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Impact of weather conditions on middle school students' commute mode choices: Empirical findings from Beijing, China

Lu Ma[a], Hui Xiong[b,*], Zhong Wang[c], Kaiqiang Xie[b]

[a] *MOE Key Laboratory for Urban Transportation Complex Systems Theory and Technology, School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China*
[b] *Laboratory of Digital Manufacturing, School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China*
[c] *School of Transportation & Logistics, Dalian University of Technology, Dalian 116024, China*

A R T I C L E I N F O

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A B S T R A C T

Weather conditions have been recognized as important factors affecting school commute mode choices. This paper aims to explore the modal shift of middle school commutes with respect to the variation in weather-related variables, with empirical emphases on the situation in Beijing, China. Data from the latest Beijing School Commute Survey (2014–2015) were adopted, and multinomial probit (MNP) and multinomial logit (MNL) models were developed. The modeling results are in favor of the MNP model because it has better statistical performance. Weather-related variables, including sky condition, wind speed, highest temperature, humidity, air quality index (AQI), and some interaction terms, were found to have a significant impact on students' commute mode choices. Based on these models, an empirical sensitivity measure was defined as the expected percentage change in the probability of choosing each mode with respect to an order of magnitude change in the influential factors. Most of the results are in line with those of previous studies, and some unique results reflect features of Beijing. For example, on days with extremely poor air quality, students are more likely to turn to public transport rather than use a car from active transportation modes. This is probably due to the special urban traffic regulations that restrict household car ownership and car travel in Beijing. These findings could have implications for promoting active transportation for students and serve as references for policy-makers and planners.

1. Introduction

School commutes are integral to urban daily commutes and have an important influence on local traffic conditions (Black et al., 2001), vehicle emissions (Singleton, 2014), travel behaviors of adults who escort students (Scheiner, 2016; He and Giuliano, 2017), and the physical health of students (Sirard and Slater, 2008; Hellinga, 2016). Understanding travel behaviors, especially school commute mode choices, has received considerable attention over the past two decades. Studies have investigated impacts on school commute mode choices based on the effects of socioeconomic and demographic variables (Kerr et al., 2007; Wati and Tranter, 2015), urban environment conditions (Elias and Katoshevski-Cavari, 2014), land use characteristics (Scheiner, 2016), etc. However, the impact of weather conditions has been rarely examined (Scheiner, 2016). Although some studies (Hellinga, 2016) have indicated the importance of weather conditions on determining student commute modes, there remains a lack of studies specifically focusing on quantitative mode choice behaviors, and most of the existing literature reflects weather conditions using only seasonal or weekly

* Corresponding author.
E-mail addresses: lma@bjtu.edu.cn (L. Ma), xionghui@bit.edu.cn (H. Xiong), zwang@dlut.edu.cn (Z. Wang), kqx0731@163.com (K. Xie).

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variations (Scheiner, 2016).

Nevertheless, the influence of weather conditions on behaviors for general travel purposes has been studied for several decades. For example, it has been shown that inclement weather, such as rain, snow, fog, cold, and high winds, impact traffic safety, roadway capacity (Maze, et al., 2006), and travel route choices (Khattak and de Palma, 1997; Böcker et al., 2013). In particular, longer travel times for a car trip are required with heavier rain or snow due to reduced travel speeds (Tsapakis et al., 2013).

Thus, it seems plausible that school commute mode choices should also be affected by weather conditions. For example, sunny weather encourages students to walk and ride bicycles (Kamargianni et al., 2015), while students opt to take a bus or car to avoid walking on rainy days even when the distance to school is suitable for cycling or walking (Müller et al., 2008). Understanding the relationship between weather conditions and school commute characteristics will help policymakers implement appropriate management strategies and create more efficient and viable policies.

In short, the existing literature analyzing the effect of weather conditions on school commute mode choices is limited. There are few studies that have examined different countries, including Norway (Fyhri and Hjorthol, 2009), Germany (Müller et al., 2008), the United States (Sirard et al., 2005; Schlossberg et al., 2006), Canada (Mitra and Faulkner, 2012), the Netherlands (Hellinga, 2016), and Australia (Nankervis, 1999). However, these studies have primarily focused on North American and Western European countries rather than developing countries. Studies have also suggested that the empirical results of school commute models are likely to vary across different regions (Sirard and Slater, 2008; Liu et al., 2015b). Therefore, this study seeks to present an econometrical analysis focusing specifically on the impact of weather conditions on school commute mode choices using the latest school commute survey data for Beijing and to provide references for similar cities in China and other countries.

The rest of the paper is organized as follows. Section 2 positions the paper in the context of past literature. In Section 3, we describe the adopted dataset and present descriptive results of the included variables. Section 4 presents the econometrical models used for analyses. In Sections 5 and 6, we summarize our key findings. Section 7 concludes the paper and discusses its limitations and directions for future research.

2. Literature review

Previous studies (e.g., Yarlagadda and Srinivasan, 2008; He and Giuliano, 2017) have usually defined travel modes for school commutes as including walking, bicycle, taking public transport, and car. One of the major concerns in studying the behaviors of travel mode choices for school commutes is to understand factors affecting the active (walk and bicycle) travel modes (Martin et al., 2014), which have been considered a key source of physical activity for adolescents, especially in the present era of excessive screen-watching activities (Lauricella et al., 2015). Walking or cycling to school becomes important opportunities for adolescents to enjoy rigorous physical exercise. It has been widely recognized that active commuting is positively associated with psychological well-being (Martin et al., 2014; Chan and Ryan, 2009) and has been proposed as a strategy for reducing the prevalence of obesity and related diseases (Sirard et al., 2005) as well as enhancing the independence of children (Fyhri and Hjorthol, 2009).

Many factors have been investigated to examine their influence on school commute mode decisions, including the age, gender, and ethnicity of the student (Elias and Katoshevski-Cavari, 2014; Fyhri and Hjorthol, 2009; Hellinga, 2016), household car ownership (Larsen et al., 2009; Pojani and Boussauw, 2014; Schlossberg et al., 2006), land-use mix (Ewing et al., 2004; Kerr et al., 2007; Larsen et al., 2009), school size (Ewing et al., 2004), travel distance/time (Ewing et al., 2004; Fyhri and Hjorthol, 2009; Müller et al., 2008), mother's working hours (Elias and Katoshevski-Cavari, 2014; He and Giuliano, 2017), number of children in the household (Hellinga, 2016), and family income (Schlossberg et al., 2006).

Some of these factors exhibit consistent influential patterns across almost all studies. For example, travel distance has been shown to have a significant impact on school commute mode choices; shorter distances promote the use of an active commuting mode (Ewing et al., 2004; Elias and Katoshevski-Cavari, 2014; Hellinga, 2016; He and Giuliano, 2017). However, some results have been inconsistent across studies due to discrepancies in the overall settings of variables and models, variable categorizations, sample sizes, and possibly unobserved heterogeneities relating to variations in student cohorts, regions, cultures, and religions (Singh and Vasudevan, 2018). For example, studies (e.g., Sidharthan et al., 2011) have found that an increase in age could result in higher odds of walking and bicycling for school commutes, although some studies (Wilson et al., 2010) have been unable to detect a well-defined relationship between age and school commute mode choices. Readers should consult a few studies (Pojani and Boussauw, 2014; Hellinga, 2016; Scheiner, 2016; Singh and Vasudevan, 2018; Li and Zhao, 2015; Cheng et al., 2017) for a more extensive and comprehensive review of the factors affecting school commute mode choices. In contrast to weather-related variables, these factors have been well studied.

For general purposes, the impact of weather conditions has been investigated in terms of public transit ridership (Arana et al., 2014; Singhal et al., 2014; Guo et al., 2007), pedestrian volume (Aultman-Hall et al. 2009), trip-purpose variation (Cools et al., 2010), departure time (De Palma and Rochat, 1999), and route choice (Khattak and de Palma, 1997). Days with adverse weather conditions, such as rain, wind, and low temperatures, are generally more likely to reduce propensities for using public transit, walking, and bicycling and correspondingly raise the use of passenger cars (Clark et al., 2014). Using regression models, quantitative results have also been presented in the literature. For example, younger travels have been found to be more sensitive to low temperatures than older age groups, and cyclists are more sensitive to precipitation, low temperatures, and wind than walkers (Flynn et al., 2012; Saneinejad et al., 2012).

These results and conclusions provide important references for understanding the weather's impact on school commute behaviors, but school commutes have distinct features. Specifically, a regular trip could be canceled (Madre et al., 2007) due to poor weather conditions, leading to reduced overall demand (Aultman-Hall et al. 2009; Liu et al., 2015a; Bergström and Magnusson, 2003).

However, the overall demand for school commutes is by nature less sensitive to weather conditions. Moreover, adverse weather conditions are associated with a higher rate of traffic accidents (Koetse and Rietveld, 2009; Changnon, 1996; Edwards, 1999; Yu et al., 2015), raising safety concerns for parents making decisions on children's school commute modes.

As mentioned above, the existing literature examining the relationship between weather conditions and school commuting behaviors is limited except for a few studies that consider weather-related variables in modeling school commute mode choices, including seasonal variations (Fyhri and Hjorthol, 2009; Müller et al., 2008), temperature characteristics (Sirard et al., 2005), precipitation (Mitra and Faulkner, 2012), and wind speed (Hellinga, 2016). Similar to a regular trip, poor weather has also been identified as a primary reason for using passenger cars (Schlossberg et al., 2006), while some studies (Nankervis, 1999; Mitra and Faulkner, 2012) have reported that weather conditions are not strong barriers for students in choosing an active mode for school commutes. Thus, the influence of weather conditions on school commute behaviors is not fixed and may depend on differences in regions, student cohorts, and other variables.

Student travel behaviors have begun to raise concerns in Beijing because they are directly related to physical activities and health conditions of adolescents, to road traffic performance, and to transportation planning and policies. Furthermore, Beijing has its own urban features and weather characteristics, e.g., poor air quality, and these can lead to special influential patterns between weather conditions and school commute mode choices. The fact that these characteristics of Beijing have not been considered in previous studies motivated the present study.

As one of China's megacities, Beijing's air quality is sometimes very poor (Li et al., 2015; Chen et al., 2016; Liu et al., 2017) due to excessive emissions from vehicles and neighboring industries, especially in winter. This study incorporates the air quality index (AQI) as an influential factor in the models of school commute mode choices. To our knowledge, this is the first time the AQI has been considered in travel demand models.

Although the weather's impact on travel mode choices has been considered in research covering over three decades, studies specifically focusing on school commutes are limited. This study contributes to the literature by providing an empirical analysis of the weather's impact on school commute mode choices using a recent large-scale survey in Beijing, China.

3. Data

3.1. Study area and the data source

Beijing is the capital city of China, with a population of more than 27 million. Based on the latest education census, the city has a school-going population of 1.8 million, creating approximately 1.0 million car-based person commutes every day. Although these car-based school commutes only account for approximately 10% of all car trips, urban traffic conditions are very sensitive to these commutes because the overall traffic pressure is high. In addition, because these school commutes are temporally and spatially concentrated, they could lead to serious traffic jams on roads near schools and create bottlenecks throughout the overall network.

Beijing is implementing two special policies for controlling passenger car demand. First, approximately 80% of private cars are allowed traveling on the road, with rotations based on the last digit of license plate numbers. Second, the number of newly purchased private cars is controlled for the entire city. Every person wishing to buy a car must participate in a drawing, and the odds of winning are very small; hence, some households in Beijing do not own cars. For those households, taxis or ride-sourcing services are always an option. Thus, it is valid to have cars as an alternative for all the observations. In the survey, private cars, taxis, and ride-sourcing vehicles are not differentiated and are all designated as cars.

The data adopted in this study originated from the latest Beijing School Commute Survey conducted in December 2014 and January 2015. The geographic coverage of the dataset is the central area of Beijing, comprising six inner districts. The survey was conducted using an online questionnaire; the sampled students were required to fill in a form via an internet website. The online questionnaire comprised questions about the student's personal and household attributes and school commute characteristics. For commute-related questions, the students had to provide information about their latest school commute made prior to the day the questionnaire was completed.

The survey collected student and commute characteristics, while weather-related variables were matched from historical weather records. These weather-related variables corresponded to the departure time of each trip, although they were averaged across the six inner districts in Beijing. Note that the highest temperature was measured on a daily basis. The original survey covered students in primary school, middle school, and high school. Middle school students experience a transition period, including a growing independence. Thus, the lower-grade students in middle school might behave similarly to primary school students who require their parents' company for their school commute, whereas the upper-grade students have more frequent opportunities to go to school by themselves. Thus, this study only focuses on middle school commutes, with the final dataset comprising 97,427 observations.

3.2. Description of variables

There are four alternative transportation modes for school commutes, i.e., walking, bicycle, public transport, and car. Specifically, the bicycle mode includes regular bicycles and e-bicycles; the car mode includes private cars, taxis, and ride-sourcing vehicles; and the public transport mode includes buses, subways, and school buses. In Beijing, very few students take school buses as their daily travel mode to school.

Weather conditions in the original data include sky condition, wind speed, highest temperature, lowest temperature, AQI, humidity, and visibility. During the survey period, there were no rainy days. Thus, precipitation was not considered in this study. The

Table 1
Descriptive characteristics of continuous explanatory variables.

Continuous variable	Mean	Std. dev.	Min.	Max.
Distance (km)	8.263	6.118	0.1	50
The highest temperature (°C)	4.463	2.187	0	10
Humidity (%)	37.070	11.410	18	79
Wind speed (m/s)	7.001	3.380	2	19

lowest temperature and visibility were also dropped because they had no evident impact on school commute mode choices at the 95% significance level.

All adopted continuous and categorical explanatory variables are described in Tables 1 and 2, respectively. Fig. 1 illustrates the variations in weather-related variables during the survey period. Each observation in the data represents a school trip and the associated information on weather conditions. Table 2 indicates that middle school students preferred public transport as a commuting mode over the other available modes. The proportion of walking to school is 19.0%, which is lower than in some countries. For example, a study in Australia indicated that 44.3% of female students and 37.4% of male students walk to school (Leslie et al., 2010). In Toronto in 2006, walking was the choice for 42.5% and 30.7% of school commutes for students 11–13 years old and 14–15 years old, respectively (Buliung et al., 2009). Regarding sky conditions, most observed commutes (73.4%) occurred on days with good conditions, while 19.9% of commutes occurred on days with poor conditions. Humidity refers to the amount of water vapor in the air and indicates the likelihood of precipitation, dew, or fog. In this paper, relative humidity was adopted, which measures the current humidity relative to the maximum humidity at that temperature. AQI is an atmosphere variable of increasing interest. In practice, people intuitively perceive AQI as "good," "poor," and "terrible" corresponding to the ranges "≤100," "> 100 and ≤200," and "> 200," respectively.

4. Econometrical models

In this study, the multinomial logit model and multinomial probit model were adopted to link the probabilities of school commute modes to explanatory variables. Suppose that the choice set includes j travel modes ($j = 1,2,...,J$) and the utility that student i ($i = 1,2,...,I$) gains from mode j takes the form

$$U_{ij} = \boldsymbol{\gamma}_j^{\top}\boldsymbol{z}_i + \varepsilon_{ij}, \tag{1}$$

where U_{ij} is student i's utility for choosing mode j, $\boldsymbol{z}_i$ is the vector of explanatory variables that vary across individuals, $\boldsymbol{\gamma}_j$ is the coefficients associated with $\boldsymbol{z}_i$ in the jth utility function, and ε_{ij} is the error term. The systematic part of the utility function $\boldsymbol{\gamma}_j^{\top}\boldsymbol{z}_i$ is a linear function of explanatory variables, with coefficients varying across different alternatives. Note that this function includes only individual-specific variables in this study, and the systematic utility of the reference mode (walking was chosen) is fixed at zero. With respect to the principal of random utility maximization (Can, 2013), the probability of choosing mode j corresponds to U_{ij} being greater than the utilities of other choices:

$$P_{ij} = P(U_{ij} > U_{i1}, U_{ij} > U_{i2}, ..., U_{ij} > U_{ij-1}, U_{ij} > U_{ij+1}, ..., U_{ij} > U_{iJ}) = P[(\varepsilon_{ij} - \varepsilon_{im}) > (\boldsymbol{\gamma}_m^{\top} - \boldsymbol{\gamma}_j^{\top})\boldsymbol{z}_i, \quad forall\ m \neq j]. \tag{2}$$

If all ε_{ij} are assumed to be identical and independent standard Gumbel distributions, the model is the multinomial logit model, and P_{ij} is given by

Table 2
Descriptive characteristics of categorical explanatory variables.

Categorical variable	Value label	Travel mode				Total
		Walking	Bicycle	Public transport	Car	
Age of student	12[a]	6221 (6.4%)	5778 (5.9%)	12,429 (12.8%)	9667 (9.9%)	34,095 (35.0%)
	13	6571 (6.7%)	4924 (5.1%)	13,509 (13.9%)	9664 (9.9%)	34,668 (35.6%)
	14	5702 (5.9%)	4101 (4.2%)	10,547 (10.8%)	8314 (8.5%)	28,664 (29.4%)
Sky condition	Good (clear)[a]	14,502 (14.9%)	12,108 (12.4%)	25,707 (26.4%)	19,237 (19.7%)	71,554 (73.4%)
	Fair (cloudy)	1133 (1.2%)	724 (0.7%)	2438 (2.5%)	2212 (2.3%)	6507 (6.7%)
	Poor (foggy or hazy)	2859 (2.9%)	1971 (2.0%)	8340 (8.6%)	6196 (6.4%)	19,366 (19.9%)
AQI	Good (≤100)[a]	13,289 (13.6%)	11,038 (11.3%)	24,611 (25.3%)	17,813 (18.3%)	66,751 (68.5%)
	Poor (> 100 and ≤ 200)	4955 (5.1%)	3740 (3.8%)	8770 (9.0%)	7706 (7.9%)	25,171 (25.8%)
	Terrible (> 200)	250 (0.3%)	25 (0.0%)	3104 (3.2%)	2126 (2.2%)	5505 (5.7%)

[a] This category was used as the "reference" in the following models.

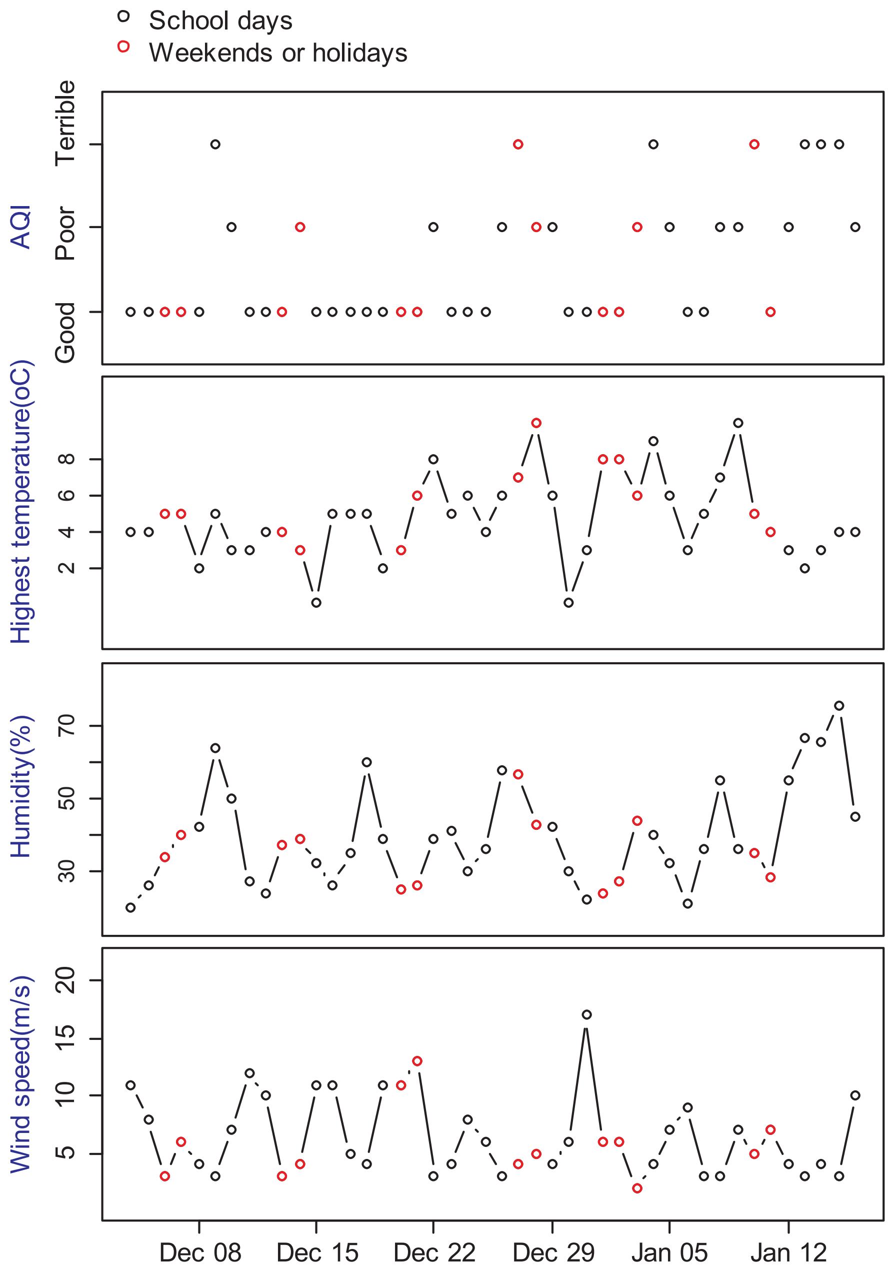

Fig. 1. Variations of weather-related variables during the survey period.

$$P_{ij} = \frac{\exp(\boldsymbol{\gamma}_j^{\top}\boldsymbol{z}_i)}{\sum_{m=1}^{J}\exp(\boldsymbol{\gamma}_m^{\top}\boldsymbol{z}_i)}. \tag{3}$$

The multinomial logit (MNL) model provides a closed form for evaluating the chosen probability, leading to fewer computation pressures and clearer inferences on explanatory variables. However, the MNL model suffers from the independence of irrelevant alternatives (IIA) property due to the assumption of the independently distributed error terms.

One way of removing this assumption is to consider a multivariate normal distribution for the error terms of the utilities, which leads to the multinomial probit (MNP) model. For individual i, ε_{ij} for $j = 1,2,...,J$ follows a multivariate normal distribution with mean zero and covariance matrix Σ. Note that these error terms are still independently distributed across different individuals. If we define the differences of the error terms $\widetilde{\varepsilon}_{im} = \varepsilon_{ij} - \varepsilon_{im}$ and the systematic terms $\xi_{im} = (\boldsymbol{\gamma}_m^{\top} - \boldsymbol{\gamma}_j^{\top})\boldsymbol{z}_i$ for $m = 1,...,j-1,j+1,...,J$, then the probability of choosing mode j is given by

Table 3
Estimated coefficients of the MNP and MNL models.

Explanatory variables	Multinomial probit (MNP) model			Multinomial logit (MNL) model		
	Bicycle	Public transport	Car	Bicycle	Public transport	Car
Intercept	−3.976 (−12.396)	32.346 (9.832)	39.671 (9.490)	−2.802 (−14.038)	−4.931 (−22.948)	−5.014 (−23.193)
Distance	1.461 (37.777)	0.809 (12.148)	3.005 (50.286)	1.036 (85.093)	1.405 (111.388)	1.366 (108.300)
Highest temperature	−0.077 (−1.345)	0.253 (0.831)	−0.870 (−2.772)	−0.063 (−1.714)	−0.172 (−4.330)	−0.199 (−4.998)
Humidity	−0.024 (−3.414)	−0.040 (−1.052)	−0.015 (−0.377)	−0.018 (−3.997)	−0.011 (−2.343)	−0.018 (−3.585)
Wind speed	0.014 (1.323)	0.217 (3.645)	−0.178 (−2.640)	0.008 (1.184)	0.017 (2.349)	0.039 (5.174)
Age of student						
13	−0.452 (−8.356)	0.968 (3.824)	−1.828 (−6.599)	−0.352 (−10.264)	−0.217 (−5.952)	−0.265 (−7.194)
14	−0.630 (−10.849)	1.469 (5.354)	−2.847 (−9.648)	−0.483 (−13.315)	−0.444 (−11.442)	−0.408 (−10.465)
Sky condition						
Fair	0.004 (0.043)	5.880 (9.769)	−5.212 (−8.450)	−0.158 (−2.247)	0.226 (3.093)	0.555 (7.618)
Poor	−0.112 (−1.272)	−0.643 (−1.360)	0.704 (1.548)	−0.137 (−2.441)	0.087 (1.451)	−0.060 (−0.992)
AQI						
Poor (> 100 and ≤200)	−0.204 (−1.817)	5.812 (7.178)	−5.633 (−7.604)	−0.037 (−0.462)	−0.454 (−4.822)	−0.547 (−5.804)
Terrible (> 200)	−3.594 (−5.293)	−3.783 (−2.414)	7.405 (4.111)	−3.526 (−6.496)	0.952 (3.199)	0.547 (1.836)
Interaction terms						
AQI (Poor) × distance	0.132 (4.619)	0.085 (1.789)	0.044 (0.960)	0.079 (3.130)	0.153 (5.819)	0.173 (6.595)
AQI (Terrible) × Distance	0.316 (2.482)	0.678 (4.375)	−0.508 (−2.985)	0.441 (3.637)	0.322 (3.085)	0.354 (3.393)
Highest temperature × Humidity	0.003 (2.411)	0.011 (1.423)	0.003 (0.454)	0.002 (2.836)	0.004 (3.719)	0.006 (5.886)
Modeling performance						
Log-likelihood	−88137			−88879		
AIC	176,369			177,843		
BIC	176,815			178,242		
McFadden R-squared	0.318			0.312		

Values in parentheses are t-statistics associated with estimated coefficients.

$$P_{ij} = \int_{\xi_{i1}}^{\infty} \dots \int_{\xi_{i(j-1)}}^{\infty} \int_{\xi_{i(j+1)}}^{\infty} \dots \int_{\xi_{iJ}}^{\infty} \phi(\widetilde{\varepsilon}_{i1},\dots,\widetilde{\varepsilon}_{i(j-1)},\widetilde{\varepsilon}_{i(j+1)},\dots,\widetilde{\varepsilon}_{iJ})d\widetilde{\varepsilon}_{i1}\dots d\widetilde{\varepsilon}_{i(j-1)}d\widetilde{\varepsilon}_{i(j+1)}\dots d\widetilde{\varepsilon}_{iJ}. \tag{4}$$

where $\phi(\cdot)$ is the probability density function of the error term differences, which is also a multivariate normal distribution.

The covariance matrix for the error term differences is usually used in model estimation. More generally, with J alternatives, the number of the identifiable parameters of the covariance matrix is $J \times (J-1)/2-1$, and it is almost impossible to interpret these parameters. The following analyses were performed with the aid of the “mlogit” package in R.

5. Estimation results from the MNP and MNL models

The MNP and MNL models were used to test the effects of sky condition, wind speed, highest temperature, AQI, humidity, commute distance, and age of student on school commute mode choices. In addition, we also tested the effects of some interaction terms, and two important interactions (highest temperature plus humidity and AQI plus distance) were found to have significant impacts. Table 3 reports the estimated coefficients for both the MNP and MNL models. In this study, the dummy coding was adopted when specifying these categorical variables (Hensher et al., 2015). The results show that the MNP model is superior to the MNL model because the former has smaller AIC and BIC values and a larger McFadden R-squared. These characteristics indicate that the MNP model is able to mine more information from the data than the MNL model.

In the MNL model, the exponential function of a particular coefficient of a categorical variable is the odds ratio of the particular travel mode relative to the reference level between the status and the reference status of this variable. However, the estimated probability depends on the magnitudes or levels of other variables (Ma et al., 2016). If the corresponding status of the variable (for the categorical variables) is taken or the magnitude of the variable (for the continuous variables) increases under the MNL specification, the probability of the travel mode with the largest coefficient will increase, whereas the mode with the smallest coefficient will decrease. For example, with an increase in wind speed, the probability of walking decreases (coefficient of zero because the walk mode is the reference level), whereas the probability of using a car increases (coefficient of 0.039 is the largest among the four modes). However, the direction of probability change of the bicycle and public transport modes cannot be inferred through the corresponding coefficients. Note that such a rule is not valid for variables having interaction terms.

For the MNP model, it is further difficult to interpret these coefficients because the estimated probability is evaluated through a multiple integral involving the coefficients of all variables. Thus, these coefficients are more useful in predicting the probability of a travel mode for a given observation; they do not provide clear and direct indications for an understanding of the behavioral effects of variables. Therefore, this study introduces an empirical sensitivity analysis to overcome this issue, as illustrated in the next section.

6. Sensitivity analyses

6.1. Definition of empirical sensitivity

In the MNP and MNL models, the estimated coefficients cannot reflect the overall impact of a particular variable directly because it also depends on the magnitudes of all other variables. Therefore, a “strict impact” for a given variable cannot be determined because there are many ways of combining one variable with the other variables. One empirical way for handling this issue is to aggregate the impact of a variable with respect to each observed sample, in which the combinations of variables are inherently contained. The results are expected to reflect how the population reacts to hypothetical changes in variables providing a considerable sample size. For example, a type of elasticity (Eluru et al., 2012; Ma et al., 2016; Cameron and Trivedi, 2009) was defined in previous studies as the expected percentage change of the probability given a one-unit increase in the variable. In this study, empirical sensitivity was defined based on the elasticity with a minor modification. Instead of fixing the change in a variable to be one unit, empirical sensitivity can be evaluated with respect to the changes in a variable of any amount. Eqs. (5) and (6) provide the formulas defining empirical sensitivity.

$$ES_j = \frac{\sum_{i\in A}(P_{ij}^{*}-P_{ij})}{\sum_{i\in A}P_{ij}} \quad \text{for } j = 1,2,\ldots,J \tag{5}$$

$$P_{ij} = f_j(\boldsymbol{z}_i,\hat{\boldsymbol{\gamma}}), P_{ij}^{*} = f_j(\boldsymbol{z}_i^{*},\hat{\boldsymbol{\gamma}}) \tag{6}$$

Here, ES_j is the empirical sensitivity of travel mode j, and P_{ij}^{*} is the estimated probability of observation i choosing travel mode j but with hypothetical changes in the variables of interest. A is the set containing all relevant samples. For a continuous variable, A is the entire dataset. For a categorical variable, A consists of the subsamples having the appropriate level of the categorical variable. For example, when measuring elasticities with respect to an AQI change from good to poor, all samples with good AQI serve as A. $f_j(\cdot)$ is the probability mass function for evaluating P_{ij} and P_{ij}^{*}, which is obtained from the estimated MNL or MNP model. $\boldsymbol{z}_i^{*}$ is the vector of the explanatory variables with hypothetical changes in the variables of interest. $\hat{\boldsymbol{\gamma}}$ is the estimated coefficients from the MNL or MNP model. Such an empirical sensitivity is easy to use to understand the effects of changes in a specific variable on the outcome probabilities of travel mode choices.

6.2. Single-variable sensitivity

Table 4 reports the empirical sensitivity for each variable according to the MNP and MNL models. These numbers are the percentage changes in the probability of a travel mode with respect to changes in each variable. Positive values of sensitivity indicate an increase in the probability, whereas negative values indicate the opposite. The empirical sensitivities in Table 4 exhibit generally consistent influence patterns across the two models with only minor discrepancies in magnitude.

Table 4
Empirical sensitivity of variables (Unit: %).

Change in variable	Walking		Bicycle		Public transport		Car	
	MNP	MNL	MNP	MNL	MNP	MNL	MNP	MNL
Distance (increase 1 km)	−34.9	−35.1	0.8	1.0	10.5	10.4	9.0	9.2
Distance (increase 2 km)	−65.9	−66.1	−3.8	−2.4	21.3	20.9	18.0	17.9
Distance (increase 5 km)	−98.7	−98.7	−47.7	−46.1	45.3	44.4	31.7	32.1
Highest temperature (increase 2 °C)	−0.9	−1.5	6.2	5.9	−3.0	−6.3	1.3	6.2
Highest temperature (increase 4 °C)	−1.8	−3.1	14.7	11.8	−6.5	−12.6	2.0	12.4
Humidity (increase 10%)	0.1	−0.1	−8.3	−8.6	1.6	−0.1	2.2	4.8
Humidity (increase 20%)	0.2	−0.3	−15.9	−16.7	3.1	−0.4	4.3	9.7
Wind speed (increase 1 m/s)	−0.4	−0.5	−0.8	−0.9	−0.1	−0.6	0.7	1.6
Wind speed (increase 5 m/s)	−1.8	−2.5	−3.5	−4.4	−0.2	−3.1	3.3	8.2
Age (12 to 13)	9.5	9.6	−12.0	−12.3	−1.4	2.6	3.0	−2.1
Age (13 to 14)	4.3	4.4	−0.8	0.4	−2.0	−4.7	0.2	3.3
Sky condition (good to fair)	−2.3	−3.2	−21.5	−28.8	−2.1	−7.2	18.1	30.2
Sky condition (fair to poor)	3.7	4.7	32.6	24.9	2.8	16.1	−16.4	−28.3
AQI (good to poor)	−3.4	−3.0	−5.9	−1.1	−6.0	−3.9	14.7	8.3
AQI (poor to terrible)	−16.4	−16.1	−93.9	−95.5	35.0	36.7	16.4	14.9

6.2.1. Sky conditions

According to Table 4, the qualitative impact of sky conditions on school commute mode choices is the same across the MNP and MNL models and differs only slightly in magnitude. With a change in sky conditions from good to fair, the probabilities of walking, cycling, and taking public transport are expected to decrease by 2.3%, 21.5%, and 2.1%, respectively according to the MNP model. Moreover, the number of students choosing a car to go to school increases by 18.1%. Such a pattern is in line with previous studies (e.g., Bergström and Magnusson, 2003) showing that poor weather promotes the use of cars. In fact, the market shares of walking and using public transport change in very slight amounts, although cycling drops substantially, which accounts for the major proportion of the students who turn to the car mode. Moreover, when sky conditions continue to change (from fair to poor), the above-discussed trend takes the opposite direction, where the car mode share decreases. When sky conditions worsen, traffic may become congested and visibility is reduced, which raises resistant concerns about using cars.

6.2.2. Wind speed

Table 4 presents the modal shift results with respect to two different levels of wind speed increments, namely, 1 m/s and 5 m/s. With an increase in wind speed, walking, cycling, and public transport are less likely to be used, resulting in the increased use of cars. It is easy to understand the decline in walking and cycling because the wind impacts these unprotected active travel modes directly (Saneinejad et al., 2012; Flynn et al., 2012). Specifically, the bicycle mode is more sensitive to the influence of high wind speeds than the walking mode. For a 1 m/s increase in wind speed, the probabilities of walking and cycling are expected to decrease by 0.4% and 0.8%, respectively, while for a 5 m/s increase in wind speed, the drop is 1.8% and 3.5%, respectively, according to the MNP model. Furthermore, public transport is also unwelcome on windy days. Note that students typically walk to bus stops, and they also have to wait for the bus, which would directly expose them to the wind. Such a result is consistent with those of previous studies (e.g., Guo et al., 2007; Arana et al., 2014). Note that these qualitative results regarding wind speed are consistent between the MNP and MNL models.

6.2.3. Highest temperature

The responding modal shifts with respect to the highest temperature increments of 2 °C and 4 °C were investigated. The trend remains consistent for the two different settings; with an increase in the highest temperature, walking and public transport become less attractive. This finding is consistent with Liu et al. (2015a), who showed that commuters tend to walk less when the temperature rises on a “colder than normal” day. The reason is that when the temperature rises in winter, cycling and driving becomes safer (Zhou et al., 2017) because, in cold winter weather, with a temperature below 0 °C (the lowest temperature ranged from −8°C to 0 °C during the survey), the pavement may be icy and prone to traffic accidents.

Of all four modes, cycling is the most sensitive to temperature variations; its market share is expected to increase by 14.7% for an increase in the highest temperature by 4 °C according to the MNP model. This is in line with the results obtained by Helbich et al. (2014), whereas some contrary results (Noland, 1995; Amiri and Sadeghpour, 2014) have also been found. Note that these qualitative results regarding the highest temperature are consistent between the MNP and MNL models.

6.2.4. AQI

To our knowledge, no studies have considered the impact of the AQI on school commuting behaviors. One possible reason is that the AQI in the study areas of past studies was low and had small variations and hence imposed a negligible influence on travel behaviors. However, the estimated model indicates that the AQI has a significant impact on school commute mode choices in Beijing. According to Table 4, the mode shares vary slightly when the AQI changes from good to poor, with the average probability of walking, cycling and taking public transport decreasing by 3.4%, 5.9%, and 6.0%, respectively, whereas choosing to use a car increases by 14.7% (MNP model). However, when air pollution changes from poor to terrible, there is a striking shift in the commute mode choices.

Children are known to be more vulnerable to the adverse effects of air pollution than adults. Epidemiological studies have reported that the developing lungs of a child are highly susceptible to damage after exposure to air pollution and may show decreased growth in lung functions (Kim, 2004). The estimation results indicate that when the AQI deteriorates from poor to terrible, an average of 16.4% of walkers and 93.9% of cyclists abandoned the active transport mode to avoid exposure to air pollution. These students turned instead to public transport and cars, resulting in a 35.0% increase in the public transport mode and a 16.4% increase in the car mode. Interestingly, public transport is more appealing than cars provided that the AQI rises to “terrible,” which is counterintuitive because the car mode provides better air quality due to its air conditioning system. One of the reasons is that some households do not own a vehicle in Beijing due to the special policy controlling citywide vehicle ownership (see Section 3.1 of this paper). Moreover, during days with extremely terrible air quality, only half of the vehicles are allowed to travel, with rotations based on the last digit of the license plate numbers in Beijing. To some extent, these special regulations prevent students from choosing cars for their commute to school. Note that these qualitative results regarding the AQI are consistent between the MNP and MNL models.

6.2.5. Humidity

As shown in many studies, humidity affects travelers’ mode choice behaviors (Aultman-Hall et al., 2009; Amiri and Sadeghpour, 2014; Nankervis, 1999; Liu et al., 2015a). In this study, empirical sensitivities corresponding to 10% and 20% humidity increases were investigated. Among the four modes, walking is the least sensitive to humidity variations, which is in line with Aultman-Hall et al. (2009), who found that humidity has a limited effect on pedestrians. In contrast, the bicycle mode share drops substantially for an increase in humidity. According to the MNP model, the sensitive effect indicates that 15.9% of cyclists turn to other modes when the humidity increases by 20%. The MNP model also indicates that the public transport and car modes are positively affected by an increase in humidity. Specifically, a 20% increase in humidity is associated with a 3.1% rise in public transport and a 4.3% rise in car usage. In the cold season, the perceived temperature is lower than the air temperature under higher humidity, making the public transport and car modes more favorable to students than the active modes. According to the MNL model, the public transport mode is not sensitive to variations in humidity. Minor reductions (0.1% and 0.4% for humidity increases of 10% and 20%, respectively) of public transport use were found. The reduction in the active mode commutes makes students turn to using cars.

6.2.6. Commute distance

Commute distance has long been recognized as an important variable affecting mode choice decisions (Ewing et al., 2004; Fyhri and Hjorthol, 2009; Müller et al., 2008). However, there are no fixed rules for which modes become more attractive with an increase in distance; how these modes shift will depend on the actual increase in that distance. Thus, this study investigates the effects of three different increments (1 km, 2 km, and 5 km) of distance on school commute mode choices. As the distance increases, the propensity for the walking mode is consistently reduced. For a 5 km increment in distance, nearly not students walk to school (a 98.7% drop). Meanwhile, the proportion of students using public transport and cars increases dramatically.

As for the bicycle mode, its use is not consistently reduced with an increase in distance. According to the MNP model, the number of students choosing the bicycle mode for their school commute is reduced by 47.7% when the distance increases by 5 km, while it slightly increases (0.8%) for a 1 km increment in distance. However, such a result has rarely been investigated in previous studies focusing on school commute mode choices. Note that these qualitative results regarding distance are consistent between the MNP and MNL models.

6.2.7. Age of student

The ages of the studied students range from 12 to 14, corresponding to grades 7 to 9. Older students are more likely to walk to school, which is in line with previous studies (e.g., Elias and Katoshevski-Cavari, 2014). However, the market share of bicycle commutes decreases substantially when the age increases from 12 to 13, which contradicts some prior studies (e.g., Wati and Tranter, 2015). In China, many parents use a children's seat on their bicycles or e-bicycles to transport their children to school. Thus, as the students become more independent as they grow older, the market share of bicycle commutes decreases because of the reduction in the number of students going to school on a children's bicycle seat.

Regarding the public transport and car modes, their shifts are relatively small in contrast to the walking and bicycle modes. This is probably because the age range in this study is too narrow to reflect a substantial variation. In fact, students have more flexibility when making mode choice decisions for their school commutes as they become more independent (e.g., He and Giuliano, 2017). Thus, for older students, more frequent car commutes are expected, which is probably because some of them are able to take a taxi or e-hail a car by themselves. Slight discrepancies were found between the MNP and MNL models in the shifts for the public transport and car modes for students of age 12 to 13. The MNP model indicates a 1.4% decrease and a 2.6% increase in the public transport and car modes, respectively, whereas the MNL model indicates a 3.0% increase and a 2.1% increase in the public transport and car modes, respectively.

6.3. Two-variable sensitivity

The above analyses considered the impact of a single variable on school commute mode choices. It is also interesting to explore how the modal split of school commutes reacts to simultaneous changes in two variables. In a linear regression model, the interaction effects between variables can be investigated directly through the coefficient associated with the interaction terms. However, in the MNP and MNL models, we can understand the interaction effects only through the coefficients associated with the interaction terms. The probability function is nonlinearly related to the interaction term and the corresponding marginal terms as well as other variables, making the effect from the interaction term confounded by other variables. Specifically, the interaction term and the corresponding marginal terms are inherently connected, leading to a more difficult situation for interpretation. This section presents the empirical sensitivities with respect to different combined changes in two variables. Figs. 2 and 3 illustrate the empirical sensitivities for the combination of the highest temperature plus humidity and the AQI plus commute distance, respectively. The trend lines of one variable for different levels of the other variable are shown. If these lines are parallel to each other, we can assume that the interaction effect between these variables is small (in the sense of the defined sensitivity).

6.3.1. Highest temperature plus humidity

Along with an increase in the highest temperature, the variation in the sensitivity of the walking mode due to humidity increases. However, there is no obvious interaction effect between the highest temperature and humidity on the sensitivities for both the bicycle and public transport modes. For the public transport and car modes, the sensitivities are substantially different between the MNP and MNL models. In the MNP model, the usage of the public transport and car modes is less sensitive to the changes in both the highest temperature and humidity, and the interaction effects between the highest temperature and humidity are not substantial, which is probably because the range of the highest temperature during the survey period is too narrow to reflect their interaction. In fact, high humidity could make the weather feel colder in winter, leading to a larger decrease in bicycle school commutes.

6.3.2. AQI plus commute distance

Fig. 3 illustrates the empirical sensitivities with respect to different combined changes in the AQI and commute distance for both the MNP and MNL models. The two models illustrate similar influence patterns for the combined changes of the two variables on all four school commute modes. For the walking mode, there is no obvious interaction effect between the two variables at the low levels

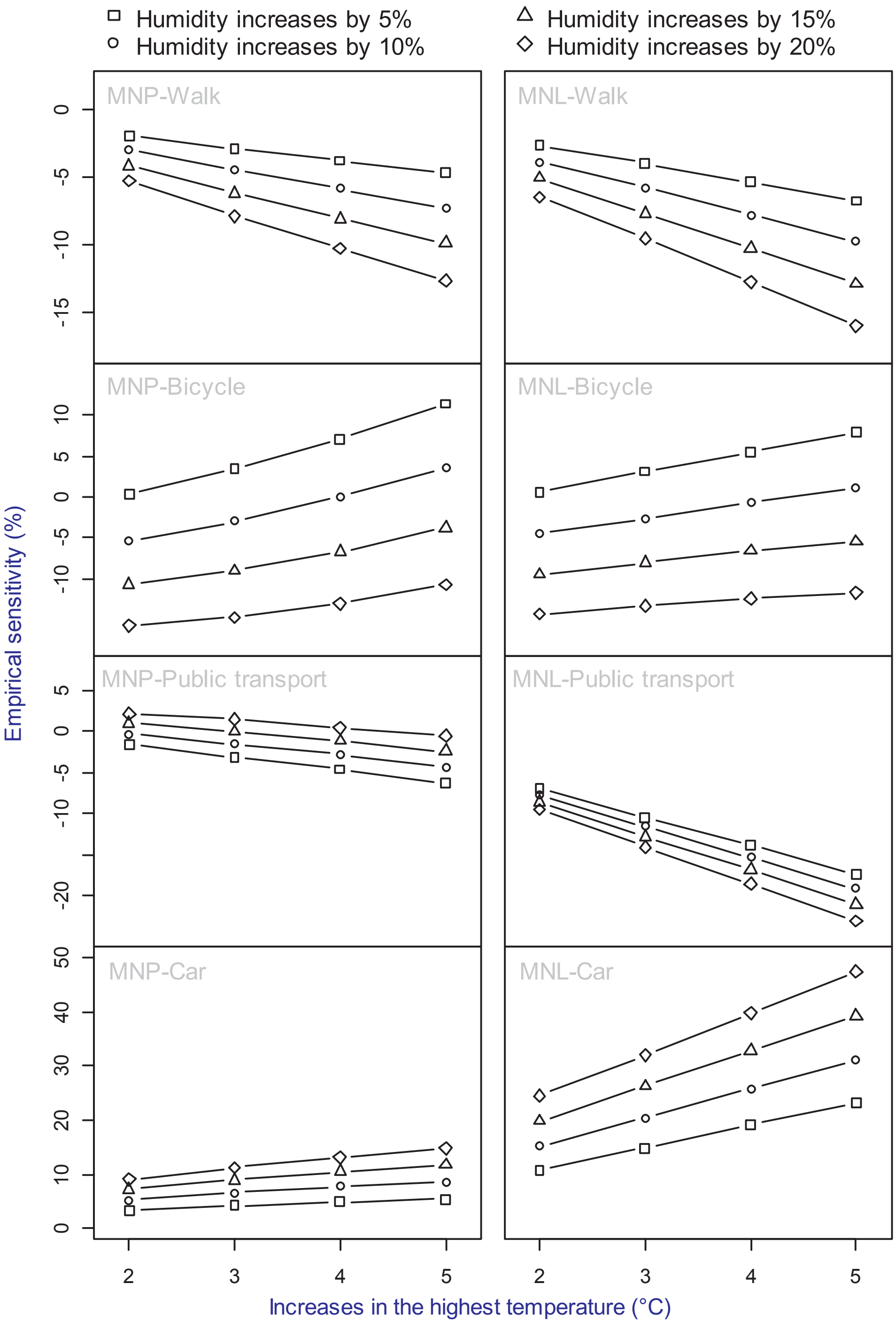

Fig. 2. Empirical sensitivities with respect to simultaneous changes in the highest temperature and humidity.

of distance increases (less than 2 km); as the distance continues to increase, the sensitivity of the walking mode decreases rapidly as the AQI changes from good to poor.

As the AQI changes from poor to terrible, there are almost no bicycle school commutes, even for a smaller increase in distance (1 km). Thus, the effect of distance is negligible. For a better AQI condition, the commute distance exhibits a large influence on the probability of the bicycle mode. For the public transport mode, the interaction effect is not substantial. For the car mode, given that the AQI changes from good to poor, the sensitivity increases along with an increase in the commute distance. However, if the AQI continues to deteriorate along with an increase in the commute distance, car usage increases at a lower rate and eventually ceases to grow, remaining at a fixed level.

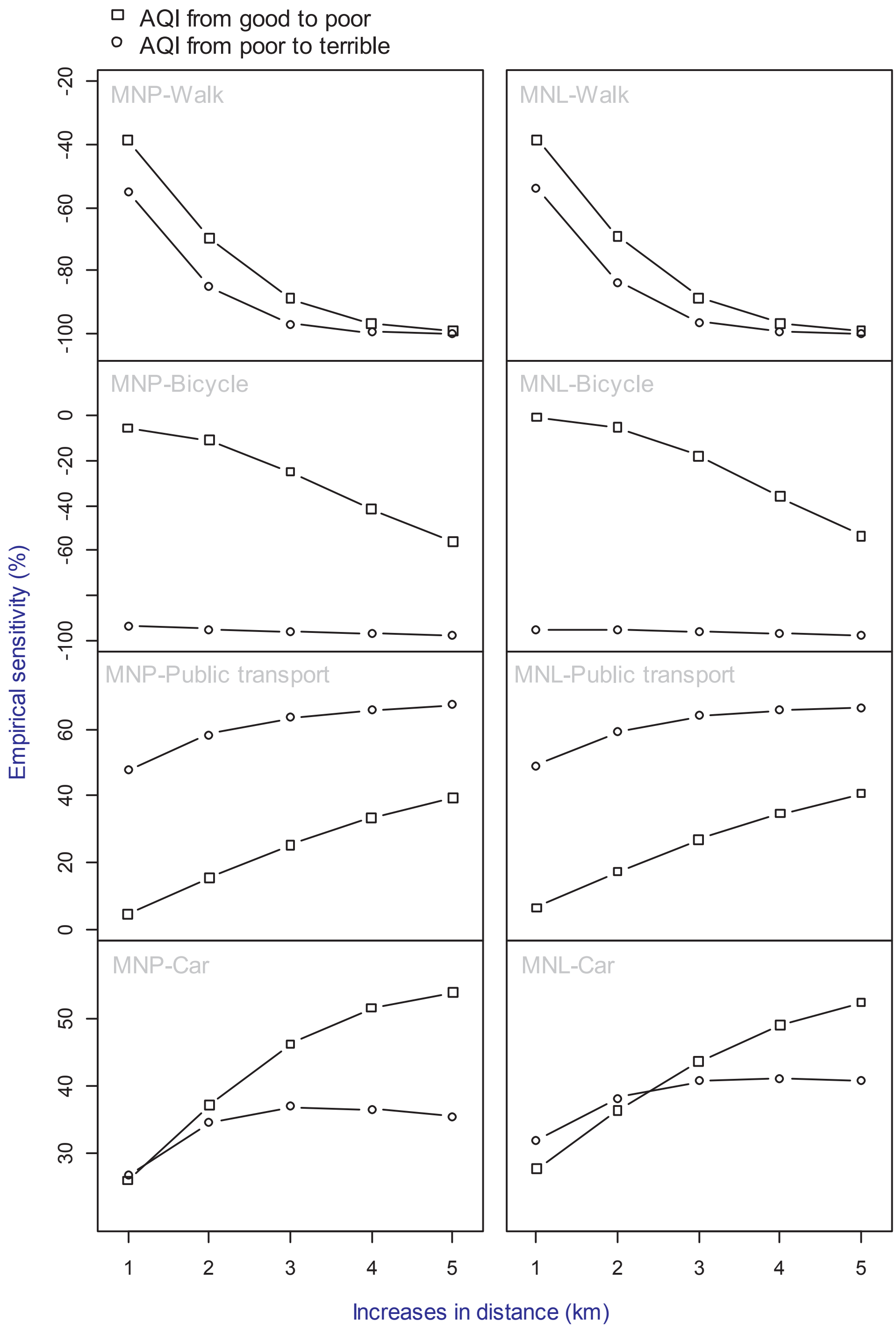

Fig. 3. Empirical sensitivities with respect to simultaneous changes in the AQI and commute distance.

7. Discussion and conclusions

7.1. General conclusions and practical implications

This paper aims to examine the impact of weather conditions on middle school students' commuting behaviors, specifically focusing on commute mode choice decisions. One of the intentions of this study is to understand how the students' decisions shift with respect to variations in influential factors, with empirical emphases on the situation in Beijing. The latest school commute survey data for Beijing was collected and input into the MNP and MNL models. The estimation results present many important findings not only in terms of identifying specific factors that influence school commute mode choice behaviors but also in terms of quantifying the magnitude of the effects and how this magnitude may vary across mode alternatives.

This study investigates the effects of each factor with respect to multi-level changes, and hence more complicated behaviors are revealed, illustrating nonmonotonic influential patterns for some variables. Most of the results can be explained by general conclusions from previous studies. There are also contrary findings, which reflect the special situation in Beijing. For example, some households do not own a car because car ownership is restricted in Beijing and car travel is also highly restricted during days of extremely terrible air quality. Therefore, when air quality attains the “terrible” level, students rely more on public transport than cars.

These results could have important implications for future transportation development and may provide references for policymakers and planners. First, developing a school bus system is strongly suggested because the regular public transport system would face high pressure on days with poor sky conditions or terrible air quality. Equipping school buses with an air filtering system is also recommended. Second, active transportation modes should be encouraged in good weather conditions. As illustrated, the commute distance is the most direct and influential factor playing a crucial role in the decision-making process of school commute mode choices. A 1 km increase in distance results in 34.9% fewer students walking to school according to the MNP model. One strategic suggestion is to consider the commute distance when selecting sites for new schools. Because the data were collected during winter, the conclusions are limited to winter situations. More general conclusions would require further verification using data collected during other seasons.

7.2. Limitations and future directions of research

The current variable setting is sufficient for an understanding of the macroscopic-level relationships between school commute mode choices and weather conditions and hence for proposing strategic policies and planning implications. However, these sensitivity measures will change under different variable settings. Some unobserved variables could play an important role in our understanding of the decision-making process of school commute mode choices. Thus, in future studies, it would be useful to include additional explanatory variables, such as household and parents’ attributes, land-use mix, urban forms, and characteristics of transportation facilities to enhance the modeling performance and to refine the behavioral results. Another avenue for tackling this issue is to use more advanced econometrical models, e.g., the random-parameters model and the finite mixture model, to consider potential heterogeneities originating from unobserved variables.

Weather conditions comprise many different aspects. Due to the survey duration, which covered only two winter months, seasonal variations and precipitation were not observed in the dataset. Hence, the models and corresponding results are necessary to be re-estimated when data for other seasons or on days with rain or snow become available.

In addition to the issue of variable setting, the modeling results also rely on different cities and student groups. It would also be interesting to compare our current results with other student groups or other cities in China as well as cities in other countries.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.trd.2018.05.008.

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