Air Pollution and Seasonality Effects on Mode Choice in China

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A modal shift from motorized to nonmotorized vehicles is imperative to reduce air pollution in developing countries. Nevertheless, whether better air quality will improve the willingness to use nonmotorized transport remains unclear. If such a reciprocal effect could be identified, a sort of virtuous circle could be created (i.e., better air quality could result in higher nonmotorized transport demand, which in turn could further reduce air pollution). Developing countries may, therefore, be more incentivized to work on air pollution reduction from other sources to exploit the extra gains in urban transport. This study investigated the impact of air pollution on mode choices and whether nonmotorized transport was preferred when air quality was better. Revealed preference data about the mode choice behavior of the same individuals was collected during two seasons (summer and winter) with different air pollution levels. Two discrete mode choice models were developed (one for each season) to quantify and compare the impacts of different air pollution levels on mode choices. Trip and socioeconomic characteristics also were included in the model to identify changes in their impacts across seasons. Taiyuan, a Chinese city that operates a successful bikesharing scheme, was selected for a case study. The study results showed that air quality improvement had a significant, positive impact on nonmotorized transport use, which suggested that improvements in air quality and promotion of nonmotorized transport must be undertaken simultaneously because of their interdependence. The results of the study could act as a harbinger to policy makers and encourage them to design measures and policies that lead to sustainable travel behavior.

The link between air pollution and the transport sector has been widely recognized for a long time (*1*). Urban transport has become an increasingly significant source of air pollution as the result of the surge in the use of motorized vehicles, especially during the past 20 years in developing countries after rapid economic growth and urbanization (*2–4*). Today, developing countries still suffer significantly from severe and frequent air pollution problems. The traditional approach to tackle the problem is through improvements in fuel products and in vehicle technologies to directly cut down pollutants (*5–7*). Reduction in the use of motorized vehicles through promotion of nonmotorized transport modes also has become a popular solution nowadays in developing countries (*8*). In fact, a large body of research has involved mode choice behavior analysis, which has effectively supported policy making to improve demand for nonmotorized transport.

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Transportation Research Record: Journal of the Transportation Research Board, No. 2634, 2017, pp. 101–109.
http://dx.doi.org/10.3141/2634-15

Nevertheless, current policies to improve air quality and to encourage the adoption of nonmotorized transport often are executed separately. In other words, nonmotorized transport as a solution to improve air quality is still seen as a one-way approach. Whether better air quality can improve the willingness to use nonmotorized transport remains unclear. So far, the impact of air pollution on mode choice behavior has rarely been explored. Most of the existing mode choice studies have had their basis in cases in developed countries, which in general have relatively limited air pollution concerns. However, to capture air pollution's impact has great implications for developing countries. If evidence can be found to reveal the impact, the current one-way approach may become old-fashioned and supplanted by a sort of virtuous circle (i.e., better air quality results in higher demand for nonmotorized transport, which in turn further reduces air pollution). Thus developing countries might be incentivized to work more on air pollution reduction from other sources (e.g., industrial, residential, and business sectors) to exploit the extra gains in urban transport.

Recently, air quality in developing countries was found to vary significantly with seasonal differences (*9, 10*). For instance in China, through a study that involved 110 cities, air pollution was found to be at its lowest in summer and to be at its most severe in winter when rainfall was lower, and energy consumption was higher (*9*). Thus it is possible to capture the impact of air pollution on mode choice behavior through a seasonality analysis. Factors that affect mode choice behavior also can have different impacts across seasons when natural-environment conditions are different (*11*). In this present study, a seasonality analysis was conducted not only to help reveal air pollution's impact but also to gain an in-depth understanding of other factor impact changes across different natural-environment conditions.

Overall, this research aimed to provide policy makers with the evidence of air pollution's impact on urban transport mode choice behavior and in particular to find out whether nonmotorized transport (i.e., privately owned bike use, walking, bikesharing) would be more popular when accompanied by better air quality. Other factors, such as trip and socioeconomic characteristics, also were covered in the analysis. Revealed preference travel behavior data were collected in two seasons, and two discrete mode choice models were developed for them, respectively.

A Chinese city, Taiyuan, with more than 3 million citizens, was selected for a case study. Two rounds of a travel behavior survey were launched, one in summer 2015 and one in winter 2015 to 2016. The goal was to study how the mode choice behavior of the same individual changed under different air quality levels. Eventually, 492 Taiyuan citizens provided valid 1-day travel information in both rounds. The city undergoes dramatic natural-environment differences in summer and winter in terms of weather condition and air quality.

Usually, the weather is moderate and the air is cleaner during the summer, whereas temperatures are freezing and air quality is poor in winter. Thus the case not only was suitable to study the impact of air pollution, but it also offered a clear difference in natural-environment conditions to reveal the impact changes of trip and socioeconomic characteristics. In addition, Taiyuan has one of the most successful bikesharing schemes in China, which gives the city great potential to promote nonmotorized transport (*12*).

This research was done to inspire policy making to reduce air pollution through the exploration of air pollution's reciprocal effect on travel behavioral change. Moreover, the seasonality analysis was done to offer in-depth understanding of factor impact changes under different natural-environment conditions. Because the case study had its basis in a Chinese city, this research study should be of particular use in China, as well as to policy makers in other developing countries.

The next section of this paper reviews the efforts that have been made in developing countries to alleviate air pollution in their urban transport sectors. Current mode choice studies that involved nonmotorized transport are reviewed. The section thereafter describes the collection and characteristics of the data in the present study. Then the mode choice models are described and the model estimation results interpreted. The concluding section describes corresponding policy implications.

LITERATURE REVIEW

Developing countries have made great efforts to reduce air pollution from their urban transport sectors. Attention has focused largely on vehicle technology and fuel product improvements to make the use of motorized vehicles a more environmentally friendly option. For instance, Faiz and Sturm found varying degrees of success with alternative fuels, such as liquefied petroleum gas and compressed natural gas, as well as with the use of electricity (*5*). Gwilliam et al. presented an emissions outlook for road transport in India through simulation of the impacts of several fuel standards and concluded that a strict standard must be enforced in near time to secure the delivery of emissions reduction targets (*6*). Guttikunda and Mohan provided comprehensive policy guidelines to promote the development of vehicle and fuel technologies by reviewing World Bank experience in the urban transport, fuel, and environmental sectors in developing countries (*7*). Nonetheless, these researches also questioned the effectiveness of relying solely on technology development. For example, the benefits would diminish when the number of vehicles increased (*6*). High initial costs and subsidies, as well as public acceptance, could all become implementation barriers (*5*). As a result, the promotion of alternative modes and of nonmotorized transport in particular has been recommended as a complementary as well as a more sustainable solution to reduce air pollution.

Thus far, a great number of studies have identified factors that affect choices with respect to the use of nonmotorized transport (i.e., use of privately owned bicycle, walking, bikesharing) to support policy making that encourages travel behavioral change. Cycling facilities, such as cycle lanes and bikesharing docking stations (*13–23*), and the hilliness of roads (*24–27*) have been the most frequently studied built-environment factors, which could have direct impacts on cycling trip decisions. Other built-environment factors studied have included the population density of a community, the existence of a university campus, the number of parks, among other factors (*13, 14, 26, 28, 29*). Moreover, trip purpose, trip distance, travel time, travel cost, and other attributes of transport modes, such as comfort level, usually have been found to play important roles in nonmotorized transport choices (*14, 16, 23, 26, 29, 30–33*). Further, a large number of socioeconomic characteristics have been captured in terms of their correlations with mode choice decisions, (e.g., age, gender, health, occupation, income, education, vehicle ownership) (*13, 14, 16, 23, 26, 30, 32, 34–37*). A more detailed review of the impacts of all of these factors was presented in an earlier study (*38*).

In that earlier study, it was discovered that air pollution could have a significant impact on mode choice behavior through the use of experimental data from a stated preference mode choice survey. The findings implied that nonmotorized transport choices could be promoted through air quality improvement, which offered an opportunity to create a virtuous circle. However, such a result on the basis of stated preference data might not be completely precise as a result of possibly inconsistent behavior in a hypothetical scenario as compared with reality (*39*).

Finally, nonmotorized transport choices could be affected by other natural-environment factors besides air pollution. Evidence has shown that extreme temperatures (in most cases extreme cold) could significantly discourage the willingness to cycle or walk (*18, 19, 26, 27, 40*). Some weather effects (e.g., rain, snow, wind) also could negatively affect cycling and walking choices (*18, 19, 25, 31, 41*). Kamargianni examined seasonality effects on cycling choice to enable more effective policy guidance across seasons (*11*). The results showed that trip and socioeconomic factors could have significantly different impacts on cycling in summer and winter when natural-environment conditions were different. Nonetheless, seasonality effect has not been widely studied, and more research on it is needed.

In summary, the literature is extensive on air pollution reduction, on the one hand, and mode choice behavior, on the other. However, not enough evidence is available on how air pollution affects mode choice behavior. The use of revealed preference travel behavior data to study the impact of air pollution should offer more reliable results than the existing stated preference data analysis, because the observed choices are subject to real-life constraints. Besides, the seasonality analysis will enrich the current literature and generate more targeted implications for use by policy makers. In the end, such research also should provide unique insights for developing countries. Several researchers have pointed out the context-sensitive nature of mode choice studies (*33, 41–44*). Thus current findings in developed countries (i.e., where most mode choice studies are concentrated) may have limited implications for developing countries, given significantly different cultural and geographical characteristics.

DATA

A survey was designed to collect trip diary as well as socioeconomic information from respondents at the individual level in Taiyuan, the case study city. For each individual respondent, the trip diary section recorded the main characteristics of all trips that occurred on the last working day at the time of the survey. The information that could be captured included number of trips (distinguished by purpose) and stages (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) were then summed up to create a single observation for each trip. The mode choice for each trip was identified to be the distance-based main mode (i.e., mode in the stage with the longest traveling distance). As a result, each stage distance was obtained on the basis of the stage travel time and the mode speed data (*45*). On the basis of the existing survey data, additional information was added on the travel cost and time of the alternative transport modes for each trip and stage (see the subsection in this paper on model specification).

The questionnaire survey was conducted in two rounds, one in summer (August and September 2015) and one in winter (December 2015 and January and February 2016). The survey rounds were supported by the Shanxi Transportation Research Institute of China. 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 data sets. In summer 2015, a paper questionnaire was distributed to 15,000 individuals in Taiyuan after 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, of which 706 individuals agreed to participate in the winter survey. In winter 2016, the 706 individuals were asked to fill out a paper questionnaire, which contained only the trip diary survey. Eventually, 492 of them provided valid responses.

This paper refers only to the revealed preference travel behavior data collected from the same 492 individuals in both seasons. Any seasonality effects of the same factors on mode choice behavior thus can be revealed more clearly. A comparison of this smaller sample with the main sample of 9,499 individuals (Table 1) shows that most key characteristics of the smaller sample were similar to those of the main sample, with only a few notable differences. More females were included in the smaller sample, as were more young professionals (i.e., between 26 and 35 years of age), while the percentage of older professionals (i.e., between 36 and 45 years of age) decreased. In the smaller sample, larger proportions of individuals possessed a driver's license and were public transport cardholders, as well as household owners of private cars, electric bikes, and ordinary bikes. Otherwise, the two samples had almost all of the same indicators. Both samples included a high rate of public transport cardholders, which meant that most of the sampled individuals could access bus and bikesharing services barrier-free. Almost all respondents stated that they were healthy enough to cycle, which ensured that bike and bikesharing could be feasible choices in the survey. Finally, occupational status (i.e., nearly 80% had fixed jobs) showed that both samples had successfully captured regular commuters whose mode choice behaviors are of most concern in urban planning and policy making. Overall, the smaller sample with 492 individuals was valid for data analysis without significant bias.

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 (*46*) and Shanxi Meteorology (*47*). Air pollution was measured by a continuous variable, air quality index, the primary air pollution indicator used in China. Weather conditions were measured by a continuous variable °C temperature and three dummy variables, which indicated if the day was rainy, snowy, or neither. Moreover, because there was one uniform air quality index for a single day, it was identically applied to all trip observations on the same day. However, temperature could change significantly during different periods in a day. Therefore, to more accurately measure the temperature impact on mode choice behavior, different temperatures were applied to different trip observations according to departure time. In particular, through a consideration of Taiyuan's daily temperature change pattern, it was assumed that trips that departed between 11 a.m. and 4 p.m. would be associated with the maximum daily temperature, while trips from 8 p.m. to 7 a.m. the next day were associated with the minimum daily temperature. The average temperature was applied to trips that departed during other periods.

The key survey statistics for 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 were associated with better air quality and higher temperatures than the winter trips. In total, eight alternative modes were identified. There were notable differences between the modal split patterns in the two seasons. From summer to winter, there was an increase in the market share of more protected

TABLE 1 Sample Descriptive Statistics

	Percent	
	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 older	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
Driver's license: percent possessing	52	61
Public transport card: percent possessing	79	83
Cycling capability: healthy enough to cycle	94	93
Household monthly income (after tax)		
Under ¥3,000	30	29
¥3,000–¥6,000	39	40
¥6,000–¥9,000	18	19
¥9,000–¥15,000	9	7
¥15,000–¥30,000	3	4
Over ¥30,000	1	1
Household car: percent possessing	48	59
Household electric bike: percent possessing	42	48
Household bike: percent possessing	51	58

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
Minimum AQI	34	115
Maximum AQI	139	285
Minimum temperature	9°C	−10°C
Maximum 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%
Bikesharing	6%	3%
Walking	35%	27%
Taxi	2%	2%

NOTE: AQI = air quality index.

transport modes (i.e., car, bus) and a decrease in the market share of more exposed modes (i.e., cycling, walking). The observed choice behavior changes corresponded to the hypothesis that the same factors might affect mode choice behavior differently under different natural-environment conditions. However, modeling analysis is still needed to provide more robust evidence.

MODEL SPECIFICATION AND RESULTS

Model Specification

Two multinomial logit mode choice models were developed on the basis of the data collected in the two seasons. The multinomial logit model is widely used to study discrete choice behavior (*48*). Random utility theory underpins the model, such that a choice made by an individual is based on his or her perceived utility generated by that choice. The utility associated with each choice is determined by its attributes, choice maker characteristics, and other explanatory variables.

Because one of the objectives was to determine if the impact of factors could be different under different natural-environment conditions, the two multinomial logit models were assigned the same explanatory variables to compare the results (see Equations 1 to 8). For instance, air pollution and temperature impacts were taken into account. However, rain and snow were excluded, because they were relevant only in one season.

To commute to and from work and to travel to and from educational institutions were the two main trip purposes selected in the study. Two similar indicators, (i.e., occupational status in fixed jobs, student status) were excluded to avoid collinearity between explanatory variables. Moreover, trip purpose was chosen instead of occupational status, because the former was more directly related to mode choice behavior.

Travel time and travel cost are the key attributes of transport modes, and in turn they can be important factors considered by travelers when they make mode choice decisions. However, each of the observed trips in the survey contained only the actual travel time and travel cost of the chosen mode without reference to information about alternative modes. Therefore, for each observed trip in summer and winter, the travel time and travel cost were calculated for each alternative transport mode option other than the one chosen. The calculation used the collected trip diary information and data provided by Taiyuan local authorities as the inputs (e.g., time of day, mode speed, trip distance, fuel consumption, fuel cost, bus and taxi prices). Given space limitations, the calculation procedures are not elaborated in this paper. Overall, travel time was included as an explanatory variable in the models in all eight utility functions, while travel cost was applied only to drivers of cars and users of buses and taxis. The other alternatives either did not involve a direct cost (i.e., traveling as a car passenger, biking, walking) or had a cost that was too low to have an impact (i.e., electric biking, bikesharing).

Three categorical socioeconomic variables were considered for their impacts on mode choice behavior, including gender, age, and household income (Table 1). However, when the impacts of age and income were tested, the pilot results showed that each of their subgroups had minor effects on mode choices. As a result, the subgroups of age and income were merged into two general groups (lower half and higher half) to more clearly demonstrate their impacts.

Finally, availability conditions with respect to transport mode alternatives were imposed for each individual. These conditions increased model validity because they helped explain the circumstances that surrounded decisions. For example, the reason someone did not choose an alternative mode for an observed trip could have been because the mode was not an available option. As a result, transport mode availability conditions were specified as follows:

- Car driver: available to individuals who have a driver's license and at least one car in their households;
- Car passenger: available to all individuals;
- Bus: available to all individuals;
- Electric bike: available to individuals who have at least one electric bike in their households;
- Bike: available to individuals who are healthy enough to cycle and have at least one bike in their households;
- Bikesharing: available to individuals who are healthy enough to cycle;
- Walking: available to all individuals; and
- Taxi: available to all individuals.

In addition, the model specification required that the parameters of a variable be normalized to the base value (i.e., 0) in at least one of the utility functions. Therefore, the resultant impact signs of the rest of the parameters would not indicate the absolute impact directions of the variable on mode choice utilities. Instead, the signs would be relative only to the chosen normalized term. Hence many model specifications have been tested to normalize the parameter that is closest to 0 for each variable to yield the most accurate results.

$$U_{cardri} = \alpha_{cardri} + \beta_{work1} * work + \beta_{tem1} * tem + \beta_{pol1} * pollution + \beta_{cardritt} * cardritt + \beta_{cardritc} * cardritc + \beta_{male1} * male + \beta_{age1} * agelow + \beta_{inc1} * inclow + \varepsilon_{cardri} \quad (1)$$

$$U_{carpass} = \alpha_{carpass} + \beta_{edu2} * edu + \beta_{carpasstt} * carpasstt + \beta_{male2} * male + \beta_{age2} * agelow + \beta_{inc2} * inclow + \varepsilon_{carpass} \quad (2)$$

$$U_{bus} = \alpha_{bus} + \beta_{work3} * work + \beta_{edu3} * edu + \beta_{tem3} * tem + \beta_{pol3} * pollution + \beta_{bustt} * bustt + \beta_{bustc} * bustc + \beta_{male3} * male + \beta_{age3} * agelow + \beta_{inc3} * inclow + \varepsilon_{bus} \quad (3)$$

$$U_{ebike} = \alpha_{ebike} + \beta_{work4} * work + \beta_{tem4} * tem + \beta_{pol4} * pollution + \beta_{ebikett} * ebikett + \beta_{male4} * male + \beta_{age4} * agelow + \beta_{inc4} * inclow + \varepsilon_{ebike} \quad (4)$$

$$U_{bike} = \alpha_{bike} + \beta_{work5} * work + \beta_{edu5} * edu + \beta_{tem5} * tem + \beta_{pol5} * pollution + \beta_{bikett} * bikett + \beta_{male5} * male + \beta_{age5} * agelow + \beta_{inc5} * inclow + \varepsilon_{bike} \quad (5)$$

$$U_{bikesh} = \alpha_{bikesh} + \beta_{work6} * work + \beta_{edu6} * edu + \beta_{tem6} * tem + \beta_{pol6} * pollution + \beta_{bikeshtt} * bikeshtt + \beta_{male6} * male + \beta_{age6} * agelow + \beta_{inc6} * inclow + \varepsilon_{bikesh} \quad (6)$$

$$U_{walk} = \alpha_{walk} + \beta_{work7} * work + \beta_{edu7} * edu + \beta_{tem7} * tem + \beta_{pol7} * pollution + \beta_{walktt} * walktt + \beta_{male7} * male + \beta_{age7} * agelow + \beta_{inc7} * inclow + \varepsilon_{walk} \quad (7)$$

$$U_{taxi} = \beta_{work8} * work + \beta_{tem8} * tem + \beta_{pol8} * pollution + \beta_{taxitt} * taxitt + \beta_{taxitc} * taxitc + \varepsilon_{taxi} \quad (8)$$

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 (min);
carpasstt = travel time by car passenger (min);
bustt = travel time by bus (min);
ebikett = travel time by electric bike (min);
bikett = travel time by bike (min);
bikeshtt = travel time by bikesharing (min);
walktt = travel time by walk (min);
taxitt = travel time by taxi (min);
cardritc = travel cost by car driver (¥);
bustc = travel cost by bus (¥);
taxitc = travel cost by taxi (¥);
male = 1 if gender is male, 0 if female;
agelow = 1 if age is under or equal to 35, 0 if above 3;
inclow = 1 if household monthly income is under or equal to ¥9,000, 0 if more than ¥9,000 (1 Chinese yuan = US$0.14 in 2017); and
ε_{cardri}, $\varepsilon_{carpass}$, ε_{bus}, ε_{ebike}, ε_{bike}, ε_{bikesh}, ε_{walk}, ε_{taxi} = the error components independent and identically distributed extreme value.

Model Estimation Results

Table 3 presents the model estimation results for summer and winter observations. The differences between the results in the two seasons are specifically identified. On the basis of earlier research, it was expected that an increase in air pollution level would discourage the use of more exposed modes (e.g., all cycling-related modes, walking) and encourage the use of more protected modes (e.g., car, bus, or taxi) (*38*).

The winter results of the survey were in line with such earlier findings. It was observed with high significance that biking, bikesharing, and walking were not preferred when the air pollution level increased. Instead travelers switched to the use of cars, buses, taxis, and electric bikes. The only different finding in this study was the choice of an electric bike, which was positively correlated with the air pollution level in the winter results. A negative correlation was found in earlier research. The phenomenon could possibly be explained by the commonly observed inconsistent behavior between revealed preference observations and stated preference experimental results (*39, 48*). In real life, a traveler might still have to use a privately owned electric bike on a day with heavy air pollution, although this mode might not be a preferred choice in a hypothesized scenario.

Given the much better air quality during the summer, the model showed more disordered results in terms of air pollution's impact. For instance, the three nonmotorized modes were even found to have inconsistent impact signs (i.e., air pollution was negatively correlated with walking but positively correlated with biking and bikesharing). The results indicated that air pollution increased the perceived utilities of the cycling modes from a modeling perspective. However, during the summer, when air quality in general was good, a traveler may have been insensitive to a change in air pollution statistics. A decision to cycle could have been made even if the air quality had degraded from perfect to very good. In other words, air pollution would become a less important concern compared with other factors. Overall, the results from the two seasonal models implied that severe air pollution could significantly discourage the use of all nonmotorized transport modes (e.g., biking, bikesharing, walking). However, when air pollution became moderate, a change in air pollution level did not have a significant impact on mode choice behavior.

Temperature was the other natural-environment factor studied besides air pollution. Similarly, the seasonal comparison revealed that mode choice was affected at different temperature levels. The summer results showed that an increase in temperature made a variety of modes relatively more popular than the use of a taxi, which was strictly a less preferred option under higher summer temperatures. This finding might have been the result of a strong local perception that the adequacy of air conditioning in taxis was an uncertainty. In winter, a temperature increase was positively associated with bikesharing, electric biking, and driving a car and negatively associated with walking, biking, and taking a bus or a taxi. Such a relatively abnormal finding may have been a special phenomenon of this case study. Nevertheless, more local evidence is needed to better interpret this result.

TABLE 3 Summer and Winter Model Estimation Results

	Summer		Winter	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
α_{cardri}	9.57	–2.75	1.89	1.46
Work–car driver	1.49	4.77	0.67	2.77
Temperature–car driver	0.08	2.79	0.02	1.16
Air pollution–car driver	0.018	2.69	0.015	5.63
Travel time–car driver	0.02	1.10	–0.03	–0.97
Travel cost–car driver	0.19	4.41	0.12	2.66
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	3.24	2.74
Education–car passenger	1.14	3.30	1.51	4.89
Travel time–car passenger	0.07	3.44	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	0.27	0.93
Education–bus	1.42	4.63	1.16	2.95
Temperature–bus	0.03	1.01	–0.04	–1.99
Air pollution–bus	0.013	2.09	0.0002	0.06
Travel time–bus	0.003	0.32	–0.12	–6.86
Travel cost–bus	–2.69	–6.00	–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–electric bike	0.84	2.51	0.17	0.60
Temperature–electric bike	0.09	2.90	0.01	0.48
Air pollution–electric bike	–0.002	–0.21	0.003	1.35
Travel time–electric bike	0.04	1.76	–0.02	–0.94
Male–electric bike	0.44	0.65	1.22	2.54
Age (lower)–electric bike	–0.005	–0.01	–0.29	–0.56
Income (lower)–electric bike	6.74	0.30	10.90	0.20
α_{bike}	–4.96	–1.41	7.88	5.23
Work–bike	0.83	2.22	0.48	1.25
Education–bike	0.83	1.94	0.92	1.69
Temperature–bike	0.03	0.74	–0.06	–2.25
Air pollution–bike	0.016	1.85	–0.009	–2.63
Travel time–bike	–0.12	–7.12	–0.21	–8.26
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	14.50	7.97
Work–bike share	0.40	1.02	1.05	2.37
Education–bike share	1.77	4.67	0.67	1.01
Temperature–bike share	0.13	4.02	0.04	1.07
Air pollution–bike share	0.017	2.20	–0.058	–6.71
Travel time–bike share	–0.07	–4.81	–0.24	–7.42
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
Work–walk	0.75	1.54	0.31	0.77
Education–walk	1.53	2.93	1.45	2.56
Temperature–walk	0.03	0.70	–0.06	–2.02
Air pollution–walk	–0.001	–0.13	–0.018	–5.12
Travel time–walk	–0.24	–15.03	–0.31	–14.54
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
Work–taxi	–1.23	–0.81	–0.0001	–0.00
Temperature–taxi	–0.38	–2.60	–0.07	–1.65
Air pollution–taxi	–0.013	–0.55	0.003	0.65
Travel time–taxi	0.57	7.62	0.03	0.61
Travel cost–taxi	–0.81	–7.81	–0.02	–0.29
Number of observations	1,797		1,722	
Initial log likelihood	–3,323.4		–3,189.3	
Final log likelihood	–1,400.2		–1,173.0	
Likelihood ratio test	3,846.4		4,032.6	
$\bar{\rho}^2$	.559		.612	

Two trip purposes were studied. For travelers going to work, the results in both seasons showed that, when the parameter of car passenger choice was normalized to zero, the taxi was the only mode choice that would not be chosen, and all other alternative modes were found to have positive correlations with work-related purposes. For travelers with education-related trip purposes, riding as a passenger in a car or a bus, biking, bikesharing, and walking all were potential choices, given their positive impact signs in both seasons. Overall, the results implied that trip purpose was a factor that could consistently affect mode choice behavior across different air quality and weather conditions.

Travel time and travel cost were important attributes that affected mode choice behavior. With respect to travel time, the winter model found the expected negative relationship with most of the mode choices (except for riding as a passenger in a car or in a taxi, which is explained shortly), which meant the utility associated with each mode would decrease when it took a longer time to arrive at the destination. By comparison, a number of impact signs turned out to be positive in the summer model, including the impacts on car choice, bus choice, and electric bike choice (as well as on the choices to ride as a passenger in a car or in a taxi, which also was the case 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 might not have resulted in significant loss in comfort and utility. In other words, the travel time savings might not have been as important as in the winter period. However, travel time impacts on nonmotorized transport choices (e.g., biking, bikesharing, walking) always were negative throughout summer and winter. Such consistent behavior could be the result of the relatively low mobility power and the resultant longer travel time associated with nonmotorized transport so that a further increase in travel time always would be less preferred by travelers despite natural-environment conditions. In contrast, the positive impact signs of the choices to ride as a passenger in a car or a taxi throughout the two seasons might be explained by the fact that each mode was a passenger form of transport and, unlike the bus, did not required the use of exclusive lanes. Thus when individuals choose passenger transport modes, they do not have the same level of foreknowledge of travel time as do those who choose self-driven travel modes. With respect to travel cost, the impacts on the three mode choices showed consistent signs in summer and winter. Higher costs reduced demand for buses and taxis. However, car cost was positively associated with its choice as a transport mode. The key reason was that, in a revealed preference survey, many drivers do not have perfect knowledge of the cost of driving a car (i.e., the fuel cost). Therefore, the travel cost of a car may not be precisely taken into account by individuals when they are making their choices.

An important discovery was that the effects of all three socioeconomic variables (gender, age, and income) were completely dominated by the impacts of other factors, given their low significance with respect to all modes across the two seasons. However, some trends were worth noting. In summer, more females chose as their travel modes to ride as passengers in a car or on a bus and to bikeshare and walk, whereas in winter they preferred to drive cars only. The elderly age group was found to have a positive relationship with bikesharing in summer but not in winter. Similarly in summer, wealthier people were open to all mode options except for the electric bike, which was preferred more by lower-income groups. In winter, however, wealthier people preferred only one option, which was to use a car, whether as a driver or as a passenger. Overall, the results with respect to the impacts of gender, age, and income could indicate the existence of seasonal influences, such that females, the elderly, and wealthier people were found to be more sensitive to worse air quality and lower temperatures. Nevertheless, these factors they were not as influential with respect to mode choice behavior as other factors.

CONCLUSIONS

This study looked at factors that might affect urban transport mode choice behavior in a developing country. It significantly advanced the knowledge boundary in the research community, and, as far as is known, was the first study to investigate the impact of air pollution on mode choice behavior. Two seasonal multinomial logit models were built to reveal any differences in impact factors under distinctive natural-environment conditions. Some implications for policy making could be drawn to more effectively help promote demand for nonmotorized transport.

This research suggests that efforts to clean the air and to promote nonmotorized transport must be undertaken simultaneously, because they are interdependent. A virtuous circle is possible: not only would an increase in the use of nonmotorized transport help improve air quality, but better air quality would in turn make nonmotorized modes increasingly attractive to travelers. Policy emphasis could, therefore, be placed on air pollution reduction in industrial, residential, and business sectors, which could in turn lead to further air quality improvement in urban transport. However, a cost–benefit analysis would be required to assess the feasibility of such a virtuous circle in practice, especially given the finding that air pollution diminishes in its impact as it drops to lower levels. In addition, females, the elderly, and wealthier people (i.e., those found to be more sensitive to a change in natural-environment conditions) would be expected to use more nonmotorized transport after air quality improved.

Individuals who commuted to and from work and who traveled for educational purposes were found to have relatively inelastic demand for nonmotorized transport across air quality and weather condition changes. A similar finding also was associated with travel time, which had a strong negative impact on nonmotorized transport use in both seasons. The results implied that policies that directly address trip purpose and travel time must be considered despite natural-environment conditions. For instance, policies could focus on satisfying commuters' stable demand for bikesharing, especially in areas in which workplaces and schools were concentrated. Measures taken could include an increase in the number of docking stations or the adoption of more flexible bike-return policies during peak times. For example, in addition to docking stations, portable card-scanning machines could be used to record bike use data so that bikes could be returned to and assembled by staff. The travel time needed in bikesharing could be reduced by introducing electric bikes to existing bikesharing schemes to enhance bikesharing mobility without causing more air pollution.

This research also reveals an important distinction between findings in developing and developed countries. In this study, socioeconomic characteristics (gender, age, and income) hardly had significant impacts on any mode choices, although many impact changes were observed across seasons. However, in developed countries, socioeconomic characteristics usually have been identified to have strong correlations with mode choice behavior (*13, 14, 23, 26, 30, 32, 33, 35–37*). The present study findings imply that, to effectively promote travel behavioral changes, policies should focus on factors that have more significant impacts (i.e., air pollution, trip purpose, travel time) than on socioeconomic groups. Nevertheless, more mode choice studies are needed in developing countries to further compare findings.

ACKNOWLEDGMENTS

The authors appreciate the support of the Shanxi Transportation Research Institute, which also provided funding and advice during the data collection. They also thank those who made the most significant contributions to the data recording task: Li Peiyu of Shanxi Experimental Secondary School, Hou Juntao of Peking University, and Zhao Helan.

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The Standing Committee on Transportation in the Developing Countries peer-reviewed this paper.