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Danger, Respect, and Indifference: Bike-Sharing Choices in Shanghai and Tokyo using Latent Choice Models*

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Abstract

While various policy instruments have attempted to raise environmental concerns in the past decades, it is unclear if these concerns are revealed in the consumer choices of our daily life. In this study, we investigate whether environmental concerns drive the choices of modes of transport through the bike-sharing example in Tokyo and Shanghai. We conducted a survey questionnaire to define three types of environmental concerns and quantitatively estimated their effects on bike-sharing choices using the latent class model, considering individual heterogeneity. The results show that environmental concerns affect bike-sharing choices differently for different people. While the fear of natural disasters and/or an indifference towards the environment would be dominant factors in commuting, the willingness to preserve a natural environment shows substantial correlations to bike-sharing when respondents return from weekend shopping. These differences indicate that relevant policies should be effectively implemented to interact with such environmental concerns.

JEL Classification: L62, Q48, Q55, Q58

Keywords: Bike-sharing; shared transportation; demand estimation; latent choice model; latent class; environmental concern

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1 Introduction

Environmental concerns, which is a broadly defined notion as "concern for environmental degradation," have been studied by many social and behavioral scientists to measure public attitudes toward environmental issues since 1970 (Van Liere and Dunlap (1981)). These studies have been largely of two kinds - 1) cognitive measures dealing with pollution and natural resources or 2) correlations between the measures of environmental concern and socio-demographic variables. The following studies have found that an individual's background played a more significant role in making environmental-friendly decisions than having factual knowledge about environmental concerns (Nilsson and Kueller (2000)).

To further investigate the relationships between individual backgrounds and people's choices for pro-environment behavior, we explore the choices behind bike-sharing in travel behavior. We choose the transportation sector, as it accounts for 30% of the global carbon dioxide emissions (Gale (2018)), and bicycles are considered to be a promising option for decreasing on-road carbon emissions in the transportation sector, as it is a zero-emission transportation mode.

To increase bicycle ridership, bike-sharing has been promoted, as it does not require an individual to purchase a bicycle. Bike-sharing is a short-term bicycle rental service offered in public spaces. To ride shared bicycles, a deposit and user fee must be paid to use the bicycles for a given duration of time, after making a reservation through a smartphone application.

The development of bike-sharing systems has gone through several stages since the launch of its first-generation model in Amsterdam in 1965 (Shaheen, Guzman and Zhang (2010)). While the first generation of bike-sharing system was not initially successful in Amsterdam, due to the occasional theft of bicycles and damages from lack of incentive to return bicycles in a good condition, in the second generation, far fewer bicycles were damaged benefiting from the membership service provided by a library in Copenhagen (Midgley (2011), Parkes, Marsden, Shaheen and Cohen (2013)). With the third generation, bike-sharing began to flourish, especially with the introduction of information technology (IT) systems. The third and fourth generations used smart card technology, smartphone applications, and Internet-based reservation systems; they were not only adopted worldwide, but also advanced with developments in IT.

In a nutshell, the concept of 'sharing' is not new, but the contemporary bike-sharing system with smartphone applications is new. We assume that a majority of bike-sharing users tend to be from the younger generation, and are proficient in using mobile applications and making consumption choices motivated by various social issues, including climate change. Thus, while some studies encouraged to increase financial incentives to both users and producers to promote bike-sharing (Cai et al. (2019)), we claim that it is vital to understand the individual motives behind their choice with a more sophisticated modeling. We focus on environmental concerns as the main motive, and analyze the effect of different types of environmental concerns in choosing bike-sharing options. We categorize environmental concerns into three types: fear of potential natural disasters, respect for environment or nature, and a lack of awareness. This categorization can potentially explain why individuals choose bike-sharing over other means of transportation. We further discuss this classification in Section 2.

1.1 Literature Review

In previous works that have similar interests, environmental concerns were treated as a single concept resulting in mixed conclusions — some authors argue that environmental concern is positively correlated with demands for bicycles (Campbell, andn Megan S. Ryerson and Yang (2016)) or public transportation (Johansson, Heldt and Johansson (2006), Cheng and Chen (2015), Nordfjærn, Lind, zlem Şimşekoğlu, Jørgensen, Lund and Rundmo (2019)). In contrast, other authors report that environmental concerns does not predict the choice of mode of transportation(Liu, Du, Southworth and Ma (2017), Hopkins (2016)). More recent works show that the environmental concerns and social norms are positively correlated to the choices in bike-sharing (Peer (2019), Wang et al. (2021), Bcker and Anderson (2020),) and some of the studies also focused on the electric bikes (Bieliski et al. (2021), Bai et al. (2020)).

There are gaps in the research, especially in the coverage of the regions that are studied. While many studies have investigated factors that motivate the use of bike-sharing in various regions (Frade and Riberio (2014), Tran, Ovtracht and d'Arcier (2015), Regue and Recker (2014), Faghih-Imani, Hampshire, Marla and Eluru (2017)), a large amount of them are based on regions in Europe and North America (Peters and MacKenzie (2019), Link et al. (2020), Younes et al. (2019), Qian and Niemeier (2019)). Except a few recent studies in China (Ge et al. (2020)), little is known of the Asian context, despite the fact that bike-sharing is a growing mode choice in many Asian countries too.

It is critical to fill this gap in the literature with more case studies, because successful policies must be designed with a full consideration of distinctive local, cultural and social contexts, and are otherwise likely to fail, as supported by numerous failed pilot projects in East Asia (Mateo-Babiano, SameeraKumar and AlvinMejiab (2017)). These failures reflect the need for a rigorous analysis of the public preferences and demands in each country to overcome the dependence on research based on other regions (Mateo-Babiano, SameeraKumar and AlvinMejiab (2017)). While significant factors affecting demands for bike-sharing were commonly found to be trip distance, temperature, precipitation, and built environment throughout previous studies (Eren and Uz (2020), it was found that air quality was another significant factor in the case of Beijing (Campbell, andn Megan S. Ryerson and Yang (2016)). Air quality is a reasonable local factor in Beijing, because of the city's highly dangerous air pollution levels compared to cities in developed Western countries. Recognizing such differences, we aim to investigate the cases of Shanghai and Tokyo to enrich the literature on demands for bike-sharing, by providing two big cities as examples for East Asia.

1.2 Study Areas

Despite a limited experience compared to the United States and Europe, Asia has recently become the fastest growing market for bike-sharing (Shaheen, Guzman and Zhang (2010)). Beginning in the 2010s, the governments of China and Japan (who have the second and sixth largest carbon emissions worldwide, respectively) introduced smartphone applications into the existing systems for bike-sharing. They expected an increase in the number of people using bike-sharing, and eventually a reduction in emissions, which had occurred in other countries. The growth of bike-sharing systems in these two countries contributed to a 37

In China, to restore the cycling environment, which had been degraded by rapid urbanization and motorization, the Chinese government actively promoted the use of bike-sharing. To do so, the Chinese government introduced European bike-sharing systems. The government attempted to increase demand for green transport by making the public aware that using bike-sharing can alleviate urban traffic problems. Within a few years, Hangzhou, Wuhan, Shanghai, and Zhuzhou had built scaled urban bike-sharing systems, and mainland China has since become the largest bike-sharing market globally (Tang, Pan and Fei (2017)). Furthermore, a new generation of dockless bike-sharing programs (e.g., ofo and Mobike) emerged in Chinese cities, with the development of the mobile internet. This new bike-sharing program integrates mobile payments and GPS tracking with big data, and is considered the fifth generation of bike-sharing Si, gang Shi, Chen and Zhao (2019). The new system was successful in encouraging Chinese people to use bike-sharing; more than 13% of all commuters used bike-sharing services during peak traffic hours in Shanghai (Zhang and Mi (2018)).

According to Tang, Pan and Fei (2017), as of May 2013, mainland China has a total of 105 bike-sharing systems in service, with 13,317 public bicycle stations, and 398,181 shared bicycles available for use. As of July 2015, the numbers had rapidly increased to more than 300 systems in service and one million shared bicycles available for use. In Tokyo, to address environmental problems, the Japanese government introduced bike-sharing within Tokyo City, promoting dependence on bicycles. The Japanese government also announced new polices, including the establishment of a bike-sharing system and an increase in on-road bike lanes in 2016. Bike-sharing in Tokyo uses multiple cycle ports installed within a given area, where people can rent and return bicycles. Additionally, the Tokyo metropolitan government is increasing the number of services and parking areas to enhance user convenience.

The Japanese government is also actively promoting the proliferation of bike-sharing services, in collaboration with private companies. Beginning in 2011, bike-sharing services were extended to Yokohama, Koto, Sendai, Chiyoda, and Minato; more than 5,600 bicycles were available nationwide in 2017, with 250,000 memberships and 521 ports.[1]

2 Methodology

We first conducted a questionnaire survey to understand the local bike-sharing travel behaviors in Tokyo and Shanghai. Then, we estimated the factors using a binary logit model, and a latent class model, which are widely used for similar studies (Paulssen, Temme, Vij and Walker (2014), Daziano and Bolduc (2013), Hess, Fowler, Adler and Bahreinian (2012)). The following subsections introduce our survey data and the scenarios assumed in this study.

2.1 Scenario Description

We set three scenarios to investigate whether or not 1) circumstances, 2) travel purpose, and 3) environmental concerns are correlated to the respondents' choice of transportation. When designing a survey, we seek to look into the modes for that takes the respondent to the subway station or a supermarket nearby. Thus, we have chosen bus, car, taxi, shared car, and shared bicycle for the attributes and the levels. We chose these modes because they

[1]Data source: https://www.japantimes.co.jp/life/2017/10/21/lifestyle/pedal-power-bike-sharing-services-expand-in-japan

are most frequently used to reach a platform for the longer travel, such as train stations, referring to the previous works (Meng et al. (2018) and Merchn et al. (2020)).[2] For the levels (costs and times) of the alternatives, we refer to the actual transportation cost/time of each mode on both cities.

For the Scenarios, in Scenario 1, we assume that the respondents are commuting (single trip) to the nearest subway station. Thus, Scenario 1 is a daily, regular, and individual routine. Therefore, choosing an environment friendly mode would indicate the willingness of the individual to choose that mode despite some inconvenience in their daily lives. For example, choosing bike-sharing requires a person to reserve a bicycle using a smartphone application, reach the bike-sharing station, and return the bicycle to the station. In Scenario 2, we assume that the respondents are traveling to a shopping mall on a weekend afternoon. We set an additional Scenario 3, which assumes that the respondents would carry a shopping bag on their return journey from the shopping mall. We set the distance to be 2km in all scenarios and the weather as cloudy. We expect the specific demographic features to be statistically significant in Scenario 3, because the respondent would have to carry the purchased items home.

2.2 Stated Preference Analysis

In March 2019, we conducted an Internet questionnaire survey, based on a conjoint analysis in Tokyo and Shanghai. The data were used to develop a choice model. The survey aimed to identify the factors affecting citizens' choice of transportation mode on the basis of socio-demographic factors (i.e., age, gender, education level, frequency of workouts, and expenditure), situational factors (travel time and expense), and types of environmental concern. Before the large-scale survey started, a pre-survey was carried out for refining the questionnaires.

[2] Thus, in some sense, we are dealing with the "last mile problem" rather than a mode choice for the full commute/shopping.

We divided the survey into two parts. In the first part, we introduced hypothetical situations to control for respondents' heterogeneous reactions to travel time and cost, as shown in Table 1, to investigate the stated preferences. Every question in the first part offered five alternatives, and respondents were asked to choose their favorite mode of transportation for the given scenario. As this survey was designed to use the stated preference approach, we offered 10 (Scenario 1) and 12 (Scenarios 2 and 3) alternatives for each scenario, varying the travel time and cost as shown in Table 1.

Table 1: Example Questions: *Please choose your favorite alternative for the given scenario from the following options.*

Means	Expense (CNY)	Expense (JPY)	Time (Min)
Example Question 1			
Bus	5 CNY	500 JPY	15 min
Private Car	1 CNY	50 JPY	20 min
Taxi	10 CNY	250 JPY	25 min
Shared Car	1 CNY	50 JPY	25 min
Bike-Sharing	3 CNY	150 JPY	20 min
Example Question 2			
Bus	1 CNY	50 JPY	15 mins
Private Car	5 CNY	500 JPY	20 min
Taxi	3 CNY	250 JPY	25 min
Shared Car	10 CNY	150 JPY	15 min
Bike-Sharing	7 CNY	100 JPY	10 min

Our sample size is 261 respondents in Shanghai, and 259 in Tokyo. Because there are 10 different versions of the questions, the total number of observations is 2,610 in Shanghai (261*10) and 2,590 in Tokyo (259*10). For Scenarios 2 and 3, which are treated as one survey set, we asked 12 different versions of the questions; therefore, the total number of observations is 3,108 in Shanghai (259*12) and 3,132 in Tokyo (261*12). After the respondents answered the questions in the first part, we gave them a second set of questions, which mainly addressed socio-demographic factors such as income, family members, and workouts. For estimating the personal frequency of exercises, we asked about the number of workouts of each individual per week. We considered it as a proxy variable that can indicate the degree of interest in personal health.

Then the respondents answered the third part, which consisted of environmental concerns. Categorizing environmental concerns would facilitate understanding the results and their policy implications by showing how various aspects of environmental concern affect people's choices. A few earlier works have also emphasized the need to examine different aspects of environmental concern. The Japanese market Hiratsuka, Perlaviciute and Steg (2018) shows that as people's acceptance of ecological values increases, they believe more strongly that the use of cars have negative environmental impacts, and feel more responsible for the problems caused by car use, and personally obligated to reduce their car use. For other countries, Nordlund, Jansson and Westin (2018) also mention that although environmentally focused attitudinal factors (positive perspectives) are critical for the demand for electric vehicles, the personal attitude toward the environment is the most crucial factor. These studies demonstrate the need to investigate different aspects of environmental concerns.

In the questions on environmental concern, in Table 2, we classify environmental concerns into three types: 'Respect', 'Danger', and 'Indifference'. The goal is to investigate how these categories of environmental concerns affect the choice of bike-sharing. We assume that people with a high 'Danger' score would care for the environment because they are afraid of the aftermath of natural disasters that could be triggered by human activity. In contrast, people with a high 'Respect' score would treat the environment with caution because they respect nature. People with a high 'Indifference' score would not express concerns about environmental problems.

To meet our goal, we established four criteria: first, a question was categorized as representing 'Danger' if it contained negative expressions. For example, Question 2: "When humans interfere with nature, they often meet a tragic end", is associated with 'Danger', as it contains the phrase "tragic end." Second, a question was categorized as 'Danger' if it mentioned negative consequences of environmental degradation. Question 3 is the best example, as it contains the phrase "degraded by human activity," which explicitly mentions the negative effects of human activity on environment.

Third, a question was categorized as representing 'Respect' if it contains positive expressions, for example, in Question 4, "right to life." Fourth, a question was categorized as representing 'Respect' if it describes admiration for nature, for example, Question 9, "The balance of nature is delicate," and Question 6, "the laws of nature." These expressions are used to indicate respect for nature.

The other questions are categorized as representing 'Indifference', as they do not express concern about environmental pollution, degradation, or natural disasters. Rather, positive answers indicate that people believe that there are currently no environmental problems (for example, Questions 5 and 7). Survey respondents were asked to answer the questions in Table 2 on a five-point scale:[3] (1) strongly disagree, (2) disagree, (3) not sure, (4) agree, and (5) strongly agree. T-tests conducted for the average score for each aspect of environmental concerns between Shanghai and Tokyo, suggest that scores for 'Danger' do not differ significantly between these cities. However, as shown in Figure A1, for 'Danger' and 'Respect', Tokyo has a higher density of high scores than Shanghai. This might be due to the fact that Tokyo is a city that is more prone to natural disasters, such as earthquakes, than Shanghai, which triggers risk-averse people to be extremely sensitive to environmental concerns. This may also explain the lower density of high scores in the 'Indifference' aspect in Tokyo, compared to Shanghai. While the higher 'Danger' and 'Respect' scores indicate that respondents care about the environment, higher scores on the 'Indifference' parameters indicate that they do not care about the environment. We take this difference into account when interpreting the estimation results.

We recognize that some of the questions in the 'Danger' and 'Respect' categories could also represent other aspects. For example, Question 1, "The population of earth is nearing

[3]The question sets were constructed with reference to the New Ecological Paradigm scale and Clark, Kotchen and Moore (2003) to obtain direct answers indicating different perspectives on the environment.

its limit" would stimulate fear but also make people express 'Respect' toward the natural environment. In the same vein, Question 9, "The balance of nature is delicate and easy to change," would also imply both perspectives, leaving the difference between 'Respect' and 'Danger' unclear. Therefore, deciding the categories associated with each question without clear criteria could result in ambiguous results, making our estimates and policy implications unreliable.

We would like to clarify that we did not show the types of environmental concerns to the respondents to prevent the possible 'psychological cue'. Therefore, different respondents can have different perceptions of each question. Although we agree that providing a psychological cue would also generate meaningful policy implications such as nudging that allows us to look into the effects of consumer choices when the psychological cue is given (Bonan et al. (2021)), however, if the type of environmental concerns were revealed, respondents' answers may be affected by the perceptions they choose. Particularly, those who choose 'Indifference' would be afraid of being seen as negligent toward environmental concerns, therefore may choose environment friendly modes to be seen as less negligent toward environmental concerns. Such a phenomenon was common in previous studies, as some of the previous works verify how respondents' stated preferences change when information about a survey's consequential character are included or excluded (Zawojska et al. (2019) and Bulte et al. (2005)). For these reasons, we choose not to reveal the type of environmental concerns to the respondents.

Table 3 presents descriptive statistics for each city. We find that the frequency of workouts in Shanghai (3.30) is almost twice that of Tokyo (1.68). Expenditure patterns in these cities are also different, as Tokyo's average income (2.05) was higher than that of Shanghai (1.51). As expenditures, workout frequencies, and frequency of using shared transportation are decisive factors in bike-sharing demand, we believe this difference would provide a basis for the comparison. In contrast, we do not find significant differences in age, number of family members, daily commuting time, and environmental concerns between the two cities. To

Table 2: Survey Questions: Environmental Concerns

Type	No.	Descriptions	Shanghai Avg. Score (Std. Dev.)	Tokyo Avg. Score (Std. Dev.)
Danger	1	The population of the earth is nearing its limit.	3.465 (1.162)	3.266 (.989)
Danger	2	When humans interfere with nature, they often meet a tragic end.	3.732 (1.176)	3.723 (.894)
Danger	3	The environment is seriously degraded by human activity.	3.685 (1.127)	3.849 (.893)
Respect	4	Animals and plants have a right to life, like humans.	3.977 (1.028)	3.913 (.935)
Indifference	5	Nature has sufficient capacity to deal with the effects of present industrial development.	3.006 (1.025)	2.822 (.935)
Respect	6	Humans have special abilities, but they cannot go against the laws of nature.	3.836 (1.072)	3.911 (.944)
Indifference	7	The "crisis of nature" that is said to be facing humanity is an exaggeration.	2.747 (1.028)	2.338 (.893)
Danger	8	The earth is like a spaceship with very limited space and resources.	3.867 (.970)	3.560 (.922)
Respect	9	The balance of nature is delicate and easy to change.	3.923 (1.279)	3.607 (.988)
Danger	10	At the present rate of human activity, we will experience terrible natural disasters in the future.	3.882 (1.230)	3.814 (.941)
Average Score				
Danger			3.72 (.846)	3.71 (.675)
Respect			3.92 (.839)	3.69 (.707)
Indifference			2.88 (1.134)	2.58 (.746)

estimate the model, we took the logarithms of all variables, except the dummy and categorical variables, to interpret the results better. We estimate the results for the two cities separately, due to the inherent differences between them. For example, the currency unit of income in both cities is different, and our survey does not consider the differences in the price levels, inflation rates, or CPIs across the two cities. We standardized our variables which are related to the environmental concerns (Danger, Respect, Indifference and Concern) in order to make comparisons across them in the result tables. The number of questions are different, even for questions in the same category. Thus, for example, simply summing up the coefficients of environment concerns without standardizing them would result in misunderstandings.[4]

[4] We appreciate our reviewer for pointing this out.

2.3 Perception of Environment

As we mentioned above, perceptions of the environment have various dimensions, and we capture them by asking three types of questions: those having to do with respect, danger, and indifference. These categories represent the reasons that people are concerned about human impact on the environment.

Although the idea that the environment should be protected underlies feelings of both Danger and Respect with respect to the environment, the reason that it should be protected is different. That is, questions on Respect capture whether a person believes that environment should be protected because it deserves respect, whereas questions about Danger capture whether a person believes that the environment must be protected owing to their fear of the negative consequences of mismanagement. People with high Indifference scores are not environmentally cautious, and they do not care about the possible adverse impacts of human activity on environment and nature. Therefore, questions about Indifference assess the perception of whether the current environmental situation merits concern. Note that a lower score in this category reflects the perception that the current environmental situation is severe.

Table 4: Pairwise Correlations Results

Shanghai	*Danger*	*Respect*	*Indifference*
Danger	1.00		
Respect	.80	1.00	
Indifference	.12	.18	1.00
Tokyo	*Danger*	*Respect*	*Indifference*
Danger	1.00		
Respect	.72	1.00	
Indifference	−.21	−.25	1.00

Table 4 summarizes the pairwise correlations between the average scores for each category of the perception of the environment. The result shows that the responses in the Danger and

Table 3: Descriptive Statistics

	N	Mean	Std. Dev.	Min.	Max.
Shanghai					
Age (Year)	518	38.84	13.44	21	65
Monthly Income (1,000 USD)	516	3.70	1.93	1	7
Number of Family Members	518	2.94	.95	1	6
Frequency of Workouts	518	3.30	1.75	0	7
Environmental concern (Total)	518	36.12	47.12	10	50
Danger	518	18.60	4.22	5	25
Respect	518	11.77	2.52	3	15
Indifference	518	5.75	2.27	2	10
Concern	518	23.94	5.86	4	38
Tokyo					
Age (Year)	508	43.48	14.14	18	69
Monthly Income (1,000 USD)	392	3.566	1.258	1	7
Number of Family Members	508	2.58	1.40	1	6
Frequency of Workouts	508	1.68	2.15	0	7
Environmental concern (Total)	508	34.79	4.99	12	50
Danger	508	18.56	3.38	5	25
Respect	508	11.07	2.12	3	15
Indifference	508	5.16	1.49	2	10
Concern	508	24.07	6.67	2	38

Respect categories are highly correlated in both Shanghai and Tokyo. However, the outcome of the Indifference category has a weaker correlation with those of the other two categories. We also present a histogram of the different types of environmental concerns in Figure A1 in the Appendix.

2.4 Binomial Logit Estimation

$$U_{ij} = \bar{U}_{ij} + e_{ij} = \boldsymbol{X_i'}\boldsymbol{\beta_j} + \boldsymbol{Z_j'}\boldsymbol{\gamma} + e_{ij}, \tag{1}$$

where $\bar{U}_{ij}$ is the mean utility, e_{ij} is an error term, and $\boldsymbol{X_i'}$ is a vector of independent variables which consists of user-specific variables (i.e., income and environmental concerns), and $\boldsymbol{Z_j'}$ is a vector of alternative-specific variables (i.e., time and cost of bike-sharing), $\boldsymbol{\beta_j}$ and $\boldsymbol{\gamma}$ are vectors of coefficients and is estimated by maximum likelihood estimation. The alternative with the highest utility is chosen. In the logit specification, the probability of choosing a shared bicycle can be written as

$$P(Y_i = j) = \frac{1}{1 + e^{\boldsymbol{X}_i'\boldsymbol{\beta}_j + \boldsymbol{Z}_j'\boldsymbol{\gamma}}}, \tag{2}$$

When estimating the model, we make the choice variables to be binary (1 if bike- sharing is chosen and 0 if bike-sharing is not chosen). Therefore, the fixed mode in our model is bike-sharing, and the coefficients of our result tables indicate the probability of bike-sharing being chosen, compared to the cases that bike-sharing where is not chosen (or other alternatives except for the bike-sharing is chosen). We have also included alternative-specific parameters for bike-sharing, which are the costs for using bike-sharing.[5]

Referring to Hensher et al. (2005), we include the travel time and travel costs of bike-sharing, which are typically used in discrete choice models to estimate travel demands, given a set of transport alternatives defined by certain attributes.

2.5 Latent Model Estimation

We further use a latent class model to estimate the bicycle demand, which represents an attempt to identify the latent factors, and include them into a discrete choice analysis in order to represent a more realistic process of choice behavior.

To capture the heterogeneity in demands for bike-sharing, we assume two discrete segments of the population. The latent class model assigns individuals to each segment according to their choice of transportation mode and their individual characteristics. The

[5] While applying multinomial logit to estimate the choice probability of each mode is also a very interesting exercise, we are focusing on the bike-choice in this paper, rather than the trade-offs or substitutions between other modes.

probability that individual i belongs to class c is

$$P(Y_i = c) = \frac{e^{\gamma_c Q_i}}{\sum_{c=1}^{2} e^{\gamma_c Q_i}}, \tag{3}$$

where γ_c is a vector of the class parameter, and Q_i is a vector of individual characteristics. The utility of choosing transport mode j for individual i in class c is

$$U_{ij|c} = \boldsymbol{A_j'}\boldsymbol{\alpha_c} + \boldsymbol{X_i'}\boldsymbol{\beta_{cj}} + e_{ij|c}, \tag{4}$$

where $\boldsymbol{X_i}$ is a vector of user-specific independent variables, $\boldsymbol{A_j}$ is an alternative-specific independent variable, $\boldsymbol{\alpha_c}$ is a coefficient of alternative-specific independent variables, $\boldsymbol{\beta_{cj}}$ is a class-specific vector of the coefficients, and $e_{ij|c}$ is a conditional error term within a class. As in the logit model, the alternative with the highest utility is chosen. For a latent class model, the probability that individual i in class c chooses alternative k can be written as

$$P(Y_{i|c} = k) = \frac{e^{\boldsymbol{A_j'}\boldsymbol{\alpha_c} + \boldsymbol{X_i'}\boldsymbol{\beta_{cj}}}}{\sum_{j=0}^{2} e^{\boldsymbol{A_j'}\boldsymbol{\alpha_c} + \boldsymbol{X_i'}\boldsymbol{\beta_{cj}}}}, k = 0, 1. \tag{5}$$

Given $P(Y_i = c)$ and $P(Y_{i|c} = k)$, we can compute the joint (unconditional) probability $P(Y_i)$ for transport mode choice k of individual i as follows.

$$P(Y_i = k) = \sum_{c=1}^{2} \frac{e^{\gamma_c Q_i}}{\sum_{c=1}^{2} e^{\gamma_c Q_i}} \frac{e^{\boldsymbol{A_j'}\boldsymbol{\alpha_c} + \boldsymbol{X_i'}\boldsymbol{\beta_{cj}}}}{\sum_{j=0}^{2} e^{\boldsymbol{A_j'}\boldsymbol{\alpha_c} + \boldsymbol{X_i'}\boldsymbol{\beta_{cj}}}} \tag{6}$$

Table 5 shows the variables and their descriptions. We estimate the model using binary logit and latent class estimations. In addition to the variables listed in Table 5, we add dummy variables to represent gender, and car ownership as the control variables.

Table 5: Variable Descriptions

Notation	description
Cost	Cost of using bike-sharing.
Time	Time of using bike-sharing.
Car Ownership	=1 If the Respondent Owns a Car
Income	Monthly Income (1,000 USD)
Age	Age
Education	Education Level
Family	Number of Family Members
Health	Number of Workouts per Week
Danger	Danger Environmental Perspective Score
Respect	Respect Environmental Perspective Score
Indifference	Indifference Environmental Perspective Score
Concern	Summation of 'Danger' and 'Respect'.

3 Results

3.1 Empirical Results

Tables 6, 7, and 8 show the estimation results of the bike-sharing demand model in Shanghai and Tokyo for Scenarios 1, 2, and 3, respectively. For all the models, we include the time and cost, demographic variables, and environmental concerns. In each table, the upper column shows the results for Shanghai and the lower panel shows the results for Tokyo. Model (1) shows the result estimated by binary logit estimation, and Model (2) shows the results for latent class model. Therefore, all the coefficients in Model (2) would be heterogeneous across classes.

We have one more additional specification; Model (2*), which takes 'Environmental Concerns', which is a summation of Danger and Respect, as one of the independent variables. 'Danger' and 'Respect' are highly correlated, as they both represent environmental concerns.

If such a high correlation between the models can affect the accuracy of the model, then if we add a new variable for 'Environmental Concerns', which is a summation of the two variables, it would produce substantial differences in the estimated coefficients. Meanwhile, we do not find such a trend, which reaffirms that our results are robust.

For interpreting the results we focus on Model (2) and treat it as the main results, as they are fully specified models that take into account the heterogeneity between individuals. Nonetheless, we do not find any substantial differences between the models. Overall, the results show that the types of environmental concerns, situational factors, and demographic factors show different correlations with bike-sharing according to the specific scenario and country, while they also share some similarities. First, we explain how the types of environmental concerns are correlated with the choice of bike-sharing for each scenario and country. More detailed explanations and interpretations are provided in the 4. Then we briefly explain other factors, including situational factors, demographic variables, frequency of workouts, and job type, across all the scenarios.

3.2 Environmental concern

Overall, we find that the specific type of environmental concern is highly correlated to bike-sharing regardless of the city and specifications, and the results were robust across the models. Interpretations on the correlation between environmental concerns and bike-sharing demands had to be made carefully. The number of questions of each type was different, and even for questions in the same category, different respondents could have different perceptions. For example, if a respondent does not get a high score in Danger or Respect, he/she is indifferent about the environment to some extent. Thus, for example, simply summing up the coefficients would induce misunderstandings. Therefore, one way to interpret the impact of environmental concern on bike-sharing demand is looking into the individual coefficients separately. Nonetheless, as we have standardized our variables, comparing across the environmental concerns is possible in this study.

Scenario 1 Table 6 shows the results of the estimated demands for bike-sharing. After considering various control variables, we find that environmental concerns show different types of correlation with the demand for bike-sharing. In particular, we find that the Danger and Indifference categories are a dominant factor in demands for bike-sharing in both cities, regardless of the model specifications. ‘Danger’ shows positive and statistically significant coefficients in both cities, while ‘Indifference’ shows statistically significant and negative coefficients. Therefore, the implications are quite straightforward: people who answer that they fear disasters are likely to choose bike-sharing for commuting, whereas people who are indifferent toward the environment are less likely to do so. Such a result does not indicate, however, that the coefficient of ‘Respect’ is not statistically significant: because we witness some positive and statistically significant coefficients of ‘Respect’ in Class 1 of Model (2) in Shanghai, and Class 2 of Model (2) in Tokyo. Regarding ‘Concern,’ we find that having a high level of concern would mostly positively correlate to bike-sharing demands, and is not likely to change the results of other parameters, including ‘Indifference’, substantially.

Scenarios 2 and 3 Table 7 presents the results for respondents considering a shopping trip (Scenario 2), and Table 8 shows the estimated coefficients for those returning from shopping (Scenario 3). Interestingly, we find that Respect shows a substantial positive correlation with demands for bike-sharing in both cities in Scenarios 2 and 3, in most of the models. In contrast to the case of commuting, we find that in both cities, for both Scenarios 2 and 3, Respect is a statistically significant and influential parameter, showing a substantial correlation with the demand for bike-sharing. Nonetheless, in Tokyo, we find that both Danger and Respect are influential parameters, while in Shanghai, both Respect and Indifference are dominant parameters in bike-sharing. Such trends indicate that heterogeneity exists in both the cities; while the ‘Respect’ parameter is dominant in both cities, for both scenarios

2 and 3.

3.3 All Scenarios

Situational Factors and Other Factors Regarding the rest of the parameters, as expected and similar to previous works, other demographic characteristics such as age, gender, and car ownership are correlated with demands for bike-sharing. The results show that situational factors which incorporate travel cost and time of bike-sharing would be negatively correlated to the choice of bike-sharing. Income shows statistically significant and positive coefficients in Tokyo in Scenario 2 and 3, while it does not show such statistically significant coefficients in Shanghai, and in Scenario 1 of both cities. Age is mostly negatively correlated with the bike-sharing demand in all scenarios. Education mostly displays statistically insignificant results. Car ownership shows negative coefficients in Tokyo, while it is not statistically significant in Shanghai.

4 Discussion and Conclusions

4.1 Discussion

This study aimed to provide evidence on how environmental concerns – Fear, Respect and Indifference – predict environment friendly behavior in choosing a transportation mode, considering the heterogeneity of the individual respondents in the case of scenarios like commuting, shopping, and returning from shopping. Overall, we find that the notion of environmental concerns does show high levels of correlation to the choice of bike-sharing regardless of the city and specifications across the models, but the effect of the specific type of environmental concern varies according to the purpose of travel.

Examining each scenario separately, the results for commuting (Scenario 1), which is a daily activity, show whether different types of environmental concerns indicate different

Table 6: Estimation Results of Scenario 1

Shanghai	Model (1)	Model (2)		Model (2*)	
	Logit	Latent Class (1)		Latent Class (2)	
		Class 1	Class 2	Class 1	Class 2
Cost	-0.687***	-0.363***	-0.674***	-0.390***	-0.698***
	(0.0811)	(0.138)	(0.106)	(0.126)	(0.118)
Time	-0.272**	-0.125	-0.282	-0.0979	-0.345*
	(0.128)	(0.193)	(0.201)	(0.183)	(0.204)
Income	0.0187	0.0723	-0.0221	0.0575	-0.0274
	(0.0501)	(0.0751)	(0.0635)	(0.0644)	(0.0723)
Age	-0.150***	-0.0881	-0.152***	-0.0918*	-0.162***
	(0.0421)	(0.0592)	(0.0539)	(0.0541)	(0.0615)
Education	-0.0858	-0.126	0.0121	-0.103	0.00520
	(0.145)	(0.204)	(0.176)	(0.190)	(0.191)
Female	-0.103	0.0979	-0.230	0.0781	-0.253
	(0.123)	(0.179)	(0.155)	(0.169)	(0.164)
Car Ownership	0.260	0.0826	0.344	0.0506	0.450
	(0.199)	(0.261)	(0.324)	(0.236)	(0.377)
Family	0.163**	-0.0476	0.259***	-0.00805	0.270**
	(0.0741)	(0.144)	(0.0933)	(0.122)	(0.105)
Health	-0.257***	-0.235	-0.194	-0.223	-0.203
	(0.0976)	(0.151)	(0.121)	(0.143)	(0.137)
Danger	0.380***	0.290**	0.337***		
	(0.0962)	(0.144)	(0.119)		
Respect	0.234**	0.319*	0.102		
	(0.0964)	(0.168)	(0.119)		
Indifference	-0.269***	-0.236***	-0.183***	-0.226***	-0.184***
	(0.0537)	(0.0747)	(0.0632)	(0.0675)	(0.0672)
Concern				0.554***	0.406***
				(0.101)	(0.0985)
Constant	3.808***		-0.323		-0.0394
	(0.892)		(0.945)		(0.985)
N	2610		2610		2610
Log Likelihood	-953.8	-1907.1		-1907.4	
Pseudo R^2	0.0944				

Tokyo	Model (1)	Model (2)		Model (2*)	
	Logit	Latent Class (1)		Latent Class (2)	
		Class 1	Class 2	Class 1	Class 2
Cost	-1.174***	-0.757***	-0.626***	-0.694***	-0.813***
	(0.0756)	(0.0551)	(0.190)	(0.129)	(0.223)
Time	-0.0348	0.130	0.00583	0.0344	0.288
	(0.117)	(0.108)	(0.319)	(0.296)	(0.386)
Income	-0.0298	-0.0226	0.00594	-0.00914	-0.0336
	(0.0280)	(0.0235)	(0.0757)	(0.0400)	(0.0499)
Age	0.000958	0.00143	-0.00388	-0.0000941	0.00143
	(0.00375)	(0.00317)	(0.00999)	(0.00419)	(0.00723)
Education	0.0893	0.0471	0.208	0.0831	0.0288
	(0.0932)	(0.0790)	(0.245)	(0.111)	(0.160)
Female	-0.0320	-0.0260	0.0931	0.00940	-0.0134
	(0.106)	(0.0894)	(0.287)	(0.123)	(0.154)
Car Ownership	-0.530***	-0.347***	-0.352	-0.318	-0.371*
	(0.118)	(0.0996)	(0.314)	(0.224)	(0.198)
Family	0.128***	0.0772*	0.153	0.0723	0.0841
	(0.0468)	(0.0395)	(0.120)	(0.0590)	(0.0709)
Health	0.278***	0.175***	0.186	0.162**	0.191***
	(0.0499)	(0.0408)	(0.133)	(0.0706)	(0.0715)
Danger	0.371***	0.294***	-0.315		
	(0.0839)	(0.0716)	(0.257)		
Respect	-0.0353	-0.0618	0.411*		
	(0.0836)	(0.0707)	(0.249)		
Indifference	-0.139*	-0.0701	-0.142	-0.0769	-0.0697
	(0.0712)	(0.0595)	(0.196)	(0.0823)	(0.0945)
Concern				0.221***	0.207**
				(0.0698)	(0.0833)
Constant	3.370***		2.347**		0.334
	(0.701)		(1.119)		(4.823)
N	2590		2590		2590
Log Likelihood	-1164.9	-3034.2		-3036.9	
Pseudo R^2	0.160				

Table 7: Estimation Results of Scenario 2

Shanghai	Model (1)	Model (2)		Model (2*)	
	Logit	**Latent Class (1)**		**Latent Class (2)**	
		Class 1	**Class 2**	**Class 1**	**Class 2**
Cost	-0.00230***	0.0608***	-0.0274**	0.0585***	-0.0271**
	(0.000307)	(0.0216)	(0.0108)	(0.0224)	(0.0109)
Time	-0.0138	-0.00149**	-0.00201***	-0.00152**	-0.00201***
	(0.0103)	(0.000726)	(0.000306)	(0.000737)	(0.000307)
Income	-0.0487	-0.121	-0.0275	-0.148	-0.0351
	(0.0485)	(0.108)	(0.0475)	(0.108)	(0.0470)
Age	-0.265***	-0.184**	-0.223***	-0.188**	-0.223***
	(0.0410)	(0.0888)	(0.0409)	(0.0898)	(0.0409)
Education	0.250*	-0.155	0.276*	-0.0645	0.292**
	(0.143)	(0.294)	(0.144)	(0.291)	(0.143)
Female	-0.0372	-0.00895	-0.0378	-0.0436	-0.0460
	(0.114)	(0.253)	(0.113)	(0.254)	(0.112)
Car Ownership	-0.165	0.0498	-0.174	0.0939	-0.163
	(0.171)	(0.376)	(0.165)	(0.378)	(0.165)
Family	-0.0488	-0.176	-0.00748	-0.147	-0.000932
	(0.0748)	(0.163)	(0.0732)	(0.162)	(0.0728)
Health	-0.157*	0.0423	-0.141	0.0183	-0.144
	(0.0908)	(0.193)	(0.0886)	(0.198)	(0.0889)
Danger	0.171*	-0.0348	0.180*		
	(0.101)	(0.217)	(0.101)		
Respect	0.361***	0.594**	0.252**		
	(0.109)	(0.246)	(0.107)		
Indifference	-0.332***	-0.205*	-0.280***	-0.221**	-0.280***
	(0.0490)	(0.106)	(0.0484)	(0.107)	(0.0484)
Concern	-0.0958			0.455**	0.395***
	(0.591)			(0.178)	(0.0761)
Constant	-0.0958		-1.622**		-1.623**
	(0.591)		(0.791)		(0.806)
N	3108		3108		3108
Log Likelihood	-1070.9		-2138.2		-2140.2
Pseudo R^2	0.111				

Tokyo	Model (1)	Model (2)		Model (2*)	
	Logit	**Latent Class (1)**		**Latent Class (2)**	
		Class 1	**Class 2**	**Class 1**	**Class 2**
Cost	-1.349***	0.146	-0.156	0.152	-0.115
	(0.0706)	(0.258)	(0.308)	(0.229)	(0.202)
Time	-0.165	-0.958***	-0.928***	-0.974***	-0.924***
	(0.138)	(0.103)	(0.0780)	(0.130)	(0.0755)
Income	0.132***	0.112**	0.0612	0.108**	0.0557*
	(0.0296)	(0.0565)	(0.0394)	(0.0481)	(0.0310)
Age	-0.0118***	-0.00875*	-0.00642	-0.00833	-0.00721*
	(0.00382)	(0.00463)	(0.00491)	(0.00551)	(0.00398)
Education	0.293***	0.114	0.265	0.109	0.268***
	(0.0913)	(0.130)	(0.197)	(0.199)	(0.0940)
Female	0.00852	0.00351	0.00689	0.0234	0.0347
	(0.107)	(0.135)	(0.123)	(0.155)	(0.110)
Car Ownership	-0.304**	-0.342	-0.108	-0.358	-0.0988
	(0.119)	(0.284)	(0.157)	(0.238)	(0.122)
Family	0.00122	0.0125	0.00178	0.0185	0.00470
	(0.0477)	(0.0608)	(0.0527)	(0.0641)	(0.0481)
Health	0.0405	-0.0148	0.0574	0.0370	0.0907
	(0.0603)	(0.0795)	(0.123)	(0.0819)	(0.0678)
Danger	-0.266***	-0.268	-0.0785		
	(0.0935)	(0.264)	(0.112)		
Respect	0.595***	0.298***	0.481*		
	(0.0939)	(0.110)	(0.248)		
Indifference	0.0360	-0.0824	0.127	-0.161	0.0904
	(0.0719)	(0.248)	(0.0919)	(0.167)	(0.0830)
Concern				-0.0245	0.323**
				(0.122)	(0.143)
Constant	4.853***		-0.183		-0.559
	(0.684)		(2.505)		(1.370)
N	3132		3132		3132
Log Likelihood	-1170.9		-2949.3		-2959.3
Pseudo R^2	0.0944				

Table 8: Estimation Results of Scenario 3

Shanghai	**Model (1)**	**Model (2)**		**Model (2*)**	
	Logit	**Latent Class (1)**		**Latent Class (2)**	
		Class 1	**Class 2**	**Class 1**	**Class 2**
Cost	-0.00236***	-0.000346	-0.000350	-0.00210***	-0.00211***
	(0.000322)	(0.000937)	(0.000935)	(0.000310)	(0.000310)
Time	-0.0161	-0.0440	-0.0440	-0.00879	-0.00884
	(0.0109)	(0.0394)	(0.0394)	(0.0103)	(0.0103)
Income	-0.0487	-0.219	-0.218	-0.0214	-0.0326
	(0.0485)	(0.155)	(0.154)	(0.0454)	(0.0448)
Age	-0.265***	-0.248*	-0.249*	-0.219***	-0.218***
	(0.0410)	(0.139)	(0.139)	(0.0383)	(0.0384)
Education	0.250*	0.864	0.863	0.168	0.195
	(0.143)	(0.540)	(0.539)	(0.133)	(0.132)
Female	-0.0372	-0.722*	-0.720*	0.0144	0.00194
	(0.115)	(0.396)	(0.394)	(0.107)	(0.107)
Car Ownership	-0.165	-0.750	-0.751	-0.0811	-0.0660
	(0.171)	(0.499)	(0.498)	(0.160)	(0.159)
Family	-0.0488	0.125	0.124	-0.0571	-0.0472
	(0.0748)	(0.242)	(0.241)	(0.0695)	(0.0691)
Health	-0.157*	-0.0340	-0.0328	-0.111	-0.116
	(0.0908)	(0.275)	(0.274)	(0.0837)	(0.0839)
Danger	0.171*	0.286		0.139	
	(0.101)	(0.348)		(0.0948)	
Respect	0.361***	0.146		0.303***	
	(0.109)	(0.360)		(0.102)	
Indifference	-0.332***	-0.356**	-0.355**	-0.261***	-0.262***
	(0.0490)	(0.167)	(0.167)	(0.0457)	(0.0456)
Concern			0.409		0.397***
			(0.273)		(0.0723)
Constant	-0.0301		-2.392**		-2.392**
	(0.600)		(1.047)		(1.047)
N	3108		3108		3108
Log Likelihood	-1070.8		-2137.8		-2138.9
Pseudo R^2	0.111				

Tokyo	**Model (1)**	**Model (2)**		**Model (2*)**	
	Logit	**Latent Class (1)**		**Latent Class (2)**	
		Class 1	**Class 2**	**Class 1**	**Class 2**
Cost	-0.00693***	-0.0561***	-0.0264	-0.0535***	-0.0487
	(0.000400)	(0.0112)	(0.0279)	(0.0105)	(0.0386)
Time	-0.0777***	-0.00521***	-0.00510***	-0.00522***	-0.00541***
	(0.0113)	(0.000356)	(0.000911)	(0.000343)	(0.00124)
Income	0.128***	0.0701***	0.161**	0.0661***	0.183**
	(0.0291)	(0.0262)	(0.0641)	(0.0242)	(0.0874)
Age	-0.0115***	-0.00584*	-0.0170*	-0.00602*	-0.0294**
	(0.00376)	(0.00328)	(0.0102)	(0.00316)	(0.0121)
Education	0.285***	0.204**	0.116	0.194***	0.412
	(0.0903)	(0.0812)	(0.220)	(0.0744)	(0.281)
Female	0.00828	0.00196	0.0281	0.0281	-0.0304
	(0.105)	(0.0918)	(0.245)	(0.0883)	(0.361)
Car Ownership	-0.293**	-0.285***	0.310	-0.231**	0.410
	(0.117)	(0.108)	(0.292)	(0.0986)	(0.389)
Family	0.00111	0.0271	-0.155	0.0226	-0.247
	(0.0470)	(0.0417)	(0.115)	(0.0392)	(0.154)
Health	0.0389	0.0311	0.0220	0.0786	-0.00957
	(0.0593)	(0.0524)	(0.149)	(0.0487)	(0.207)
Danger	-0.258***	-0.131	-0.449**		
	(0.0920)	(0.0817)	(0.224)		
Respect	0.576***	0.404***	0.345		
	(0.0923)	(0.0811)	(0.213)		
Indifference	0.0342	0.0664	-0.256	0.00741	-0.288
	(0.0709)	(0.0666)	(0.161)	(0.0595)	(0.241)
Concern				0.210***	-0.277
				(0.0593)	(0.231)
Constant	0.364		1.727*		2.409**
	(0.434)		(0.956)		(1.058)
N	3132		3132		3132
Log Likelihood	-1180.8		-2949.9		-2959.3
Pseudo R^2	.189				

tendencies to change a daily routine. In the case of Shanghai, we find that Danger is a dominant environmental factor that affects the decision to use bike-sharing. Indifference is negatively correlated with bike-sharing usage, but because Danger and Respect have higher and positive coefficients, the overall impact of environmental concerns on the use of bike-sharing is positive. Going shopping (Scenario 2) and returning from shopping (Scenario 3) are more likely to be family events, and carrying heavy shopping bags may require that these additional factors (e.g., age) be considered in the decision-making process. These additional factors could override environmental concerns. For example, younger people could find it easier to carry bags than elderly ones, which could lead them to use shared bicycles. In such cases, people who have difficulty carrying bags would not prioritize environmental concerns.

Examining the issue through areas of case study, similar trends are captured in both Shanghai and Tokyo for the case of shopping scenarios where Respect was more highly correlated to the bike-sharing demand than Danger and Indifference, in general. Commonly contrasting features between Shanghai and Tokyo are hardly found, and not enough to withdraw meaningful interpretations across all scenarios. This is due to the variations by scenarios, except that the coefficients for females showed positive correlations in Tokyo and negative correlations in Shanghai, with low statistical significance. This also supports our earlier claim that different types of environmental concerns are more determined by travel purposes, and that more case studies are required to reflect the location-specific factors. It can be inferred that the location-specific factors play a bigger role in determining the bike-sharing demand and it is hard to find a shared commonality, even though Shanghai and Tokyo share a lot of similarities as two of the world's biggest metropolitan cities, both located in East Asia.

Our research contributes to the field by analyzing factor comparisons in bike-sharing demands using different types of environmental concerns and travel purposes (i.e., commuting, leisure, and shopping). While it appears to be natural that the factors in bike-sharing demand would vary according to the travel purposes, this is a critical difference which was not captured in most papers that focused on the mode choices that assumed a static situation (Bamberg, Ajzen and Schmidt (2013) Heath and Gifford (2002)). Consequently, previous works did not consider the travel purposes for the expected outcome, resulting in different priorities. For instance, in the case of commuting, on-time arrival at the destination would be the most important factor when choosing a transportation mode. On the other hand, in the case of leisurely mobility, sufficient vehicle capacity for multiple passengers could be the most critical factor when choosing a transportation mode, for example, people who are going on a vacation with their family.

It is also noteworthy that environmental concerns was usually regarded as a single-sided notion in the previous literature – public awareness of the importance of environmental protection (Yoo et al. (2021)). However, as noted earlier, people's notion of environmental concerns varies by issue areas and personal background. Our study results indicate that while Danger and Indifference are very important factors in both the cities' bike-sharing demands, Respect is insignificant in the commuting scenario. This validates the argument that the choice of transportation mode varies by different types of environmental concern and leads to different outcomes. Given that bicycles are a zero-emission transportation mode, it can be inferred that the biggest environmental benefits of choosing bike-sharing are mostly related to improving issues of air pollution. Because such benefits are not directly correlated to the conservation of the natural environment or preservation of biodiversity, there is a lesser likelihood of finding higher utilities in bike-sharing among people who prioritize such biodiversity issues, rather than lower air pollution.

Therefore, our study results leave some takeaways for policy implications. We know that different types of environmental concerns induce different degrees of effects in bike-sharing, depending on different travel motives. Therefore, it can be inferred that effective policy implementation to promote bike-sharing needs an integrated analysis of users' travel patterns and different notions of environmental concern by environmental categories, when it comes to understanding the public awareness of environmental issues. The lesson is withdrawn because there is a general tendency among policymakers to believe that raising environmental concerns could promote a gradual shift to more environment friendly transportation modes, and thereby decrease on-road carbon emissions in the transportation sector (Whitmarsh and O'Neill (2010)). To fully benefit from policies that encourage the choice of greener modes of transportation by raising environmental concerns, it is crucial to examine and categorize these perspectives. Without such considerations, simply encouraging people to make pro-environmental choices by emphasizing that preserving the natural environment is "the right thing to do" or increasing financial incentives, would not be very effective if their behaviors are likely to be determined by a fear of the adverse outcomes of natural disasters or environmental pollution.

4.2 Conclusion

This study fills in the research gap regarding whether and to what degree different types of environmental concerns affect people's transportation choices in various settings. The contribution of this paper is that we showed how different types of environmental concern result in different outcomes. We also provided empirical evidence that high levels of environmental concern do not always result in positive outcomes. For example, our results indicate that positive attitudes such as a desire to preserve the natural environment are not correlated with the demands for bike-sharing when people are commuting. In addition, fears of the consequences of environmental destruction, which differs somewhat from a desire to preserve the environment, does not encourage people to choose bike-sharing. In contrast, when people go shopping and return from shopping, positive attitudes are highly correlated with demands for bike-sharing. Our results, therefore, provide insights for policymakers regarding the need to consider the various aspects of environmental concerns when promoting environment friendly behavior.

This study focuses on the transportation sector in Shanghai and Tokyo. Investigations of whether different types of environmental concern also have various effects in countries other than Japan and China, such as developing countries, would add value to future research, since developing countries may require environment friendly behavior in the context of rapid urbanization.

Another possible direction for future research is the thorough investigation of the detailed reasons for the differences between these two cities, and the factors that affect these differences. For example, our results show that for shopping (Scenarios 2 and 3), Indifference is generally statistically insignificant for Tokyo. However, we find that Indifference is a statistically significant variable with positive coefficients, possibly indicating that having a high level of Indifference in Tokyo would be positively correlated to greater bike-sharing demands. Understanding these results would require more nuanced data, which might include bicycle ownership and frequency of shopping, and more detailed questions on environmental concerns that enable the precise categorization of environmental concerns.

Even though categorizing environmental concerns is a nice approach, there are still possible concerns about the results due to the high correlations between the variables that are related to environmental concerns. Future research could develop a better methodological way to decompose such factors without concerns for the high correlation.

A hybrid-choice model that incorporates unobservable (latent) factors into a discrete choice analysis would represent a more realistic behavioral choice process. Our current model includes some unobservable variables in the choice process through latent classes, identifying latent variables and conducting factor analyses, in order to determine which survey item belongs to which latent category. Nonetheless, creating latent factors, and estimating them with the latent class simultaneously, would need indicator variables that compose the latent factors. The inclusion of the latent variables explains the peoples behavior based on their intentions, which is determined by attitudes (Ben-Akiva et al. (2002)). Such approach, however, would require us to have a better survey design with more questions (which can possibly be indicator variables), to construct latent variables with a sizeable number of factors. This process may, therefore, be conducted in future research.

Lastly, incorporating all the modes of transport, last-mile problems as well as longer traveling would also provide insights for the choices of modes of transport. As we are not focusing on such modes (i.e., train) in this research, studying on such modes is left to future research.

Appendix

Figure A1 presents a histogram of environmental attitudes in Shanghai and Tokyo. Panel (A) shows the Danger score, which suggests that there are more people with low Danger scores in Shanghai than in Tokyo. Panel (B) presents the Respect scores, which indicate that there are more people with a low Respect score in Shanghai and Tokyo. The Indifference score is shown in Panel (C); the variance is larger in Shanghai than in Tokyo.

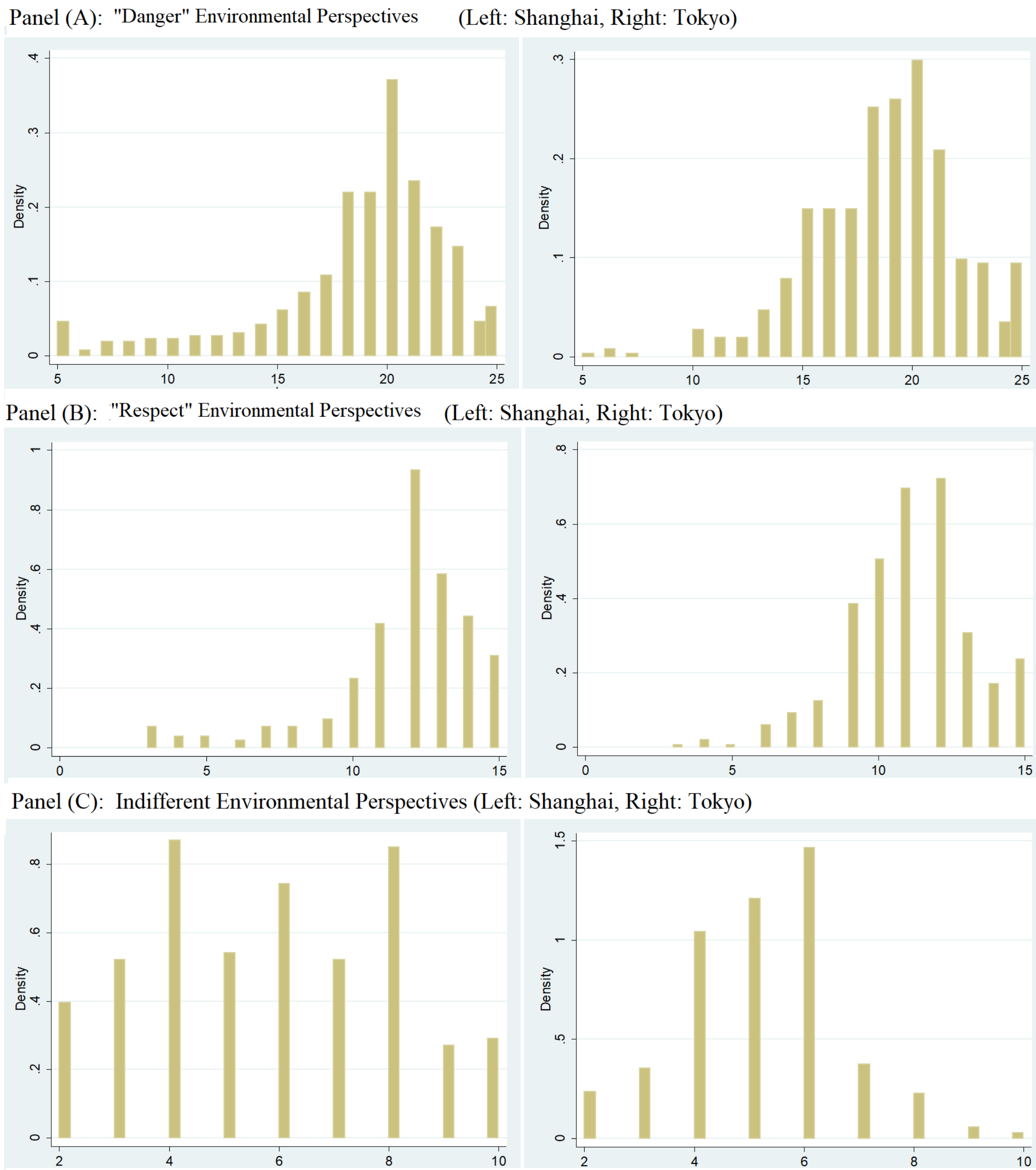

Figure A1: Histogram of environmental attitudes in Shanghai and Tokyo: (A) Danger, (B) Respect, and (C) Indifference.

As the number of our sample data might be not enough to represent the entire populations of each cities, we have included Appendix Table A1 that shows the comparison between socio-economic variables (Income, age and the number of family members) and the differences between our sample and actual census data ranges around 10%. Such difference shows that our data is approximately ranges around the average levels of two cities.

Table A1: Census Data and Comparison to Our Sample

	Tokyo		
	Statistics (of 2019)	Our Sample Data	Difference (%)
Income (1,000 USD)	4.04	3.67	9.16%
Age	46.2	43.48	5.89%
Number of Family Members	2.8	2.51	10.36%
	Shanghai		
	Statistics (of 2019)	Our Sample Data	Difference (%)
Income (1,000 USD)	4.05	3.61	10.93%
Age	38	42.39	-11.55%
Number of Family Members	2.64	2.9	-9.85%

Data Source: Japanese Government and Shanghai Municipal Government Website. (Accessed 2021/05/24).

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