economic attributes including gender, age, occupation, income, education, vehicle ownership, biking capability and driving license ownership. Finally, the third part of the survey request a respondent to locate his or her trip endpoint (destination or origin) and travel route between metro station and trip endpoint on a map. According to the location records, built environment attributes around trip endpoints and along travel routes for every respondent were obtained using various databases. The survey also recorded transportation mode used by the respondent to arrive at or leave from the metro station for the surveyed trip.

The questionnaire survey was performed during the afternoon-peak-hours (17:00-20:00) of weekdays between 5 January and 16 February in 2015. The survey controlled for weather conditions by excluding rainy days from the survey. The survey targeted four metro stations in Xinyi District, Taipei City, which was the first district to be equipped with PBS rental stations and has the most PBS rentals for work trips among the 12 Districts of Taipei City based on the survey of Thi Consultants Inc. (2015). A systematic random sampling method was conducted by intercepting metro users leaving or entering metro stations at exists nearby PBS rental stations for interviews. The sampling locations include Taipei 101/World Trade Center station (Exit 2), Taipei City Hall station (Exit 3), Yongchun station (Exit 2) and Xiangshan station (Exit 3).

The survey obtained 311 responses and 1,555 effective observations (311×5, four stated choices on pricing scenarios and one revealed choice in existing pricing for each respondent). The percentage of males was 41.5%, which approximated the male ratios (35.2%, 36.2%, 34.1%, 35.7% and 37.9%) of Taipei metro users during 2010- 2014 (Ministry of Transportation and Communications, 2015); and, about 50.5% of respondents used YouBike as their connecting travel modes. Thus, the study sample adequately represented PBS usage of metro passengers.

Variables

Because this study had a binary outcome (use or non-use of PBS), this research applied binary logit (BL) models to explore the influences of built environment on PBS usage. Segment-specific preferences were analyzed with latent class BL models to identify differences in influence among different passenger segments.

Table 1 defines the explanatory variables used in discrete choice models and their hypothetical influences on using PBS. The variables were categorized as built environment variables and control variables. This study determines built environment variables by six dimensions: density, diversity, design, distance to transit, destination accessibility, and distribution of rental stations. The first five dimensions are from the 5Ds attributes raised in Cervero *et al*. (2009) for explaining general bike usage and the 6th dimension is specifically considered for public bikes. Because PBS users rent and return bikes at rental stations, the distribution of rental stations was expected to affect PBS usage. The previous surveys including Bordagaray (2012), Faghih-Imani *et al*. (2014), Fishman *et al*. (2014) and Rixey *et al*. (2013) found that increasing numbers of nearby rental stations encourage people to use public bikes. Therefore, the station number in a trip endpoint area and the distance from a trip endpoint to the nearest rental station were hypothesized to have positive and negative effects, respectively, on public bike usage. A trip endpoint area refers to the area within 350 m buffer-ring using travel distance on practical road network and center of a respondent’s destination (for whom leaving metro station) or origin (for whom entering metro station). The distance of 350 m is the service distance of a rental station used in the station setting criteria of Taipei (Department of Transportation, Taipei City Government, 2016).

Regarding 5D attributes, this study selects variables and tested their effects on PBS usage as hypothesized in previous works. Densities of population, employment and students have shown a positive association with public bike use in the aggregate studies of Faghih-Imani *et al*. (2014), Rixey *et al*. (2013) and Tran *et al*. (2015), while Soltani and Allan (2006) found a negative association exists between building density and private bike uses. The limited road space in a dense building environment is commonly unfavorable to biking. The above relationships could also exist in the current disaggregate and public bike research. Various measures of land use diversity used in previous studies have shown a positive association with private bike usage owing to shortened travel distances. Those measures include the land use entropy index (Winters *et al*., 2010; Zhao, 2014), the commercial ratio (Moudon, *et al*., 2005) and the job-housing balance index (Zhao, 2014), and they are also used in this study to explain public bike usage as defined in Table 1. Meanwhile, this study modified the job-housing balance index developed by Zhao (2014) as described in note b of Table 1 in order to maintain a similar value meaning to the other two diversity variables, i.e., the higher the index value, the higher the diversity degree. Numerous road design attributes have been reported to be associated with biking. These attributes include intersections, lengths, area, directness, traffic signs and lights, lamps, trees and green fields along roads (Broach *et al*., 2012; Cervero *et al*., 2009; Cervero and Duncan, 2003; Faghih-Imani *et al*., 2014; Moudon *et al*., 2005; Rixey *et al*., 2013; Soltani and Allan, 2006; Tran *et al*., 2015; Winters *et al*., 2010; Zhao, 2014). Since these attributes are interrelated with each other, this study conducted a principle component analysis and got three independent components, which explain near 62% of sample variation, as listed in Appendix 1. This study named the three components according to the variables revealing absolute values of loadings over 0.6 (Hair *et al*., 1992). The Bike friendliness component is positively related to bike-friendly facilities, including bikeways, green fields and street trees, and is negatively related to street intersections and traffic signs and lights that could interrupt biking. Hence, this study hypothesized that Bike friendliness has a positively influence on PBS usage. The Road facility component is positively related to intersections, length and area of arterials that could result in both positive and negative effects on biking. Arterials provide more road space to bikers while attract heavier vehicle volume and safety concerns than local streets. The Vehicle mobility component is positively related to road space, traffic signs and lights and road lamps, all of which increase traffic flow speeds and discourage biking owing to safety concerns. Faghih-Imani *et al*. (2014), Tran *et al*. (2015) and Zhao (2014) reported a negative association between bike uses and distances to transit stations, which is also hypothesized in the current research. This study used three distance variables to measure the distances from a respondent's trip endpoint to the nearest metro station, the nearest bus stop and the actually used metro station. Finally, the destination accessibility variables in Table 1 were used to measure access to interesting locations including local commercial centers, trip attractions and retailers. These accessibilities are all expected to positively influence PBS usage according to the findings of Broach *et al*. (2012), Faghih-Imani *et al*. (2014), Fishman *et al*. (2014), Moudon *et al*. (2005), Rixey *et al*. (2013), Tran *et al*. (2015) and Zhao (2014). However, owing to the significant correlations among the interesting locations, this study used principle component analysis to obtain the Destination accessibility component shown in Appendix 1. A positive relationship is expected between the component and PBS usage.

Table 1 has three groups of control variables: individual, environment and PBS. Many individual socio-economic attributes have been reported to be related to biking in the literatures. The positive individual attributes that encourage biking for work-commuting are male gender (Bordagaray, 2012; Cervero *et al.,* 2009; Moudon *et al*., 2005; Murphy and Usher, 2015; Shaheen *et al.*, 2011; Winters *et al*., 2010) and bike ownership (Cervero *et al.*, 2009; Cervero and Duncan, 2003; Moudon *et al*., 2005); and, the individual attributes that discourage biking are age (Cervero *et al.,* 2009; Moudon *et al*., 2005; Murphy and Usher, 2015; Shaheen *et al.,* 2011), income (Murphy and Usher, 2015; Rixey *et al.,* 2013; Shaheen *et al.,* 2011; Zhao, 2014), and motorized vehicle ownership (Cervero *et al.,* 2009; Zhao, 2014). Many environmental attributes other than built environments are expected to discourage biking, including steep slopes (Cervero *et al.,* 2009; Broach *et al*., 2012; Faghih-Imani *et al*., 2014) and heavy traffic flows (Broach *et al*., 2012). Environmental safety concerns, including traffic accidents (Cervero *et al*., 2009) and poor public security, are also expected to reduce interest in cycling. As for PBS attributes, Tran *et al*. (2015) argued that the numbers of public bikes (or numbers of docks) in rental stations are positively associated with public bike use, which was also hypothesized in our study. Costs (money, time, distance, etc.) of using a travel mode are also well known negative determinants of travel mode usage (Campbell, 2012; Cheng and Kuo, 2010; Hopkinson and Wardman, 1996; Ortuzar *et al*., 2000; Wen and Lai, 2010). Therefore, this study hypothesized that the basic fee is negatively associated with PBS usage and that the basic period is positively associated with PBS usage. Because less than 5% of rentals were over the basic period (30 minutes) among work trips during weekdays (Thi Consultants Inc., 2015), the variable fee was not included as an explanatory variable.

< Table 1 is about here>

Sample data

Sample data were collected by three approaches. First, the questionnaire survey described in the *Survey* sub-section was used to collect data for control variables of individual and PBS pricing attributes. Second, according to the respondent locations of trip endpoints (destinations or origins) and travel routes between metro stations and trip endpoints, data related to the built environment variables and the control variables of environment attributes were obtained from existing databases and published documents. Data on population, students, households, bikeways, street trees and lamps, bus stops, local commercial centers, trip attractions, retailers, car and pedestrian volumes, YouBike rental stations and crime records were obtained from Taipei City Government. Land use data were from the Land Use Investigation Database provided by the National Land Surveying and Mapping Center. Floor area data were from the house tax databases of Revenue Service Offices of Taipei City. Employment data were from the Commerce and Service Census published by the Directorate-General of Budget, Accounting and Statistics. Traffic accident data were from the National Police Agency. Slops were estimated using the digital topography database provided by the Department of Land Administration in Ministry of the Interior. Intersections, road lengths and travel distances were estimated using digital maps of roadway networks from the Institute of Transportation in Ministry of Transportation and Communications. Finally, data of traffic signs and lights were obtained by performing field investigations. All variable data were for the base year of 2015. Since some of the newest databases and documents did not match the base year, 2011-2015 were used as the variable data years.

Appendix 2 summarizes the descriptive statistics for explanatory variables of sample data. All values for continuous variables ranged between reasonable minimums and maximums. Generally, the medians approximated the means. Only the two Slop variables perform a significant right-skewed distribution because a few hills are located at the southeastern boundary of the study area. The variation coefficients revealed that most continuous variables had adequate variations for regression analysis. Significantly diverse values exist only in the variables of Student density, Slop-R and Crime-R. Among the respondents, females outnumbered males, about three-quarters owned car or motorcycle driver licenses, and over one half owned bikes, cars or motorcycles. In addition, the respondents covered a wide income range.

Results

The NLOGIT 5.0 software package and the maximum likelihood method were used to estimate model coefficients. Table 2 lists the estimation results, in which explanatory variables with a coefficient significance below the confidence level of $1\text{-}\alpha=90\%$ in all utility functions were withdrawn from the estimation. All of the estimated models had acceptable goodness-of-fit, and the coefficient signs for most of the estimated models were consistent with the hypothetical relationships in Table 1. This study thus used the results for the following discussions.

< Table 2 is about here >

Built Environments

The BL models in Table 2 include a base model considering only control variables and an extended model considering control and built environment variables. A likelihood ratio test to examine the significance of the difference between models found that the extended model had superior goodness-of-fit to the base model; therefore, built environment attributes contribute significantly to efforts to explain PBS usage for accessing metro stations.

The significant built environment variables in the extended BL model covered all six of the dimensions discussed in the Method section. As densities of workers and students around metro passenger trip endpoints increased, PBS usage increased. However, as population density increased, PBS usage decreased. This negative relationship is contrary to the expectation in Table 1 and the findings of previous aggregate studies. For example, Faghih-Imani *et al*. (2014), Riexry (2013) and Tran *et al*. (2015) found that increasing population density near a rental station increases the aggregate numbers of public bike uses whereas the current research revealed that increasing population density around trip endpoints declines a traveler's intention to use public bike. One possible explanation for the negative relationship is that increasing population density and public bike uses increases the possibility of bike-unavailability in rental stations, which then decreases intention for an individual traveler to use public bike. Thus, a built environment attribute like population density could bring quite different meanings to PBS usage in aggregate and disaggregate views.

Two attributes of land use diversity near metro passengers' trip endpoints are significantly related to PBS usage: the Commercial ratio reveals a negative relationship and the JH balance reveals a positive relationship. The negative relationship is contrary to the expectation in Table 1 and the survey of private bike usage by Moudon *et al*. (2015). The negative association has two possible explanations. First, increasing commercial floor area usually attracts increasing shopping trips that could use public bikes. The availability of bikes in rental stations and returns of bikes to rental stations then decrease due to lack of available bikes or docks. The unavailability results in a declined intention of using public bikes. Second, home-based work travels in a commercial area usually have multiple stops, for example, stopping at a supermarket and a laundry along the way from a metro station to a worker's home. Because stop durations also cost PBS users, metro passengers may prefer using transport modes other than PBS for connecting travels between metro stations and trip endpoints that are surrounded by commercial activities. The above two explanations are not related to using private bike and using private bike is convenient for multi-stop travels within an area; therefore, a built environment attribute like commercial floor space could have different meanings for private bike and public bike users.

The design dimension affects PBS usage via two component variables. Road facility encourages, and Vehicle mobility discourages, PBS usage. These effects are consistent with the expected effects shown in Table 1 and denote that sufficient road space and safe biking circumstance are essential design concerns for using public bikes.

Regarding the distances to transit from a respondent's trip endpoint, a distance to the nearest bus stop is not related to PBS usage while distances to the nearest and the actually used metro stations positively influence PBS usage. The results are inconsistent with the expectations in Table 1 and Zhao (2014)'s survey on private bike usage. Owing to bikers' physical limitations, biking is commonly viewed as a short-distance transport mode, and hence a negative relationship is usually expected between travel distances and bike uses. However the above expectation may be inapplicable for public bike uses. Since a PBS charges its users, and since connecting travel distances of metro passengers are usually within a limited range, metro passengers tend to walk for short connecting travel distances and consider using PBS for longer connecting travel distances. Taking the study sample as an example, the connecting travel distances ranged between 21 meters and six kilometers with an average of less than one kilometer. In this short distance range, biking is physically acceptable for most commuters. Thus, in addition to the commercial floor space mentioned above, the connecting travel distance could also bring quite different meanings to private bike and public bike usage.

Finally, the dimensions of destination accessibility and PBS distribution significantly affected PBS usage. Better access to local commercial centers, trip attractions or retailers and shorter distance to rental stations both encourage public bike usage. These empirical results are consistent with Table 1.

According to the above discussions, the current research not only confirms that the 5D attributes proposed in Cervero *et al*. (2009) affects public bike usage, but also reveals that another D-attribute, distribution of rental stations, affects public bike usage. The effects of the conventional 5D attributes were consistent with previous research on private bike usage excepting a few of attributes owing to the uniqueness of PBS. Increasing commercial floor space and decreasing connecting travel distance both encourage private bike usage but discourage public bike usage because PBS users are charged and must rent and return bikes at rental stations. Moreover, decreasing distances to the nearest rental station encourages public bike usage but does not matter private bike usage.

Controls

Most of the significant coefficients of control variables in the BL models of Table 2 confirm the expected effects of PBS use shown in Table 1. Aging, owning driving licenses of car, owning motorcycles, increasing pedestrians and traffic accidents along travel routes and increasing the basic fee for a rent discourage metro passengers from using PBS for connecting trips; meanwhile, owning bikes and increasing the basic period encourage metro passengers to use PBS for connecting trips. However, three relationships are inconsistent with the expectations in Table 1 and these unexpected relationships should not be causal effects. First, respondents who had motorcycle driving licenses should be capable of using two-wheel vehicles, including bikes, and hence, having a motorcycle driving license is positively associated with using PBS. Second, wider roads usually provide more space for paving sidewalks and bikeways, which encourages biking, and also provide more vehicle lanes, which attract car volumes. Therefore, Car volume-R is positively associated with using PBS. Third, to meet the needs of the last (or first) mile travels for public transport systems, PBS rental stations near transit stations are mostly equipped with more docks than other rental stations. Increasing the number of docks in the nearest PBS rental station of a respondent's trip endpoint denotes that his or her trip endpoint is close to a metro station and PBS is not necessary for a connecting travel. Thus, the Dock is negatively associated with PBS use. In general, the controls in Table 2 reveal similar relationships to the previous bike studies.

Segmentation

The latent class model in Table 2 contains four segments. This study used the individual variables as membership function variables and the other explanatory variables as utility function variables. The four-segment model was selected because it had a lower AIC value and a higher ρ^2 value compared to the two-segment and three-segment models listed in Appendix 3 and because the five-segment model was unable to be estimated. Since the goodness-of-fit of the latent class model (ρ^2 = 0.499) is significantly better than that of the extended BL model (ρ^2 = 0.296), this study confirms that heterogeneous preferences existed among the sample metro passengers in selecting PBS as a connecting travel mode.

Based on the membership functions, the respondents of segment 1 can be characterized by who were young, middle-income earners and owning bikes (*young middle-income bike-owners*), the respondents of segment 2 can be characterized as young with high incomes (*young high-income earners*), the respondents of segment 3 can be characterized as young males without driving licenses of car and owning bikes (*young male bike-owners*) and the respondents of segment 4 were named as *others*. Among these segments, the young male bike-owners were most concerned about built environments in selecting PBS as a connecting travel mode because the coefficients of built environment variables are only significant in the Segment 3 model. These discriminated results imply that the effects of built environments on PBS usage should differ among various socio-economic contexts of commuters.

In addition to built environments, the control variables also reveal different effects on PBS usage among segments. The young middle-income bike-owners were mainly concerned about the basic period for a rent while the young male bike-owners were mainly concerned about traffic accidents, car volumes and the basic fee for a rent. It seems that a higher-income commuter prefers a longer rental period but a lower-income commuter prefers a lower charge for a rent. According to the above differences among segments, local governments and PBS operators could develop customized strategies for promoting a

PBS-friendly city.

Limitations

For further clarification of the relationships between built environment and public bike usage, future studies should examine three issues, which reflect the limitations of this study. The first issue is connected with the contexts of study area. This study selected the Xinyi District in Taipei City as the study area. As a typical East Asian city, Taipei reveals two unique characteristics to western cities: a high level of mixed land uses and a high motorcycle use. Furthermore, the YouBike is one of successful PBS projects in the world and it is operated in a unique pricing system (e.g., it is free of membership fee and users are subsidized by the local government). The empirical findings should be meaningful to cities with similar contexts rather than to all cities worldwide. To generate comprehensive information about the study issue, future research should investigate different cities with diverse contexts.

The second issue is related to the study sample. This study only interviewed metro passengers entering or leaving metro stations for home-based work trips and recorded whether they used PBS for connecting travels between metro stations and trip endpoints. Thus, the empirical findings reveal travel behaviors of connecting travels of transit users for work-commuting purpose. In addition to work-commuting, PBS is widely used for many other purposes. For example, the survey of Thi Consultants Inc. (2015) in 2013 found that school-commuting, shopping/entertainment, work-commuting, business and recreation/sport were the top-five purposes of Taipei PBS uses. What differences are the influences of built environments on PBS usage among various travel purposes? To answer this question, further surveys on the other travel purposes should be necessary in the future.

The third issue is associated with the research design. This study surveyed a binary choice problem, i.e., whether a metro passenger chose YouBike or not, and the empirical findings are limited to PBS itself. Since an urban transport system usually provides multiple travel modes, detailed information about choices among all travel mode alternatives should be further meaningful. Surveys in future studies should collect data for different travel modes. For example, choices of a connecting travel mode could include walking, biking by private bike, renting public bike, driving a motor vehicle, traveling as a passenger in a motor vehicle, and using bus. Via such a multiple choice survey design, trade-off relationships between PBS and individual travel mode alternatives influenced by built environments are able to be explored.

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Table 1 Definitions of explanatory variables and hypothesized effects on PBS use

Name	Definition	Unit	Hypothesized effect
Built environments			
Density			
Population density	Number of residents / area of land, in a *trip endpoint area*[a]	people/m^2	+
Employment density	Number of employees / area of land, in a trip endpoint area	people/m^2	+
Student density	Number of senior high school, undergraduate and graduate students / area of land, in a trip endpoint area	people/m^2	+
Building density	Area of floor space / area of land, in a trip endpoint area	m^2/m^2	-
Diversity			
Land use mix	Land use entropy in a trip endpoint area, $entropy = \{-\sum_{i=1}^{s}[(D_i)\ln(D_i)]\}/\ln(s)$, where D_i is the proportion of floor space i, $\sum_{i=1}^{s} D_i = 1$, i denotes a land use type and s is the total number of i.	-	+
Commercial ratio	Area of floor space of commercial and business uses / area of total floor space, in a trip endpoint area	%	+
JH balance	*Job-housing balance index*[b] in a trip endpoint area	--	+
Design			
Street intersection-A	Number of *street*[c] intersections / area of land, in a trip endpoint area	(intersection/m^2)×1000	
Street intersection-R	Number of street intersections / length of route, along a *travel route*[d]	intersection/m	
Street length	Length of streets / area of land, in a trip endpoint area	m/m^2	
Arterial intersection-A	Number of *arterial*[e] intersections / area of land, in a trip endpoint area	(intersection/m^2)×1000	
Arterial intersection-R	Number of arterial intersections / length of route, along a travel route	intersection/m	
Arterial length	Length of arterials / area of land, in a trip endpoint area	m/m^2	
Bikeway-A	Length of bikeways / area of land, in a trip endpoint area	m/m^2	
Bikeway-R	Length of bikeways / length of route, along a travel route	m/m	
Directness	Ratio of shortest distance to actual travel distance along a travel route	%	
Road space-A	Area of road space in a trip endpoint area	km^2	
Road space-R	Area of road space / length of route, along a travel route	m^2/m	
Sign-A	Number of traffic signs and lights in a trip endpoint area	piece	
Sign-R	Number of traffic signs and lights along a travel route/ length of travel route	piece/m	
Greenness	Area of parks, green fields, squares and playgrounds / area of land, in a trip endpoint area	m^2/m^2	
Tree-A	Number of trees in a trip endpoint area	tree	
Tree-R	Number of trees / length of route, along a travel route	tree/m	
Lamp-A	Number of lamps in a trip endpoint area	lamp	
Lamp-R	Number of lamps / length of route, along a travel route	lamp/m	
Bike friendliness	Refer to Appendix 1	-	+
Road facility	Refer to Appendix 1	-	+/-
Vehicle mobility	Refer to Appendix 1	-	-
Distance to transit			
Metro distance	The shortest travel distance between a respondent's trip endpoint (origin or destination) and the nearest metro station	m	-
Bus distance	The shortest travel distance between a respondent's trip endpoint and the nearest bus stop	m	-
Transfer distance	A respondent's actual travel distance between a surveyed metro station and his or her trip endpoint	m	-
Destination accessibility			
Local center	The shortest travel distance between a respondent's trip end point and the nearest local commercial center	m	
Attraction	Number of trip attractions in a trip endpoint area, including government agencies, police stations, fire stations, libraries, museums, culture centers, art galleries, hospitals, restaurants post offices, gas stations and service stations of telecommunication, electric power and tap-water	-	
Retailer	Number of retailers in a trip endpoint area, including convenience stores, department stores and super markets	-	
Destination accessibility	Refer to Appendix 1	-	+

Distribution of PBS			
PBS number	Number of PBS rental stations in a trip endpoint area	-	+
PBS distance	The shortest travel distance between a respondent's trip endpoint and the nearest PBS rental station	m	-
Controls			
Individual			
Age	A respondent's age	year	-
Male	A respondent is male (=1) or female (=0)	-	+
Income 1	A respondent has a monthly income between 30-50 thousand NT$ (=1) or not (=0)	-	-
Income 2	A respondent has a monthly income over 50 thousand NT$ (=1) or not (=0)	-	-
License-car	A respondent is licensed to drive a car (=1) or not (=0)	-	-
License-motorcycle	A respondent is licensed to ride a motorcycle (=1) or not (=0)	-	-
Ownership-car	A respondent owns car(s) (=1) or not (=0)	-	-
Ownership-motorcycle	A respondent owns motorcycle(s) (=1) or not (=0)	-	-
Ownership-bike	A respondent owns bike(s) (=1) or not (=0)	-	+
Environment			
Slope-A	The maximum slope in a trip endpoint area	%	-
Slope-R	The maximum slope / length of route, along a travel route	%/m	-
Crime-A	Number of crimes in a trip endpoint area	-	-
Crime-R	Number of crimes / length of route, along a travel route	crime/m	-
Accident-A	Number of traffic accidents in a trip endpoint area	-	-
Accident-R	Number of traffic accidents along travel route	accident/m	-
Car volume-A	Volume of cars during afternoon peak-hours / area of land, in a trip endpoint area	pcu/m^2/hr	-
Car volume-R	Volume of cars during afternoon peak-hours / length of route, along a travel route	pcu/m/hr	-
Pedestrian volume-A	Volume of pedestrians during afternoon peak-hours / area of land, in a trip endpoint area	people/m^2/hr	-
Pedestrian volume-R	Volume of pedestrians during afternoon peak-hours / length of route, along a travel route	people/m/hr	-
PBS			
Basic fee	Constant charge for a rental	NT$	-
Basic period	Maximum rental period charging basic fee	minute	+
Dock	Number of docks equipped at the nearest PBS rental station of endpoint of a trip by a respondent	-	+

[a] A trip endpoint area refers to the area within 350m buffer-ring using travel distance on practical road network and center of the travel destination (for whom leaving metro station) or travel origin (for whom entering metro station) of the respondent.

[b] The job-housing balance index $= [|\ln\left(\frac{J}{H}\right)|_{\max} - |\ln\left(\frac{J}{H}\right)|] / |\ln\left(\frac{J}{H}\right)|_{\max}$, where J is the number of employees, H is the number of households, and $|\ln\left(\frac{J}{H}\right)|_{\max}$ denotes the maximum $|\ln\left(\frac{J}{H}\right)|$ value among all of the respondents' trip endpoint areas.

[c] A street refers to collector or local street.

[d] A travel route refers to the route used by a respondent traveling between metro station and destination or origin.

[e] An arterial refers to arterial or expressway.

Table 2 Regression models (outcome: using PBS=1)

Variables	Binary logit model		Latent class model			
	Base	Extended	Segment 1	Segment 2	Segment 3	Segment 4
Utility function						
Intercept	1.63996***	-5.29569***				
Built environments						
Population density		-33.8567***	-50.193	111.365	-86.433*	-115.984
Employment density		18.9344***	29.737	-44.038	71.567*	16.630
Student density		18.7837***	-9.744	90.616	154.862**	-38.916
Commercial ratio		-0.05121***	-0.033	-0.452	-0.332***	0.244
JH balance		6.00769***	0.498	-20.232	4.241	16.274
Road facility		0.21505	0.562	-1.109	4.838***	1.046
Vehicle mobility		-0.46530***	-0.301	0.696	-1.720	-2.712
Metro distance		0.00213***	0.002	0.008	0.008***	0.024
Transfer distance		0.00090***	0.001	0.007	0.008***	0.003
Attraction accessibility		0.30411**	1.250	0.926	2.705***	-1.188
PBS distance		-0.00306***	0.001	0.002	-0.026***	-0.008
Controls						
Age	-0.03325***	-0.01670**				
License-car	-0.21407	-0.28763*				
License-motorcycle	0.53680***	0.69105***				
Ownership-motorcycle	-0.52102***	-0.12313				
Ownership-bike	0.76324***	0.77425***				
Accident-A	-0.00628***	0.00230	-0.012	0.030	-0.047**	0.007
Car volume-R	1.47817***	1.44051***	-0.807	14.398	10.941***	-5.947
Pedestrian volume-R	-8.67844**	-7.06279	37.345	-31.761	-57.568	-37.277
Basic fee	-0.54664***	-0.69525***	-0.250	-7.140	-3.112***	-2.123***
Basic period	0.21844***	0.29385***	1.013***	3.162	0.327	-1.203
Dock	-0.00771***	-0.00623**	0.012	-0.247	0.028	-0.595
Membership function						
Intercept			-0.074	1.000	-13.549	fixed
Age			-0.099**	-0.089*	-0.101**	fixed
Male			0.250	1.231	1.861*	fixed
Income 1			1.320*	1.715*	19.188	fixed
Income 2			2.183	2.426*	20.580	fixed
License-car			-0.837	0.681	-1.611*	fixed
License-motorcycle			1.702	-1.166	-0.138	fixed
Ownership-car			-0.879	-0.112	-0.352	fixed
Ownership-motorcycle			1.049	0.584	-1.083	fixed
Ownership-bike			2.257***	1.008	1.496*	fixed
Proportion			20.6%	22.8%	36.3%	20.3%
ρ^2	0.156	0.296		0.499		
χ^2	354.706***	673.232***		1271.37382***		
Likelihood ratio test	637.0513***($\chi^2_{11,0.05}$ = 19.675)					

Notes: Number of observations: 1,555; *** significant at α=0.01; ** significant at α=0.05; * significant at α=0.1

Appendix 1 Results of principle component analyses (loadings of variables[a])

Dimension	Design			Dimension	Destination accessibility
Component	Bike friendliness	Road facility	Vehicle mobility	Component	Destination accessibility
Street intersection-A	-0.932	0.006	-0.138	Local center	-0.718
Street intersection-R	-0.706	0.074	-0.036	Attraction	0.959
Street length	-0.955	0.005	-0.119	Retailer	0.850
Arterial intersection-A	0.383	0.866	-0.005		
Arterial intersection-R	0.323	-0.185	0.069		
Arterial length	0.452	0.811	-0.004		
Bikeway-A	0.880	0.154	0.102		
Bikeway-R	0.664	-0.345	0.071		
Directness	-0.129	-0.261	0.498		
Road space-A	-0.374	0.841	-0.010		
Road space-R	-0.072	0.093	0.832		
Sign-A	-0.825	0.408	-0.141		
Sign-R	-0.138	0.022	0.716		
Greenness	0.850	0.251	-0.047		
Tree-A	0.656	0.137	-0.187		
Tree-R	0.499	-0.201	-0.278		
Lamp-A	-0.129	0.446	0.149		
Lamp-R	0.000	0.082	0.614		
Eigen value	6.228	2.869	2.040		2.158
Variance (%)	34.601	15.936	11.336		71.930
Cumulative variance (%)	34.601	50.537	61.873		71.930

[a] The loadings are the eigenvectors of the variables scaled by the component's square roots of the eigenvalues respectively.

Appendix 2 Descriptive statistics of study variables of study sample

Continuous variables	Minimum	Maximum	Median	Mean	Variation coefficient
Built environments					
Density					
Population density	0.0010	0.1146	0.0722	0.0615	0.5055
Employee density	0.0059	0.0980	0.0416	0.0472	0.3476
Student density	0.0000	0.0495	0.0000	0.0053	2.1585
Building density	0.3256	5.4453	2.7936	2.8182	0.4181
Diversity					
Land use mix	0.1870	2.8148	1.0471	1.1824	0.5104
Commercial ratio	2.1331	39.2485	17.1433	16.0282	0.5677
JH balance	0.0000	0.9977	0.8713	0.8155	0.2087
Design					
Street intersection-A	0.0000	1.0056	0.4028	0.4280	0.6057
Street intersection-R	0.0000	0.0906	0.0099	0.0167	1.1209
Street length	0.0000	0.0270	0.0134	0.0127	0.5680
Arterial intersection-A	0.0104	0.7224	0.2443	0.2384	0.5359
Arterial intersection-R	0.0000	0.0611	0.0223	0.0207	0.6030
Arterial length	0.0011	0.0263	0.0111	0.0107	0.4197
Bikeway-A	0.0000	0.0135	0.0025	0.0040	1.0172
Bikeway-R	0.0000	1.1550	0.1633	0.3315	1.0587
Directness	0.1574	1.0004	0.6981	0.6720	0.2257
Road space-A	0.0356	0.1316	0.0776	0.0798	0.2147
Road space-R	43.4583	190.9346	61.7980	63.1524	0.1825
Signs (A)	92.0000	485.0000	244.0000	245.3119	0.4526
Signs (R)	0.0000	0.1854	0.0081	0.0111	1.2394
Greenness	0.0079	0.1972	0.0528	0.0590	0.6338
Tree-A	0.0000	1294.0000	625.0000	596.0064	0.5772
Tree-R	0.0000	0.1091	0.0192	0.0212	0.9582
Lamp-A	173.0000	916.0000	496.0000	494.3987	0.2665
Lamp-R	0.0000	0.3961	0.0447	0.0470	0.6430
Distance to transit					
Metro distance	6.3663	1307.9115	482.6945	500.5739	0.5596
Bus distance	2.0059	425.2481	102.4908	121.4348	0.6694
Transfer distance	21.5789	6090.178	814.2971	982.3805	0.7699
Destination accessibility					
Local center	41.2947	4304.838	1111.4438	1084.3928	0.4839
Attraction	8.0000	506.000	114.0000	136.3408	0.7104
Retailer	2.0000	31.000	11.0000	12.1608	0.4951
Distribution of PBS					
PBS number	0.0000	6.0000	1.0000	1.7331	0.5826
PBS distance	0.2985	703.4728	185.1066	200.2449	0.6610
Controls					
Individual					
Age	18	67	31	34.0257	0.3153
Environment					
Slope-A	0.6	130.8	3.8	21.2672	1.6226
Slope-R	0.0	257.2	1.5	3.1958	4.6842
Crime-A	0	14	3	3.2605	0.7938
Crime-R	0	0.0073	0	0.0003	2.4829
Accident-A	30	453	170	163.7331	0.4856
Accident-R	0	0.2704	0.0424	0.0447	0.7406
Car volume-A	68.0345	7628.9517	3236.3913	3403.9818	0.4698
Car volume-R	0.0497	1.5738	0.6310	0.6235	0.5277
Pedestrian volume-A	15.4895	1290.2073	255.0639	282.4573	0.5077
Pedestrian volume-R	0.0119	0.1442	0.0412	0.0516	0.4483
PBS					
Basic fee	1	4	2	2.2	0.5303
Basic period	1	4	2	2.4	0.4251
Dock	24	180	48	58.7653	0.7098

Category variables	Category percentage

Controls	
Individual	
Income	Below 30 thousand NT$: 24.7%; 30-50 thousand NT$: 45.7%; over 50 thousand NT$: 29.6%
Gender	Male: 41.5%; Female: 58.5%
License-car	Yes: 74.6%; No: 25.4%
License-motorcycle	Yes: 76.5%; No: 23.5%
Ownership-car	Yes: 62.1%; No: 37.9%
Ownership-motorcycle	Yes: 76.2%; No: 23.8%
Ownership-bike	Yes: 55.3%; No: 44.7%

Appendix 3 Latent class BL models in various segment numbers

Segment	Two-segment		Three-segment			Four-segment			
	1	2	1	2	3	1	2	3	4
Proportion	50.3%	49.7%	40.1%	31.7%	28.2%	20.6%	22.8%	36.3%	20.3%
$L(\beta_k)$	-540.18935		-498.71525			-442.15696			
$L(\beta_0)$	-1077.84387		-1077.84387			-1077.84387			
ρ^2	0.4580019		0.4714306			0.4988542			
AIC	1168.4		1139.4			1080.3			

叁、公共自行車費率對使用之影響：台北市 YouBike 之實證研究

Public Bike System Pricing and Usage in Taipei

Abstract

Although widely implemented, public bike systems (PBSs) are facing a conflict between system usage and sustainable financing. The relationships between PBS pricing and usage must be clarified to formulate solutions for the conflict. This research used the Taipei PBS, YouBike, as a case study. A stated preference survey was conducted on metro passengers and a binary logit model was applied to analyze the pricing effects of PBS on passengers' choice of using PBS as their transfer mode. A latent class model was also used to identify segment-specific preferences. The empirical data show that whether commuters used PBS as a transfer mode was highly dependent on the basic fee and basic period but not on the variable fee after the basic period; the basic fee mattered to a commuter's choice more than the basic period; irregular PBS users were more sensitive to the basic fee than regular PBS users; and, regular PBS users were more sensitive to the basic period than irregular PBS users. The current results broaden the understanding of how PBS pricing affects its usage and illustrate a pricing policy analysis for YouBike that considers sustainable financing and system usage.

Keywords: public bike system, pricing, stated preference survey, discrete choice analysis, latent class model

Introduction

Biking is a green intra-city travel mode consuming very little energy and producing almost zero pollution. To encourage travelers to use bikes for short-distance trips within neighborhoods or connecting trips between public transit stations and final destinations, many cities developed public bike systems (PBSs), which are also called bike-sharing systems (BSS). Steinsiek (2015) reported that PBSs have been implemented in over 800 cities worldwide, and the number continues to grow. Most PBS projects are developed using public–private partnership approaches in which local governments (who act as supervisors) contract with enterprises or non-profit organizations (who act as operators) to provide services. Governmental supervisors aim to increase PBS ridership, whereas system operators usually seek for profits or self-financing at least. A potential conflict between the concerns of supervisor and operator is that raising the price of PBS usage benefits operator financing but reduces system ridership. For example, the Barclays Cycle Hire system in London doubled access fees to generate an additional revenue of ￡6 million per year in 2013, which resulted in a 29% decline of ridership and a significant number of complaints from citizens (MayorWatch Publications Limited, 2013). The question is whether we can determine a balanced pricing structure that simultaneously meets the financing goals of operators and the ridership goals of supervisors. Clarifying the relationships between PBS pricing and usage is critical to answer the question.

The problem is information about the relationships between pricing and usage is unavailable to transport policy makers because the contemporary PBS began to be popularly implemented and studied only a decade ago. Existing PBS research is limited to general reviews of history and implementations (DeMaio, 2009; Fishman *et al*., 2013; Shaheen *et al*., 2010), worldwide comparisons among systems (O'Brien *et al*., 2014), user behaviors (Corcoran *et al*., 2014; Efthymious *et al*., 2013; Etienne and Latifa, 2014; Faghih-Imani *et al*., 2014; Fishman *et al*., 2012; Fishman *et al*., 2014; Goodman and Cheshire, 2014; Kraemer *et al*., 2012; Martin and Shaheen, 2014; Rixey, 2013; Shaheen *et al*., 2011; Vogel *et al*., 2011; Vogel *et al*., 2014), user perceptions (Nakamura and Abe, 2014), operational studies for rebalancing bikes among stations (Caggiani and Ottomanelli, 2013; Chemla *et al*., 2013; Dell'Amico, 2014; Li *et al*., 2012; Raviv and Kolka, 2013; Raviv *et al*., 2013; Sayarshad *et al*., 2012) and optimization of the spatial distributions of rental stations (Garcia-Palomares *et al*., 2012; Hu and Liu, 2014; Lin and Yang, 2011; Lin *et al*., 2013; Romero *et al*., 2012). Although these studies provide meaningful knowledge about PBS, empirical evidence of pricing effects on PBS usage has yet to be reported.

To fill the research gap on the relationships between PBS pricing and usage, this study used the Taipei PBS, YouBike, as a case study and performed a stated preference survey of metro passengers. Binary logit (BL) models were utilized to analyze PBS pricing effects on whether passengers choose to use PBS as their transfer mode. Latent class BL models were also utilized to identify segment-specific preferences. The empirical results clarify the pricing effects on PBS usage and the effect differences between regular and irregular users. On the basis of identified pricing effects, a policy analysis for YouBike was performed under different pricing scenarios. The current results broaden the understanding of how PBS pricing affects its usage and provide a meaningful basis to pricing policy analyses considering sustainable financing and system ridership.

Transit Pricing Research

The transit pricing research in urban areas pertains to studies that explore traveler responses to fare changes of transit systems. According to the reviews of the Transportation Research Board (2004), the most common objective of transit pricing changes is to increase revenues in response to increases in operation cost. Such changes usually involve fare increases for most transit users. An associate objective is to minimize the ridership loss involved in fare increases. Transit pricing changes can influence revenues and ridership, which significantly concern system operators and governmental supervisors, respectively, and these concerns are usually conflicting. Transit pricing research is known and explored in literature on conventional transit systems, including bus and rail transit services.

Comprehensive reviews and synthesis analyses on transit pricing research can be found in Cervero (1990), Kirby (1982), Litman (2004), and Transportation Research Board (2004).

Existing literature on transit pricing research is mostly either ridership-oriented or revenue-oriented and commonly neglects balanced considerations between revenue and ridership changes. Ridership-oriented pricing studies focus on the effects of fare changes on transit ridership, and they mostly involve governmental policy evaluations. Wong and Skinner (1984) studied the sample data of seven transit authorities and clarified the effects of transit fare increases on monthly ridership. Concas et al. (2005) investigated the effects of fares and fare subsidies on the demand for vanpool services in the Puget Sound region. Zhou and Schweitzer (2011) examined the influences of a fare-free and discounted transit pass program on transit usage in Los Angeles. By contrast, revenue-oriented pricing studies focus on the effects of pricing change on fare revenues of system operators and partially examine the equity of cost-benefit distributions among different user groups. Cervero (1981) concluded that fares differentiated by distance and time of day can reduce inequities and improve the financial performance of transits based on a study of California transit agencies' data. Cervero (1982) used a ratio of revenue and cost per passenger-mile to evaluate the efficiency and equity effects of fare policy proposals in the Southern California Rapid Transit District. Nuworsoo *et al*. (2009) evaluated the effects of fare policy proposals on rider expenditures and agency revenues in the Alameda–Contra Costa Transit District.

A number of transit pricing studies evaluated both ridership and revenue changes and discussed the trade-off between these aspects to identify a balanced pricing policy. Hickey (2005) provided an empirical evidence from New York City, which reveals an offset relationship between revenue and ridership effects after the transit fare increase in 2003. Borndorfer *et al*. (2012) proposed a nonlinear optimization approach to transit fare planning with different optimization objectives, which include maximizing revenue, profit, passengers, user benefit, and social welfare. They conducted a model application study on Potsdam, Germany and evaluated the trade-off between transit demand and revenues for different policies, including subsidies, new ticket type, and new fare system.

Previous studies on transit pricing mostly focused on conventional transit systems, such as bus and rail transit, but did not provide any information about PBS. Two studies in the literature used fare-related variables to explain public bike usage. Zhao *et al*. (2014) adopted the deposit-income per capita ratio (DIR) and the penalty-income per capita ratio (PIR) to explain daily uses and turnover rates of 69 PBSs in China. Deposit means a constant membership fee for PBS usage, and penalty pertains to the charge after the first free use hours. Campbell *et al*. (2016) used PBS travel cost with the levels of 0, 1, and 2 Ren Min Bi (RMB) for a stated preference survey in Beijing, China to explain a traveler's likelihood of using public bike. Both studies reached a similar conclusion, that is, the adopted fare-related variables are insignificant in explaining PBS usage. Such insignificance can be attributed to the low charges and small variances. The PBS travel cost levels used in Campbell *et al*. (2016) are relatively low because the current basic fee of subway is 3 RMB (within 6 km) and that of bus is 2 RMB (within 10 km) in Beijing. The variance coefficients of DIR and PIR in Zhao *et al*. (2014) are 0.7 and 0.5, respectively, and the ratios are below the third decimal place. The review reveals that information about the relationships between PBS pricing and usage is limited. The current study fills the research gap and considers both ridership and revenue changes in policy analysis.

Method

This section describes the stated preference survey of metro passengers and the collected study sample. The models are specified, and the relationships of explanatory variables to the study outcome are hypothesized.

Stated Preference Survey

The survey of this study targets metro passengers leaving or entering metro stations for home-based work trips because Taipei PBS is the major metro transfer mode and work-commuting is one of the major rental purposes. Thi Consultants Inc. (2014) conducted a survey in October 2013 and reported that, among the top 20 origin-destination (O-D) pairs of YouBike rental stations in terms of daily average rentals, 19 O-D pairs included rental stations located beside metro stations during weekdays; approximately a quarter of rentals was for work-commuting and the other two major purposes were school-commuting and recreation.

The outcome in this research is binary, i.e., whether a metro passenger chooses PBS as his or her transfer mode between a metro station and his or her final destination (or origin). This outcome is important to governmental supervisors for promoting green transportation and system operators for increasing revenue. To explain the study outcome, PBS pricing, trip attributes, and individual socio-economic attributes were selected as explanatory variables, and variable data were obtained via a stated preference survey.

The decisions by metro passengers to use PBS as a transfer mode given different PBS pricing scenarios were covered by the first part of survey questions. The YouBike pricing system features three attributes: the basic fee is a constant charge for a rental, the basic period is the maximum rental period charging the basic fee, and the variable fee is a variable charge for a rental after the basic period. The Taipei PBS does not charge membership fees. Its pricing system during the survey period of this study (before March 31, 2015) was as follows: 0 Taiwan Dollar (TWD) for the basic fee, 30 minutes for the basic period, and 10 TWD/30 minutes for the first-four-hour variable fee. This study disregarded the pricing after four hours of a rental because less than 0.5% of rentals were over four hours (Thi Consultants Inc., 2014). Considering the current charge levels of public transportation systems (including bus, metro, and taxi) for short-distance travels in Taipei, the current study determined the attribute levels for setting pricing scenarios, as listed in Table 1. Pricing included four levels for the basic fee, four levels for the basic period, and two types of variable fee; therefore, 32 total combinations were used as pricing scenarios. The attribute levels are sufficiently broad to relate to various pricing scenarios; thus, the study adopted unlabeled experiments and determined the number of total scenarios using the formula L^A in Hensher *et al*. (2005: 112). To simplify the survey for interviewees, this study provided four diverse scenarios in each questionnaire sheet for the interviewees' responses. Eight versions of questionnaire sheets were developed in the survey.

The second part of the survey recorded information about the trip made by passengers and their socio-economic attributes. The trip attributes include a passenger's trip destination (or origin) leaving (or entering) a metro station and travel mode used for this transfer trip. The socio-economic attributes of a passenger include gender, age, occupation, income, education, vehicle ownership, biking capability, and driving license ownership.

To develop an effective survey process and question set, a pioneering survey was conducted in late November 2014. Thirty-nine metro commuters were successfully interviewed in a metro station, and the final version of the stated preference survey in this study was determined according to the commuters' responses.

Study Sample

A stated preference survey was performed during the afternoon peak hours (17:00-20:00) of weekdays between January 5 and February 16, 2015. Weather conditions were controlled for by excluding rainy days from the survey. The four metro stations in Xinyi District were selected as survey stations because the district is the first location to be equipped with PBS rental stations and houses the most PBS rentals for work trips among 12 districts based on the survey of Thi Consultants Inc. (2014). Systematic random sampling method was performed by intercepting metro passengers leaving or entering metro stations at exits nearby PBS rental stations for interviews. The sampling locations include Taipei 101/World Trade Center Station (Exit 2), Taipei City Hall Station (Exit 3), Yongchun Station (Exit 2), and Xiangshan Station (Exit 3).

The survey obtained 372 responses and 1,488 effective observations (372×4, four pricing scenarios for each respondent). The percentage of males was 38.98%, which approximates the male ratios (35.2%, 36.2%, 34.1%, 35.7%, and 37.9%) of Taipei metro passengers between 2010 and 2014 (Ministry of Transportation and Communications, 2015). Roughly 51.88% of the respondents used YouBike as their transfer mode. The study sample adequately represented PBS usage by metro passengers. The answers of respondents to the pricing scenarios were compared with their real travel mode used for transfer trips. If a respondent's answers were inconsistent with real action, the respondent's responses were excluded. For example, if a respondent did not use YouBike as transfer mode for the surveyed trip but answered that he or she would use YouBike given the pricing scenario of 5 TWD for the basic fee, 15 minutes for the basic period, and 10 TWD/30 minutes for the first-four-hour variable fee, then the respondent's responses were viewed as inconsistent with his or her real action because the actual pricing system was 0 TWD for the basic fee, 30 minutes for the basic period, and 10 TWD/30 minutes for the first-four-hour variable fee at that time.

Models

The outcome was binary; thus, BL models were used to clarify the effects of PBS pricing on choosing PBS as a transfer mode. To explore differences in the effects among different passenger segments, this study applied latent class BL models to identify segment-specific preferences.

Table 2 shows the variables used to explain the outcome in discrete choice models. These variables were selected based on Kanafani (1983)'s argument for variables that describe mode choices. Kanafani (1983) drew two variable categories for explaining travel mode choices: socio-economic demand variables and service or supply level variables. Travelers' socio-economic attributes, such as income or age, influence their capability and preference in choosing travel modes. The supply attributes of transport systems, such as costs or service quality, denote the performances of travel mode options that affect travelers' choices. The selected variables in Table 2 are categorized into three attribute groups, of which pricing and trip attributes are supply variables and socio-economic attributes are demand variables.

This research provided the hypothetical effects of explanatory variables on PBS usage (see Table 2) according to the empirical evidence of existing literature. The monetary cost of using a travel mode is recognized as a negative determinant of travel mode usage in the literature (e.g., Campbell, 2012; Chen and Kuo, 2010; Chou *et al*., 2008; Hopkinson and Wardman, 1996; Ortuzar *et al*., 2000; Wen and Lai, 2010), and thus this study hypothesized that the negative effects existing between the basic and variable fees for PBS usage and that the basic period is positively related to PBS usage.

Regarding trip attributes, a transfer distance between metro station and destination or origin should be negatively associated with PBS usage because of the physical limitation of bikers and the empirical evidence of previous studies, such as Broach *et al*. (2012) and Zhao (2014). Bamberg *et al*. (2003) reported that past travel mode choice contributes to the prediction of later behavior if circumstances remain relatively stable; the actual transfer mode chosen by a respondent during interview must be related to his or her choices among various pricing scenarios. Previous studies, including Broach *et al*. (2012), Cervero and Duncan (2003), Cervero *et al.* (2009), Faghih-Imani *et al*. (2014), Moudon *et al*. (2005), Rixey (2013), Soltani and Allan (2006), Tran *et al*. (2015), Winters *et al*. (2010), and Zhao (2014), concluded that providing bike facility positively affects bike usage. Therefore, this study hypothesized that bikeway availability between a metro station and a commuter's destination or origin is positively related to PBS usage. For similar reasons, bus service availability between a metro station and a commuter's destination or origin is expected to be negatively related to PBS usage.

Numerous socio-economic attributes applied in previous studies were also applied in this study to explain PBS usage. Males prefer biking more than females do (Moudon *et al*., 2005; Cervero *et al.*, 2009; Winters *et al*., 2010; Shaheen *et al*., 2011; Bordagaray, 2012; Murphy and Usher, 2015). A commuter's age is positively related to biking (Cervero *et al.*, 2009; Moudon *et al*., 2005; Murphy and Usher, 2015; Shaheen *et al.*, 2011; Zhang, 2004). Shaheen *et al*. (2011) argued that service industry workers ride bikes more than other workers; therefore, a respondent's occupation is expected to be related to PBS usage. Education level shows a well-recognized positive association with bike usage (Shaheen *et al.*, 2011; Rixey, 2013). Bike usage varies by income level according to the previous investigations of Murphy and Usher (2015), Rixey (2013), Shaheen *et al.* (2011), and Zhao (2014). Increased motorized vehicle ownership can decline biking likelihood (Cervero *et al*., 2009; Zhao, 2014), whereas increased bike ownership can elevate bike usage (Cervero and Duncan, 2003; Moudon *et al*., 2005; Cervero *et al*., 2009). A commuter with experience using personal or public bikes as transfer mode tends to use PBS because of the choice of past travel mode contributes to the prediction of later behavior (Bamberg *et al*., 2003). PBS usage is higher among commuters who can ride bikes than among who cannot (Cervero *et al*., 2009). Owning a driving license for motorized vehicle exerts similar effects of owning a motorized vehicle on PBS usage.

Table 3 lists the percentage distributions of explanatory variables for the study sample. The observations are equally distributed among pricing attribute levels because of the design of the stated preference questions. For regression analysis, the values of continuous variables, that is, age and transfer distance, present adequate variations, and the percentage distributions of category variables are generally sufficient among categories. The data showed that most respondents were female, aged 20–40 years old, doing commercial, service or government works, highly educated, with median income level, owning 0–1 bike, 1–2 motorcycles, or 0–1 passenger cars, with experiences in using bus and PBS or walking as transfer modes within the metro, capable of biking, and owning driving licenses for motorized vehicles. Most transfer trips made by the respondents were completed by walking and PBS and within a distance of 3 km. Most respondents indicated that bus services and bikeways were available between their destinations (or origins) and metro stations.

Results

Based on the outcome and explanatory variables defined above, this study employed NLOGIT 5.0 software package and the maximum likelihood method to estimate coefficients of BL and latent class BL models. Table 4 lists the estimation results, in which explanatory variables with a coefficient significance below the confidence level of $1-\alpha=90\%$ in all models were withdrawn from the estimations. All estimation models exhibited an acceptable goodness-of-fit and coefficient signs consistent with the hypothetical relationships in Table 2. This study used the results for the following discussions.

Empirical Evidence

The BL model shows that the basic fee and the basic period are the pricing attributes with the largest effects on PBS usage. Decreasing the basic fee or increasing the basic period encourages metro passengers to use PBS as a transfer mode. However, the variable fee does not significantly affect the transportation preference of metro passengers. The variable fee was not considered important by the surveyed commuters because over 80% of YouBike rentals were less than the basic period (30 minutes) during weekdays (Thi Consultants Inc., 2014). The above results for pricing variables also appear in the latent class BL models; thus, the basic fee and the basic period must be more critical than the variable fee in developing PBS pricing policies. Regarding trip attributes, transfer distances and used transfer modes of walking and riding bus are negatively related to PBS usage as predicted in Table 2. Contrary to the hypothesized effect, the presence of a bus service between a destination (or origin) and a metro station positively affects PBS usage. A possible explanation for this contradicting result is that some metro passengers changed their transfer modes from taking buses to riding public bikes when YouBike was equipped. In Taipei, bus fares are much higher than PBS fares for a short-distance travel within a couple of bus stops. Based on the survey of Thi Consultants Inc. (2014), 31.3% of YouBike rentals were from bus users. Regarding socio-economic attributes, individual income, car ownership, and owning driving license for passenger car are negatively related to PBS usage. By contrast, bike ownership, biking experience, and biking capability are positively related to PBS usage. The above results are all consistent with the expected outcomes. The positive effect of owning driving license for motorcycle on PBS usage is inconsistent with the expectation in Table 2 and needs further exploration. Equipping bike facilities along a transfer route and the gender, age, occupation, and education of commuters are insignificant in explaining PBS usage.

The latent class model contains two segments. The pricing and trip attributes are used as utility function variables, and the socio-economic attributes are used as membership function variables. The two-segment model was selected because its Bayesian information criterion (BIC) value was lower than the three-segment model (1057.8 < 1173.2). Compared with that in Table 4, tests of the other two membership functions, trip attribute variables, and trip plus socio-economic attribute variables reveals a worse goodness-of-fit (Adj. ρ^2 = 0.4083 and 0.3307, respectively). The likelihood ratio test result reveals that discriminating utility functions between different socio-economic segments significantly improves goodness-of-fit in explaining PBS usage. Based on the membership function, the respondents of segment 1 can be characterized by those who were rich, seldom use PBS, and owning driving license for cars. This study referred to the respondents of segments 1 and 2 as irregular and regular PBS users. The comparisons show two important differences in utility functions. First, almost all trip attribute variables are positively related to PBS usage among regular PBS users, whereas irregular users indicate a contrasting result. Thus, regular users are more likely to change their transfer modes (especially walking and taking bus) to using public bikes than irregular users. Second, for pricing attributes, the effects of basic fee and basic period on PBS usage follow the same direction with a slight difference. Table 5 lists the elasticity and willingness-to-pay of the significant pricing variables. The results indicate that irregular users are more sensitive to changes in the basic fee than regular users, and regular users are more sensitive to the changes of basic period than irregular users. The above differences offer policy implications. For example, when a PBS operator raises the basic fee for financial concerns, a local government can extend the basic period, at least for regular users, to haul back PBS ridership.

Policy Analysis

The empirical data were used to conduct a pricing policy analysis for YouBike. Taipei City Government was reviewing YouBike's pricing system for financial reasons from February–March 2015. The government implemented a free-30-minutes policy after YouBike was launched in 2009 to promote PBS usage. In the contract with the system operator, the basic fee is 10 TWD for the first 30 minutes of a rental. The free-30-minutes policy requires the government to pay the basic fee to the system operator for each rental. The policy yielded an obvious boost in usage and increase of YouBike rental stations. Despite the high YouBike ridership, revenues lagged because most riders returned bikes within 30 minutes. Therefore, the pricing system must be designed to reduce the financial burden on the government, maintain reasonable revenue for system operators, and achieve desirable PBS ridership. The above concerns are all related to PBS usage, which is associated with the basic fee and basic period for the transfers of metro passengers.

A policy analysis was performed using the latent class BL model in Table 4 under the following assumptions: a million metro commuters for home-based work travel must choose a transfer mode; for a single weekday without rain during afternoon peak hours, the hypothesized commuters have the same distributions of trip attributes and socio-economic attributes that the surveyed sample in this study have; and 72.1% of rentals are 15 minutes or less, 23.1 % of rentals are 15±30 minutes, and the others are 30±60 minutes, based on the YouBike rentals of work trips surveyed in Thi Consultants Inc. (2015). The pricing scenarios were set as follows:

Scenario 1: Basic fee is 0 TWD and basic period is 30 minutes. The pricing system was implemented until March 31, 2015.

Scenario 2: The conditions are the same as those in Scenario 1 except the city increases the basic fee to 5 TWD after April 1, 2015.

Scenario 3: The first 15 minutes are free, and the basic fee is increased to 7 TWD. The basic period remains 30 minutes.

Scenario 4: The conditions are the same as those in Scenario 3 except the basic fee is changed to 5 TWD.

Scenario 5: Basic fee is increased to 5 TWD and basic period is increased to 45 minutes.

Scenario 6: Basic fee is increased to 5 TWD and basic period remains 30 minutes for segment 1; basic fee is increased to 2.5 TWD and basic period remains 30 minutes for segment 2.

Scenario 7: Basic fee is increased to 2.5 TWD and basic period remains 30 minutes.

Table 6 lists the policy analysis results that only consider rentals within 30 minutes. Among the scenarios, Scenario 1 is the original pricing system and results in the highest PBS ridership and operator revenue, which is fully from municipal subsidy. Scenario 2 is the municipal decision and has been implemented since April 1, 2015. This decision significantly decreases municipal subsidy while substantially decreasing PBS ridership and operator revenue. These dramatic decreases of revenue and ridership raised concerns because these conditions can adversely affect sustainable PBS development and the municipal goals of green transportation. The next question was whether an alternative can be considered aside from the original pricing and the municipal decision. Scenarios 3 and 4 maintain a free 15-minute use and operate the similar basic fee and period as in Scenario 2. Thus, PBS ridership and operator's revenue are better than those in Scenario 2 but the governmental shares of payment remain higher than 80%. Scenario 5 simultaneously charges the same basic fee of Scenario 2 and extends the basic period to 45 minutes. Scenario 7 maintains the same basic period of Scenario 2 and charges lower basic fee than that in Scenario 2. Comparing with the municipal decision, these two scenarios increase 4%–13% of PBS ridership, 45%–60% of operator's revenue, and 17%–25% of governmental shares of payment. Scenario 6 follows Scenario 2 but provides a 50% discount of basic fee to regular users. The scenario makes a relatively low municipal share of payment and limited increases of ridership and revenue. Among the last five scenarios, Scenarios 4, 5, and 7 must be more acceptable to system operators than the other scenarios because these scenarios create relatively high levels of revenue. Among these three scenarios, municipal supervisors must prefer Scenarios 5 and 7 because of the relatively low levels of governmental shares of payment in these scenarios. Scenario 7 is the best option to balance the objectives of usage and financial sustainability because this scenario results in a significantly higher share of PBS use than that in Scenario 5. Actual events in the real world were consistent with the estimations of the above policy analysis. Before the Scenario 2 was launched in Taipei, the average number of monthly YouBike rentals was two million. After raising the basic fee to 5 TWD on April 1, 2015, the average number of monthly YouBike rents decreased to 1.5 million, which indicates a 25% decrease. The number of monthly rentals remained low recently. The latest data show that ridership was approximately 1.6 million in October 2016 (YouBike, 2016).

Conclusions

This case study of the Taipei YouBike scheme explored the relationships between PBS pricing and usage. The empirical data showed that the basic fee and basic period significantly affect metro passengers' decision to use PBS as a transfer mode, whereas the variable fee after the basic period is insignificant. The basic fee exerts a larger effect than the basic period. Irregular PBS users are more sensitive to the basic fee than regular PBS users, and regular PBS users are more sensitive to the basic period than irregular PBS users. To the best of our knowledge, such evidence does not exist in extant research. Applying empirical data in policy analysis showed that multiple pricing alternatives exist and must be considered to balance sustainable financing and system usage more than municipal decisions, which caused a significant decrease of PBS usage and operator revenue.

Further studies of the relationships between pricing and PBS usage are needed to examine three issues, which reflect limitations of this study. The first issue is related to the study sample. This study surveyed metro passengers who were conducting home-based work travels in Xinyi. Aside from work travel, Fishman *et al.* (2013) reported that school commutes and recreational biking are two other significant purposes of PBS usage. The price elasticity of public transit systems is known to vary by trip purposes and study regions (Litman, 2004); thus, future research must investigate populations with different trip purposes in more areas to generate comprehensive information.

The second issue is associated with pricing systems. The YouBike pricing system is only one of the many pricing systems used in the world. The empirical results of this study could be referenced by the PBSs whose pricing systems are similar to YouBike, i.e., charging a basic fee within a basic period without membership fee. At least three pricing systems are used in other cities. One option is charging a periodical membership fee (annually, monthly, weekly, or daily) or a deposit and providing a free basic period for each rental. This pricing system is widely implemented in most of the PBSs in European, American, and Chinese cities. Another option, which is used by Bycyklen in Copenhagen, Denmark, is to charge a deposit and provide free use forever. A third option, which is used by OV-fiets in Amsterdam, the Netherlands, involves charging an annual membership fee and a constant daily fee for each rental. Further surveys of pricing systems and city contexts are required to compare how pricing affects PBS usage in various pricing systems and the causes of the differences.

The last issue concerns the research method. This study applied BL models to analyze a binary choice of using PBS as a transfer mode. Although this approach clarified how PBS pricing affects PBS usage, it could not explore the relationships between alternative transfer modes (walking, taking a bus, and riding a motorcycle) and PBS. How do bus fee changes affect PBS usage? How do PBS pricing changes affect the likelihood of walking, taking a bus, and riding a motorcycle? To answer the questions, multinomial choice models must be applied in future studies.

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Table 1 Attributes and levels in the stated preference survey

Attributes	Levels
Basic fee	0, 5, 10, 15 (TWD)
Basic period	15, 30, 45,60 (Minutes)
Variable fee	*Progressive rate* (5 TWD for the 1st half-hour and 10 TWD per half-hour afterward) and *Constant rate* (7 TWD per half-hour)

Table 2 Definitions of explanatory variables and hypothetical effects on using PBS

Name	Definition	Unit	Effect
Pricing			
Basic fee	Constant charge for a rental of YouBike.	TWD	-
Basic period	Maximum rental period charging basic fee.	min.	+
Variable fee	Variable charge for a rental period after the basic period: progress rate (=1) or constant rate (=0).	--	-
Trip			
Transfer distance	Travel distance between a respondent's destination (or origin) and metro station.	m	-
Transfer mode	A respondent traveled between destination (or origin) and metro station by walking (Tra-walk = 1), YouBike (Tra-pbs = 1) or bus (Tra-bus = 1) when he or she was interviewed; using the other modes is the base.	--	+/-
Bus service	There is (=1) or is no (=0) bus route directly connecting a respondent's destination (or origin) and metro station.	--	-
Bike facility	There is (=1) or is no (=0) bikeway connection between a respondent's destination or origin and metro station.	--	+
Socio-economy			
Gender (male)	Gender of respondent: male (=1) or female (=0).	--	+
Age	Age of respondent.	year	-
Occupation	Occupation of respondent: Occ 1 = 1, manufacture; Occ 2 = 1, commerce; Occ 3 = 1, service; Occ 4 = 1, governmental officer; Occ 5 = 1, self employed; other is the base.	--	+/-
Education	Highest education level of respondent: Edu 1 = 1, bachelor degree; Edu 2 = 1, master degree or higher; senior high school or lower is the base.	--	+/-
Income	Monthly income of respondent: Inc 1 = 1, $30\sim50^-$ thousand TWD; Inc 2 = 1, $50\sim70^-$ thousand TWD; Inc 3 = 1, 70^+ thousand TWD; $0\sim30^-$	--	-

	thousand TWD is the base.		
Bike ownership	Bikes owned by respondent: Bike 1 = 1, owning one bike; Bike 2 = 1, owning two bikes or more; not owning bike is the base.	--	+
Motorcycle ownership	Motorcycles owned by respondent: Moto 1 = 1, owning one motorcycle; Moto 2 = 1, owning two motorcycles or more; not owning motorcycle is the base.	--	-
Car ownership	Passenger cars owned by respondent: Car 1 = 1, owning one car; Car 2 = 1, owning two cars or more; not owning car is the base.	--	-
Experience	Experience of respondent using personal bikes (Exp-bike = 1) or public bikes (Exp-pbs = 1) as transfer modes; other is the base.	--	+
Biking capability	A respondent is (=1) or is not (=0) capable of riding bikes.	--	+
License ownership	A respondent is licensed to drive motorcycle (Lic-motorcycle = 1) or passenger car (Lic-car = 1); other is the base.	--	-

Table 3 Percentage distributions of explanatory variables for the study sample

Variable	Percentage
Pricing	
Basic fee	0: 25%; 5: 25%; 10: 25%; 15: 25%
Basic period	15: 25%; 30: 25%; 45: 25%; 60: 25%
Variable fee	Progressive rate: 50%; Constant rate: 50%
Trip	
Transfer distance	500 m or less: 27.42%; 501-1,500 m: 51.08%; 1,501-3,000 m: 15.32%; 3,001 m or more: 6.18%
Transfer mode	Walking: 40.59%; YouBike: 51.88%; bus: 6.45%; motorcycle: 1.08%
Bus service	Yes: 66.13%; no: 33.87%
Bike facility	Yes: 76.88%; no: 23.12%
Socio-economy	
Gender (male)	Male: 38.98%; female: 61.02%
Age	19 or less: 1.08%; 20-29: 43.01%; 30-39: 30.38%; 40-49: 15.59%; 50-59: 6.72%; 60 or more: 3.23%
Occupation	Manufacture: 4.84%; commerce: 27.42%; service: 29.03%; governmental officer: 17.74%; self employed: 4.03%; other: 16.94%
Education	Bachelor degree: 64.52%; master degree or higher: 28.76%; senior high school or lower: 6.72%
Income	0~30^- thousand TWD: 23.39%; 30~50^- thousand TWD: 47.58%; 50~70^- thousand TWD: 19.35%; 70^+ thousand TWD: 9.68%
Bike ownership	Not owning bike: 44.09%; owning one bike: 31.99%; owning two bikes or more: 23.92%
Motorcycle ownership	Not owning motorcycle: 23.39%; owning one motorcycle: 43.28%; owning two motorcycles or more: 33.33%
Car ownership	Not owning car: 35.48%; owning one car: 48.12%; owning two cars or more: 16.40%
Experience	Personal bikes: 22.04%; public bikes: 71.77%
Biking capability	Yes: 97.85%; no: 2.15%
License ownership	Motorcycle: 75.34%; passenger car: 72.11%

Table 4 BL and latent class BL models (outcome: using PBS=1)

Variable	BL model Coefficient (t-value)	Latent class BL model Coefficient (t-value)	
		Segment 1	Segment 2
Pricing	*For utility function*	*For utility function*	
Basic fee	-0.2026 (-13.29***)	-0.3682 (-11.01***)	-0.2000 (-5.06***)
Basic period	0.0182 (4.18***)	0.0179 (2.19**)	0.0333 (2.97***)
Variable fee	-0.0879 (-0.61)	-0.2722 (-1.11)	0.4494 (1.12)
Trip	*For utility function*	*For utility function*	
Transfer distance	-0.0002 (-3.04***)	-0.0002 (-1.56)	-0.0007 (-3.44***)
Tra-walk	-3.0411 (-14.17***)	-4.5439 (-5.18***)	0.9387 (1.75*)
Tra-pbs		4.0771 (7.84***)	0.8755 (1.65*)
Tra-bus	-1.5605 (-3.38***)		
Bus service	0.4061 (2.18**)	-0.7474 (-1.77*)	3.0149 (5.22***)
Socio-economic	*For utility function*	*For membership function*	
Inc 3	-0.5513 (-2.05**)	1.6596 (1.68*)	-
Bike 2	0.3577 (1.94*)		
Car 1	-0.3225 (-1.85*)		
Car 2	-0.6474 (-2.77***)		
Exp-bike	0.8066 (4.31***)		
Exp-pbs	1.1546 (5.18**)	-0.9780 (-2.11**)	-
Biking capability	0.7420 (1.84*)		
Lic-motorcycle	0.4295 (2.44**)	-0.9911 (-1.95*)	-
Lic-car	-0.3598 (-2.15**)	0.7559 (2.19**)	-
Constant of membership function		2.0818 (3.66***)	-
Segment size		76.1%	23.9%
Final log-likelihood	-596.6510	-485.0578	
AIC	1225.3	994.1	
BIC	1310.2	1057.8	
Likelihood ratio	0.4102	0.5294	
Adjusted likelihood ratio	0.3944	0.5233	
Likelihood ratio test vs. BL		223.1864***	

Notes: Number of observations: 1,488; *** significant at α=0.01; ** significant at α=0.05; * significant at α=0.1

Table 5 The elasticity and (willingness-to-pay) of pricing variables

Variable	BL model	Latent class BL model	
		Segment 1	Segment 2
Basic fee	-0.5056	-1.2058	-0.6316
Basic period	0.2274	0.2925	0.5198
	(0.0899)	(0.0486)	(0.1666)

Table 6 Policy analysis results

Scenario	Share of PBS use (%)		A = user payment (TWD) [A/(A+B)]	B = municipal payment (TWD) [B/(A+B)]	A+B = operator revenue (TWD)
1	S.1: 39.84		0	5,804,100	5,804,000
	S.2: 18.20	T: 58.04	[0%]	[100%]	
2	S.1: 10.79		1,379,900	1,379,900	2,759,800
	S.2: 16.81	T: 27.60	[50%]	[50%]	
3	S.1: 34.46		558,817	2,284,771	2,843,588
	S.2: 17.65	T: 52.11	[20%]	[80%]	
4	S.1: 29.21		362,862	4,081,485	4,444,347
	S.2: 18.16	T: 47.37	[8%]	[92%]	
5	S.1: 13.56		1,463,780	2,927,559	4,391,339
	S.2: 17.65	T: 31.20	[33%]	[67%]	
6	S.1: 10.79		1,157,327	1,686,773	2,844,100
	S.2: 17.65	T: 28.44	[41%]	[59%]	
7	S.1: 22.55		1,004,996	3,014,988	4,019,985
	S.2: 17.65	T: 40.20	[25%]	[75%]	

Note: S.1 and S.2 denote the segments 1 and 2 respectively; T denotes the total share.

肆、建成環境對公共自行車使用之影響：台北、北京與東京之比較

Built Environment and Public Bike Usage for Metro Access: A Comparison of Beijing, Taipei and Tokyo

Abstract

This article presents a transnational comparison study to clarify how different the influences of built environment on public bike usage are among three cities in eastern Asia. The study sampled passengers entering or leaving metro stations in Beijing, Taipei and Tokyo. Their mode choices of connecting travels between trip endpoints and metro stations were analyzed using logit and latent class models. The empirical evidence reveals that the built environment influences on public bike usage of the survey cities are significantly different from each other and cities having similar cultural bases reveal relatively similar influences. The results imply that the empirical knowledge of built environment influences on public bike usage would be not transferable among transnational cities even though they are geographically close. Empirically cumulating local knowledge of travel behavior is critical to develop bike-friendly built environments for a city.

Keywords: built environment, public bike, metro access, logit model, latent class model.

Introduction

The success of the public bike system (PBS; also named as bike sharing system) launched in Lyon in 2005 initiated an explosive growth of PBS services globally in the past decade. According to The Bike-sharing Blog (http://bike-sharing.blogspot.tw/), 1,188 PBS programs worldwide operated near 2.3 million public bikes in the end of 2016. Given the fact that PBS is an innovative transport solution and PBS programs have been sharply increased worldwide in the past decade, the previous bicycle research provides very limited knowledge to support PBS development. Consequently, increasing PBS studies contribute understanding the system recently. The existing PBS studies majorly cover general reviews of history and implementations (e.g., Fishman *et al*., 2013; O'Brien *et al.*, 2014), user behaviors (e.g., Corcoran *et al*., 2014; Etienne and Latifa, 2014), repositioning bikes among rental stations (e.g., Caggiani and Ottomanelli, 2013; Dell'Amico, 2014), optimizing spatial distributions of rental stations (e.g., Lin and Yang, 2011; Lin *et al*., 2013), and determinants of PBS usage (e.g., Fishman *et al*., 2014; Tran *et al*., 2015).

Built environments have been recognized as significant determinants of travel demand in either theoretical research (e.g., Boarnet and Crane, 2001) or empirical studies (e.g., Ewing and Cervero, 2010). Clarifying built environment influences on travel demand benefits developing travel demand management strategies to meet local development goals via urban planning and design. Consequently, the relationships between built environment and PBS usage are important to develop a PBS-friendly environment. Despite the importance, very few studies have explored the relationships. Faghih-Imani *et al*. (2014), Rixey (2013) and Tran *et al*. (2015) applied regression methods to analyze the influences of built environments on arrivals and departures of a PBS rental station; and, Cheng and Lin (2016) applied discrete choice models to explore built environment influences on an individual commuter's decision of choosing PBS as his/her metro access mode. These studies discovered a number of environmental attributes that are significant determinants of PBS usage in their study cities, and their empirical evidence is from either a single city (Cheng and Lin, 2016; Faghih-Imani *et al*., 2014; Tran *et al*., 2015) or multiple cities in a single nation (Rixey, 2013). A number of previous research found that built environment influences on travel demand are inconsistent among cities of different nations. For example, the empirical evidence of Mertens *et al*. (2017) reveals significant dissimilarities of built environment influences on cycling existing among cities in five nations across Europe. If empirical findings are dissimilar among nations, it should be careful to refer to empirical findings of other nations.

To clarify how similar the built environment influences on PBS usage are among transnational cities that are geographically and culturally close, the present research conducted a comparison study of three cities in Eastern Asia. The sample observations are metro commuters entering or leaving the survey metro stations in Beijing, Taipei and Tokyo. The transportation mode used by a respondent to travel between a metro station and his/her trip endpoint (origin or destination) and the built environment attributes around his/her trip endpoint and travel route were recorded and analyzed. Binary logit and latent class models were applied to analyze the sample data. The empirical results not only contribute novel evidence to the study cities but also remind local administrations of their cautiousness when referring empirical knowledge abroad.

Method

Survey

Table 1 lists background information on the investigated PBSs. The present research selected Beijing, Taipei and Tokyo as study cities because they are geographically close (Fig. 1 (a)), have similar cultural contexts (Zhang *et al*., 2005), formally launched their PBSs in the same year (2012) and are all in well operation currently. The investigated PBSs are all so-called the 3^{rd} generation system (DeMaio, 2009) that users rent and return bikes at service stations applying telecommunication technologies. There is a little difference among the PBSs in pricing. The Municipal PBS in Beijing charges membership fee and provide one-hour free riding for each use (membership-based); the YouBike in Taipei is free for membership registration and charge using fee by time (use-based); and, the Tokyo Bike Share operates membership-based and use-based pricing simultaneously.

The survey works stared at Taipei in January, 2015 and ended at Beijing in May 2016. To control weather conditions, rainy days were excluded from the survey dates and average temperatures in the survey months are between 8 and 20 ^{o}C. The survey target was metro passengers leaving or entering metro stations for home-based work trips in order to maintain a consistent trip purpose. The metro stations having similar contexts in their surrounding areas were selected as survey stations as shown in Fig. 1 (b), (c) and (d). These seven metro stations are all located at flat, dense and inner city areas. The surroundings of survey stations are all mixed land uses of office buildings, restaurants, retailing, amenities and multi-family dwellings.

The questionnaire surveys were conducted during afternoon-peak-hours of weekdays. A systematic random sampling was used to intercept metro users leaving or entering metro stations at exists nearby PBS rental stations for interviews. On-site interviews were applied to the respondents in Beijing and Taipei while delivering instruments on-site and self-reporting by mail were applied to the respondents in Tokyo. The instruments used in the three cities contain three parts of questions. The first part collected information about a decision made by a metro passenger to choose PBS as a connecting travel mode. The second part of questions requests a respondent to locate his or her trip endpoint (destination or origin) and travel route between metro station and trip endpoint on a map. By using of the location records, built environment attributes around trip endpoints and along travel routes for every respondent were obtained using various database. Finally, the third part of questions records information about socio-economic attributes including gender, age, income, vehicle ownership and driving license ownership.

The survey obtained 946 effective observations, of which 332, 311 and 304 observations were from Beijing, Taipei and Tokyo respectively. Among the observations, Taipei respondents revealed the highest percentage (50%) of using PBS as their connecting travel modes while Tokyo respondents revealed the lowest (but still significant) percentage (20%).

Variables

The model specification and variable selection in this study are based on the research of Cheng and Lin (2016). They explored the influences of built environments on PBS usage in Taipei and provide the Taipei results for comparison in the present research. Binary logit (BL) models were adopted to analyze binary outcomes (use or non-use of PBS), and latent class BL models were applied to identify differences in influence among different passenger segments.

Table 1 lists the definitions of explanatory variables used in discrete choice models and their hypothetical influences on using PBS. These variables are all used to explain the Taipei observations but partially used to explain the Beijing and Tokyo observations owing to data limitations. The variables contain built environment variables and control variables. The present research determined built environment variables by six dimensions: density, diversity, design, distance to transit, destination accessibility, and distribution of rental stations. The first five dimensions are from the 5Ds attributes raised in Cervero *et al*. (2009) for explaining general bike usage and the 6th dimension is specifically considered for public bikes. Because PBS users rent and return bikes at rental stations, distributions of rental stations was expected to affect PBS usage. The previous surveys including Bordagaray (2012), Faghih-Imani *et al*. (2014), Fishman *et al*. (2014) and Rixey *et al*. (2013) found that increasing numbers of nearby rental stations encourage people to use public bikes. Therefore, the station number in a trip endpoint area and the distance from a trip endpoint to the nearest rental station were hypothesized to have positive and negative effects, respectively, on public bike usage. A trip endpoint area refers to the area within 350 m buffer-ring using travel distance on practical road network and center of a respondent's destination (for whom leaving metro station) or origin (for whom entering metro station). The distance of 350 m is the service distance of a rental station used in the station setting criteria of Taipei (Department of Transportation, Taipei City Government, 2016). To maintain a similar comparison basis, the 350 m buffer-ring was also applied in Beijing and Tokyo models.

Regarding 5D attributes, this study selected variables and hypothesized their effects on PBS usage according to previous works. Densities of population, employment and students have shown a positive association with public bike use in the aggregate studies of Faghih-Imani *et al*. (2014), Rixey *et al*. (2013) and Tran *et al*. (2015), while Soltani and Allan (2006) found a negative association exists between building density and private bike uses. The limited road space in a dense building environment is commonly unfavorable to biking. The above relationships could also exist in the present disaggregate study of public bike usage. Various measures of land use diversity used in previous studies have shown a positive association with private bike usage owing to shortened travel distances. Those measures include the land use entropy index (Winters *et al*., 2010; Zhao, 2014), the commercial ratio (Moudon, *et al*., 2005) and the job-housing balance index (Zhao, 2014), and they are also used in this study to explain public bike usage as defined in Table 1. Meanwhile, this study modified the job-housing balance index developed by Zhao (2014) as described in note b of Table 1 in order to maintain a similar value meaning to the other two diversity variables, i.e., the higher the index value, the higher the diversity degree. Numerous road design attributes have been reported to be associated with biking. These attributes include intersections, lengths, area, directness, traffic signs and lights, lamps, trees and green fields along roads (Broach *et al*., 2012; Cervero *et al*., 2009; Cervero and Duncan, 2003; Faghih-Imani *et al*., 2014; Moudon *et al*., 2005; Rixey *et al*., 2013; Soltani and Allan, 2006; Tran *et al*., 2015; Winters *et al*., 2010; Zhao, 2014). Since these attributes are interrelated with each other, this study conducted principle component analyses and got two to four independent components, which explain 58% to 63% of sample variation, for the three cities as listed in Appendix 1. This study named the components according to the variables revealing absolute values of loadings over 0.6 (Hair *et al*., 1992). The Bike friendliness components are positively related to bike-friendly facilities, including bikeways, green fields, street trees and street lamps, and is negatively related to intersections, road space and traffic signs that could interrupt biking. Hence, this study hypothesized that Bike friendliness has a positive influence on PBS usage. The Road facility components are positively related to intersections, arterial/street length and road amenities that could result in both positive and negative effects on biking. Arterials provide more road space to bikers while attract heavier vehicle volume and safety concerns than local streets. The Vehicle mobility components are positively related to road space, traffic signs and lights and road lamps, all of which increase traffic flow speeds and discourage biking owing to safety concerns. Faghih-Imani *et al*. (2014), Tran *et al*. (2015) and Zhao (2014) reported a negative association between bike uses and distances to transit stations. This study used three distance variables to measure the distances from a respondent's trip endpoint to the nearest metro station, the nearest bus stop and the actually used metro station. Finally, the destination accessibility variables in Table 1 were used to measure access to interesting locations including local commercial centers, trip attractions and retailers. These accessibilities are all expected to positively influence PBS usage according to the findings of Broach *et al*. (2012), Faghih-Imani *et al*. (2014), Fishman *et al*. (2014), Moudon *et al*. (2005), Rixey *et al*. (2013), Tran *et al*. (2015) and Zhao (2014). However, owing to the significant correlation among the interesting locations, this study used principle component analyses to obtain the Destination accessibility components shown in Appendix 1. A positive relationship was expected between the components and PBS usage.

Table 1 has three groups of control variables: individual, environment and PBS. Many individual socio-economic attributes have been reported to be related to biking in the literatures. The positive individual attributes that encourage biking for work-commuting are male (Bordagaray, 2012; Cervero *et al.*, 2009; Moudon *et al*., 2005; Murphy and Usher, 2015; Shaheen *et al.,* 2011; Winters *et al*., 2010) and bike ownership (Cervero *et al.,* 2009; Cervero and Duncan, 2003; Moudon *et al*., 2005); and, the individual attributes that discourage biking are age (Cervero *et al.,* 2009; Moudon *et al*., 2005; Murphy and Usher, 2015; Shaheen *et al.*, 2011), income (Murphy and Usher, 2015; Rixey *et al.,* 2013; Shaheen *et al.,* 2011; Zhao, 2014), and motorized vehicle ownership (Cervero *et al.,* 2009; Zhao, 2014). Many environmental attributes other than built environments are expected to discourage biking, including steep slopes (Cervero *et al.,* 2009; Broach *et al*., 2012; Faghih-Imani *et al*., 2014) and heavy traffic flows (Broach *et al*., 2012). Environmental safety concerns, including traffic accidents (Cervero *et al*., 2009) and poor public security, are also expected to reduce interest in cycling. As for PBS attributes, Tran *et al*. (2015) argued that the numbers of public bikes (or numbers of docks) in rental stations are positively associated with public bike use, which was also hypothesized in our study. Costs (money, time, distance, etc.) of using a travel mode are also well known negative determinants of travel mode usage (Campbell, 2012; Cheng and

Kuo, 2010; Hopkinson and Wardman, 1996; Ortuzar *et al*., 2000; Wen and Lai, 2010). Therefore, this study hypothesized that the basic fee is negatively associated with PBS usage and that the basic period is positively associated with PBS usage. A stated preference survey for the YouBike pricing and usage was conducted in Taipei and its details can be found in Cheng and Lin (2016). Because of data limitation and the absence of pricing survey, only individual variables were used in Beijing and Tokyo models.

Data

Sample data were collected by three approaches. First, the questionnaire survey described in the *Survey* sub-section was used to collect data for control variables of individual and PBS pricing attributes. Second, according to the respondent locations of trip endpoints (destinations or origins) and travel routes between metro stations and trip endpoints, data related to the built environment variables and the control variables of environment attributes were obtained from existing databases and published documents. Finally, data of traffic signs and lights were obtained by conducting field investigations. All variable data were for the base year of 2015. Since some of the newest databases and documents did not match the base year, 2011-2015 were used as the variable data years.

Results and Discussions

The NLOGIT 5.0 software package and the maximum likelihood method were used to estimate model coefficients. Appendix 2 lists the estimation results, in which explanatory variables with coefficient-significances below the confidence level of 1-α=90% in all utility functions were withdrawn from the estimation. All of the estimated models had acceptable goodness-of-fit, and the coefficient signs for most of the estimated models were consistent with the hypothetical relationships in Table 2. Detailed discussions on the Taipei results and their implications can be found in Cheng and Lin (2016) and are not repeatedly stated here. The present research places an emphasis on comparisons of the studied cities.

Built Environments

Table 3 lists the empirical effects of explanatory variables on PBS usage for the survey cities. The significant built environment variables in Taipei model cover all six of the dimensions while the variables of diversity and distance to transit are unable to explain Beijing and Tokyo observations' behaviors of using PBS.

Regarding density variables, as population density increased, PBS usage increased in Beijing and Tokyo. This positive relationship is consistent with the expectation in Table 2 and the findings of previous research including Faghih-Imani *et al*. (2014), Riexry (2013) and Tran *et al*. (2015). However, population density was negatively related to PBS usage in Taipei and its possible explanation is that increasing population density increases the possibility of bike-unavailability at rental stations, which then decreases intention for a commuter to use PBS (Cheng and Lin, 2016). Because Taipei PBS has a high turn-over rate (8.7 rentals per bike per day in June 2017) and does not charge membership fee, commuters easily tend to use alternative travel modes when there is no available public bike. The employment density is positively related to PBS usage in Tokyo but is negatively related to that in Taipei. The former is contrary to the hypothesized effect and is owing to land uses nearby the survey metro station in Tokyo. Office buildings are mostly located nearby Toyosu station and hence it is unnecessary to use bike between the station and trip ends. The building density is negatively related to public bike usage in Beijing and this result echoes Soltani and Allen (2006)'s findings on private bike usage. However, building density does not explain Taipei and Tokyo observations.

As for design variables, the PBS uses in three cities are all significantly explained by road facility components, which are positively associated with road (arterial or street) intersections, length and space. Noteworthily, the coefficients of road facility are positive in Beijing and Taipei models and negative in Tokyo model. These contrary results imply that Beijing and Taipei observations could concern ample road space for biking while Tokyo observations could care about safety concerns of heavy traffic volume.

The PBS usage in three cities are all related to destination accessibility variables but their relationships are mostly dissimilar among cities. The only consistent result is the negative relationships between distances to local commercial centers and PBS usage in Beijing and Taipei. Besides that, Beijing and Taipei models reveal contrary relationships between retail accessibility and PBS usage, and Taipei and Tokyo models reveal contrary relationships between the attraction variable and PBS usage.

Finally, a distance to PBS station is negatively related to PBS usage in both Beijing and Taipei models, and it confirms the expectation in Table 2.

Controls

There are three control variables revealing significant coefficients in two city models simultaneously. The negative coefficients of age and license-car in Taipei model and income variables in Tokyo model are consistent with the hypothesized effects; however, the positive coefficients of age, income and license-car in Beijing model are contrary to not only the other two cities but also the findings of previous bike use surveys including Cervero *et al.* (2009), Moudon *et al*. (2005), Murphy and Usher (2015), Rixey *et al.* (2013) and Shaheen *et al.* (2011). The above positive effect of age on PBS uses is consistent with the empirical evidence of Zhao (2014) and Zhao and Li (2017) for general bike uses in Beijing. Such unique results in Beijing need further explorations in the future.

Segmentation

The latent class models in Appendix 2 identify utility functions of different observation segments for the survey cities. This study used the individual variables as membership function variables and the other explanatory variables as utility function variables. The segment numbers were determined according to lower AIC values and higher ρ^2 values compared to the other models with different segment numbers. The two-segment model of Beijing suggests that young and low-income commuters who do not own driver license of car tend to select travel modes other than PBS in a compact built environment; on the contrary, elder and median-income commuters who own driver license of car tend to use PBS in a resident-concentrated area. Regarding Taipei observations, the four-segment model reveals that young and male commuters who own bike and do not own driver license of car most concerned about built environments in selecting PBS as a connecting travel mode because the coefficients of built environment variables are only significant in the Segment 3 model. Finally, the two-segment model of Tokyo implies that male and low-income commuters tend to select PBS in an area where has more arterials and less trip attractions.

Transferability

Is empirical knowledge of built environment influences on public bike usage transferable among transnational cities? Based on the above results, the answer to the question should be negative. Figure 2 (a) shows that very few explanatory variables are simultaneously significant in two city models to explain PBS usage. Six, three and three variables are simultaneously significant in Taipei and Beijing models, Beijing and Tokyo models and Tokyo and Taipei models respectively. Further few explanatory variables whose coefficients are simultaneously significant in two city models reveal a same sign. The variables of road facility, PBS distance and local center reveal the same influences on PBS usage in Taipei and Beijing models. Only one variable, population density, has a same influence on PBS usage in Beijing and Tokyo models. There is no variable performing a similar effect in Tokyo and Taipei models. Furthermore, Fig. 2 (b) suggests that only one or two variables whose coefficients are simultaneously significant in membership functions of latent class models of two cities.

Despite the significant dissimilarities among the three city models, Fig. 2 suggests that more similarities exist between Taipei and Beijing models than that between Beijing and Tokyo models and between Tokyo and Taipei models. Considering the fact of that Beijing and Taipei are both developed in a Chinese culture context, cities having similar cultural bases could be expected to reveal relatively similar influencing factors on PBS usage.

Conclusions

According to the comparison results, the present research argues that the built environment influences on public bike usage of the survey cities are significantly different from each other, and cities having similar cultural bases reveal relatively similar influences. The results imply that the empirical knowledge of built environment influences on public bike usage would be not transferable among transnational cities even though they are geographically close. To develop bike-friendly built environments for a city, empirically cumulating local knowledge of travel behavior is critical.

The empirical findings contribute to the literature through the following two implications. The first implication is that the findings provide a novel evidence of disaggregate analysis on the role of built environment in explaining public bike usage in Beijing and Tokyo. The disaggregate evidence of present research is a complement to the existing knowledge from the disaggregate analysis of Lin and Cheng (2016) and the aggregate analyses of Faghih-Imani *et al*. (2014), Rixey (2013) and Tran *et al*. (2015). Secondly, the comparison results highlight a limitation of knowledge transferability among transnational cities. Local administrations should be cautious about referring to empirical findings of other cities in terms of built environment influences on PBS usage.

For further clarification of the relationships between built environment and public bike usage, future studies should examine two issues to benefit knowledge transferability among cities. The first issue is connected with city contexts. This study selected three transnational cities for comparison and found that Taipei and Beijing observations reveal more similarities to each other than to Tokyo observations. Because Beijing and Taipei are both developed in a Chinese culture context, it is presumable that cities having similar cultural bases could be expected to reveal relatively similar influencing factors on PBS usage. To test the above presuming, future research is suggested to investigate and compare cities within a nation and to examine whether they have more similarities among each other than the transnational cities surveyed in this research have. The second issue is related to the reasons of dissimilarity. The present research discovered the fact that influencing factors on PBS usage were significantly dissimilar among the survey cities and raised possible explanations to some of the dissimilarities. However, the similarities have not been explained completely and concretely. The future research is suggested to explore the reasons to the dissimilarities via further deep and qualitative survey works like interviews, field observations, experiments, etc. Clarifying the reasons of dissimilarity certainly benefits theory developments for the relationships between built environment and travel behaviors.

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Table 1 Background information on the surveyed PBSs

City	Beijing	Taipei	Tokyo
PBS[1]	Municipal PBS	YouBike	Tokyo Bike Share
Launch	June 16, 2012	August 1, 2012	November 21, 2012
Stations	538	196	180
Bikes	17,000	6,406	1,810
Survey month	May, 2016	January-February, 2015	December, 2015
Average temperature in the survey month[2]	20 ^oC	15 ^oC	8 ^oC
Survey District / metro station	Chaoyang / Chaoyangmen Liangmaqiao	Xinyi / Taipei 101 Taipei City Hall Yongchun Xiangshan	Koto / Toyosu
Population density of survey district[3]	8.3 10^3-residents per km^2	20.2 10^3-residents per km^2	12.2 10^3-residents per km^2
Number of effective responses	332	311	304
Number of PBS users among effective responses	123	157	61

1. Data year: 2013 for Beijing, 2015 for Taipei, 2016 for Tokyo; data sources: Bike-sharing Blog (http://bike-sharing.blogspot.tw/) for Beijing and Taipei, Docomo Bikeshare, Inc. for Tokyo.
2. Data source: Official web site of Hong Kong Observatory
3. Data year: 2014 for Beijing, 2017 for Taipei, 2015 for Tokyo

Table 2 Definitions of explanatory variables and hypothesized effects on PBS use

Name	Definition	Unit	Hypothesized effect	Cities[f]
Built environments				
Density				
Population density	Number of residents / area of land, in a *trip endpoint area*[a]	people/m^2	+	Be, Ta, To
Employment density	Number of employees / area of land, in a trip endpoint area	people/m^2	+	Be, Ta, To
Student density	Number of senior high school, undergraduate and graduate students / area of land, in a trip endpoint area	people/m^2	+	Be, Ta, To
Building density	Area of floor space / area of land, in a trip endpoint area	m^2/m^2	-	Be, Ta
Diversity				
Land use mix	Land use entropy in a trip endpoint area, $entropy = \{-\sum_{i=1}^{s}[(D_i)\ln(D_i)]\}/\ln(s)$, where D_i is the proportion of floor space *i*, $\sum_{i=1}^{s} D_i = 1$, *i* denotes a land use type and *s* is the total number of *i*.	-	+	Be, Ta
Commercial ratio	Area of floor space of commercial and business uses / area of total floor space, in a trip endpoint area	%	+	Be, Ta
JH balance	*Job-housing balance index*[b] in a trip endpoint area	--	+	Be, Ta, To
Design				
Street intersection-A	Number of *street*[c] intersections / area of land, in a trip endpoint area	(intersection/m^2)×1000		
Street intersection-R	Number of street intersections / length of route, along a *travel route*[d]	intersection/m		
Street length	Length of streets / area of land, in a trip endpoint area	m/m^2		
Arterial intersection-A	Number of *arterial*[e] intersections / area of land, in a trip endpoint area	(intersection/m^2)×1000		
Arterial intersection-R	Number of arterial intersections / length of route, along a travel route	intersection/m		
Arterial length	Length of arterials / area of land, in a trip endpoint area	m/m^2		
Bikeway-A	Length of bikeways / area of land, in a trip endpoint area	m/m^2		
Bikeway-R	Length of bikeways / length of route, along a travel route	m/m		
Directness	Ratio of shortest distance to actual travel distance along a travel route	%		
Road space-A	Area of road space in a trip endpoint area	km^2		
Road space-R	Area of road space / length of route, along a travel route	m^2/m		
Sign-A	Number of traffic signs and lights in a trip endpoint area	piece		
Sign-R	Number of traffic signs and lights along a travel route/ length of travel route	piece/m		
Greenness	Area of parks, green fields, squares and playgrounds / area of land, in a trip endpoint area	m^2/m^2		
Tree-A	Number of trees in a trip endpoint area	tree		
Tree-R	Number of trees / length of route, along a travel route	tree/m		
Lamp-A	Number of lamps in a trip endpoint area	lamp		
Lamp-R	Number of lamps / length of route, along a travel route	lamp/m		
Bike friendliness	Refer to Appendix 1	-	+	Be, Ta
Road facility	Refer to Appendix 1	-	+/-	Be, Ta, To
Vehicle mobility	Refer to Appendix 1	-	-	Be, Ta
Distance to transit				
Metro distance	The shortest travel distance between a respondent's trip endpoint (origin or destination) and the nearest metro station	m	-	Be, Ta
Bus distance	The shortest travel distance between a respondent's trip endpoint and the nearest bus stop	m	-	Be, Ta
Transfer distance	A respondent's actual travel distance between a surveyed metro station and his or her trip endpoint	m	-	Be, Ta, To
Destination accessibility				
Local center	The shortest travel distance between a respondent's trip end point and the nearest local commercial center	m		
Attraction	Number of trip attractions in a trip endpoint area,	-	+	To

	including government agencies, police stations, fire stations, libraries, museums, culture centers, art galleries, hospitals, restaurants post offices, gas stations and service stations of telecommunication, electric power and tap-water			
Retailer	Number of retailers in a trip endpoint area, including convenience stores, department stores and super markets	-		
Destination accessibility	Refer to Appendix 1	-	+	Be, Ta
Distribution of PBS				
PBS number	Number of PBS rental stations in a trip endpoint area	-	+	Be, Ta, To
PBS distance	The shortest travel distance between a respondent's trip endpoint and the nearest PBS rental station	m	-	Be, Ta
Controls				
Individual				
Age	A respondent's age	year	-	Be, Ta, To
Male	A respondent is male (=1) or female (=0)	-	+	Be, Ta, To
Income 1	A respondent has a monthly income between 5-10 thousand CNY (=1) or not (=0) for Beijing, 30-50 thousand TWD (=1) or not (=0) for Taipei, 290-430 thousand JPY (=1) or not (=0) for Tokyo	-	-	Be, Ta, To
Income 2	A respondent has a monthly income over 10 thousand CNY (=1) or not (=0) for Beijing, 50 thousand TWD (=1) or not (=0) for Taipei, 430 thousand JPY (=1) or not (=0) for Tokyo	-	-	Be, Ta, To
License-car	A respondent is licensed to drive a car (=1) or not (=0)	-	-	Be, Ta, To
License-motorcycle	A respondent is licensed to ride a motorcycle (=1) or not (=0)	-	-	Be, Ta
Ownership-car	A respondent owns car(s) (=1) or not (=0)	-	-	Be, Ta, To
Ownership-motorcycle	A respondent owns motorcycle(s) (=1) or not (=0)	-	-	Be, Ta
Ownership-bike	A respondent owns bike(s) (=1) or not (=0)	-	+	Be, Ta, To
Environment				
Slope-A	The maximum slope in a trip endpoint area	%	-	Ta
Slope-R	The maximum slope / length of route, along a travel route	%/m	-	Ta
Crime-A	Number of crimes in a trip endpoint area	-	-	Ta
Crime-R	Number of crimes / length of route, along a travel route	crime/m	-	Ta
Accident-A	Number of traffic accidents in a trip endpoint area	-	-	Ta
Accident-R	Number of traffic accidents along travel route	accident/m	-	Ta
Car volume-A	Volume of cars during afternoon peak-hours / area of land, in a trip endpoint area	pcu/m^2/hr	-	Ta
Car volume-R	Volume of cars during afternoon peak-hours / length of route, along a travel route	pcu/m/hr	-	Ta
Pedestrian volume-A	Volume of pedestrians during afternoon peak-hours / area of land, in a trip endpoint area	people/m^2/hr	-	Ta
Pedestrian volume-R	Volume of pedestrians during afternoon peak-hours / length of route, along a travel route	people/m/hr	-	Ta
PBS				
Basic fee	Constant charge for a rental	NT$	-	Ta
Basic period	Maximum rental period charging basic fee	minute	+	Ta
Dock	Number of docks equipped at the nearest PBS rental station of endpoint of a trip by a respondent	-	+	Ta

[a] A trip endpoint area refers to the area within 350m buffer-ring using travel distance on practical road network and center of the travel destination (for whom leaving metro station) or travel origin (for whom entering metro station) of the respondent.

[b] The job-housing balance index $= [|\ln(\frac{J}{H})|_{max} - |\ln(\frac{J}{H})|]/|\ln(\frac{J}{H})|_{max}$, where J is the number of employees, H is the number of households, and $|\ln(\frac{J}{H})|_{max}$ denotes the maximum $|\ln(\frac{J}{H})|$ value among all of the respondents' trip endpoint areas.

[c] A street refers to collector or local street.

[d] A travel route refers to the route used by a respondent traveling between metro station and destination or origin.

[e] An arterial refers to arterial or expressway.

[f] Used as an explanatory variable in what city: Be is Beijing, Ta is Taipei and To is Tokyo.

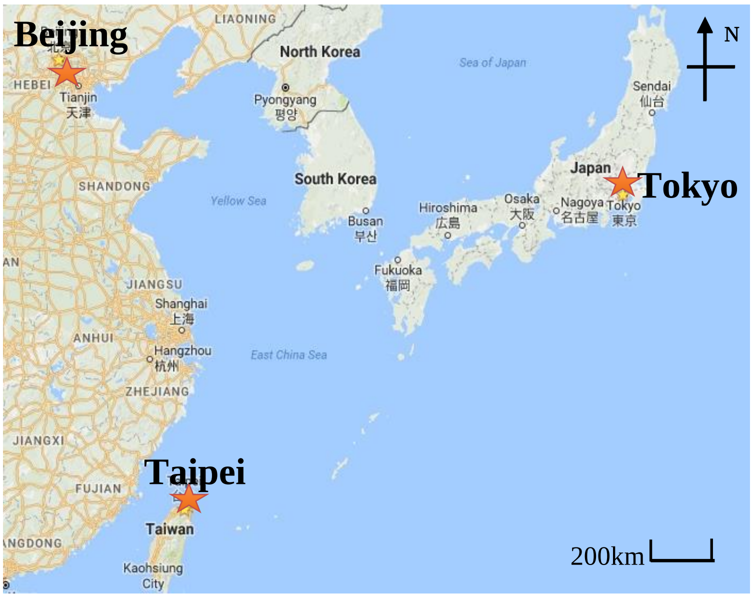
Table 3 Empirical effects of explanatory variables on PBS use

Variable	Hypothesized effects	Empirical effects		
		Beijing	Taipei	Tokyo
Built environments				
Density				
Population density	+	+	-	+
Employment density	+		+	-
Student density	+		+	
Building density	-	-		
Diversity				
Commercial ratio	+		-	
JH balance	+		+	
Design				
Road facility	+/-	+	+	-
Vehicle mobility	-		-	
Distance to transit				
Metro distance	-		+	
Transfer distance	-		+	
Destination accessibility				
Attraction	+			-
Destination accessibility	+	-	+	
Distribution of PBS				
PBS distance	-	-	-	
Controls				
Individual				
Age	-	+	-	
Income 1	-	+		-
Income 2	-			-
License-car	-	+	-	
License-motorcycle	-		+	
Ownership-motorcycle	-		-	
Ownership-bike	+		+	
Environment				
Accident-A	-		-	
Car volume-R	-		+	
Pedestrian volume-R	-		-	
PBS				
Basic fee	-		-	
Basic period	+		+	
Dock	+		-	

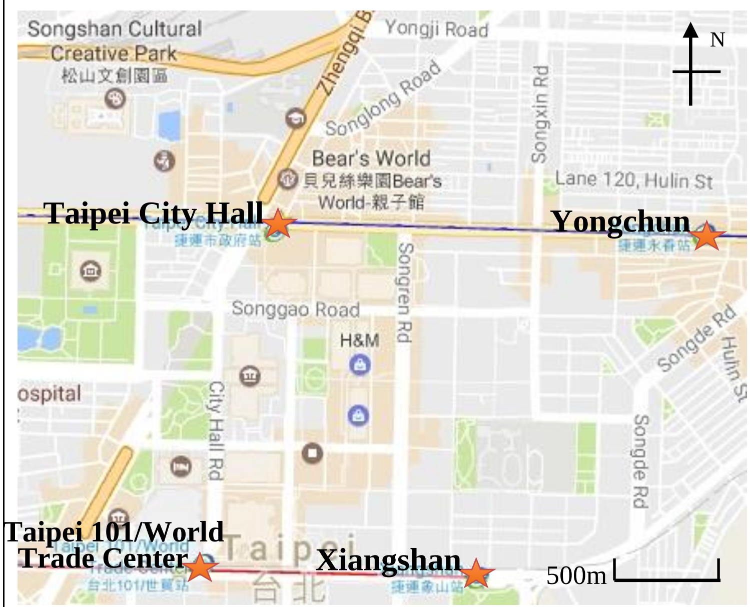
Notes: +: positive effect; -: negative effect; all of the effects are significant at $\alpha = 0.1$, details can be found in Appendix 2.

Survey stations in Beijing

Survey station in Tokyo



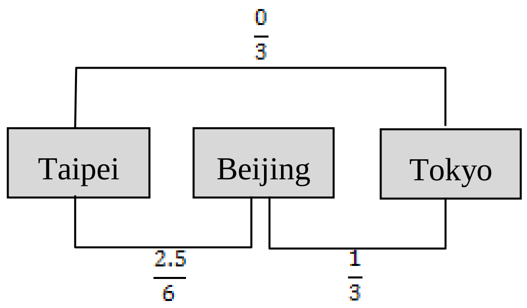
Survey cities



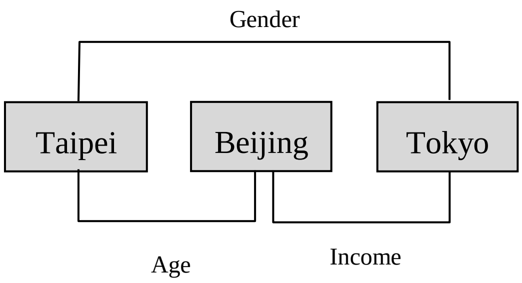
Survey stations in Taipei

Source: The base maps are from Google Map

Figure 1 Survey cities and metro stations



(a) Binary logit models: a denominator denotes number of variables whose coefficients are significant in utility functions of two cities; a numerator denotes number of variables whose coefficients are significant and in a same sign in utility functions of two cities



(b) Latent class models: variables whose coefficients are significant in membership functions of two cities

Figure 2 Model comparisons among cities

Appendix 1 Results of principle component analyses (loadings of variables[a])

Beijing:

Dimension	Design				Dimension	Destination accessibility
Component	Bike friendliness	Road facility 1	Road facility 2	Vehicle mobility	Component	Destination accessibility
Street intersection-A	.282	.616	.181	.460	Local center	0.918
Street intersection-R	.407	-.249	-.264	.447	Retailer	0.918
Street length	.342	.833	-.344	.003		
Arterial intersection-A	.477	-.124	.528	.130		
Arterial intersection-R	-.634	.273	.295	-.102		
Arterial length	-.032	.066	.807	.277		
Bikeway-A	.674	.314	.325	-.123		
Bikeway-R	-.679	-.129	.447	.072		
Directness	.304	-.242	.195	.015		
Road space-A	-.221	.169	.287	-.628		
Road space-R	-.692	.130	-.101	.289		
Sign-A	-.500	.639	.268	.216		
Sign-R	.716	-.188	.047	-.179		
Greenness	-.152	.358	.262	-.347		
Tree-A	.021	.938	-.074	.019		
Tree-R	.655	-.297	.396	.021		
Lamp-A	.708	.611	-.107	-.149		
Lamp-R	.743	.041	.151	.044		
Eigen value	4.797	3.365	2.015	1.238		1.685
Variance (%)	26.653	18.696	11.192	6.878		84.266
Cumulative variance (%)	26.653	45.349	56.541	63.418		84.266

[a] The loadings are the eigenvectors of the variables scaled by the component's square roots of the eigenvalues respectively.

Taipei:

Dimension	Design			Dimension	Destination accessibility
Component	Bike friendliness	Road facility	Vehicle mobility	Component	Destination accessibility
Street intersection-A	-0.932	0.006	-0.138	Local center	-0.718
Street intersection-R	-0.706	0.074	-0.036	Attraction	0.959
Street length	-0.955	0.005	-0.119	Retailer	0.850
Arterial intersection-A	0.383	0.866	-0.005		
Arterial intersection-R	0.323	-0.185	0.069		
Arterial length	0.452	0.811	-0.004		
Bikeway-A	0.880	0.154	0.102		
Bikeway-R	0.664	-0.345	0.071		
Directness	-0.129	-0.261	0.498		
Road space-A	-0.374	0.841	-0.010		
Road space-R	-0.072	0.093	0.832		
Sign-A	-0.825	0.408	-0.141		
Sign-R	-0.138	0.022	0.716		
Greenness	0.850	0.251	-0.047		
Tree-A	0.656	0.137	-0.187		
Tree-R	0.499	-0.201	-0.278		
Lamp-A	-0.129	0.446	0.149		
Lamp-R	0.000	0.082	0.614		
Eigen value	6.228	2.869	2.040		2.158
Variance (%)	34.601	15.936	11.336		71.930
Cumulative variance (%)	34.601	50.537	61.873		71.930

[a] The loadings are the eigenvectors of the variables scaled by the component's square roots of the eigenvalues respectively.

Tokyo:

Dimension	Design	
Component	Road facility 1	Road facility 2
Street intersection-A	0.781	-0.516
Street intersection-R	0.313	0.484
Street length	0.815	-0.510

Arterial intersection-A	0.837	0.390
Arterial intersection-R	0.112	0.576
Arterial length	0.531	0.607
Directness	-0.137	0.339
Eigen value	2.387	1.726
Variance (%)	34.098	24.661
Cumulative variance (%)	34.601	58.759

[a] The loadings are the eigenvectors of the variables scaled by the component's square roots of the eigenvalues respectively.

Appendix 2 Regression models (outcome: using PBS=1)

Beijing:

Variables	Binary logit model		Latent class model	
	Base	Extended	Segment 1	Segment 2
Utility function				
Intercept	-4.28432***	-4.02146***		
Built environments				
Population density		30.4924***	88.0240	49.8701***
Student density		290.091	1539.79	41203.5
Building density		-4.81581*	-61.0262*	-2.30145
Road facility 2		0.29758**	3.76926	0.33242
Destination accessibility		-0.20801	-6.18169*	-0.4508
Controls				
Age	0.07844***	0.07295***		
Income 1	0.96100***	0.97948***		
License-car	0.73297**	0.86855***		
Ownership-bike	0.53436**	0.56632**		
Membership function				
Intercept			5.68232***	Fixed
Age			-0.12913***	Fixed
Male			-0.25357	Fixed
Income 1			-0.86995*	Fixed
Income 2			0.75356	Fixed
License-car			-1.01449**	Fixed
License-motorcycle			1.86020	Fixed
Ownership-car			-.50766	Fixed
Ownership-motorcycle			-.45788	Fixed
Ownership-bike			-.42646	Fixed
Proportion			53.4%	46.6%
ρ^2	0.149	0.239	0.344	
χ^2	55.41224***	84.70132***	118.20353***	
Likelihood ratio test	2.684 ($\chi^2_{8,0.05}$ = 15.507)			

Notes: Number of observations: 332; *** significant at α=0.01; ** significant at α=0.05; * significant at α=0.1

Taipei:

Variables	Binary logit model		Latent class model			
	Base	Extended	Segment 1	Segment 2	Segment 3	Segment 4
Utility function						
Intercept	1.63996***	-5.29569***				
Built environments						
Population density		-33.8567***	-50.193	111.365	-86.433*	-115.984
Employment density		18.9344***	29.737	-44.038	71.567*	16.630
Student density		18.7837***	-9.744	90.616	154.862**	-38.916
Commercial ratio		-0.05121***	-0.033	-0.452	-0.332***	0.244
JH balance		6.00769***	0.498	-20.232	4.241	16.274
Road facility		0.21505	0.562	-1.109	4.838***	1.046
Vehicle mobility		-0.46530***	-0.301	0.696	-1.720	-2.712
Metro distance		0.00213***	0.002	0.008	0.008***	0.024
Transfer distance		0.00090***	0.001	0.007	0.008***	0.003
Destination accessibility		0.30411**	1.250	0.926	2.705***	-1.188
PBS distance		-0.00306***	0.001	0.002	-0.026***	-0.008
Controls						
Age	-0.03325***	-0.01670**				
License-car	-0.21407	-0.28763*				
License-motorcycle	0.53680***	0.69105***				
Ownership-motorcycle	-0.52102***	-0.12313				
Ownership-bike	0.76324***	0.77425***				
Accident-A	-0.00628***	0.00230	-0.012	0.030	-0.047**	0.007
Car volume-R	1.47817***	1.44051***	-0.807	14.398	10.941***	-5.947
Pedestrian volume-R	-8.67844**	-7.06279	37.345	-31.761	-57.568	-37.277
Basic fee	-0.54664***	-0.69525***	-0.250	-7.140	-3.112***	-2.123***
Basic period	0.21844***	0.29385***	1.013***	3.162	0.327	-1.203
Dock	-0.00771***	-0.00623**	0.012	-0.247	0.028	-0.595

Membership function						
Intercept			-0.074	1.000	-13.549	fixed
Age			-0.099**	-0.089*	-0.101**	fixed
Male			0.250	1.231	1.861*	fixed
Income 1			1.320*	1.715*	19.188	fixed
Income 2			2.183	2.426*	20.580	fixed
License-car			-0.837	0.681	-1.611*	fixed
License-motorcycle			1.702	-1.166	-0.138	fixed
Ownership-car			-0.879	-0.112	-0.352	fixed
Ownership-motorcycle			1.049	0.584	-1.083	fixed
Ownership-bike			2.257***	1.008	1.496*	fixed
Proportion			20.6%	22.8%	36.3%	20.3%
ρ^2	0.156	0.296	0.499			
χ^2	354.706***	673.232***	1271.37382***			
Likelihood ratio test	637.0513***($\chi^2_{11,0.05}$ = 19.675)					

Notes: Number of observations: 1,555; *** significant at α=0.01; ** significant at α=0.05; * significant at α=0.1

Tokyo:

Variables	Binary logit model		Latent class model	
	Base	Extended	Segment 1	Segment 2
Utility function				
Intercept	-0.66717***	1.84394***		
Built environments				
Population density		5173.48***	140794	-10729.8
Employment density		-12412.4***	-333172	22423.1
Road facility 1		-0.73529**	-93.1672	0.10908
Road facility 2		-0.89015***	-93.1672	4.37805*
Attraction accessibility		-0.35511***	3.34768	-0.41989***
Controls				
Income 1	-1.17536***	-0.95841		
Income 2	-1.73072***	-1.82303***		
Membership function				
Intercept			0.48371	Fixed
Age			-0.02028	Fixed
Male			-0.56461$^{\#}$	Fixed
Income 1			0.64535$^{\#}$	Fixed
Income 2			-0.05735	Fixed
License-car			-0.29592	Fixed
Ownership-car			-0.24524	Fixed
Ownership-motorcycle			-10409.5	Fixed
Ownership-bike			-0.12274	Fixed
Proportion			63.7%	31.4%
ρ^2	0.055	0.592	0.232	
χ^2	22.817***	196.552***	161.64145***	
Likelihood ratio test	22.8173**($\chi^2_{6,0.05}$ = 12.592)			

Notes: Number of observations: 304; *** significant at α=0.01; ** significant at α=0.05;

* significant at α=0.1, $^{\#}$ significant at α=0.15