A SEASONAL ANALYSIS ON FACTORS AFFECTING BIKE-SHARING CHOICE: WITH A FOCUS ON AIR POLLUTION'S IMPACT

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ABSTRACT

There has been a rapid expansion of bike-sharing schemes in developing countries. However, many of those were launched without the support of adequate demand-side research and hence failed to create the expected amount of usage. Given the increasingly significant urban transportation challenges in developing countries, such as congestion and air pollution caused by the continuously growing private vehicle usage, there is a great need to exploit the potential of the existing bike-sharing services. This research studies the mode choice behavior (including bike-sharing) in a developing country by analyzing revealed preference travel behavior data and incorporating seasonality influence on the factors affecting choice behavior. Specifically, the impacts of air pollution and other factors are captured in great details by revealing any impact differences under different natural environment conditions. A Chinese city Taiyuan, which operates one of the most successful bike-sharing schemes in developing countries, is selected for case study. Two discrete choice models are developed to analyze the data collected in two different seasons. The results show that an increase in air pollution level has the expected significant negative impact on bike-sharing choice only when the air is polluted at relative severe levels. The results also show that many trip-related factors and socio-economic factors would also affect mode choice behavior differently under different air pollution levels and weather conditions. Based on the findings, a number of policy implications are drawn for promoting the demand for bike-sharing in developing countries.

Keywords: Bike-sharing, Air pollution, Seasonality, Mode choice, Discrete choice model,
          Revealed preference, Developing country

1. INTRODUCTION

Bike-sharing has become a popular green transportation choice in many cities around the world (1). There have been many years of development in Europe and North America (2, 3), followed by a rapid expansion in developing countries at recent time (4). For instance, after only few years of construction, the total number of shared bikes in China has exceeded even the sum of all other countries (5). However, many of the bike-sharing schemes in developing countries were launched without adequate research in understanding market demand. As a result, a large number of those schemes did not create the expected demand and instead received numerous criticisms (6, 7, 8, 9, 10).

Given the increasingly significant urban transportation challenges in developing countries, such as congestion and air pollution caused by the continuously growing private vehicle usage, there is a great need to exploit the potential of the existing bike-sharing services. Although the service cannot offer the same mobility as private vehicles, it can still be a competitive alternative especially in city centers given its various benefits to users (11, 12, 13).

A good understanding on the factors that could affect bike-sharing choice can effectively support policy making in improving the demand for the service. So far in developed countries, there are many mode choice behavior studies involving bike-sharing. However, there is an extreme lack of knowledge towards understanding bike-sharing choice behavior in developing countries. Many researches have also shown the context-sensitive nature of mode choice study (14, 15, 16, 17, 18) meaning that findings in developed countries have limited implications to developing countries given significantly different culture and local/geographical characteristics. Hence, there is an imperative need to conduct bike-sharing choice studies in the cities of developing countries in order to provide evidence for scientific design of bike-sharing schemes.

The authors of this paper have made an attempt to study bike-sharing choice in a developing country based on the data collected from stated preference experiment (19), including the reveal of air pollution impact which has been an omitted element in earlier mode choice studies. By contrast, this paper aims to advance the research by analyzing revealed preference travel behavior data and incorporating seasonality influence on the factors affecting choice behavior. Specifically, the impacts of air pollution and other factors will be captured in greater details by revealing any impact differences under different natural environment conditions. As such, policy makers and urban planners can design more accurate policy measures based on the discovered seasonal differences. A Chinese city Taiyuan, which operates one the most successful bike-sharing schemes in developing countries, is selected for case study. Two discrete choice models are developed to analyze the data collected in two different seasons.

For the remainder of this paper, section 2 briefly reviews the current literature on bike-sharing choice behavior and introduces the importance of seasonal analysis. The survey design and the characteristics of the sample are described in section 3. Section 4 explains the mode choice models and interprets the model estimation results. At last, section 5 concludes the paper by comparing the findings with the authors' earlier work and providing corresponding policy implications.

2. LITERATURE REVIEW

There are a great number of studies that have identified factors that could affect the choices of cycling and bike-sharing. Cycling facilities such as cycle lanes and bike-sharing docking stations (20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30), hilliness of roads (31, 32, 33, 34) are the mostly studied built environment factors which could have direct impacts on cycling decisions; other built environment factors that have been covered by research include population density in community,

existence of university campus and number of parks etc. (11, 28, 29, 31, 35). Moreover, trip purpose, trip distance, travel time, travel cost and other attributes of transport modes such as comfort level are usually found to play important roles in determining cycling and bike-sharing choices (15, 20, 29, 30, 31, 35, 36, 37, 38), although occasionally these trip-related characteristics may be less significant. Furthermore, a large number of socio-economic characteristics are also captured in terms of their correlations with mode choice decisions, including age, gender, health, occupation, income, education and vehicle ownership etc. (13, 20, 28, 29, 30, 31, 36, 37, 39, 40, 41). A more detailed literature review on all these factors' impacts is presented in the authors' earlier study (19).

Additionally, bike-sharing choice could be heavily affected by natural environment factors, or more specifically weather conditions. Evidences have shown that extreme temperatures (in most cases the extremely cold temperature) could significantly discourage the willingness to use bicycle (24, 25, 31, 34, 42). Besides, some weather effects (i.e. rain, snow and wind) are studied, such that these effects could also negatively affect cycling choice (16, 24, 25, 33, 38).

Overall, given the fact that mode choice behavior could be influenced by natural environment, it is worth exploring if factors (i.e. built environment, trip-related and socio-economic) would affect the choice behavior differently under "good" and "bad" natural environment conditions in order to have more specific and targeted policy implications. In fact, there are many studies that have generated similar type of results by adopting sub-groups or interacted effects. For instance, Faghih-Imani et al. (15) found that trip purpose could have different impacts on cycling choice in morning time and in evening time (i.e. more commuting trips in the morning and more meal-related trips in the evening); Motoaki and Daziano specified that hilliness of roads could significantly reduce cycling usage among the less-fit cyclist group whereas the impact on those well-fit cyclists is limited (34). However for natural environment conditions, to our knowledge only Kamargianni did similar analysis via setting up seasonal models and the findings indeed showed that factors could have different impacts on cycling choice in summer and winter given the significantly different temperatures in the two seasons (43). As a result, it is needed to further explore such natural environment influence in mode choice studies.

Besides, a developing country is involved in this research. Therefore, in order to have separate models for "good" and "bad" natural environment conditions, temperature and weather will not be the only determinant. Air pollution must also be included when considering natural environment due to its earlier discovered significant impact on bike-sharing choice (19).

3. CASE STUDY AND DATA

Revealed preference travel behavior data is used to study factors that could affect bike-sharing choice. The data is collected in the case study city, Taiyuan, which has more than 3 million citizens and has China's most demanded bike-sharing scheme that can be easily accessed by public transport card (44). Lessons can be learned to identify factors that have caused such a success. More importantly, Taiyuan has dramatic seasonal differences in terms of natural environment conditions. Usually there is warm weather as well as good air quality in summer in comparison with much lower temperature and worse air quality in winter. Therefore, it is an ideal case for applying seasonal analysis to study that under different natural environment conditions, any differences in the factors' impacts on mode choice behavior.

A questionnaire was designed to collect both revealed preference (RP) and stated preference (SP) data at individual level. Specifically, the following data are collected:

- Personal socio-economic characteristics;
- Household socio-economic characteristics;

- Trip diary revealing trip characteristics and mode choice for a single day;
- Attitudes and perceptions towards bike-sharing and car-sharing;
- Retrospective survey collecting past socio-economic and travel behavior data;
- SP mode choice experiment.

In this paper, trip diary data is used for developing the models. The trip diary section records the main characteristics of all trips that occurred in the last working day at the time of survey for each individual respondent. The information that can be captured include number of trips (i.e. distinguished by purpose) and stages (i.e. distinguished by mode), trip purpose, origin, destination, travel time and cost as well as the revealed transport mode choice in each stage. The stage data (e.g. travel time, travel cost etc.) will then be summed up to create a mode choice observation for each trip. Moreover, the identified mode choice for each trip is the "distance-based main mode", i.e. mode in the stage with the longest travelling distance. Furthermore, the travelling distance of each stage in a trip is calculated based on the stage travel time and the mode speed data (45). Overall, such RP travel behavior data has higher reliability than the SP data as the observed choices are all committed to real-life constraints (46). Besides, based on the existing survey data, additional data such as the anticipated travel times and travel costs that if a trip/stage is conducted by different alternative modes need to be derived as well for modeling (see section 4.1). In addition, personal and household socio-economic indicators will also be used in the models.

Two rounds of questionnaire survey were conducted, one in summer (August and September) and one in winter (December, January and February). The surveys were supported by Shanxi Transportation Research Institute. Fifteen researchers were hired to assist with the distribution of the questionnaires, the collection of the questionnaires and the incorporation of the data into electronic datasets. In summer 2015, the paper questionnaire was distributed to 15,000 individuals in Taiyuan following a pilot survey in January. The sample was set to be consistent with Taiyuan census data on two levels to minimize the bias. First, the sampled individuals were selected from each of the six districts in Taiyuan and the sample size in each district was proportional to the population in each district. Next, the gender distribution of the sampled individuals in each district was examined to be proportional to the population gender distribution in each district. As a result, 9,499 individuals provided valid questionnaire responses in the summer survey and among which 706 individuals agreed to continue the participation in the winter survey. In winter 2016, the 706 individuals were asked to fill a paper questionnaire which only contains the trip diary survey and eventually 492 of them provided valid responses.

This paper uses only the RP travel behavior data collected from the same 492 individuals in both seasons to make socio-economic and even trip characteristics as consistent as possible in the two datasets. Hence, any different impacts of the same factors on mode choice behavior can be more clearly revealed. By comparing this smaller sample with the main sample of 9,499 individuals (Table 1), it is found that the most key characteristics of the smaller sample are close to the main; there are only few notable differences. More females are included in the smaller sample. More young professionals (i.e. aged between 26 and 35) are captured while the percentage of elder professionals (i.e. aged between 36 and 45) decreases. There are also larger proportions of driving license and public transport card holders, as well as those having private cars, electric bikes and bikes in households. Besides, all other indicators are almost the same between the two samples. Meanwhile, both samples show a high possession rate of public transport card meaning that most of the sampled individuals can access bus and bike-sharing services "barrier-free". Almost all respondents state that they are healthy enough to cycle which ensures that bike and bike-sharing can be feasible choices in the survey. Finally, the occupational status (i.e. nearly 80% are fixed-job individuals) shows that both samples have successfully captured regular commuters whose mode

choice behaviors are the mostly concerned in urban planning and policy-making. Overall, the smaller sample is valid for data analysis without incurring significant bias.

TABLE 1 Sample Descriptive Statistics

		N=9,499	N=492
Gender	Male	52%	48%
	Female	48%	52%
Age	under 18	7%	9%
	18-25	25%	27%
	26-35	32%	35%
	36-45	24%	19%
	46-59	11%	9%
	60 or above	1%	1%
Marital status	Single	40%	39%
	Married	60%	61%
Educational level	High school or below	27%	28%
	College	32%	31%
	Undergraduate	35%	36%
	Graduate and above	6%	5%
Occupational status	Fixed job	76%	78%
	Student	17%	14%
	Retired	1%	1%
	Self-employed or unemployed	6%	7%
Driving license	Percentage of possession	52%	61%
Public transport card	Percentage of possession	79%	83%
Cycling capability	Health enough to cycle	94%	93%
Household monthly income (after tax)	Under ￥3000	30%	29%
	￥3000 - ￥6000	39%	40%
	￥6000 - ￥9000	18%	19%
	￥9000 - ￥15000	9%	7%
	￥15000 - ￥30000	3%	4%
	Over ￥30000	1%	1%
Household car	Percentage of possession	48%	59%
Household electric bike	Percentage of possession	42%	48%
Household bike	Percentage of possession	51%	58%

In addition to the questionnaire survey, daily air pollution and weather condition data for the corresponding travel days in the summer and winter surveys were collected from China's Ministry of Environment Protection (47) and Shanxi Meteorology (48). Air pollution is measured by a continuous variable, air quality index (AQI), the primary air pollution indicator used in China. Weather conditions are measured by a continuous variable °C temperature and three dummy variables showing if the day is rainy, snowy or neither. Moreover, as there is one uniform AQI for a single day, it will be identically applied to all trip observations in the same day. However, temperature can change significantly during different periods in a day. Therefore, to more accurately measure the temperature impact on mode choice behavior, different temperatures will be applied to different trip observations according to their departure time. In particular, maximum daily temperature is applied to trips departing during 11am to 4pm, minimum daily temperature is used from 8pm to 7am in the next day, and the average temperature is applied to the trips departing in the rest periods.

At last, the key survey statistics from the two seasons are outlined in Table 2. The 492 individuals conducted 1,797 trips in summer and 1,722 trips in winter. As expected, the summer trips are associated with better air quality and higher temperature than the winter trips. In total, eight alternative modes are identified. There are notable differences between the modal split patterns in the two seasons. From summer to winter, there is an increase in the market share of more "protected" modes (i.e. car and bus) and a decrease in the market share of more "exposed" modes (i.e. cycling and walk). Although the observed choice behavior changes correspond to the hypothesis that the same factors may affect mode choice behavior differently under different natural environment conditions, modeling analysis is still needed to provide more robust evidence.

TABLE 2 Key Statistics from Summer and Winter Surveys

		Summer	Winter
Number of trip observations:		1,797	1,722
AQI split	Excellent quality (0-50)	28%	0
	Good quality (51-100)	67%	0
	Light pollution (101-150)	5%	30%
	Medium pollution (151-200)	0	11%
	Heavy pollution (201-300)	0	59%
	Terrible pollution (above 300)	0	0
Min. AQI		34	115
Max. AQI		139	285
Min. temperature		9°C	-10°C
Max. temperature		32°C	16°C
Weather split	Rain	62%	0
	Snow	0	2%
	Without rain or snow	38%	98%
Mode choice split	Car driver	15%	17%
	Car passenger	9%	18%
	Bus	18%	22%
	Electric bike	8%	7%
	Bike	7%	4%
	Bike-sharing	6%	3%
	Walk	35%	27%
	Taxi	2%	2%

4. MODEL SPECIFICATION AND RESULTS

4.1 Model Specification

Two multinomial logit (MNL) mode choice models are developed based on the data collected in the two different seasons. MNL model is widely used to study discrete choice behavior (49). Random utility theory underpins the model such that a choice made by an individual is based on his/her perceived utility generated by that choice and the utility associated with each choice is determined by its attributes, choice maker's characteristics and other explanatory variables. By incorporating all eight transport modes in the choice set, the model can show why an alternative would be chosen rather than bike-sharing or why bike-sharing would be preferred over other alternatives. Such simultaneous comparison between choices of bike-sharing and alternative modes can enrich the insights on impacts of factors and lead to more robust policy implications.

The explanatory variables used in the MNL models are presented in the Equations 1 to 8 below. Air pollution and temperature impacts are taken into account. The weather variables, rain

and snow are dropped out since snow only occurred in 2% trips in the winter as shown in Table 2 (rain is excluded too to retain consistency between the two models).

Going to work and going to education as the two main trip purposes are selected. Meanwhile, two similar indicators, the occupational status in fixed job and in student are excluded in order to avoid collinearity between explanatory variables. Moreover, trip purpose is chosen instead of occupational status is due to the former is more directly related to mode choice behavior.

Travel time and travel cost are the key attributes of transport modes, and in turn could be important factors considered by travellers when making mode choice decisions. However, each of the observed trips in the survey only contains the actual travel time and travel cost of the chosen mode without telling the information of alternative modes. Therefore, for each observed trip in summer and winter, the authors calculated the anticipated travel time and travel cost for each alternative mode other than the observed choice. The data and the methodology used here are not elaborated in this paper due to space limitation. Nonetheless, all necessary inputs (e.g. mode speed, trip distance, fuel consumption, fuel cost, bus and taxi prices etc.) are provided by Taiyuan local authorities and based on the collected trip diary information. As a result, travel time is included as an explanatory variable in the models in all eight utility functions, while travel cost is only applied to car driver, bus and taxi since the rest alternatives are either free to use (i.e. car passenger, bike and walk) or the cost is too small to have an impact (i.e. electric bike and bike-sharing).

Three categorical socio-economic variables are also considered for their impacts on mode choice behavior, including gender, age and household income. The subgroups under each of the latter two variables are merged into two groups (i.e. lower half and higher half) in order to more clearly demonstrate their impacts.

Finally although RP data implies that the observed choices have all occurred in reality, availability conditions on any alternative choices still need to be included in the models. These conditions will increase model validity by helping explain the circumstances such as someone did not choose an alternative mode for an observed trip could be due to the fact that the mode was an unavailable option. As a result, the availability conditions are specified as follows:

▪"Car driver" is available to the individuals who have driving licenses and at least one car in their households;

▪"Car passenger" is available to all individuals;

▪"Bus" is available to all individuals;

▪"Electric bike" is available to the individuals who have at least one electric bike in their households;

▪"Bike" is available to the individuals who are healthy enough to cycle and have at least one bike in their households;

▪"Bike-sharing" is available to the individuals who are healthy enough to cycle;

▪"Walk" is available to all individuals;

▪"Taxi" is available to all individuals.

In addition, there is a model specification rule that the parameters of a variable must be normalized to the base value (i.e. zero) in at least one of the utility functions. Therefore, it must be noticed that the resulted impact signs of the rest parameters will not indicate the absolute impact directions of the variable on mode choice utilities. Instead, the signs will only be relative to the chosen normalized term. Hence, a lot of model specifications have been tested to normalize the parameter that is closest to zero for each variable in order to yield the most accurate results.

$$U_{cardri} = \alpha_{cardri} + \beta_{work1}*WORK + \beta_{tem1}*TEM + \beta_{pol1}*POLLUTION$$
$$+\beta_{cardritt}*CARDRITT + \beta_{cardritc}*CARDRITC + \beta_{male1}*MALE \quad (1)$$
$$+\beta_{age1}*AGELOW + \beta_{inc1}*INCLOW + \varepsilon_{cardri}$$

$$U_{carpass} = \alpha_{carpass} + \beta_{edu2}*EDU + \beta_{carpasstt}*CARPASSTT + \beta_{male2}*MALE$$
$$+\beta_{age2}*AGELOW + \beta_{inc2}*INCLOW + \varepsilon_{carpass} \quad (2)$$

$$U_{bus} = \alpha_{bus} + \beta_{work3}*WORK + \beta_{edu3}*EDU + \beta_{tem3}*TEM + \beta_{pol3}*POLLUTION$$
$$+\beta_{bustt}*BUSTT + \beta_{bustc}*BUSTC + \beta_{male3}*MALE + \beta_{age3}*AGELOW \quad (3)$$
$$+\beta_{inc3}*INCLOW + \varepsilon_{bus}$$

$$U_{ebike} = \alpha_{ebike} + \beta_{work4}*WORK + \beta_{tem4}*TEM + \beta_{pol4}*POLLUTION + \beta_{ebikett}*EBIKETT$$
$$+\beta_{male4}*MALE + \beta_{age4}*AGELOW + \beta_{inc4}*INCLOW + \varepsilon_{ebike} \quad (4)$$

$$U_{bike} = \alpha_{bike} + \beta_{work5}*WORK + \beta_{edu5}*EDU + \beta_{tem5}*TEM + \beta_{pol5}*POLLUTION$$
$$+\beta_{bikett}*BIKETT + \beta_{male5}*MALE + \beta_{age5}*AGELOW + \beta_{inc5}*INCLOW + \varepsilon_{bike} \quad (5)$$

$$U_{bikesh} = \alpha_{bikesh} + \beta_{work6}*WORK + \beta_{edu6}*EDU + \beta_{tem6}*TEM + \beta_{pol6}*POLLUTION$$
$$+\beta_{bikeshtt}*BIKESHTT + \beta_{male6}*MALE + \beta_{age6}*AGELOW \quad (6)$$
$$+\beta_{inc6}*INCLOW + \varepsilon_{bikesh}$$

$$U_{walk} = \alpha_{walk} + \beta_{work7}*WORK + \beta_{edu7}*EDU + \beta_{tem7}*TEM + \beta_{pol7}*POLLUTION$$
$$+\beta_{walktt}*WALKTT + \beta_{male7}*MALE + \beta_{age7}*AGELOW + \beta_{inc7}*INCLOW + \varepsilon_{walk} \quad (7)$$

$$U_{taxi} = \alpha_{taxi} + \beta_{work8}*WORK + \beta_{tem8}*TEM + \beta_{pol8}*POLLUTION + \beta_{taxitt}*TAXITT$$
$$+\beta_{taxitc}*TAXITC + \varepsilon_{taxi} \quad (8)$$

Where:
WORK = 1 if trip purpose is work-related, 0 if otherwise;
EDU = 1 if trip purpose is education-related, 0 if otherwise;
TEM = °C temperature (continuous);
POLLUTION = air quality index (continuous);
CARDRITT = travel time by car driver (in min);
CARPASSTT = travel time by car passenger (in min);
BUSTT = travel time by bus (in min);
EBIKETT = travel time by electric bike (in min);
BIKETT = travel time by bike (in min);
BIKESHTT = travel time by bike-sharing (in min);
WALKTT = travel time by walk (in min);
TAXITT = travel time by taxi (in min);
CARDRITC = travel cost by car driver (in ￥);
BUSTC = travel cost by bus (in ￥);
TAXITC = travel cost by taxi (in ￥);
MALE = 1 if gender is male, 0 if female;
AGELOW = 1 if age is "under 18" or "18-25" or "26-35", 0 if "36-45" or "46-59" or "60 or above";

INCLOW = 1 if household monthly income is "under ￥3000" or "￥3000-￥6000" or "￥6000-￥9000", 0 if "￥9000-￥15000" or "￥15000-￥30000" or "over ￥30000";

$\varepsilon_{cardri}, \varepsilon_{carpass}, \varepsilon_{bus}, \varepsilon_{ebike}, \varepsilon_{bike}, \varepsilon_{bikesh}, \varepsilon_{walk}, \varepsilon_{taxi}$ = the error components i.i.d. Extreme Value.

4.2 Model Estimation Results

Table 3 presents the model estimation results for summer and winter observations. Variables with coefficients statistically significant at 95% confidence interval or higher are highlighted. The differences between the results in the two seasons will be specifically identified.

According to the authors' earlier work (19), it is expected that an increase in air pollution level could discourage the use of more "exposed" modes for example bike-sharing, electric bike and walk, and encourage the take up of more "protected" modes such as car, bus and taxi in this case. On the one hand, the winter results are in line with such earlier findings. It is observed with high significance that the active transport modes including bike, bike-sharing and walk are not preferred when air pollution level increases; instead travellers will switch to car, bus, electric bike and taxi. The only different finding is the choice of electric bike, which is positively correlated with air pollution level in the winter results and however found negative correlation in the earlier research. The phenomenon could possibly be explained by the commonly observed inconsistent behavior between RP observations and SP experimental results (46, 49), such that a traveller may still have to use the privately owned electric bike in a polluting day in real life though this may not be a preferred choice in a hypothesized polluting scenario. On the other hand, the summer results do not have the same trend as which in the winter model. In particular, bike and bike-sharing choices are now positively correlated with air pollution level, and taxi choice also has different impact sign from the winter finding. Such behavioral changes may be attributed to the fact that summer's air quality is much better than winter so that the resulted health damage may be limited or at least not an important concern in summer travel activities. Overall, the direct comparisons between the summer and the winter results imply that severe air pollution can significantly discourage the usage of bike-sharing and other active transport modes; however, when it is at low level (i.e. excellent air quality, good air quality or light air pollution), a change in air pollution level does not have significant impact on mode choice behavior.

Temperature is the other natural environment factor studied in this research besides air pollution. Similarly, the seasonal comparison reveals that mode choices will be affected differently in 'hot' and 'cold' temperatures. The summer results show that an increase in temperature will raise the popularity of a variety of modes except taxi, which is the only less preferred option under higher temperature in summer. This may be due to the strong local perception that it is uncertain to receive adequate air condition treatment from taxi drivers. However in winter, a smaller number of modes (only bike-sharing, electric bike and car) are still preferred when the weather becomes warmer. Specifically, walk, bike and bus will no longer be chosen if the temperature increases and instead become the preferred choices alongside taxi when temperature drops.

Two different trip purposes are studied. For travellers going to work, the results in both seasons show that when the parameter of car passenger choice is normalized to zero, taxi is the only mode choice that will not be chosen and all other alternative modes are found to have positive correlations with work-related purposes. In addition, the impact on bike-sharing choice is only significant in the winter model and car choice is the only alternative associated with significant impacts in both seasons. As expected, car passenger, bus, bike, bike-sharing and walk are all the potential choices for travellers with education-related purposes given the positive impact signs and high significance levels in both seasons (except for bike, the impact on which is not statistically significant above 95% in neither seasons). Besides, the impact significance on bike-sharing choice

decreases a lot in the winter model although the positive impact sign remains. Overall, the results of trip purposes on bike-sharing suggest that it is a choice that is more significantly associated with education-related purpose in summer and associated with work-related purpose in winter. In other words, bike-sharing users who go to work have more inelastic demand towards adverse air quality and temperature conditions than those going to education.

Travel time and travel cost are important attributes in affecting mode choice behavior. For travel time, the winter model found the expected negative relationship with most of the mode choices (except for car passenger and taxi, which will be explained shortly) so that the utility associated with each mode will decrease when it takes longer time to arrive at destination. In comparison, a number of impact signs turn out as positive in the summer model including the impacts on car choice, bus choice and electric bike choice (as well as the choices of car passenger and taxi as in the winter model). Such sign changes could be caused by the better natural environment conditions (i.e. better air quality and warmer weather) in the summer period so that longer travel time may not result in significant comfort loss. In other words, the travel time saving may not be as important as in the winter period. However, it must be noticed that travel time impacts on active transport choices such as bike, bike-sharing and walk are always negative throughout summer and winter. Such consistent behavior could be due to the relatively low mobility power and the resulted longer travel time of active transport, so that an increase in travel time may be more concerned by travellers than the same increase when travel time is short. In contrast, the positive impact signs of car passenger and taxi choices throughout the two seasons could be explained by the fact that they are both passenger transport and unlike bus they do not have any exclusive lanes. Thus, the decision maker does not have the same level of control or knowledge on travel time as using other self-driven modes. As for travel cost, the impacts on the three mode choices have consistent signs in summer and winter. Higher costs will reduce the demand towards bus and taxi; however, car cost is positively associated with its mode choice. The key reason is that in a revealed preference survey, many drivers do not have perfect knowledge on the cost of car driving (i.e. the fuel cost). Therefore, the travel cost of car is perhaps not precisely taken into account by individuals in choice making. At last, the positive signs of travel time and the negative signs of travel cost altogether imply the existence of negative willingness to pay (i.e. unwilling to reduce travel time by paying extra travel cost) for transport services. However, this study more specifically shows that the negative willingness to pay is valid only in summer with better natural environment conditions and only on bus and taxi which have faster mobility than bike-sharing.

At last, there are similar trends in gender, age and income effects. More females will choose car passenger, bus, bike-sharing and walk as the travel modes in summer; whereas in winter females will only prefer to be car drivers. The elderly age group is found to have positive relationship with using bike-sharing in summer; they will not choose it anymore in winter. Similarly, in summer wealthier people are open to all mode options except for electric bike, which is more preferred by the lower income group. However in winter, car driver and car passenger are the only options preferred by wealthier people. Overall, the results of gender, age and income impacts all denote the existence of seasonal influence even though in general the impacts are less significant. In other words, travellers from different socio-economic groups could behave differently under different natural environment conditions. Specifically, females, elderly and wealthier people are found more sensitive to worse air quality and lower temperature.

TABLE 3 Summer and Winter Model Estimation Results

	Summer	Winter

	Coefficient	t-stat	Significance	Coefficient	t-stat	Significance
α_{cardri}	- 9.57	- 2.75	95%	1.89	1.46	-
Work-car driver	1.49	4.77	99%	0.67	2.77	95%
Temperature-car driver	0.08	2.79	95%	0.02	1.16	-
Air pollution-car driver	0.018	2.69	95%	0.015	5.63	99%
Travel time-car driver	0.02	1.10	-	- 0.03	- 0.97	-
Travel cost-car driver	0.19	4.41	99%	0.12	2.66	95%
Male-car driver	0.06	0.08	-	- 0.23	- 0.47	-
Age (lower)-car driver	- 0.12	- 0.16	-	- 0.40	- 0.81	-
Income (lower)-car driver	- 1.81	- 0.99	-	- 0.45	- 0.65	-
$\alpha_{carpass}$	- 6.86	- 1.99	95%	3.24	2.74	95%
Education-car passenger	1.14	3.30	99%	1.51	4.89	99%
Travel time-car passenger	0.07	3.44	99%	0.005	0.17	-
Male-car passenger	- 0.30	- 0.45	-	0.62	1.40	-
Age (lower)-car passenger	- 0.44	- 0.59	-	- 0.06	- 0.13	-
Income (lower)-car passenger	- 2.40	- 1.33	-	- 0.52	- 0.80	-
α_{bus}	- 5.18	- 1.49	-	43.40	0.79	-
Work-bus	0.85	2.86	99%	0.27	0.93	-
Education-bus	1.42	4.63	99%	1.16	2.95	99%
Temperature-bus	0.03	1.01	-	- 0.04	- 1.99	95%
Air pollution-bus	0.013	2.09	95%	0.0002	0.06	-
Travel time-bus	0.003	0.32	-	- 0.12	- 6.86	99%
Travel cost-bus	- 2.69	- 6.00	99%	- 37.90	- 0.69	-
Male-bus	- 0.71	- 1.06	-	0.10	0.21	-
Age (lower)-bus	- 0.53	- 0.72	-	- 0.44	- 0.87	-
Income (lower)-bus	- 0.87	- 0.48	-	0.32	0.45	-
α_{ebike}	- 16.90	- 0.75	-	- 8.26	- 0.15	-
Work-ebike	0.84	2.51	95%	0.17	0.60	-
Temperature-ebike	0.09	2.90	99%	0.01	0.48	-
Air pollution-ebike	- 0.002	- 0.21	-	0.003	1.35	-
Travel time-ebike	0.04	1.76	-	- 0.02	- 0.94	-
Male-ebike	0.44	0.65	-	1.22	2.54	95%
Age (lower)-ebike	- 0.005	- 0.01	-	- 0.29	- 0.56	-
Income (lower)-ebike	6.74	0.30	-	10.90	0.20	-
α_{bike}	- 4.96	- 1.41	-	7.88	5.23	99%
Work-bike	0.83	2.22	95%	0.48	1.25	-
Education-bike	0.83	1.94	-	0.92	1.69	-
Temperature-bike	0.03	0.74	-	- 0.06	- 2.25	95%
Air pollution-bike	0.016	1.85	-	- 0.009	- 2.63	95%
Travel time-bike	- 0.12	- 7.12	99%	- 0.21	- 8.26	99%
Male-bike	0.14	0.20	-	0.07	0.13	-
Age (lower)-bike	- 0.21	- 0.27	-	- 0.01	- 0.01	-
Income (lower)-bike	- 1.68	- 0.91	-	0.87	1.05	-
α_{bikesh}	- 9.06	- 2.57	95%	14.50	7.97	99%
Work-bike share	0.40	1.02	-	1.05	2.37	95%
Education-bike share	1.77	4.67	99%	0.67	1.01	-
Temperature-bike share	0.13	4.02	99%	0.04	1.07	-
Air pollution-bike share	0.017	2.20	95%	- 0.058	- 6.71	99%
Travel time-bike share	- 0.07	- 4.81	99%	- 0.24	- 7.42	99%
Male-bike share	- 0.66	- 0.94	-	0.73	1.18	-

Age (lower)-bike share	- 0.51	- 0.67	-	0.41	0.65	-
Income (lower)-bike share	- 1.11	- 0.60	-	0.32	0.34	-
α_{walk}	1.60	0.44	-	14.60	9.21	99%
Work-walk	0.75	1.54	-	0.31	0.77	-
Education-walk	1.53	2.93	99%	1.45	2.56	95%
Temperature-walk	0.03	0.70	-	- 0.06	- 2.02	95%
Air pollution-walk	- 0.001	- 0.13	-	- 0.018	- 5.12	99%
Travel time-walk	- 0.24	- 15.03	99%	- 0.31	- 14.54	99%
Male-walk	- 0.74	- 0.99	-	0.08	0.15	-
Age (lower)-walk	0.12	0.14	-	0.38	0.64	-
Income (lower)-walk	- 1.29	- 0.69	-	1.02	1.31	-
α_{taxi}	0.00	-	-	0.00	-	-
Work-taxi	- 1.23	- 0.81	-	- 0.0001	- 0.00	-
Temperature-taxi	- 0.38	- 2.60	95%	- 0.07	- 1.65	-
Air pollution-taxi	- 0.013	- 0.55	-	0.003	0.65	-
Travel time-taxi	0.57	7.62	99%	0.03	0.61	-
Travel cost-taxi	- 0.81	- 7.81	99%	- 0.02	- 0.29	-
Number of observations	1797			1722		
Initial log-likelihood	- 3323.4			- 3189.3		
Final log-likelihood	- 1400.2			- 1173.0		
Likelihood ratio test	3846.4			4032.6		
$\bar{\rho}^2$	0.559			0.612		

5. CONCLUSIONS

The paper studies the factors that may affect urban transport mode choice behavior in a developing country. It significantly advances the knowledge boundary in research community by capturing the impact of air pollution at the first time using RP mode choice data following the authors' earlier work based on SP data (19). The one-day travel behaviors of 492 individuals are recorded in both summer and winter days. In particular, two seasonal MNL models are built to reveal the differences in the factors' impacts under distinctive natural environment conditions. The findings provide significant insights on the choice of bike-sharing, which has great potential in developing countries to reduce private car usage in city centers. By taking into account the discovered seasonal differences, more targeted policy measures can be implemented to effectively promote bike-sharing demand. A number of policy implications are drawn below:

▪In developing countries, current policies on improving air quality and encouraging the take up non-motorized transport such as bike-sharing are often separated. In other words, non-motorized transport is seen as one of the solutions to improve air quality. This research, however suggests that cleaning the air and promoting non-motorized transport must be tackled simultaneously due to their inter-dependence. As such, a virtuous circle could be created (i.e. better air quality could result in higher demand for non-motorized transport, and more non-motorized transport use could further reduce air pollution). Nevertheless, it must be noticed that the effectiveness of such virtuous circle will diminish when air pollution drops to relatively low levels.

▪In the previous research involving only short distance trips (19), the discovered negative willingness to pay towards bike-sharing service implies that maintaining a low price is effective to attract users. However, in this research, the negative willingness to pay for bike-sharing service disappears when longer distance trips are involved, since travel time becomes more important. Therefore, there is also a great need to enhance bike-sharing mobility for longer distance trips (e.g. introducing electric bikes to existing bike-sharing schemes).

▪Given commuters' more inelastic demand towards adverse weather and air quality, measures must be taken to satisfy their stable demand. It is important to improve bike-sharing service standards especially in areas that have high workplace densities (e.g. Central Business District). Measures can include increasing the number of docking stations or adopt more flexible bike return policies during peak time. For example, portable card scanning machine can be used to record bike usage data so that bikes can be returned to and assembled by a staff in addition to docking stations.

▪Similarly, there is opportunity to make use of the relatively inelastic bike-sharing demand potential of lower income groups, younger generations and males by designing bespoke policies to secure bike-sharing as their primary urban transport option. For example, special discounts can be offered to users under certain age and income criteria.

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