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A Mode Choice Study on Shared Mobility Services

Policy Opportunities for a Developing Country

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By

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I, Weibo Li, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Content

ABSTRACT 1

IMPACT STATEMENT 2

ACKNOWLEDGEMENTS 4

CHAPTER 1. INTRODUCTION 6

1.1 Background and Motivation 6
1.2 Research Questions and Objectives 10
1.3 Research Design and Methodology 11
1.3.1 Data Preparation 11
1.3.2 Analysis Method 12
1.4 Innovations and Expected Contributions 12
1.5 Thesis Outline 13

CHAPTER 2. LITERATURE REVIEW 16

2.1 The Choice of Bike-sharing 16
2.2 The Choice of Car-sharing 20
2.3 Attitudinal Effects on Shared Mobility Choices 23
2.4 Habitual Mode Choice Change and the Role of Life Course Events 26
2.5 Discussions of the Gaps 28

CHAPTER 3. DATA PREPARATION 31

3.1 Case Study Choice 31
3.2 Survey Design 33
3.2.1 The Questionnaire 33
3.2.2 A Pilot Survey 34
3.2.3 The SP Mode Choice Experiment 35
3.3 Sampling and Data Collection 39
3.4 Data Cleaning and Handling 40

CHAPTER 4. THE MODAL SUBSTITUTION PATTERN FOR BIKE-SHARING: AIR POLLUTION'S EFFECT 45

4.1 Data 45
4.2 Modelling Framework 48
4.3 Model Estimation Results 53
4.3.1 Models Performance and Comparison 53
4.3.2 Model Estimation Results: Bike-sharing 59
4.3.3 Model Estimation Results: Rest of the Modes 60
4.3.4 Value of Time 62
4.4 Policy Impact Analysis 62
4.5 Conclusions 65

CHAPTER 5. THE MODAL SUBSTITUTION PATTERN FOR CAR-SHARING: SOURCES OF DEMAND 67
5.1 Data 67
5.2 Modelling Framework 70
5.3 Model Estimation Results 74
5.4 Value of Time and Elasticity Indicators 83
5.5 Policy Impact Analysis 86
5.6 Conclusions 91
CHAPTER 6. THE INFLUENCE OF ATTITUDINAL FACTORS ON SHARED MOBILITY CHOICES 93
6.1 Data 94
6.2 Modelling Framework 99
6.3 Results 103
6.3.1 Latent Variable Model 103
6.3.2 Discrete Choice Model 107
6.3.3 Value of Time 113
6.4 Conclusions 116
CHAPTER 7. CONTROLLING CAR USAGE FROM A HABITUAL PERSPECTIVE 118
7.1 Data 119
7.2 Modelling Framework 123
7.3 Results 125
7.3.1 Model Estimation Results 125
7.3.2 Discussions and Policy Implications 130
7.4 Conclusions 133
CHAPTER 8. CONCLUSIONS 135
8.1 A Quick Review of the Work 135
8.2 Comparisons between Developing and Developed Countries 137
8.3 Contributions and Wider Implications 140
8.4 Limitations on Data and Analysis Method 144
8.5 Embracing the Future: A Last Bit of Thinking 148
APPENDIX A: An Example Questionnaire 152
APPENDIX B: Studying Air Pollution's Impact on Mode Choice Behaviour via A Seasonality Analysis 163
B.1 Data 165
B.2 Modelling Framework 169
B.3 Results 172
B.4 Conclusions 177
REFERENCES 180

List of Figures

Figure 3-1 Bike-sharing docking stations in central Taiyuan (approx. 20km^2 shown in the map) 32

Figure 5-1 The NL Structure Detected in the Mid-dist Model 82

Figure 5-2 The NL Structure Detected in the Long-dist Model 82

Figure 6-1 The Indicators of “Willingness to be a Green Traveller” (N = 3,486) 96

Figure 6-2 The Indicators of “Satisfaction with Cycling Environment” (N = 3,486) 97

Figure 6-3 The Indicators of “Advocacy of Car-sharing Service” (N = 3,486) 97

Figure 6-4 An ICLV Model with 3 Latent Variables and a Nested Logit Discrete Choice Model 101

Figure 6-5 VTTS for Bike-sharing by Measurement Equation Groups 115

Figure 6-6 VTTS for Car-sharing by Measurement Equation Groups 115

List of Tables

Table 3-1 The SP Survey Design 36

Table 3-2 Sample Data versus Census Data 42

Table 4-1 Sample Statistics and SP Modal Splits 47

Table 4-2 RP Modal Splits 48

Table 4-3 Explanatory Variables and Measurements 52

Table 4-4 Model Estimation Results Using SP Data 54

Table 4-5 Model Estimation Results Using Combined SP and RP Data 56

Table 4-6 Willingness to Pay for Access Time Savings (per minute) 62

Table 4-7 Scenarios and Modal Substitution Patterns 63

Table 4-8 Direct and Cross Point Elasticity 64

Table 5-1 Sample Statistics and SP Modal Splits 68

Table 5-2 RP Modal Splits in Mid- and Long-dist Trips 69

Table 5-3 Explanatory Variables and Measurements 73

Table 5-4 Mixed NL Results for Mid-dist Case 74

Table 5-5 Mixed NL Results for Long-dist Case 77

Table 5-6 VTTS for Car-sharing, Car, Taxi, Bus and Bike-sharing 83

Table 5-7 Direct and Cross Point Elasticity 85

Table 5-8 Scenarios and Modal Substitution Patterns for Mid-dist Case 87

Table 5-9 Scenarios and Modal Substitution Patterns for Long-dist Case 88

Table 6-1 Sample Descriptive Statistics 94

Table 6-2 Explanatory Variables and Measurements 102

Table 6-3 Results: Latent Variable Model 104

Table 6-4 Results: Discrete Choice Model 110

Table 6-5 Value of Travel Time Savings across Models 113

Table 6-6 VTTS by Structural Equation Groups 115

Table 7-1 Sample Descriptive Statistics 119

Table 7-2 Life Course Event Occurrences on Individuals over the Study Period (2006-2012) 122

Table 7-3 Mode Switching Pattern over the Entire Study Period (2006-2012).................. 123

Table 7-4 Mixed Binary Logit Regression Result: Mode Switch from Car to non-Car 126

Table 7-5 Mixed Binary Logit Regression Results: Mode Switches to Car 127

Table B-1 Sample Descriptive Statistics.. 167

Table B-2 Key Statistics from Summer and Winter Surveys 168

Table B-3 Summer and Winter Model Estimation Results 175

List of Abbreviations

SP = Stated Preference

RP = Revealed Preference

MNL = Multinomial Logit

NL = Nested Logit

ML = Mixed Logit

LV = Latent Variable

ICLV = Integrated Choice and Latent Variable

VTTS = Value of Travel Time Savings

Short-dist = Short-distance

Mid-dist = Medium-distance

Long-dist = Long-distance

ABSTRACT

This research aims to investigate the mode choice behaviour associated with bike-sharing and car-sharing, and the strategies for encouraging their demand in order to pull people away from using private cars. In particular, we reveal the factors that could affect the choices of both services and explore their associated modal substitution patterns. Key interests are put on air pollution's impact on bike-sharing choice and the sources of demand for car-sharing (i.e. from private car users or public transport users). Moreover, we look at in what ways attitudinal factors could influence shared mobility choices and hence identify any implications. Furthermore, we are also interested in any measures from the habitual level that may help control private car usage in addition to the tactical-level efforts. The mode choice and related data employed in this work were collected by a paper-based questionnaire survey launched in 2015 at a Chinese city. Discrete choice modelling techniques are extensively applied, including the mixed logit (ML), mixed nested logit (mixed NL) and integrated choice and latent variable (ICLV) models. Our findings are compared to those from developed countries for any similarities and differences that lie between, though by addressing several key research gaps in the field, the findings will also significantly enrich the literature on shared mobility choice behaviour as well as disclosing implications for practitioners from both developed and developing countries for take-away and formulating the corresponding demand management policies.

IMPACT STATEMENT

The work delivers benefits to both inside and outside academia. It aims to fill several knowledge gaps and enhance the current understanding of shared mobility choice behaviour. It is one of the first works that discloses the effect that air pollution could have on mode choice behaviour; in particular, it quantitatively reveals the extent to which an improvement of air quality could be able to boost bike-sharing's demand. The thesis also provides in-depth evidence regarding the sources that the demand for car-sharing would come from, i.e. more private car users or public transport users, and discovers the results could vary substantially by trip distance. Moreover, the study enriches the literature on how shared mobility choices could be correlated with decision makers' attitudes, while also demonstrating in value of time estimations the importance of taking into account individuals' differentiated attitudes. Furthermore, the work extends the results on habitual mode switching behaviour from few earlier binary analyses, i.e. car to non-car and non-car to car, by revealing the different behaviours from several non-car mode user groups. In addition, the work allows a comparison between the findings from this case study in a developing country and the common findings in developed countries to reveal any similarities and differences which would further enrich the literature.

With respect to wider benefits outside academia, the research can yield implications for practitioners from both developed and developing countries for take-away and formulating shared mobility demand management policies as per the discovered evidence on mode choice behaviour. In particular, we collaborated with a government-owned local partner, Shanxi Transportation Research Institute, to collect travel behavioural data from the case study city, Taiyuan (China). Hence, the findings from this research could be directly used by the Municipality of Taiyuan to assist policy making in its jurisdiction for the promotion of bike-sharing and car-sharing usage while controlling the demand for private car. Besides, private operators which plan to deploy shared mobility services in Taiyuan could also take away the results or the analysis framework to assess their corresponding market strategies.

The impact would be brought about through disseminating outputs via conference presentations and publications with prestigious peer-reviewed journals. The conferences at which our research has been presented include the:

- 96th and 97th Transportation Research Board Annual Meeting,

- 14th World Conference on Transport Research,
- 44th European Transport Conference,
- 20th EURO Working Group on Transportation Meeting and,
- 15th International Conference on Travel Behaviour Research.

Regarding journal publications:

- one paper reflecting the work in Chapter 4 has been published at *Transportation Research Part A*,
- one for Chapter 5 is under the 2nd round of peer-review at *Transportation*,
- one for Chapter 6 is under the 1st round of peer-review at *Transportation Science* and,
- one for Chapter 7 has been accepted for publication at *Transportation Research Record: Journal of the Transportation Research Board*;
- another paper reflecting the work in Appendix B has also been published at *Transportation Research Record: Journal of the Transportation Research Board*.

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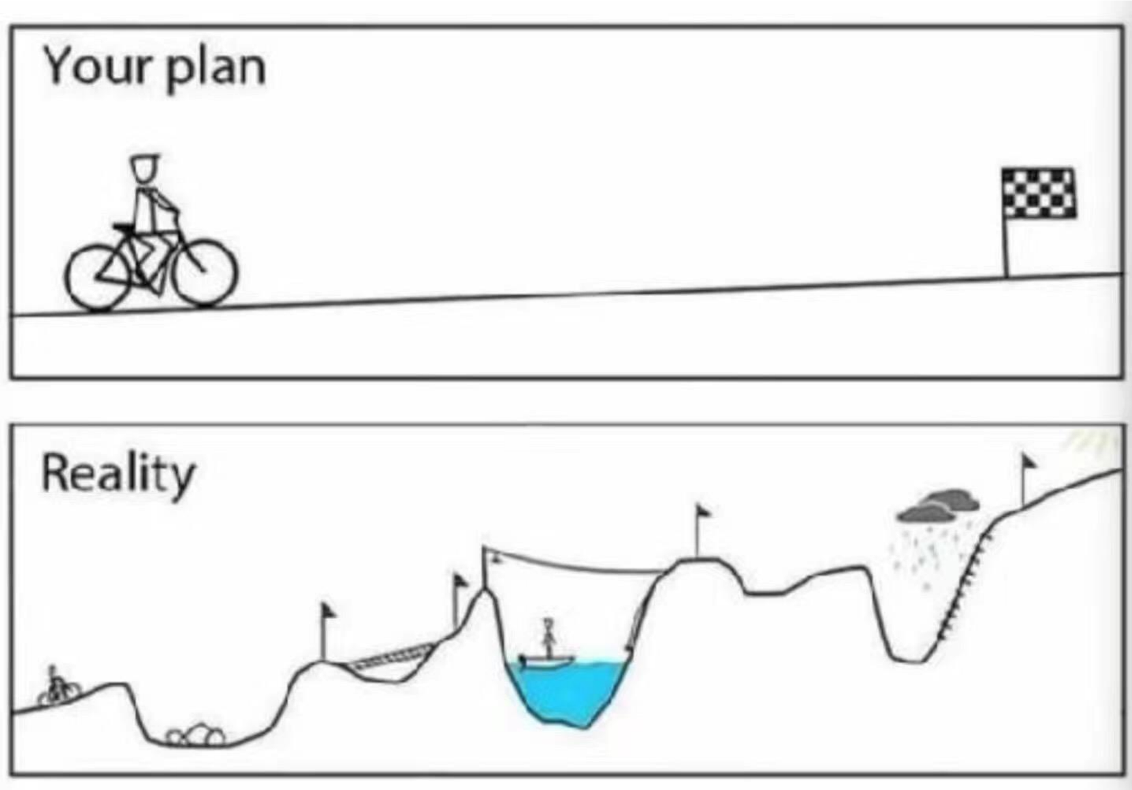

Looks funny huh~ but when I start thinking what to say about my life as a PhD student in the past four years, what shown in this picture is actually the first thing that pops into my mind. It shouldn't be just me, as most of the PhD students, from anywhere in the world, must all have walked through (or may be enjoying right now) a path like this. I don't know how they felt and what they ended up with, but I know I am certainly a lucky one.

Maria Kamargianni, my supervisor, who has been teaching me, guiding me and taking care of me since the first time I met her, is the person to whom I would like to and should definitely say from my heart a big "THANK YOU" at this point. Without her, I would have no way to be where I am standing right now.

Maria, time flies and I am leaving. But you know, and I know, this will not be the end. I don't like to say big words regarding how much I appreciate the every kind of help and support I received from you; but this is what I want you to know:

In the future,

When I chat with friends and look back our youth ages, When I lie in the bed after a day of celebration, and

When I sit in a tent and counting stars somewhere wild…

I may remember you, remember the team, and remember the things we have been through.

I will have a smile on my face, and

I will pick up the phone and give you a call, wherever I am.

Mom and dad, I am so lucky to have Maria by side during these four years of study, and you both know this. However, without you, I could not make it through this period. Although you don't know English, and you will probably not read what I am writing down here, I am sure you know how much I love you and how much I want to make you proud, and I will keep doing so in the future.

For those many of you, who supported me spiritually or technically over all these years, I know it clearly and I simply can never forget, as I am a person that always remembers. Please forgive me for not listing your names here, as there are just so many of you, but you all know the way that I treat the kindness I received: Weibo is here for all of you.

Finally, a sincere thanks to the project partner, Shanxi Transportation Research Institute, which offered me valuable help with the data collection. Without their generous and professional support, this project could never have developed to what it looks like right now.

This four-year time is a very special phase in my life, because I will never experience anything like this again at any time in the future. I learned a lot of things, from a lot of you, in a lot of ways, and I appreciate. I will stay humble, stay hungry, and give back all the things that I learned, to the land where I grew up and where I belong to.

Long March never ends. 万里长征，还在路上。

CHAPTER 1. INTRODUCTION

1.1 Background and Motivation

Although continuously increasing car usage is an issue that has grabbed attention across the globe, there are more and more cases popping up in developing countries where the number of cars on the road has breached a rational level, causing severe problems with respect to congestion and air pollution. By 2017 there were more than 200 million registered cars in China, an all-time high figure, leading to 10 of the cities in this country being listed among the top 25 most congested cities in the world (Zheng, 2017). In Thailand car drivers' annual average hours spent in peak congestion was the highest, ahead of three other developing countries, Columbia, Indonesia and Russia, which ranked next, out of a survey including 38 main countries worldwide, excepting China (Lee, 2017). For many big cities in the developing countries, such as Delhi (Chattopadhyay, 2017), Beijing (Zhuang, 2018), and Bangkok (Janssen, 2018), the use of conventional fossil-fuelled cars has been identified as one of the main sources of urban air pollution. In fact, by comparing to the developed world, it can be argued that the rapid increase of car usage in developing countries could be attributed to two general causes, the "supply of car on road" (i.e. income growth and urbanisation leading to more car purchases which make cars an available travel option) and the "demand for car on road" (i.e. relatively under-developed public transport or other substitute services resulting in a strong preference for cars). Efforts have been made to tackle car usage through both the supply and demand sides, for example the notorious license plate restrictions and odd-even day travel schemes which target car availability and the expansion and upgrade of the public transport system which aims to offer a good alternative travel option. Nevertheless, it has turned out cars are still a highly dominant choice with respect to mode of transport in today's developing countries, as discussed above. Thus, an imperative task would be to explore how to more effectively pull people away from using their cars while not compromising regular travel needs, which is a goal that many conventional measures have found difficult to address.

In the last couple of years one emerging concept has attracted massive public attention, broadly referred to as shared mobility. Although public transport and taxi could also fit in the definition, nowadays the term more often reminds people of some newly emerged forms of service such as bike-sharing[1], car-sharing[2], ride-hailing[3], ride-sharing[4] and micro-transit[5] etc. (Shared-Use Mobility Centre, 2018). Unlike the traditional public transport these shared mobility services usually offer greater flexibility, privacy and comfort; in other words, a generally more enjoyable travel experience from a user's perspective. Comparing to a private car, these new services transform the owner-ship to a user-ship (Kamargianni et al., 2016), and hence there could potentially be significant cost-savings by avoiding the need to purchase a car and the associated parking and maintenance troubles. As we can see from numerous cases around the world, bike-sharing, car-sharing and ride-hailing are among those shared mobility forms that have been through the most rapid expansions in these years. While from the perspective of tackling congestion and air pollution, bike-sharing and car-sharing may potentially be of greater values than ride-hailing services. Apparently, a simply reason is that ride-hailing still relies upon private car fleets which are generally fossil-fuel based, whereas bike-sharing is emission-free and most of the existing car-sharing services have been operating with electric or hybrid vehicle fleets which would certainly be a relief to the urban air pollution challenge (Bakker and Trip, 2013; Shaheen and Chan, 2015). Another argument is that ride-hailing could potentially cause far more traffic jams than it prevents, as per some of the latest evidence (Clewlow and Mishra, 2017; Schaller, 2017; Gehrke et al., 2018; Schaller, 2018). This is mainly because many ride-hailing travellers were moving across from public transport services, which they would have used for travel if they did not have the option of ride-hailing. Although car-sharing could possibly incur the same puzzle by absorbing public transport users, it was found in many cases as effective in reducing car ownership (Cervero et al., 2007; Loose, 2010; Martin et al., 2010; Mishra et al., 2015; Bondorová and Archer, 2017; Vij, 2017), which means the aforementioned "supply of car on road" could at least be controlled and in turn result in an ease of congestion. As for

[1] Bike-sharing is a service making bicycles available for shared use to individuals on a short term basis for a fee.
[2] Car-sharing is a service making cars available for shared use to individuals on a short term basis for a fee.
[3] Ride-hailing offers a service that picks up passengers and drives to designated destinations for a fee. It uses online platforms to connect passengers with drivers who use personal, non-commercial, vehicles.
[4] Ride-sharing essentially fills empty seats in vehicles. It can be seen in the form of the traditional private carpooling (grouping of travellers into a privately owned vehicle) or a real-time ride-sharing service (matching of drivers and passengers based on similar destinations through a mobile app before the trip starts).
[5] Micro-transit is a service model that sits between ride-hailing and traditional fixed-route transit. It is demand-responsive but typically uses ad-hoc pickup and drop-off points, and generally operates within limited service zones.

bike-sharing, there are also cases demonstrating it could help to take cars off the road, especially when trip distance is short (Wang and Zhou, 2017; Xinhua, 2018).

Both bike-sharing and car-sharing services are developing fast nowadays. Free-floating car-sharing is more often seen on the street than the traditional round-trip mode; dock-less bike-sharing has emerged and quickly been embraced by travellers alongside those with docking stations. Nevertheless, in contrast to the maturity of both services (in terms of operation history, business model and public acceptance etc.) in the developed world (Shaheen and Cohen, 2007; DeMaio, 2009; Shaheen et al., 2009; Shaheen et al., 2010; Shaheen and Cohen, 2013; Deloitte, 2017), there are potentially more growth opportunities for developing countries which are generally falling behind the time schedule for “clearing certain social, economic, and demographic thresholds”, a prerequisite to the development of shared mobility (Bert et al., 2016). Following the recent success of both station-based and dock-less services in several Chinese cities, India, Thailand and some other developing countries are expected to embrace the next wave of the massive bike-sharing deployment (Cheetah Lab, 2018). Car-sharing, though still unfamiliar to the wider public in the developing world, is also expected to incur rapid supply expansion there in the near future (Dhingra and Stanich, 2014; Carrigan, 2015; Alam, 2016). Given such a trend, good demand-side management would be a key determinant in the sustainable growth of shared mobility in these emerging markets; since otherwise a large program could also turn into a large failure if the demand cannot promptly follow, as the experience of Wuhan in China has shown (Wang, 2015). One of the core needs would be to understand the factors that could influence the transport mode choice behaviour associated with shared mobility and hence the modal substitution pattern that is hidden beneath, in order to find ways to encourage the demand for choosing these newly emerged services to conduct daily trips.

Attempts have been made towards such a direction of research; however, questions remain. First of all, there is a general concern in terms of a relative shortage of mode choice studies focusing on cases in developing countries, and such an oversight has significantly hindered the demand-side policy making in those areas due to the frequently revealed context-sensitive nature of travel behaviour (Barnes and Krizek, 2005; Tang et al., 2011; Maurer, 2012; Kamargianni, 2015; Faghih-Imani et al., 2017); in other words, findings and implications from developed countries may not be relevant to the developing world, especially given the cultural, geographical and other local differences between them. Secondly, and more importantly, there are several critical subjects still awaiting investigation:

- Air pollution is a rather common challenge in developing countries which often have more severe air pollution levels over prolonged periods of time when compared to many of the developed nations. It could possibly be a critical factor affecting mode choice behaviour, especially when considering whether or not to choose active transport to travel. Hence exploring this factor may reveal some new insights and pathways for promoting bike-sharing usage. So far the topic has rarely been touched while studies have been largely limited to developed countries, for which air pollution is generally a less significant concern.
- Though some evidence has been revealed with respect to the sources of demand for ride-hailing services (Clewlow and Mishra, 2017; Schaller, 2017; Gehrke et al., 2018; Schaller, 2018), there is still a lack of evidence with respect to car-sharing and its modal substitution pattern, especially regarding if more people using car-sharing "reduces the use of private vehicles or if, on the contrary, it reduces the number of public transport users" (Jorge and Correia, 2013; p.216). This is the information that policy makers are usually keen to find out, especially when they need to determine whether or not to endorse such a type of service (via subsidies and legislation etc.).
- Apart from the conventional mode choice research that studies bike-sharing and car-sharing preferences there could be further opportunities to enhance the behavioural realism of shared mobility choices. One potential path is exploring the influence of personal attitudes on individuals' mode choice decisions. To date a good understanding of how shared mobility choices might be influenced by attitudinal factors is still largely absent.
- Most of the existing mode choice analyses deal with how individuals make trade-offs between different attributes. Meanwhile, choice behaviours could also be habitual and sometimes mode use decisions may not be sensitive to the surrounding tactical-level conditions. Hence, attention has been focused on the habitual change of mode choice, usually as a result of the occurrence of life course events. Nevertheless, one puzzle is

that a switch from non-car modes to car has occurred more frequently than the opposite (Oakil et al., 2011; Clark et al., 2016a), posing an additional challenge to travel demand management as to how to tackle such a direction of change; since otherwise, once a car is picked up and over time its usage becomes habitual, it becomes even more difficult to alter the mode choice behaviour (Ouellette and Wood, 1998). Research in this area may generate additional inspiration as to how to control private car usage besides boosting the demand for shared mobility services.

All in all, investigating these issues will not only fill the specific knowledge gaps under each of the subjects, but the findings can also disclose the implications for practitioners from both developed and developing countries, on the basis of which they can formulate demand management policies as per the discovered evidence.

1.2 Research Questions and Objectives

Following on from the issues outlined above we specify below the questions which need to be answered and the corresponding research objectives.

The questions that would help to initiate this research are:

- What are the factors that could affect the mode choices of bike-sharing and car-sharing in the case of a developing country? Will there be any key differences when compared to the findings in developed countries?
- What are the modal substitution patterns hidden behind the choices of using bike-sharing and car-sharing to travel? In particular, could air pollution have a significant influence on bike-sharing's modal substitution pattern, and also, will more people choosing a car-sharing service reduce the usage of private cars or public transport?
- Are there other important factors impacting shared mobility choices, such as the decision-makers' personal attitudes; and if so, are there any useful implications?
- In addition to any tactical-level strategies for promoting the choices of shared mobility, could there also be measures at the habitual level to help control private car usage?

To provide insights to these questions, we identify the following key research objectives, which will be addressed throughout this work:

- Revealing the factors that could affect bike-sharing choice and exploring the associated modal substitution pattern; in particular, testing if an increase in air pollution level would depress the willingness to cycle and to what extent an improvement in air quality would increase the demand for bike-sharing.
- Revealing the factors that could affect car-sharing choice and exploring the associated modal substitution pattern; in particular, demonstrating to what extent the demand for car-sharing would come from private car usage as opposed to public transport usage.
- Investigating in what ways attitudinal factors could influence the mode choices of both bike-sharing and car-sharing, and identifying the associated implications.
- Given the frequently observed habitual switch from non-car modes to car, searching for any potential counter-measures that could help to reduce such a behavioural change to avoid car usage becoming a long-term habit which may offset any tactical-level efforts.

1.3 Research Design and Methodology

1.3.1 Data Preparation

Given the aforementioned research goals, we choose to focus on China, as the largest developing economy in the world, to conduct a case study. Specifically, Taiyuan, the capital city of a northern province Shanxi, with more than 3 million population, is selected for us to analyse its citizens' mode choice behaviour; while we expect other cities in developing countries can also see the evidence and take away insights to assist policy making in their own jurisdictions. Both revealed preference (RP) and stated preference (SP) data are collected via a questionnaire survey that we launched in 2015. Meanwhile, socio-economic information at individual and household levels, travellers' attitudes towards various transportation-related issues, and retrospective travel behaviour data from several years in the past are also collected. We distributed paper questionnaires to 15,000 Taiyuan citizens, with the support from our local partner, Shanxi Transportation Research Institute. Detailed descriptions regarding the case study choice, survey design and data collection procedure are provided in Chapter 3.

1.3.2 Analysis Method

Discrete choice models are extensively used in this study, although the means of application differ according to the research goals that will be subsequently addressed. Essentially this modelling technique is underpinned by random utility theory, namely that a choice made by an individual is attributed to his/her perceived utility associated with that choice (Ben-Akiva and Lerman, 1985). Various advancements have been made since the early era, such as the joint estimation of RP/SP datasets to compensate for each other's bias (Hensher and Bradley, 1993; Ben-Akiva et al., 1994; Bradley and Daly, 1997; Polydoropoulou and Ben-Akiva, 2001), an approximation to many model forms via the use of a more flexible mixed logit (ML) model (McFadden and Train, 2000; Hensher and Greene, 2003), a further advancement to a mixed nested logit (mixed NL) structure to address the confounding effect when introducing more than one type of error component in a single utility function (Hess et al., 2004; Ortúzar and Willumsen, 2011), and an increasingly adopted integrated choice and latent variable (ICLV) framework for explicitly modelling the unobserved heterogeneity (Ben-Akiva et al., 2002; Walker and Ben-Akiva, 2002; Bolduc et al., 2005; Bolduc and Alvarez-Daziano, 2010). All of these features will be reflected in this research, with more details regarding the modelling frameworks and specifications given in later chapters.

1.4 Innovations and Expected Contributions

We expect this work to contribute to a number of dimensions that reflect the gaps identified earlier. First of all, it will allow a direct comparison between the findings from this case study in a developing country and the common findings from the literature carried out in developed nations. Any key similarities and differences that are revealed will add direct evidence to the literature regarding whether the context-sensitive nature of travel behaviour is widely evident (Barnes and Krizek, 2005; Tang et al., 2011; Maurer, 2012; Kamargianni, 2015; Faghih-Imani et al., 2017), and hence if there are any important considerations for policy practices. Next, our research on bike-sharing and car-sharing choice behaviour will allow practitioners to clearly see the modal substitution patterns as a result of the different measures that they could possibly adopt to promote shared mobility demand, and meanwhile, there will also be a focus on how to more effectively decrease private car usage, which is a key pursuit in today's urban transportation planning. Moreover, recall the two specific puzzles for which we aim to provide important answers in the field, i.e. to what extent an improvement in air quality would increase bike-sharing demand and if more people using car-sharing would reduce private car or public transport usage more significantly. The findings are not only expected to enrich the literature around these topics, but can also serve as useful insights to support relevant policy designs in the real world. Then, through a robust integrated modelling analysis, the impacts of various attitudinal factors on bike-sharing and car-sharing choices will be revealed, which could enhance our current understanding of shared mobility choice behaviour. Additionally, in this part of the work, a further insight will be offered to enrich the literature, around how much difference the presence of personal attitudes could make to the estimates of value of travel time savings (VTTS); in other words, this will reveal whether different VTTS estimates should be derived for policy use when individuals have differentiated attitudes. Finally, the analysis of mode switching behaviour can disclose measures from the habitual level that may help control private car usage in addition to the aforementioned tactical-level insights. Moreover, by exploring the possibly different mode switching behaviour among different non-car mode users, policy implications specific to each of these mode user groups could be acquired.

An additional innovative aspect of this work is the adoption of an effective yet rarely utilised modelling framework, i.e. the mixed NL choice model (Hess et al., 2004; Ortúzar and Willumsen, 2011). The application of a mixed NL framework will not only help distinguish the inter-alternative correlation and panel effect as in our case, but any publications containing the use of this approach may also help a wider range of researchers notice and address this issue in their future studies.

1.5 Thesis Outline

The thesis has the following structure:

Chapter 2 aims to shed light on the aforementioned research gaps by going over some of the latest literature on various topics: our current understanding of bike-sharing choice behaviour, car-sharing choice behaviour, relevant research on attitudinal factors and shared mobility choices, as well as the mode choice change from a habitual perspective. A concluding remark is provided summarising the research opportunities.

Chapter 3 introduces the data inputs for this work. In the beginning we explain our case study choice. Next, a thorough description is given on the survey design with a particular focus being put on the design of the SP mode choice experiment. We also present details of the sampling approach and data collection procedure in the end.

Chapter 4 studies the factors that could affect bike-sharing choice and the associated modal substitution pattern. A mode choice analysis adopting a mixed NL framework is developed followed by a scenario analysis using sample enumeration to simulate the modal split changes under different policy pathways. Pooled RP and SP mode choice data from short-dist (within 2km) trips are employed for this study. In particular, we test a hypothesis that an increase in air pollution level would decrease the willingness to cycle, and question to what extent an improvement in air quality would increase the demand for bike-sharing. In the end, we derive the key implications for policy making based upon all the findings. Note also that since there is a core interest in air pollution, we include in Appendix B complementary research on air pollution's impact on mode choice behaviour by making use of the collected seasonal RP mode choice data (though the sample size is much smaller) to enrich the insights.

Chapter 5 shares a similar strategy of research to Chapter 4 (apart from not having the seasonality study), but focuses on the choice behaviour of car-sharing. Besides, this part of the work employs the mode choice data from mid-dist (2km to 5km) and long-dist (more than 5km) trips to reflect the common scenarios for car-sharing usage. We investigate under each of the distance cases, the extent to which increased demand for car-sharing would come from private car or public transport usage. In addition, a number of informative indicators (e.g. VTTS, direct and cross point elasticity) are derived to enrich the findings and policy take-away.

Chapter 6 explores in what ways the choices of using shared mobility services could possibly be influenced by personal attitudes. An ICLV model is adopted to study the effects of three attitudinal factors on the SP choices of bike-sharing and car-sharing to conduct commute trips, while simultaneously investigating the causes associated with each of the attitudes. Moreover, the study further reveals how the VTTS estimation for shared mobility could be affected by the presence of personal attitudes, especially when their interactions with travel time are captured.

Chapter 7 addresses the habitual change of mode choice. The work studies the mode switching behaviour from various non-car modes to car, in order to identify opportunities for policy intervention to hold back such a habitual change towards car usage. Retrospective commute mode choice and life course event data over four observation periods are employed. We apply first a mixed binary logit regression model to study the mode switching behaviour from car to non-car modes, and introduce a set of “mirror models” (also mixed binary logit) which evaluate the mode switches from different non-car modes to car.

Chapter 8 concludes the work. A review of the research objectives, data inputs, analysis methods and key results is given at first, followed by a comparison of the findings from this case study and the common findings from the literature for developed countries to reveal any similarities and differences. An overall evaluation is then made of the wider implications of this research for the real world. To conclude we consider the limitations of this work and the possible opportunities for conducting further research.

CHAPTER 2. LITERATURE REVIEW

This chapter reviews the literature on four individual topics, namely bike-sharing choice behaviour, car-sharing choice behaviour, attitudinal effects on shared mobility choices and habitual mode choice changes, in order to provide in-depth evidence to the earlier proposed knowledge gaps. For the first topic in section 2.1, since numerous studies have evaluated the choice of cycling-based modes including also bike-sharing, we structure the section by presenting a broad range of factors with their widely discovered effects, to give a full picture of our current understanding to the topic. Next, for the choice of car-sharing in section 2.2, we focus more on some recent works to discuss the puzzle regarding the source of demand for car-sharing given its great importance to our research and also due to a literature review study has already summarised the earlier research activities on such a topic. Then, in section 2.3 and 2.4, our sight is extended to further look at the mode choice behaviour as a result of attitudinal factors and at a habitual level respectively. At last, a final discussion is provided in section 2.5 to shed light on the current knowledge gaps after reviewing all the above literature. In addition, the insights gained from this chapter could help us design the questionnaire survey which will be presented next in Chapter 3 and later on could also contribute to the specification of the mode choice models.

2.1 The Choice of Bike-sharing

Existing literature has identified a variety of factors that could affect bike-sharing choice as well as the general cycling usage. These many factors can be grouped into three categories: 1. Natural and built environmental conditions, 2. Trip and mode related attributes, and 3. Socio-economic characteristics.

Natural environmental conditions, such as weather, temperature, air-pollution, seem to heavily affect cycling choice. Some researchers incorporated different weather conditions (e.g. sunny, rainy or snowy) in their mode choice models (Daito and Chen, 2013; Kamargianni, 2015; Caulfield et al., 2017; Sun et al., 2018; Wang et al., 2018), while others also accounted for temperature impact (Parkin et al., 2008; Saneinejad et al., 2012; Motoaki and Daziano, 2015; De Chardon et al., 2017; El-Assi et al., 2017). In general, these studies came to similar conclusions;

namely that adverse weather conditions and colder temperature would significantly discourage travellers from cycling. Many studies also analysed the impact of topography. In particular, steeper roads would significantly discourage the choice of bicycle (Waldman, 1977; Rietveld and Daniel, 2004; Parkin et al., 2008; Mateo-Babiano et al., 2016; De Chardon et al., 2017; Sun et al., 2018), although Motoaki and Daziano (2015) argued that the impact of hills on the cycling route choice heavily depended on the fitness of cyclist. Additionally, the effect of air pollution has been studied, but, to our knowledge, among the vast number of studies for developed countries, only Zahran et al. (2008) covered this effect via a cross-sectional analysis at the US county level and found pollution could decrease the number of cycling commuters on the road.

About built environmental and land use impacts, cycling-related infrastructures have attracted significant attention in the existing literature. Many studies have focused on the importance of increasing the number of cycle lanes and bike-sharing stations in promoting the use of cycling or bike-sharing, in terms of reduced travel time, increased safety and convenience (Akar and Clifton, 2009; Larsen and El-Geneidy, 2011; Hankey et al., 2012; Daito and Chen, 2013; Kamargianni and Polydoropoulou, 2013; Deenihan and Caulfield, 2015; Kamargianni, 2015; Maness et al., 2015; Wang et al., 2015; Mateo-Babiano et al., 2016; De Chardon et al., 2017; El-Assi et al., 2017; Nikitas, 2018). Nevertheless, there are also papers showing such an understanding is not widely held by revealing in their cases a highly insignificant relationship between the number of cycling facilities and cycling choice (Rodríguez and Joo, 2004; Moudon et al., 2005; Xing et al., 2010). Meanwhile, a few other factors have been occasionally looked at and their correlations with cycling usage were also found with significance. For instance, living in a densely populated community, the presence of a university campus nearby and having parks along the journey route could all potentially encourage people to choose cycling-based modes to travel (DeMaio and Gifford, 2004; Rodríguez and Joo, 2004; Barnes and Krizek, 2005; Moudon et al., 2005; Parkin et al., 2008; Maurer, 2012; Whalen et al., 2013; Kamargianni and Polydoropoulou, 2014; Sun et al., 2018; Wang et al., 2018), and moreover, living within a proximate distance to public transit stations could be particularly important to bike-sharing usage (Raux et al., 2017; Wang et al., 2018).

Trip-related characteristics are also important factors that determine mode choices. First, with regard to trip purpose, cycling has been found to be used for recreational trips in several studies (Moudon et al., 2005; Xing et al., 2010; Mateo-Babiano et al., 2016). While others, such as Faghih-Imani et al. (2017) showed the result could depend on time of the day, i.e. noon and evening trips were often associated with recreational purposes and morning trips with commute purposes; Sun et al. (2018) demonstrated specifically for bike-sharing that the registered members would use it for commute and non-members would use for recreation. Meanwhile, there is also a study arguing the usage of bike-sharing could be open to any purposes, rather than sticking to any one type in particular (Raux et al., 2017). Next, since bicycles move more slowly than motorized vehicles, there is overwhelming evidence confirming the negative relationship between cycling choice and trip distance (Parkin et al., 2008; Zahran et al., 2008; Akar et al., 2013; Wang et al., 2015; Faghih-Imani et al., 2017; Du and Cheng, 2018), and Xing et al. (2010) even argued that perceived trip distance had the most significant influence compared to any other types of factors. As for mode-related characteristics, the travel time and cost associated with a potential cycling trip generally have a negative correlation with its mode choice and both effects have been extensively studied (Kamargianni and Polydoropoulou, 2013; Kamargianni and Polydoropoulou, 2015; Ricci, 2015; Du and Cheng, 2018), though occasionally longer travel time may pose a positive utility on cycling usage (Whalen et al., 2013). Other attributes that are specific to a bike-sharing service and could potentially improve its usage include lower membership cost, shorter access and egress time, higher availability rate of in-station bicycles, longer operation hours and even helmet provisions (Lin and Yang, 2011; Fishman et al., 2015; Ahillen et al., 2016; De Chardon et al., 2017; Du and Cheng, 2018).

Socio-economic characteristics have been widely studied, with age and gender emerging as among the most influential factors, i.e. younger generations and males are usually keener to cycle (Shafizadeh and Niemeier, 1997; Rodríguez and Joo, 2004; Moudon et al., 2005; Parkin et al., 2008; Baker, 2009; Akar et al., 2013; Fishman et al., 2015; Ricci, 2015; Wang et al., 2015; Raux et al., 2017; Nikitas, 2018). Meanwhile, occupation and economic status may also play important role in determining cycling choice. Xing et al. (2010) showed that travellers with lower income cycled more because those with a higher income would attach higher values on their time, and thus, chose faster modes. Faghih-Imani et al. (2017) reached similar conclusions by arguing that the unemployed usually preferred cycling. However, some studies found that higher cycling rate could be associated with those that have better economic or social status, possibly as a result of pursuing healthier lifestyles (Parkin et al., 2008; Zahran et al., 2008; Fishman et al., 2015; Kamargianni, 2015; Raux et al., 2017). Additionally, cycling was found to be a popular mobility choice among students in several cases (Baltes, 1996; Whalen et al., 2013; Wang et al., 2015; Du and Cheng, 2018). Vehicle ownership seems to be a more direct determinant of mode choice. In general, owning a car could potentially decrease the incentive or the need to cycle, either for educational (Rodríguez and Joo, 2004) or work-related purposes (Parkin et al., 2008). However, such an inverse relationship might also be attributed to collinearity with other factors; that is those who do not own vehicles and have to cycle could do so because of their disadvantaged income status that makes the purchase of a vehicle unaffordable; or the travel distance was too short to make it worthwhile to own a car (Baltes, 1996). Other socio-economic factors that are positively associated with cycling usage can include a good health or body status (Moudon et al., 2005) and a well-educated background (Xing et al., 2010).

Another popular approach to study socio-economic characteristics (instead of assuming their direct effects on mode choice utilities) is exploring systematic taste heterogeneity (Amador et al., 2005; Cherchi and Ortúzar, 2011). More insightful results could be gained by also taking into account this effect. In the case of cycling, for instance, it reveals how different socio-economic groups would react to the impacts of natural and built environmental conditions, as well as trip and mode attributes, e.g. female travellers were still reluctant to cycle even if in sunny days which in general could increase the attractiveness of cycling (Kamargianni, 2015).

Although many studies have assessed cycling and bike-sharing choices, there are still gaps to be addressed. First of all, there is a general lack of mode choice studies in developing countries, particularly with respect to the choice of bike-sharing. The results in developed countries may have limited implications for developing countries since different local characteristics could lead to different results and conclusions. The existing literature has demonstrated such differentiations even among works carried out within developed countries and some studies directly showed the context-specific nature of travel behaviour through simultaneously studying multiple cases (Barnes and Krizek, 2005; Tang et al., 2011; Maurer, 2012; Kamargianni, 2015; Faghih-Imani et al., 2017). Next, more specifically, there is a lack of literature focusing on the impact of air pollution, which is generally a less important concern in developed countries. However, it might be essential to take into account such effects in the developing world where air pollution is a much more severe challenge. A recent study should be acknowledged (Campbell et al., 2016), in which the authors took into account air pollution's impact when using SP survey data from 623 participants and a multinomial logit model to study bike-sharing choice in Beijing. In our research, despite having a different scope and methodology as well as a larger sample, we will also extend further the findings on air pollution by revealing its effect on the modal substitution pattern via a scenario analysis (see Chapter 4).

2.2 The Choice of Car-sharing

Given the expected benefits of car-sharing, many research attempts have also been made with respect to the demand for using this service. Jorge and Correia (2013) conducted a literature review study summarising all the important works by the time. One of the gaps they identified was a lack of clear evidence on the modal substitution pattern, and in particular, if more people using car-sharing "reduces the use of private vehicles or if, on the contrary, it reduces the number of public transport users (p.216)". This is the information that policy makers are keen to find out, especially when they need to determine whether or not to endorse car-sharing (via subsidies, legislation etc.). Later, Le Vine et al. (2014) investigated how an introduction of car-sharing service could influence car and public transport usage. The work showed the answer to such a puzzle could be a joint outcome of travellers' long-term and short-term behaviours; in other words, tactical-level behaviours at the short-run (i.e. mode choice for a trip, such as car-sharing, car or public transport) could be influenced by strategic-level behaviours at the long-run (i.e. mobility resource choice, such as car ownership and subscription to a car-sharing program).[6] Nevertheless, given the limited amount of car-sharing choice data collected, the contribution of this work is more on the joint analytical framework it developed, rather than providing empirical answers to the aforementioned puzzle. Kopp et al. (2015) also explored modal substitution pattern by comparing the travel behaviour across a car-sharing member group and a non-member group. They found public transport demand was similar, while the demand for motorized private transport was significantly lower in the member group. However,

[6] Recall that our survey only focused on the mode choice behaviour at a tactical level, and this is due to almost all of the car-sharing services in China do not require regular membership fees or any long-term commitments which make the effect of strategic choice trivial.

they noticed that the result could be biased due to the sampled car-sharing user group already had a low rate of motorized private transport usage before joining the car-sharing scheme, and hence, further research was called for. One earlier attempt not mentioned by Jorge and Correia (2013), was made by Martin and Shaheen (2011), in which the authors looked directly at their survey statistics and saw car-sharing's impact on travel pattern was rather complex, where members from some organizations increased their public transits, while others shifted away, and the magnitudes were largely variable across member groups. In general, more robust evidence on modal substitution pattern is needed to better inform policy decisions. Unfortunately, to our best knowledge, the puzzle has remained overlooked apart from the few studies mentioned above, though some more recent works have shown up and significantly enhanced our understanding of car-sharing choice behaviour. Their main contributions are highlighted below.

Carteni et al. (2016) used a binomial logit choice model to analyse the mode choice between car-sharing and private car. The key finding from the choice model and the follow-up elasticity analysis was that travel cost has a much greater impact than travel time on affecting car-sharing choice. Similarly, in De Luca and Di Pace (2015), travel cost was identified as one of the critical factors alongside access time to car-sharing spots, trip frequency, car availability and the type of trip etc. Moreover, De Luca and Di Pace (2015) showed via a cross-elasticity analysis that a change in car-sharing travel cost has much larger effect on the probability to choose to carpool than on the probabilities to choose bus and private car. Martinez et al. (2017) highlighted an important conclusion that the preference towards car-sharing would increase with trip length; in other words, the service could more likely be chosen as trips became longer. Becker et al. (2017) put particular attention on the socio-economic groups from which the usage of free-floating and station-based car-sharing services could come from. The results demonstrated both schemes could attract younger and educated people, which were in line with the key findings from the other two studies dedicated to revealing the influence of socio-economic factors on the general car-sharing choice (Dias et al., 2017; Prieto et al., 2017). However, a critical difference was emphasised such that a free-floating service was normally used by those higher incomes earners whose home location poorly served by public transportation whereas the station-based was preferred by self-employed workers who would appreciate the flexibility of using a car when needed. Apart from those rather fundamental factors and effects, a few more novel subjects were also explored, such as a parking price increase (Balac et al., 2017), introducing autonomous vehicle fleets (Winter et al., 2017), placing a station outside a technology firm (El Zarwi et al., 2017), all of which could potentially boost car-sharing adoption.

Some studies applied more advanced modelling techniques to investigate the impacts of latent variables/unobserved attributes on car-sharing choice, such as Efthymiou and Antoniou (2016), Kim et al. (2016), Kim et al. (2017a), Kim et al. (2017b) and Vinayak et al. (2018), which will be reviewed next in section 2.3 when looking at the attitudinal effect on mode choice behaviour. Many earlier works that involved factors affecting car-sharing choice and demand have been captured by Jorge and Correia (2013) and for which repeated reviews should be avoided, for example Catalano et al. (2008), Zheng et al. (2009), Morency et al. (2012), Ciari et al. (2013) and De Lorimier and El-Geneidy (2013), though two of them (Catalano et al., 2008; Zheng et al., 2009) also attempted to study modal substitution patterns; nevertheless, both works have rather specific focuses (i.e. Catalano et al. (2008) analysed 500 commuters' morning rush-hour trips heading to city centre; Zheng et al. (2009) studied car-sharing in a university campus) and more research would certainly be needed to offer broader insights. In addition, there were two other studies aiming at assessing the choice between electric and hybrid vehicle types within a car-sharing system (Zoepf and Keith, 2016; Wielinski et al., 2017), which should also be acknowledged.

Overall, the existing studies offered valuable insights on car-sharing choice behaviour, though more effort is needed to understand better the modal substitution pattern hidden behind a potential increase of car-sharing's demand. Our following research aims to contribute to such a domain. Particularly, we would like to focus on a later phase for the case study in China (comparing to Le Vine et al. (2014) on car-sharing's market entry phase due to the matter of strategic choice), where membership subscription is not a universal concern and the key challenge is likely to be how to promote car-sharing usage; in other words, how could policy interventions effectively step in and make car-sharing a more popular choice among various daily mobility options.

2.3 Attitudinal Effects on Shared Mobility Choices

So far, numerous studies have been made with regard to the decisions to use bike-sharing and car-sharing for daily mobility. However, there are further opportunities to enhance the behavioural realism of shared mobility choices, and one potential path is by exploring the influence of personal attitudes on mode choice decisions.

Research in this dimension has substantial benefits, i.e. explicitly modelling unobserved heterogeneity, increasing estimation efficiency and goodness-of-fit, enhancing behavioural realism, and extending policy relevance (Abou-Zeid and Ben-Akiva, 2014), and has already been found in various mode choice related topics. For instance, Johansson et al. (2006) took into account travellers' attitudes towards a number of issues, such as environment, safety, comfort, convenience and flexibility, to help explain the choices of car and public transport. Paulssen et al. (2014) studied a similar set of mode choices and attitudes, and they even further brought in and analysed the impacts of personal values (i.e. the factors that "lie at the heart of an individual's belief system") on both mode choices and attitudes. Apart from car and public transport, Sarkar and Mallikarjuna (2018) discovered also the significance of flexibility perception in affecting the demand for two and three-wheeled motorcycles. Kamargianni et al. (2015) found that the mode choices when travelling to school could be influenced by teenagers' attitudes towards safety, green lifestyle and physical activity. There were also direct comparisons on model performance where mode choice models by adding in latent attitudes and perceptions always outperformed the corresponding base models in terms of predictive power (Yanez et al., 2010; Chen and Li, 2017). In addition, some similar practices can be found in Bolduc et al. (2008), Daziano and Bolduc (2013), Kim et al. (2014), Beck et al. (2017) and Smith et al. (2017) on vehicle type choices (i.e. usually involving electric vehicle), Belgiawan et al. (2017) on student's car purchase decision, Fleischer et al. (2012) on flight choice and Song et al. (2018) on high-speed rail choice.

Although to our knowledge, bike-sharing choice has rarely been evaluated through attitudinal influence, works have tried to reveal how this type of factors might affect the general cycling choice. Pro-bike attitudes, which could include general willingness to cycle and consciousness towards environment and sustainability issues, were popular factors that have been analysed in many studies and were often identified as important driving forces to cycling usage (Kamargianni and Polydoropoulou, 2013; Maldonado-Hinarejos et al., 2014; Fernandez-Heredia et al., 2016). Similarly, the feelings towards internal (e.g. personal fitness) and external (e.g. weather and topography etc.) conditions could also heavily affect a traveller's decision to cycle, as being identified in several cases (La Paix Puello and Geurs, 2015; Motoaki and Daziano, 2015; Fernandez-Heredia et al., 2016). Nonetheless, these mostly studied attitudes may sometimes be less important according to the results of a Spanish case study by Munoz et al. (2016), in which the authors found the impacts of pro-bike lifestyles, environmental awareness and the perceptions on cycling capability were rather insignificant. Finally, some other attitudinal factors have also been examined in the aforementioned cycling choice studies, such as the perceptions of convenience and comfort, safety concerns and social norms, which could influence cycling choice as well to some extent.

With respect to car-sharing choice, only a few recent studies have started to explore the potential influence of a limited range of attitudinal factors. Efthymiou and Antoniou (2016) and Kim et al. (2017a) identified in both of their case studies that the intention to join a car-sharing scheme could be significantly affected by people's satisfaction with their current travel patterns and habits. Kim et al. (2017b) discovered further that car-sharing choice was highly associated with pro-environmental and privacy-seeking attitudes, and perceptions on the symbolic value of cars. Moreover, in Vinayak et al. (2018), the frequency of using car-sharing was found not only being affected by attitudes such as pro-environmental and neo-urban lifestyle preferences, but also by socio-interactions (i.e. someone's behaviour depends on the behaviours of those nearby). A similar result was revealed by Kim et al. (2016) in which the authors argued that social influence was indeed significant in car-share decisions, and more importantly, the magnitude of social influence could vary as per the strength of social relationship across individuals. In addition, Fleury et al. (2017) looked at a specific corporate car-sharing scheme and highlighted that perceived effort expectancy (i.e. degree of ease associated with use) was probably among the most important psychological factors that could determine the intention to use this type of a service. Another work by Correia et al. (2010) focused on carpooling instead and found such a mode choice could be heavily affected by people's positive/negative attitudes and familiarity with the concept.

Besides the relatively limited understanding of how shared mobility choices might be influenced by attitudinal factors, another matter that could contribute to travel demand management but yet rarely looked at is the estimation of VTTS under the presence of personal attitudes. To our knowledge, Abou-Zeid et al. (2010) for the first time noticed the opportunity to capture the interaction effects between attitudinal factors and travel time or cost in order to have a more accurate calculation for VTTS. This is due to people with different attitudes could have different valuations towards trip-related factors and thus the willingness to pay for travel time savings could also be different. In other words, VTTS will no longer be identical across the population and need to be integrated over all individuals to derive a value at the societal level. Nevertheless, we noticed from the results of Abou-Zeid et al. (2010) that there is only a trivial difference (around 7%) between the VTTS estimated from a base mode choice model and from an ICLV mode choice model which captures an attitudinal factor's interaction with travel cost. Such amount of difference is significantly smaller than a few earlier results when the impact of systematic and random taste heterogeneity on value of time was studied (Algers et al., 1998; Hensher, 2001a; Amador et al., 2005). In fact, the three works here all discovered around 40% difference when comparing the VTTS estimated from a base MNL model and from an ML model that captures taste heterogeneity. Algers et al. (1998) found the more flexible ML model decreased VTTS, while the other two (Hensher, 2001a; Amador et al., 2005) found the results in a completely opposite way[7]. Now a question may pop up that if the much smaller difference revealed by Abou-Zeid et al. (2010) would imply the non-significant influence of personal attitudes in VTTS estimation or there could be other explanations behind. As a result, we looked into their study and found from the survey statistics that 3 out of the 4 modelled indicators which reflect people's attitude towards car use were highly skewed in one direction, which strongly suggests the sampled individuals were sharing close rather than differentiated attitudes.[8] Thus, it may be able to explain why capturing taste heterogeneity contributed so little to VTTS estimation (because there is no significant taste heterogeneity), though this hypothesis should be further tested. Unfortunately, to date, no other evidence was found apart from Bahamonde-Birke et al. (2017), which noticed as well the opportunity to calculate VTTS after

[7] In another study, Alpizar and Carlsson (2003) argued value of time could either increase or decrease with a more flexible model specification depending on the chosen mode.
[8] See p.10 for the skewed indicators and see p.14 for which four indicators were modelled (Abou-Zeid et al., 2010).

seeing the interactions between attitudes and travel time, though no empirical results were provided in the study.

Thus, in our subsequent analysis, we are not only aiming to enrich the literature by revealing how several types of personal attitudes could possibly affect bike-sharing and car-sharing choices, but also trying to investigate the extent to which VTTS estimation for shared mobility could be affected by the presence of personal attitudes, especially when the interaction with travel time or cost is captured, and hence compare to the result in Abou-Zeid et al. (2010).

2.4 Habitual Mode Choice Change and the Role of Life Course Events

Most of the mode choice studies have focused their analyses at a tactical level by exploring how individual travellers make trade-offs among different attributes. Nevertheless, there have also been works since early ages recognising that a choice behaviour could be habitual and a mode use decision might not easily be affected by the surrounding tactical-level conditions (Verplanken et al., 1997; Ouellette and Wood, 1998; Van der Waerden and Timmermans, 2003). With such an understanding, many studies have incorporated the dynamic elements in their models, i.e. by taking into account the influence of mode choices observed in earlier periods/states on the current mode choice behaviour (Ramadurai and Srinivasan, 2006; Dargay and Hanly, 2007; Srinivasan and Bhargavi, 2007; Kitamura, 2009), and in most cases the influence turned out to be significant. The revealed importance of mode choice habit could bring substantial challenges to effective travel demand management. For instance, if policy efforts only focus on the tactical-level mode choice behaviour, the expected modal shift from car to more sustainable modes may not easily occur due to the behaviour could be dominated by the mature car-use habit. So, what could be the solutions? In other words, can the choice habit be somehow changed?

Research has proposed and shown that life course events could potentially lead to a change of mode choice habit. There could be a variety of such life course events (Scheiner and Holz-Rau, 2013), for example, household or family-related (getting married, child birth, etc.), employment-related (income change, employer change, etc.), residential or contextual-related (home relocation, trip distance change, etc.), and a number of studies have attempted to investigate the connections between these events and long-term mode choice changes. Oakil et al. (2011) found that employment-related changes such as in work status and employer were among the most important factors that could trigger commute mode shift decisions through both directions, i.e. from car to non-car and from non-car to car, while a mode switch to car was largely associated with a child birth event. Moreover, the authors also highlighted the impacts of socio-economic factors generally turned out as insignificant, especially as a comparison to the significance discovered on those life course events. A later work of Clark et al. (2016a) also focused on these two-way changes of the commute mode choice habit. The results regarding life event impacts were pretty much in line with which in Oakil et al. (2011). Although the key conclusion this time was expressed as commute mode changes were primarily driven by working distance changes, it was further clarified that the occurrence of such a contextual-related event was usually caused by employment switches. Nevertheless, one notable difference by comparing these two works was Clark et al. (2016a) argued socio-economic factors could be critical to modal shift decisions, for instance, those highly educated would be less likely to switch to car commuting; besides, in this study built-environment characteristics were generally found with significant effects as well on mode choice changes. Meanwhile, there were also works looking at the mode switches to and away from bicycle use (Chatterjee et al., 2012; Oakil et al., 2016). The results in both works confirmed the significant role of life course events, and more or less they could reflect the conclusions made from the previous two studies which focused on car use. For example, child birth would encourage a switch to car, and likewise, it could also stop people from cycling; changes in work status and employer were again found their effects on both directions of mode switches, i.e. from cycling to non-cycle and from non-cycle to cycling; and more specifically, a longer commute trip would tend to discourage cycling while a shorter commute was associated with a shift toward cycling. In the end, the impacts of life course events have also been explored on other types of travel behaviour such as car ownership changes (Dargay, 2001; Prillwitz et al., 2006; Oakil et al., 2014; Clark et al., 2014; Clark et al., 2016b) and commute distance changes (Clark et al., 2003; Prillwitz et al., 2007).

Nevertheless, the challenge remains. It is probably desirable to see a switch away from using car following the occurrences of some life events; however, meanwhile, switching to car is also a possible outcome. In fact, Oakil et al. (2011) compared between a “Modal shift to car” sample and a “Modal shift from car” sample, both from a 21-year longitudinal data series capturing nearly 200 individuals’ behaviours, and it was revealed that the modal shifts from non-car modes to car were more frequently observed than the opposite. With the use of a much larger dataset (over 10,000 individuals) though only containing two waves of observations, Clark et al. (2016a) found the same result by seeing the percentage of car users who switched to other modes in the following period was less than 9% (in total). The figure is even smaller than the proportion of any other individual mode users who made a switch to car. Thus, given such a fact, it is crucial if efforts could be made to hold back any mode switches to car that are induced by life course events; since otherwise, once car is picked up and over time its usage becomes habitual, it would be even more difficult to alter the mode choice behaviour (Ouellette and Wood, 1998). As a result, we identified the following question that needs to be answered: given the presence of life course events that could result in the mode switches from non-car modes to car, what could be the counter-measures to hold back such a change? This is a subject that we cannot find many insights from the literature. Clark et al. (2016a) offered a policy discussion on how to make non-car modes more likely to be chosen for regular commute, given the occurrences of life course events. They offered policy recommendations in the circumstances of job changes and residential relocations, such as issuing transport information packs and travel offers to young entrants to the labour market and new community residents, who often contemplate commute options to a greater extent than mature employees and residents. However, to our knowledge, this is so far the only research that has explicitly discussed the relevant policy implications, even though they only studied non-car modes as a whole rather than breaking down the analysis and insight to specific modes, which could be more informative to the policy designs in practice.

2.5 Discussions of the Gaps

As a summary, several opportunities for conducting further research do turn up. Firstly, the impact of air pollution on mode choice behaviour has rarely been explored. In particular, since it is a challenge prevailing in most of the developing countries, whether or not and to what extent air pollution may significantly affect bike-sharing and other active transport choices become a subject that could worth more research attention. In terms of policy practice, if evidence can be found to unveil such an impact, the current “one-way approach” (i.e. non-motorised transport is often seen as a solution to improve air quality) would become an old fashion and instead a “virtuous circle” could be created (i.e. better air quality could result in higher demand for using non-motorised transport, and higher non-motorised transport usage could further help reduce air pollution). Therefore, developing countries may be more incentivised to work on air pollution reduction from other sources (e.g. industrial, residential and business sectors) in order to exploit the extra gains from urban transport. Secondly, unlike bike-sharing which aims to serve travellers’ short-dist trips, a car-sharing service is in general expected to be a much stronger and more feasible substitute for the widely used private car. Hence, a lack of clear insights on its modal substitution pattern, and especially whether the demand would mainly come from private car or public transport, becomes a rather prominent issue to today’s policy making on car-sharing’s demand management. In our subsequent analysis, the in-depth evidence is going to be revealed with respect to such a gap of knowledge. Thirdly, apart from a lack of good understanding of the impacts of attitudinal factors on shared mobility choices, another hypothesis concerning how the VTTS estimation could be affected also matters. An integrated choice and latent variable modelling analysis, later on, would help disclose how much difference the presence of attitudinal factors could have on VTTS estimates. In other words, this will provide evidence of whether different VTTS estimates for travellers with differentiated attitudes would be needed (instead of a single VTTS measure across population) and should be taken into account for any pricing-related designs of policies. Fourthly, given the concern that any tactical-level efforts for demand management may be compromised due to the potential dominance of mode choice habit, it would be rather useful to search for any complementary measures for controlling private car usage. One important question is if it would ever be possible to avoid a habitual mode switch towards private car when certain events took place during people’s life courses. Our analysis looking at the habitual mode switches both to/from car is expected to bring some inspirations to the puzzle, while the insights will be further extended by investigating the different mode switching behaviour among different non-car mode users. Finally, and in addition, for all the areas of research being discussed above, due to the reviewed studies and their findings were rarely coming from the wider developing world, it could be worth delivering a case study focusing on a developing country in order to generate and compare to the developed nations the results and the corresponding implications for policy take-away.

CHAPTER 3. DATA PREPARATION

3.1 Case Study Choice

To achieve the aforementioned research goals, we would like to conduct a case study in a developing country. We choose to focus on China, which is the largest developing economy in the world while being puzzled by severe congestion and urban air pollution problems owing to private car usage in many of its cities. At a glance, the country has accommodated bike-sharing services in hundreds of cities over the last couple of years and many of the schemes including both station-based and dock-less have gained remarkable international reputations (Song et al., 2017; Richter, 2018). In comparison, the concept of car-sharing has only started to be familiarised by the Chinese public recently after a number of pilot and small-scale schemes were introduced to several big cities. Thus, car-sharing is still not yet a widely available travel option in China even though it has grabbed a significant amount of attention and is expected to grow fast in the near future (Hao, 2017; Xinhua, 2017).

To select a case study city that is compatible with this research, two general criteria were considered. Firstly, we would like to have a city that suffers from increased car usage and aims to curb the resulted congestion and urban air pollution. Secondly, the city should have an interest in and potential to promote the usage of shared mobility services. As a result, the case study city would not only benefit directly from the findings of this work to assist policy making in its jurisdiction, but could also serve as a representative case for other cities in developing countries to see the evidence and take away insights to address their own issues. Eventually, Taiyuan, the capital city of a northern province Shanxi, with a population of over 3 million, is selected for this project. Traffic jams and air pollution have been problems in Taiyuan for a long time owing to the massive amount of car usage (CGTN, 2014; Liang, 2017), and hence, the city has been delivering continuous efforts to create a future with less dependence on private car and fossil fuel. In 2012 Taiyuan participated as one of the first few member cities in China's "Transit Metropolis" project (Jiang et al., 2013); in the same year a publicly operated station-based bike-sharing scheme was launched (see Figure 3-1) and has become one of the most in-demand schemes in the country (Burkholder, 2015; Hiles, 2015); in 2016, Taiyuan undertook an extensive taxi overhaul project and replaced all of its 8,292 taxis with electric vehicles, making it the first city in China to do so (Global Opportunity Explorer, 2016); finally, since 2017, several electric car-sharing pilot schemes have been deployed in the city following the aforementioned nationwide interest in such a type of service (Sohu, 2018). Overall, Taiyuan offers a fertile ground for this research and we would expect the findings of this project to be of practical value to wider society.

Figure 3-1 Bike-sharing docking stations in central Taiyuan (approx. 20km^2 shown in the map)[9]

[9] Source: Taiyuan Public Transport Holdings, http://www.ty7772345.com/moremap.asp?Parent=3

3.2 Survey Design

3.2.1 The Questionnaire

The data analysed in this work comes from a paper-based questionnaire survey launched in 2015 at our case study city, Taiyuan. Both revealed preference (RP) and stated preference (SP) travel behavioural data are collected. The questionnaire consists of six sections as listed below, and an example of the questionnaire is given in Appendix A:

- Personal socio-economic characteristics;
- Household socio-economic characteristics;
- RP trip diary revealing trip characteristics and mode choices in a single day;
- Attitudes towards shared mobility and other related issues;
- Retrospective survey collecting past socio-economic and mode choice data; and
- SP mode choice experiment.

For the first two sections, we aimed to capture a broad range of socio-economic data from each of the individual respondents. Some characteristics could potentially be the explanatory variables in a choice behavioural analysis (e.g. gender, age, household income, educational level), some could be the availability conditions to help specify a mode choice model (e.g. ownership of different mobility tools, possession of a driving license, cycling capability), some could serve as the criteria for data cleaning (e.g. trip diary data would be considered as invalid if one's occupation was driving-related), and some were the back-up information we collected for other research purposes in future.

In terms of the RP mode choice data, the survey participants were asked to fill in their trip diary for one day (i.e. their most recent working day). Due to resource constraints and local cultural barriers the use of GPS or Smartphone-based travel survey tools that could collect more advanced travel data was not possible. As such, only essential travel information was gathered in the trip diary (e.g. trip purpose, starting/end time of the trip, origin/destination, travel time, travel cost and mode used), though they could further help derive additional information that might be used in the modelling analyses (e.g. travel times and costs of any alternative modes, as well as the real-time air pollution level, temperature and weather conditions when a trip was conducted).

With regard to the way that attitudinal information was captured, we presented in the questionnaire a list of statements where the respondents were asked to indicate to what extent they agree with each of them. These statements belonged to four subjects: general environmental consciousness, attitudes towards public transport, towards bike-sharing and towards car-sharing. The degrees of agreement were measured using a 7-point Likert-scale (Likert, 1932) where: 1. Completely disagree; 2. Strongly disagree; 3. Disagree; 4. Neutral; 5. Agree; 6. Strongly agree and 7. Completely agree.

As for the retrospective survey, respondents were asked to recall their most frequently used commute mode in 2006, 2008, 2010 and 2012, and also to provide a variety of information with respect to their life status in the same years.

Finally, for the SP mode choice data, our experiment presented to each individual respondent hypothetical daily trip scenarios and asked them to choose which transport mode they would use. In particular, the method offers a means of capturing the choice of car-sharing, as the service was not yet available in Taiyuan at the time of the survey. It is also a useful technique for deriving wider policy implications, as SP data usually captures "a wider and broader array of preference-driven behaviours" (Louviere et al., 2003; p. 231) than the conventional RP data.

3.2.2 A Pilot Survey

A pilot survey was conducted before we came up with the final questionnaire design. The main objective is to test if the questions presented were appropriate and clear to respondents. Hence, we chose to use two non-probability sampling techniques, convenience sampling and snowball sampling, to quickly secure around 150 Taiyuan citizens who were willing to participate. Although in this testing phase of the survey the sample can hardly be representative to the population, most of the participants turned out to be commuters who had regular travel activities and provided good amount of information in the trip diary survey (which helped to improve the SP survey design; see the next section).

Many changes were made to the questionnaire as per the feedback from the pilot survey.

This includes several important matters such as adding a question in the socio-economic survey checking if occupation is driving-related to filter out the corresponding individuals in mode choice analyses (Appendix A: S1. Q9), showing an example trip diary to help the respondents clearly understand what information they should provide (Appendix A: S3. Q1), and replacing the original 5-point Likert-scale measurement in the attitudinal survey with a 7-point measurement, which can yield more information while can still be well comprehended by the respondents (Appendix A: S4). Nevertheless, the most significant take-away from the pilot survey is knowing what elements should to be taken into account in the SP scenario designs.

3.2.3 The SP Mode Choice Experiment

For the SP experiment, the first important insight that we gained from the pilot survey was the need to have different SP scenarios based on the distance travelled; this was an outcome both from analysing the RP trip diary data and from the comments made by the participants. In particular, we observed that when distances went beyond 2km, the number of walking trips dropped substantially whereas when distances went below 2km, taxi trips were rarely seen. In light of such rather distinct trends, we decided to split the scenarios in our SP survey by trip distance and assign different choice sets accordingly, i.e. making “walk” available only for short trips (within 2km) and making “taxi” available only for longer trips (over 2km) to approximate the mode choice situation towards a real-life case. Moreover, by hearing from participants describing their daily travel experience in Taiyuan, we further split the trips over 2km to “between 2km and 5km” and “more than 5km” to reflect what local people perceive as a medium-distance trip and a long-distance trip for moving around in the city. In fact, such a split has also helped us identify if the mode choice behaviour and modal substitution pattern would differ by distance, and hence yield more targeted insights for policy take-away (see more details in Chapter 5).

Eventually, in the SP experiment, we included six alternatives in the choice set: 1. car, 2. electric bike, 3. bus, 4. car-sharing[10], 5. bike-sharing and 6. walk for the case of short-distance (“short-dist”, within 2km) trip; while for medium-distance (“mid-dist”, between 2km and 5km) and

[10] As per the pilot survey feedback there was imperfect knowledge among Taiyuan citizens about what car-sharing really represents. Thus, the concept and key features of a free-floating car-sharing scheme were described in the survey to reduce the bias in their understanding.

long-distance ("long-dist", more than 5km) trips, walk was replaced by taxi as per our discussion above. Overall, we aim to capture all the urban transport modes that are frequently used by Taiyuan citizens (except car-sharing), with the private bike being excluded due to its continuously decreasing usage as a result of the continuous expansion of the city's bike-sharing program.

Table 3-1 shows the SP experimental design for the three trip-distances. Each of the aforementioned alternatives possesses several mode-specific attributes, with trip purpose, temperature, weather and air pollution as the external conditions. Apart from doing a literature review, the selection of these attributes was also based on findings from the pilot survey. For instance, the "Walking time to/from station" was included after observing some potential connections (though we did not test the correlation) between respondents' stated walking times to/from bus or bike-sharing stations and whether any bus or bike-sharing trips were made in the diary (Appendix A: S3); similarly, "Mobile app availability" was captured by seeing quite a few individuals stated they would use smartphone to call taxi and check real-time bike-sharing information (Appendix A: S1). Besides, the pilot survey results also helped derive the levels/values for some of the attributes. For example, to generate the possible travel time and travel cost values for each alternative mode, we adopted the observed average values from the trip diary part of the pilot survey and multiplied by ±10%, ±20% etc. Although, due to the lack of official trip diary data we are not able to make a comparison for our observed travel times and costs, we still expect the values can be trusted given the sample size we had for the pilot survey. In addition, we discussed with experts from the local transport authorities to make sure the attribute values were generated on reasonable scales.

Table 3-1 The SP Survey Design

Short-dist						
Trip purpose: work/education, leisure, shopping. **Weather:** sunny (-10°, -5°, 0°, 5°, 10°, 20°, 25°, 30°), snow (-10°, -5°, 0°), rain (5°, 10°, 20°, 25°, 30°). **Air pollution level:** excellent, good, light pollution, medium pollution, heavy pollution, terrible pollution.						
	Car	**E-bike**	**Bus**	**Car-share**	**Bike-share**	**Walk**
Travel time	2, 3, 5, 7, 10min.	5, 6, 7, 9min.	5, 7, 10, 12, 15min.	2, 3, 5, 7, 10min.	8, 10, 12min.	10, 15, 20, 25, 30min.
Travel cost*	￥1, 1.2, 1.4,		￥0.5, 1,	￥0.8, 1,	￥0, 0.5, 1.	

	1.6, 1.8.		1.5, 2, 2.5.	1.5, 2, 3, 4, 5.		
Parking space	Easy/hard to park					
Parking cost*	free, ￥2, 5, 8/h.					
Walking time to/from station			5, 10, 15min.	5, 10, 15min.	2, 5, 10min.	
Bus Frequency			every 2, 5, 10, 15min.			
Mobile app availability			Yes, no.	Yes, no.	Yes, no.	
Mid-dist						
Trip purpose: work/education, leisure, shopping. **Weather:** sunny (-10°, -5°, 0°, 5°, 10°, 20°, 25°, 30°), snow (-10°, -5°, 0°), rain (5°, 10°, 20°, 25°, 30°). **Air pollution level:** excellent, good, light pollution, medium pollution, heavy pollution, terrible pollution.						
	Car	**E-bike**	**Bus**	**Car-share**	**Bike-share**	**Taxi**
Travel time	5, 10, 15, 20, 25min.	8, 10, 12, 15, 20min.	10, 12, 15, 20, 25, 30min.	5, 10, 15, 20, 25min.	12, 15, 20, 25, 30min.	5, 10, 15, 20, 25min.
Travel cost*	￥1.8, 2, 2.5, 3, 3.5, 4, 5.		￥0.5, 1, 1.5, 2, 2.5.	￥3, 5, 8, 10, 15, 20.	￥0, 0.5, 1, 1.5.	￥10, 12, 15, 18, 20, 25, 30.
Parking space	Easy/hard to park					
Parking cost*	free, ￥2, 5, 8/h.					
Walking time to/from station			5, 10, 15min.	5, 10, 15min.	2, 5, 10min.	
Bus Frequency			every 2, 5, 10, 15min.			
Mobile app availability			Yes, no.	Yes, no.	Yes, no.	Yes, no.
Long-dist						
Trip purpose: work/education, leisure, shopping. **Weather:** sunny (-10°, -5°, 0°, 5°, 10°, 20°, 25°, 30°), snow (-10°, -5°, 0°), rain (5°, 10°, 20°, 25°, 30°). **Air pollution level:** excellent, good, light pollution, medium pollution, heavy pollution, terrible pollution.						

	Car	E-bike	Bus	Car-share	Bike-share	Taxi
Travel time	15, 20, 25, 30, 40min.	20, 30, 40, 50, 60min.	15, 20, 30, 40, 50, 60min.	15, 20, 25, 30, 40min.	30, 45, 60, 75, 90, 120min.	15, 20, 25, 30, 40min.
Travel cost*	￥5, 8, 10, 12, 15, 18, 20.		￥0.5, 1, 1.5, 2, 2.5.	￥10, 15, 20, 25, 30, 40.	￥0, 1, 1.5, 2, 3.	￥15, 20, 25, 30, 40, 50.
Parking space	Easy/hard to park					
Parking cost*	free, ￥2, 5, 8/h.					
Walking time to/from station			5, 10, 15min.	5, 10, 15min.	2, 5, 10min.	
Bus Frequency			every 2, 5, 10, 15min.			
Mobile app availability			Yes, no.	Yes, no.	Yes, no.	Yes, no.

* ￥1 ≈ $0.15

In light of the attributes and attribute levels that have been obtained, theoretically, SP scenarios could then be generated following a full factorial design (Hensher et al., 2005). However, in many cases (ours as well), it would produce an endless number of scenarios which result in a need to embrace a fractional factorial design by extracting only a group of scenarios from the full set. The practice we followed to extract the scenarios for this survey was commonly known as orthogonal design[11] which could help reduce the correlation between the attribute levels. More specifically, we adopted an “orthogonal main effects” design by assuming no interaction effects exist across the attributes, though it is an assumption that can hardly be tested in reality (Hensher et al., 2005; chapter 5.2.3). In order to preserve orthogonality, the key task is to identify the required degree of freedom (DoF), or in other words, the minimum number of scenarios that needs to be extracted (Caussade et al., 2005). By assuming main effects only, we calculated the required DoF for each of the distance cases by following the procedure explained in Louviere et al. (2003) and Hensher et al. (2005). As a result, we had a DoF of 56 for the

[11] Although an orthogonal design is not as advanced as several later proposed designs, such as the various forms of D-efficient design (Bliemer et al., 2009; Rose and Bliemer, 2009; Bliemer and Rose, 2010), we still employed this technique given the constraints we had on project cost (i.e. more advanced software such as Ngene is usually needed to handle an efficient design).

short-dist scenarios and 58 for the mid- and long-dist scenarios.[12] Thus, for each of the three distance cases, we chose to generate 60 different scenarios and the software we used is SPSS, which can ensure the process of scenario generation preserves orthogonality (Hensher et al., 2005). Next, to further reduce the number of scenarios presented to a respondent, the 60 scenarios in each case were assigned to 30 blocks, and hence, a group of 2 scenarios would be presented in one questionnaire making in total 6 of them by presenting all three distance cases, i.e. two for short-dist trips, two for mid-dist trips, and two for long-dist trips.[13] Eventually, one out of every 30 respondents would be given the same set of SP scenarios in our survey.

3.3 Sampling and Data Collection

The survey was launched through two waves in the city of Taiyuan over the year of 2015. The first wave was the main part of our data collection. The questionnaire was distributed to 15,000 Taiyuan citizens over the summer months. Due to the population size of more than 3 million in the urban area of Taiyuan, we employed a 2-stage stratified sampling technique to calibrate our sample in light of the city's census data. Specifically, for the first stage, the sampled individuals were proportionally spread over the six districts in the urban area as per the population size in each district; and then, for the second stage, the gender distribution of sampled individuals in each district was set to be proportional to the population gender distribution in each district. Moreover, given such a large number of individuals that we would like to approach, we co-operated with Shanxi Transportation Research Institute, which provided 15 researchers assisting with the questionnaire distribution, questionnaire collection and incorporation of the data into electronic datasets[14].

Given the large number of individuals (15,000) we would like to approach and the relatively lengthy time we estimated for completing a questionnaire (around 20 minutes in average), instead of randomly capturing people on streets, the employed researchers were sent to liaise with communities, enterprises, organization from public sectors as well as universities

[12] The difference is due to there are different number of attributes between short-dist scenarios and mid- & long-dist scenarios as a result of the different choice sets involved.

[13] We also tested how many choice tasks being presented in the SP experiment were acceptable to respondents. In the pilot survey we included 10 for each individual to answer, and we found in general the respondents were averse to a number of scenarios larger than 8.

[14] The assistants were trained to understand the questionnaire and the related data ethics in case they need to address any doubts raised by survey respondents. After data collection, they were also trained to use EpiData (http://epidata.dk/) and SPSS (https://www.ibm.com/analytics/spss-statistics-software) for data recording.

and other educational institutions to search for survey participants (information of these work/education/living places are not revealed to comply with the data collection protocol). This approach allowed us to effectively assemble the required number of individuals and eventually we had over 40 liaised partners to disseminate the questionnaires. Nevertheless, the approach may have also posed an influence on the analysis results later on. As the conclusions in Chapter 8 will show, we do not discover a generally significant effect of socio-economic factors on mode choice behaviour in our research, and this may partly be attributed to the fact that the sampled respondents could sometimes share close characteristics, such as those with similar ages, educational background and income levels when they were from the same work place, so that not enough variations were captured among socio-economic groups (see also a discussion in Chapter 8).

Next, we launched the second wave of our survey over the winter time (end of 2015). This wave had a much smaller scale in terms of the number of participants involved and the amount of information we gathered. During the summer survey (i.e. the first wave), individuals were asked if they would be willing to come back and provide again their trip diary information in a winter day. This was mainly because the air quality in Chinese cities was found to have significant seasonal differences (Jiang et al., 2014; Rich, 2015). Hence it might also be possible to capture the impact of air pollution on mode choice behaviour via a seasonality analysis, i.e. evaluating the same individuals' mode choice behaviours across summer and winter. Eventually, 706 individuals who agreed to continue with their participation for another round joined us in the follow-up winter survey.

3.4 Data Cleaning and Handling

Following the collection of questionnaires from the two waves of survey, we did a preliminary data cleaning which was conducted through several steps. First, missing values were removed from the following sections: personal and household socio-economic characteristics, RP trip diary and SP mode choice experiment; while we left the attitudinal survey and retrospective survey untouched till a later stage when these data need to be used as model inputs (see Chapter 6 and 7). Next, by examining through the responses provided in the questionnaires, we identified the following information as invalid and removed the data accordingly: if there is more than one mode choice made in an SP scenario, if the observed SP mode choice breaches the mode choice availability conditions that we will apply later on in modelling analyses (e.g. car is assumed unavailable to those who do not have any household owned cars; more details are given in later chapters when specifying the models), and the questionnaires filled by those whose occupation was driving-related. Finally, to increase the credibility of RP trip diary data, we removed for each mode the lowest and highest 5% travel time values to avoid extreme observations to be involved in data analyses.

For the main survey in summer time, the above procedure discarded questionnaires from over 5,000 individuals and left us with 9,499 individuals who remained in the sample. We then introduced a comparison between this cleaned sample and the city's census data[15] (Table 3-2), and the outcome showed a good compatibility between the two data sources in terms of the two-level strata we applied (i.e. population distribution across districts and gender distribution within each district). Nevertheless, this whole sample with 9,499 individuals will not be the final dataset that we use throughout the thesis. Later on, for each research topic, further selections from the data will be made in light of the corresponding research objectives, and more details on the sample statistics will also be disclosed accordingly.

For the follow-up survey in winter time, the data cleaning procedure gave us 492 individuals who provided with valid trip diary data, which is then used for conducting a seasonality analysis, as described above. However, since such an analysis can only offer partial insights to our research question with regard to air pollution's effect, the details of this part of the study are eventually presented in Appendix B, as complementary source of knowledge for interested readers to check.

[15] Census data source: Shanxi Statistical Yearbook 2014, available at: China Statistics Press, http://csp.stats.gov.cn/

Table 3-2 Sample Data versus Census Data

Districts of Taiyuan	Sample (Main Data Collection)			Census		
	Population	Male	Female	Population	Male	Female
						In: number of people
Xiaodian	2,293	1,192	1,101	820,004	429,098	390,906
Wanbailin	2,091	1,066	1,025	765,956	390,413	375,543
Xinghualing	1,794	879	915	653,854	321,154	332,700
Yingze	1,632	816	816	601,109	299,120	301,989
Jiancaoping	1,127	741	386	424,294	205,182	219,112
Jinyuan	562	238	324	225,849	115,219	110,630
Total	9,499			3,491,066		
						In: percentage
Xiaodian	24%	52%	48%	23%	52%	48%
Wanbailin	22%	51%	49%	22%	51%	49%
Xinghualing	19%	49%	51%	19%	49%	51%
Yingze	17%	50%	50%	17%	50%	50%
Jiancaoping	12%	66%	34%	12%	48%	52%
Jinyuan	6%	42%	58%	7%	51%	49%
Total	100%			100%		

Note: after the data was cleaned, the sample data (N=9,499) remains consistent with the census data except for the gender distribution in the least two populated districts “Jiancaoping” and “Jinyuan”.

Before the cleaned data is used for any mode choice analyses, another critical step in data handling is the generation of modelling input variables that were not originally captured in the questionnaire. The SP survey offers a full set of data on trip and mode related attributes for both the chosen mode and the rest alternative modes. However, this is not the case in the RP trip diary, as it only gives the observed mode choice for a trip and the associated attributes; where the attribute information, especially travel time and travel cost, of any alternative modes that could potentially be chosen, is not available. Hence, for each of the observed trips in summer and winter, we need to derive this information before the RP data can be used as inputs in mode choice models. Eventually, the derivation relied upon the trip diary data collected on our own and some data from external sources. For instance, to calculate travel time values for any alternative transport modes, we used the travel time (duration) of the chosen mode and time of the day when a trip was made (both information available from trip diary), as well as the peak and off-peak average travelling speed of the chosen mode in the context of Taiyuan (obtained from Taiyuan Public Transport Holdings) to estimate the trip distance travelled, which was then used in conjunction with the speed information of other alternative modes to calculate their travel times (durations) respectively. To derive travel cost values, a broader range of factors were taken into account, such as for private car the amount of fuel consumption by engine displacements, fuel cost by different types of fuel, and for bus, bike-sharing and taxi services their pricing schemes in Taiyuan, in order to obtain the estimates with a good level of accuracy.

Nevertheless, there are some challenges that cannot be easily overcome and could have inevitably biased the derived values more or less. For instance, for alternative modes, we cannot find out the information of route choice, which in reality can sometimes be different to the observed modes. This could result in different distances travelled and hence the estimates for both travel time and travel cost could be affected. We also relied upon mode speed information to calculate the corresponding travel time values. Although attempts were made to adopt differentiated speeds in peak and off-peak periods by knowing from the survey when a trip was made in a day, they were still very abstract measures and the different travel habits across individuals could not be captured. As for travel cost, by having relevant pricing scheme information, it was relatively simple to have the estimates for bus, bike-sharing and taxi services, which are also widely reported in many journey planners nowadays. However, as explained above, the value for car travel would need more specific cost information depending on vehicle type and fuel type. Although the survey collected such information, the challenge arose when an individual has more than one car available to use and hence our calculation was based on assuming the first reported vehicle (Appendix A: S2. Q4) would be used for travel; apparently, this may also yield biased car travel cost.

Finally, to enrich the RP trip diary data, daily air pollution and weather condition information was also gathered[16] for all the recorded travel days in both summer and winter RP mode choice surveys. Air pollution is measured by a continuous variable, air quality index (AQI), the primary air pollution indicator used in China. Weather conditions are measured by a continuous variable °C temperature and three dummy variables showing if the day is rainy, snowy or neither. As there is a single AQI value throughout a day, we assigned identical values to all trips that occurred in the same day. The temperature measure fluctuates across hourly slots, and thus, we relied on the collected departure time information in the trip diary to match between the observed trips and the corresponding temperature values.

[16] Data source: China's Ministry of Environment Protection (Ministry of Environment Protection, 2016) and Shanxi Meteorology (Shanxi Meteorology, 2016)

CHAPTER 4. THE MODAL SUBSTITUTION PATTERN FOR BIKE-SHARING: AIR POLLUTION'S EFFECT[17]

This chapter investigates the modal substitution pattern for bike-sharing. We will first reveal the factors affecting bike-sharing choice behaviour through a mode choice analysis and then evaluate the modal substitution pattern via a scenario analysis which will disclose the pattern of modal split changes as a result of the different policy options aiming at increasing bike-sharing ridership. A particular focus is placed on the impact of air pollution on mode choices; specifically, we will test if an increase in air pollution level would depress the willingness to cycle and to what extent an improvement in air quality would increase the demand for bike-sharing.

Mode choice models that are developed include nested logit and mixed nested logit (Hess et al., 2004; Ortúzar and Willumsen, 2011) to handle the issues of inter-alternative correlation and panel effect. For model development, SP and RP mode choice data are combined to acquire the results with less behavioural bias (Hensher and Bradley, 1993; Ben-Akiva et al., 1994). The models are compared across each other and the one with the best performance is selected to study policy impacts on modal substitution pattern in the SP environment[18]. This research focuses on short-dist trips (within 2km), as it is the most frequently observed bike-sharing travelling range in our case study (Gu Dong, 2016).

The chapter is structured as follows. Section 4.1 presents the data sources. Section 4.2 explains the modelling framework and describes the model specifications in detail. Section 4.3 discusses model estimation results, followed by a policy impact analysis in section 4.4. Section 4.5 concludes the research findings and policy implications. Readers are also encouraged to check a seasonality study in Appendix B, as complementary research showing air pollution's effect on mode choice behaviour.

4.1 Data

As presented before, 9,499 individuals provided with their SP and RP mode choice responses after the preliminary data cleaning. However, SP data is often criticised for not

[17] See a published version at: https://doi.org/10.1016/j.tra.2018.01.019
[18] This study does not aim to forecast market demand in the real world.

reflecting the exact circumstance in reality due to an individual may not incur precisely a choice scenario described in the survey (Louviere et al., 2003). Thus, as a way to improve the reliability of our SP mode choice data, we apply the following strategy to refine further the observations that will be analysed in this study: if someone made SP choices in the short-dist scenarios but did not reveal any “within 2km” trips in the trip diary, these SP choices would be excluded from the analysis. In other words, we keep only the participants’ SP observations that are rigorously consistent with their RP trip diary information. Eventually, there are 4,769 individuals offering 9,028 valid observations for the short-dist trips SP experiment.

Table 4-1 presents the socio-economic statistics of these individuals. Age and occupational status statistics indicate that adults with fixed jobs constitute the main group in the sample, indicating that the sample has successfully captured regular commuters whose mode choice behaviours are most considered in urban planning and policy-making. There is a high possession rate of public transport cards meaning that most of the sampled individuals can access both bus and bike-sharing services hassle-free. Almost all respondents are healthy enough to cycle, which ensures that bike-sharing is a feasible choice in a sufficient number of scenarios. The SP modal choice patterns are also given in the table, although they are not comparable to the observed RP modal splits which are followed in Table 4-2. This is because the SP modal splits are the outcome based on hypothetical scenarios, which have no implications to the real world. Nevertheless, it can be noticed that the choice set is different across the two data sources. Apart from car-sharing being unavailable in the RP data as it was not yet a mature travel option in Taiyuan at the time of the survey, private bike was deliberately excluded from the SP survey leading to another distinction between the two choice sets. As explained before, this is due to private bike usage has dropped substantially after the city’s huge success in bike-sharing and is expected to diminish further as bike-sharing continues to grow (Oortwijn, 2017; Poon, 2017). The statistics in Table 4-1 reveals a similar trend that bike possession rate is much lower than the other private modes in the sample.

Table 4-1 Sample Statistics and SP Modal Splits

		N=4,769
Gender	Male	51%
	Female	49%
Age	under 18	9%
	18-25	31%
	26-35	27%
	36-45	20%
	46-59	11%
	60 or above	2%
Marital status	Single	47%
	Married	53%
Educational level	High school or below	29%
	College	32%
	Undergraduate	34%
	Graduate and above	5%
Occupational status	Fixed job	68%
	Student	24%
	Retired	2%
	Self-employed or unemployed	6%
Public transport card	Percentage of possession	74%
Cycling capability	Health enough to cycle	94%
Household monthly income	Under ￥3000	34%
(after tax)*	￥3000 -￥6000	36%
	￥6000 -￥9000	16%
	￥9000 -￥15000	9%
	￥15000 -￥30000	4%
	Over ￥30000	1%
Household car	Percentage of possession	46%

Household electric bike		Percentage of possession			42%
Household bike		Percentage of possession			17%
					SP modal splits (9,028 obs.)
Bike-sharing	Walk	Electric bike	Bus	Car-sharing	Car
22%	30%	9%	29%	2%	8%

Table 4-2 RP Modal Splits

RP modal splits (6,614 obs.)					
Bike-sharing	Walk	Electric bike	Bus	Car*	Bike
18%	31%	12%	26%	8%	5%

* In the RP data, it is also known that the 8% car trips consist of 6% car driver trips and 2% car passenger trips.

4.2 Modelling Framework

To estimate the mode choice models we utilise the SP dataset as well as the pooled SP/RP dataset. Since the SP survey only presents hypothetical scenarios to respondents, the mode choices observed from the questionnaire sometimes may not be consistent with the respondents' mode choice behaviour in reality where it often involves more factors and contexts that could affect decision-making. Therefore, bringing in the RP data to jointly estimate a model can potentially reduce the behavioural bias and increase the precision of estimated parameter values. Such a strategy has become a popular practice in mode choice studies (Hensher and Bradley, 1993; Ben-Akiva et al., 1994; Bradley and Daly, 1997; Polydoropoulou and Ben-Akiva, 2001; Bhat and Sardesai, 2006; Cherchi and Ortúzar, 2011; Lavasani et al., 2017). This work takes advantage of having access to both data sources and joins the SP and RP mode choice data based on the distance criteria (within 2km, see Table 4-1). Moreover, a model based only on the RP data is tested before developing the pooled model. This procedure is to confirm there are not significant differences in the estimated parameter values (e.g. opposite impact signs) between the SP model and the RP model, in which case pooling the two datasets for a joint model estimation should be handled with more cautions (Ortúzar and Willumsen, 2011). However, as this research focuses on the SP data which contains a broader range of information than the RP data, we will only present the model estimation results from the SP model and the pooled SP/RP model in the next section.

Regarding the models, an NL structure is developed first to account for any potential correlation among the alternatives in the choice set. This is applied on both the SP and the pooled SP/RP data. Next, due to the panel structure of the SP data (i.e. repeated choice observations from a single respondent), corresponding mixed NL models are further developed to capture the correlation across choice observations. Mixed logit is a flexible model structure that can approximate any random utility model (McFadden and Train, 2000; Hensher and Greene, 2003). A mixture of multinomial logit can simultaneously address the aforementioned inter-alternative correlation and panel effect by adding error components. However, arguments have arisen supporting the use of a mixture of nested logit in order to avoid any potential confounding effects when introducing more than one type of error component (Hess et al., 2004; Ortúzar and Willumsen, 2011). Hence, we follow the mixed NL approach to develop the mode choice models for this study. The mathematical equations used to specify the model are provided below (Eq.(1) – Eq.(7)) (for more information see: Hess et al., 2004; Ortúzar and Willumsen, 2011).

The utility function for an alternative i ($i \in C_n$) chosen by an individual n ($n = 1,...,N$) at the t^{th} ($t = 1,...,T$) number of SP scenario is given by:

$$U_{int} = \sum_{k=1}^{K} \beta_k X_{intk} + \sigma_i \eta_{in} + \varepsilon_{int} \quad (1)$$

while the measurable part of the utility is defined as:

$$V_{int} = \sum_{k=1}^{K} \beta_k X_{intk} + \sigma_i \eta_{in} \quad (2)$$

where C_n is the choice set, U is the utility associated with a mode choice, X is the vector of explanatory variables, and the normally distributed error component η with zero mean captures the panel effect. The estimated parameters are β_k and σ. V is the measurable utility and ε is the unobserved term i.i.d. Extreme Value and independent from η.

The choice probability functions are:

Choice of a nest (upper level):

$$P_{M_s nt} = \frac{e^{\lambda_s IV_{snt}}}{\sum_{z=1}^{Z} e^{\lambda_z IV_{znt}}} \quad (3)$$

Choice of an alternative inside a nest (lower level):

$$P_{int|M_s} = \frac{e^{V_{int}/\lambda_s}}{\sum_{j \in M_s} e^{V_{jnt}/\lambda_s}} \quad (4)$$

General choice of an alternative:

$$P_{int} = P_{M_s nt} P_{int|M_s} \quad (5)$$

where P is choice probability, M_s represents the nest s ($s = 1,...,z$), IV is the expected maximum utility for the choice of alternatives inside a nest, λ is the scale parameter measuring the different variances across nests.

The general choice probability function is integrated over η, gives (now P_{int} is fully denoted as the conditional probability $P_{nt}(i_t \mid X_{int}, \beta_k, \eta_{in}, C_n)$):

$$L_n(i \mid X_{in}, \beta_k, \sigma_i, C_n) = \int \prod_{t=1}^{T} P_{nt}(i_t \mid X_{int}, \beta_k, \eta_{in}, C_n) f(\eta_{in}) d\eta_{in} \quad (6)$$

Log-likelihood function that needs to be maximized:

$$LL(\beta, \eta) = \sum_{n=1}^{N} \sum_{i \in C_n} y_{in} InL_n(i \mid X_{in}, \beta_k, \sigma_i, C_n) \quad (7)$$

where y_{in} takes the value of 1 if an individual n chooses an alternative i and 0 otherwise.

Several models have been estimated to identify the correct explanatory variables and their appropriate forms. For each variable, we measured its impact on all mode choice utilities and identified the one which parameter value is closest to zero for normalisation. Variables that displayed highly insignificant effects on mode choice utilities were dropped out to avoid type I errors[19]. These include snowy weather, car parking space availability and bus frequency etc. A linear relationship was adopted to measure the impact of temperature as it showed much higher significance than a curvilinear relationship (i.e. extreme and moderate temperature). Socio-economic factors were tested in two ways: 1.by assuming their direct effects on mode choice utilities, and 2. by interacting with other attributes (i.e. systematic taste heterogeneity). The results showed that model fitness improved significantly with the latter manner. To capture systematic taste heterogeneity, the sub-categories of the socio-economic variables were merged into two general groups (i.e. low and high) to more explicitly reveal their impacts. For inter-alternative correlation, many possibilities were tested including bike-sharing and electric bike as two-wheeled vehicles, bike-sharing and walk as active modes, bike-sharing and car-sharing as newly emerged sharing economy, car and car-sharing as comfortable automobiles, bus and car-sharing as shared automobiles. Eventually, only bus and car-sharing were found to have a significant correlation. Table 4-3 presents the variables included in the final models and the ways they were measured.

Regarding, the NL and mixed NL models using the combined SP and RP, the RP trip diary data was utilised to estimate the parameter values on the following variables: “Rain”, “Commute”, “Travel cost”, “Travel time” and all the socio-economic factors. “Air pollution”, “Temperature”, “Parking cost”, “Access time” and “App availability” were not captured in the RP data and such as we cannot estimate these parameters. Meanwhile, the values of “Air pollution” and “Temperature” displayed little variations across the observed RP trips and were therefore considered as redundant. It is because the trip diary survey was conducted only in summer days and the case study city Taiyuan has very stable pollution and temperature levels in this season. Different scaling factors (to correct variance difference) were adopted in the model estimation[20].

Finally, three availability conditions were included in the mode choice models: 1. Car is available to households that own a car, 2. Electric bike is available to households that own an electric bike, and 3. Cycling is available to those who can cycle given their state of health. The availability conditions can increase model validity by helping to explain the circumstances within

[19] Incorrect rejection of a true null hypothesis
[20] In this study SP data is the primary data source and the RP utilities were scaled relative to it (Hensher and Bradley, 1993).

which someone does not choose a particular mode because the mode is not an available option. Possession of a driving license was not considered an availability condition since the choice of car or car-sharing could be made by drivers as well as passengers; possession of public transport card was also excluded as travellers would still access bus or bike-sharing service by paying cash or borrowing others' card.

Table 4-3 Explanatory Variables and Measurements

Variable	Measurement
Air pollution	air quality index (AQI) by taking the average value of each level (25 for excellent level '0-50'; 75 for good level '51-100'; 125 for light pollution '101-150'; 175 for medium pollution '151-200'; 250 for heavy pollution '201-300'; 400 for terrible pollution 'above 300')
Rain	1 if weather is rainy, 0 if otherwise
Temperature	temperature in °C
Commute	1 if trip purpose is commute (i.e. work/education), 0 if otherwise
Travel cost	in RMB (￥)
Parking cost	in RMB (￥)/hour
Travel time	in min
Access time	in min, walking time to stations/parking spots
App availability	1 if a smart phone application is available, 0 otherwise
Male	1 if gender is male, 0 if female
Lower age	1 if age is "under 18" or "18-25" or "26-35", 0 if "36-45" or "46-59" or "60 or above"
Lower income*	1 if household monthly income is "under ￥3000" or "￥3000-￥6000" or "￥6000-￥9000", 0 if "￥9000-￥15000" or "￥15000-￥30000" or "over ￥30000"
Lower education	1 if educational level is "high school or below" or "college", 0 if "undergraduate" or "graduate and above"

4.3 Model Estimation Results

To estimate the NL and mixed NL models, PythonBiogeme (Bierlaire, 2016a) was used. Table 4-4 shows the model estimation results using the SP data, and Table 4-5 shows the model estimation results using the pooled data (combined SP and RP data). We first compare across these modelling outputs and then discuss the factors affecting the choice of bike-sharing and other mode choices in general.

4.3.1 Models Performance and Comparison

The first model is an NL model based on the use of SP data. Bus and car-sharing are found to share some common unobserved attributes under the so-called nest "shared automobile". The output μ value 2.24, complies with the specification requirement of nested logit as it is greater than 1, where $\mu = 1/\lambda$ [21] (Hess et al., 2004; Ortúzar and Willumsen, 2011). There is no other significant correlation being detected among the remaining alternatives. Panel effect is revealed next using a mixed NL model and the error terms appear to be significant on all alternative modes. The nesting parameter μ shrinks as expected (Hess et al., 2004) since the mixed NL model decomposes the error term further than the NL model. The model fitness improves by capturing the additional explanatory power resulted from panel effect, and hence we observe significant increases in the values of likelihood ratio test and adjusted rho-bar squared. The more fitted model can yield more reliable estimates of the parameters. For example, without taking into account individuals' differentiated tastes, most of the coefficients associated with the car-sharing alternative turn out to be much larger than those with other alternatives; these values reduce substantially in the mixed NL model, as the model detects the choice of car-sharing is not utterly explained by the observed variables, but could also be affected by individuals' unique preferences on car-sharing.

When the RP data is added, the model performance increases further compared to the two models based on only SP data. Meanwhile, panel effect is estimated simultaneously in the RP data as there are also repeated observations from an individual in the RP trip diary. Nests are

[21] λ was defined earlier in Eq. 3 and Eq. 4.

tested on the RP mode choices as well although they did not turn out significant as in the SP case. Overall, the mixed NL model based on combined SP and RP data shows the best performance and will, therefore, be used next to study the factors' impacts on mode choices.

Table 4-4 Model Estimation Results Using SP Data

	NL		Mixed NL	
	Coef.	**t-stat**	**Coef.**	**t-stat**
$\alpha_{bikeshare}$	0.97	1.88	2.85	3.62
α_{walk}	2.23	7.71	4.02	7.72
α_{ebike}	0.23	0.57	0.80	1.10
$\alpha_{carshare}$	- 17.80	- 4.20	- 0.03	- 0.06
α_{car}	0.98	2.21	1.07	1.28
Natural environmental conditions				
Air pollution-bikeshare	- 0.0032	- 4.66	- 0.0081	- 6.20
Air pollution-walk	- 0.0049	- 9.20	- 0.0111	- 9.48
Air pollution-ebike	- 0.0028	- 4.59	- 0.0078	- 6.40
Air pollution-bus	- 0.0041	- 4.63	- 0.0062	- 4.27
Air pollution-carshare	0.0213	3.36	0.0011	0.74*
Rain-bikeshare	- 0.51	- 2.63	- 0.64	- 2.54
Rain-walk	- 1.10	- 8.15	- 1.74	- 8.89
Rain-ebike	- 0.74	- 4.39	- 0.73	- 2.92
Rain-carshare	5.37	3.51	1.46	4.72
Rain-car	0.16	0.84*	1.06	3.40
Temperature-bikeshare	0.01	3.23	0.02	3.89
Temperature-walk	0.01	2.38	0.01	2.60
Temperature-carshare	- 0.24	- 4.45	- 0.08	- 7.09
Temperature-car	- 0.02	- 4.23	- 0.05	- 6.17
Trip and mode attributes				

Commute-bikeshare	- 0.76	- 7.22	- 1.23	- 7.61
Commute-walk	0.25	2.96	0.22	1.31*
Commute-car	- 0.23	- 1.43*	- 0.79	- 2.66
Travel cost-bikeshare	- 0.69	- 6.17	- 0.78	- 4.92
Travel cost-bus	- 0.41	- 3.45	- 0.08	- 0.62*
Travel cost-carshare	- 2.05	- 3.37	- 0.27	- 2.63
Travel cost-car	- 0.29	- 0.74*	- 0.90	- 1.22*
Parking cost-car	- 0.06	- 2.78	- 0.09	- 2.26
Travel time-bikeshare	0.27	5.03	0.38	4.37
Travel time-walk	- 0.03	- 2.60	- 0.05	- 2.17
Travel time-ebike	0.24	4.28	0.38	3.82
Travel time-bus	0.12	6.93	0.18	7.72
Travel time-carshare	0.18	1.07*	0.13	3.39
Travel time-car	0.04	0.81*	0.01	0.14*
Access time-bikeshare	- 0.17	- 8.17	- 0.24	- 7.45
Access time-bus	- 0.11	- 6.60	- 0.24	- 8.10
Access time-carshare	- 0.17	- 0.94*	- 0.08	- 1.98
App availability-bikeshare	- 0.87	- 9.58	- 1.11	- 8.10
App availability-bus	0.12	1.28*	0.70	5.44
App availability-carshare	2.14	3.30	0.24	1.40*
Systematic taste heterogeneity				
Air pollution * Male-bus	- 0.0017	- 4.94	- 0.0018	- 3.67
Air pollution * Lower age-bus	0.0024	6.29	0.0020	3.75
Air pollution * Lower income-bus	0.0013	2.31	0.0013	1.61*
Commute * Lower income-car	- 0.33	- 2.67	- 0.53	- 1.99
Commute * Lower education-walk	- 0.18	- 3.18	- 0.18	- 1.31*
Inter-alternative correlation & Panel effect				
$\mu_{sharedmotor}$	2.24	7.30#	1.84	6.75#
$\sigma_{bikeshare}$	-	-	0.84	4.60

σ_{walk}	-	-	3.28	23.23
σ_{ebike}	-	-	2.58	13.25
σ_{bus}	-	-	1.78	15.39
σ_{car}	-	-	3.27	12.66
Number of observations	9028		9028	
Initial log-likelihood	- 14122.8		- 14122.8	
Final log-likelihood	- 12188.0		- 11079.7	
Likelihood ratio test	3869.5		6086.1	
Adjusted rho-bar squared	0.13		0.21	

* parameter values not meeting the 95% significance level

t-test against base value of 1

Table 4-5 Model Estimation Results Using Combined SP and RP Data

	NL		Mixed NL	
	Coef.	**t-stat**	**Coef.**	**t-stat**
$\alpha_{bikeshare}$ (SP)	1.64	8.62	1.89	10.19
α_{walk} (SP)	1.82	8.57	1.91	9.43
α_{ebike} (SP)	0.33	1.97	0.75	4.79
$\alpha_{carshare}$ (SP)	- 21.9	- 3.81	- 1.66	- 2.59
α_{car} (SP)	0.11	0.61	0.50	2.79
$\alpha_{bikeshare}$ (RP)	- 0.04	- 0.42	0.24	2.88
α_{bike} (RP)	- 0.43	- 3.65	0.39	5.01
α_{walk} (RP)	- 0.03	- 0.29	0.45	5.72
α_{ebike} (RP)	- 0.03	- 0.32	0.43	5.61

$\alpha_{cardriver}$ (RP)	- 0.72	- 5.26	0.16	2.08
$\alpha_{carpassenger}$ (RP)	- 1.29	- 7.11	- 0.05	- 0.56
Natural environmental conditions				
Air pollution-bikeshare (SP)	- 0.0048	- 8.89	- 0.0045	- 8.29
Air pollution-walk (SP)	- 0.0046	- 9.24	- 0.0045	- 9.17
Air pollution-ebike (SP)	- 0.0029	- 5.01	- 0.0022	- 3.93
Air pollution-bus (SP)	- 0.0052	- 6.06	- 0.0020	- 2.65
Air pollution-carshare (SP)	0.0274	3.27	0.0023	1.96
Rain-bikeshare (SP & RP)	- 0.15	- 6.37	- 0.10	- 3.89
Rain-walk (SP & RP)	- 0.48	- 4.41	- 0.62	- 6.99
Rain-ebike (SP & RP)	- 0.26	- 1.71*	- 0.40	- 2.77
Rain-carshare (SP)	8.60	3.91	1.26	4.11
Rain-car (SP & RP)	0.88	8.37	0.41	8.32
Temperature-bikeshare (SP)	0.01	2.19	0.01	3.16
Temperature-walk (SP)	0.01	1.67*	0.01	4.12
Temperature-carshare (SP)	- 0.27	- 4.45	- 0.05	- 4.95
Temperature-car (SP)	- 0.03	- 6.04	- 0.02	- 4.37
Trip and mode attributes				
Commute-bikeshare (SP & RP)	- 0.12	- 5.36	- 0.18	- 10.27
Commute-walk (SP & RP)	0.05	2.83	0.06	7.90
Commute-car (SP & RP)	0.30	6.66	0.03	2.48
Travel cost-bikeshare (SP & RP)	- 0.61	- 6.69	- 0.72	- 8.33
Travel cost-bus (SP & RP)	- 0.15	- 1.42*	- 0.10	- 0.10*
Travel cost-carshare (SP)	- 1.66	- 3.40	- 0.30	- 3.16
Travel cost-car (SP & RP)	- 0.12	- 2.11	- 0.04	- 1.22*
Parking cost-car (SP)	- 0.04	- 2.17	- 0.03	- 1.66*
Travel time-bikeshare (SP & RP)	0.06	6.60	0.04	5.75
Travel time-bike (RP)	0.11	7.93	0.05	6.16
Travel time-walk (SP & RP)	- 0.02	- 6.58	- 0.01	- 5.56

Travel time-ebike (SP & RP)	0.14	6.94	0.09	5.83
Travel time-bus (SP & RP)	0.08	7.85	0.05	6.04
Travel time-carshare (SP)	0.36	2.04	0.07	2.01
Travel time-car (SP & RP)	0.09	5.50	0.07	6.26
Access time-bikeshare (SP)	- 0.09	- 5.09	- 0.09	- 4.58
Access time-bus (SP)	- 0.08	- 5.05	- 0.10	- 6.78
Access time-carshare (SP)	- 0.07	- 0.35*	- 0.05	- 1.57*
App availability-bikeshare (SP)	- 0.66	- 8.49	- 0.66	- 8.14
App availability-bus (SP)	0.07	0.82*	0.33	4.51
App availability-carshare (SP)	2.38	3.08	0.27	1.96
Systematic taste heterogeneity				
Air pollution * Male-bus (SP)	- 0.0016	- 4.84	- 0.0010	- 3.23
Air pollution * Lower age-bus (SP)	0.0025	6.53	0.0010	2.89
Air pollution * Lower income-bus (SP)	0.0014	2.40	0.0005	0.94*
Commute * Lower income-car (SP & RP)	- 0.41	- 7.10	- 0.01	- 0.01*
Commute * Lower education-walk (SP & RP)	- 0.17	- 6.59	- 0.02	- 3.47
Inter-alternative correlation & Panel effect				
$\mu_{sharedmotor}$ (SP)	2.21	4.91#	1.68	4.89#
$\sigma_{bikeshare}$ (SP & RP)	-	-	1.51	10.88
σ_{walk} (SP & RP)	-	-	1.05	7.04
σ_{ebike} (SP & RP)	-	-	1.31	12.32
σ_{bus} (SP & RP)	-	-	1.74	14.01
σ_{car} (SP & RP)	-	-	1.15	7.20
Scaling factor (RP)	4.83	7.93#	5.96	9.53#
Number of observations	15642		15642	
Initial log-likelihood	- 24788.3		- 24788.3	
Final log-likelihood	- 21010.1		- 16994.7	

Likelihood ratio test	7556.4	15587.1
Adjusted rho-bar squared	0.15	0.31
* parameter values not meeting the 95% significance level		
# t-test against base value of 1		

4.3.2 Model Estimation Results: Bike-sharing

Regarding natural environmental conditions, firstly, air pollution is found to have a significant negative effect on bike-sharing choice. Due to the possible concern on health damage an increase in air pollution level would discourage travellers from using bike-sharing. Next, the impacts of weather and temperature are shown to be similar to those found in earlier studies. Rainy weather can significantly decrease the demand for bike-sharing and warmer weather can increase the probability to use bike-sharing.

The impacts of trip and mode attributes are revealed next. When conducting commute trips (for work or education) bike-sharing is a less preferable option. In other words, as the most literature shows, bike-sharing is more likely to be used for leisure purposes. As for travel cost and travel time, bike-sharing choice is, as expected negatively correlated with the former and however positively correlated with the latter. A discussion on this finding is given in the next sub-section. Access time to bike-sharing parking spots is negatively associated with its choice which means longer walking distance will discourage people from using the service. It is also found a negative coefficient on bike-sharing app availability. Such a result is nevertheless in line with the fact that the existing bike-sharing app in Taiyuan is not popular at all among the registered bike-sharing users as shown in the operator’s latest report (Taiyuan Public Transport Holdings, 2016). The bike-sharing docking stations in Taiyuan is quite dense (there is a docking station every 500m on average) and probably this has made a smartphone app (e.g. provide real-time information on bike availability) somewhat redundant.

Finally, the choice of bike-sharing is not significantly associated with any critical socio-economic characteristics (gender, age, household income, and education level) although their effects are analysed in the way of systematic taste heterogeneity (results not included in the final models due to high insignificance). Such a finding is similar to the results of the aforementioned Beijing study (Campbell et al., 2016) in which the authors showed bike-sharing users could emerge across the social spectrum with no significant preference from any particular groups of people.

4.3.3 Model Estimation Results: Rest of the Modes

Apart from bike-sharing, air pollution also has a significant negative impact on walk, electric bike and bus choices. Car-sharing is the only mode that displays a positive correlation between its utility and higher air pollution level (in fact car choice shows a positive relationship too, but it is normalised to base when specifying the model). The impact of adverse weather is consistent with air pollution, such that rain will discourage the choices of electric bike and walk while increasing the attractiveness of car and car-sharing. As for temperature, another mode choice besides bike-sharing that is preferred under warmer weather is walking, whereas car and car-sharing are more likely to be chosen when the temperature falls.

Regarding trip purpose, walking is a significantly preferred mode for short-dist commute trips. A more interesting result is found on private car choice. In Table 4-4, people's stated choices imply that they do not like to use cars for commuting; however, when their actual behaviour is incorporated (combined SP and RP data), private car choice turns out to be positively associated with commute trips (Table 4-5). Regarding, the rest of the modes (electric bike, bus, and car-sharing) no significant correlation has been found between their choices and trip purposes.

An increase in travel cost will decrease the utility of all mode choices, although such an impact on bus choice and car choice is insignificant as shown by the mixed NL model in Table 4-4 and 4-5. However, for travel time, its effect is positively associated with all mode choice utilities except for walk. Hess et al. (2005) offered a comprehensive explanation for such a phenomenon and positive travel time coefficients would simply indicate the existence of conjoint activities[22] and travel-experience factors[23] (Salomon and Mokhtarian, 1998) that people perceive when making mode choice decisions. In microeconomic term, the marginal opportunity

[22] That is the negative marginal utility of a travel-time increase is compensated by the gains in utility resulting from simultaneously conducted activities.
[23] Such as the comfort, pleasure or the positive social perception associated with traveling by a particular mode.

cost of travel time would be offset or even overwhelmed by the marginal benefit of travel time associated with a mode choice. Another possible reason for observing positive travel time coefficients is related to the design of SP mode choice experiment. When trip distance is short, the levels/values assigned to the attribute, travel time, are close (see Table 3-1) and there may not be enough variations to incentivise survey respondents to make trade-offs with other observed attributes. As a result, it is not appropriate to conclude that utilities increase with travel time by having the positive coefficients, but travel time could be dominated by other more influential attributes when an individual was evaluating the information in an SP scenario and based on which trying to make a mode choice decision. Such a hypothesis can be supported by the model estimation results from the next chapter which studies longer trip cases (larger differences in travel time levels in the SP survey, Table 3-1) and the model reveals negative travel time coefficients for all mode choices.

The access time variables on the choices of bike-sharing, car-sharing and bus all display negative signs meaning that longer walking journeys to the stations or parking spots can reduce the perceived utilities associated with these choices. Several remaining mode-related attributes also have the expected signs of impact: bus app availability (positive), car-sharing app availability (positive) and car parking cost (negative).

Systematic taste heterogeneity is firstly captured in the NL models with its significant impact being found on the choices of bus, car and walk (no other systematic taste heterogeneity is detected as significant apart from those presented). It has been shown that bus usage is negatively correlated with air pollution. As a result, the positive coefficients on the two interacted terms (air pollution and lower age group, air pollution and lower income group) can suggest that younger and less wealthy people would still use bus service even if air quality becomes worse. On the contrary, the group of male travellers is found to prefer bus less than female travellers, while air pollution would further push the male group away from using the service. For the taste heterogeneity on trip purpose, in the SP only model (Table 4-4), the lower income group do not prefer either car or walk for commuting, no matter the mode itself is a preferable option (walk) or a less preferable option (car) for commute journeys. In the pooled dataset (Table 4-5), the lower income group still dislikes car and walk for commute purpose even though car is now positively associated with commuting as we showed earlier. Nevertheless, these results have become slightly different when panel effect is incorporated; the t-statistics measuring systematic taste heterogeneity decrease in the mixed NL models and some values then become insignificant (Table 4-4 and 4-5).

4.3.4 Value of Time

Given the observed positive travel time coefficients, the willingness to pay for travel time saving is not possible to derive (Hess et al., 2005). It is because in such a case the “travel time” variable captures not only the effect of travel time, but also the effect of any conjoint activities and travel-experience factors. However, the willingness to pay for access time savings can be estimated using the ratio of marginal utilities of access time over travel cost. In the case of a short-dist trip, the estimated willingness to pay values are ￥0.12, ￥0.16 and ￥1.02 per minute for bike-sharing, car-sharing and bus respectively (Table 4-6). The value for bus turns out to be much higher. This may be due to we unintentionally captured people’s willingness to pay for bus waiting time savings as well, if, in the SP mode choice experiment, some respondents see the access time for bus as it includes the waiting time at station. Future studies, especially in the context of China, are welcome to compare to the results.

Table 4-6 Willingness to Pay for Access Time Savings (per minute)

Bike-sharing	Car-sharing	Bus
￥0.12	￥0.16	￥1.02

4.4 Policy Impact Analysis

A number of scenarios are proposed to explore the effectiveness of different policy options that may help promote the usage of bike-sharing. (Table 4-7). The model estimation results of the mixed NL model based on combined SP and RP data are used for simulation. The simulation method is sample enumeration.

A key objective is to investigate to what extent better air quality could help increase bike-sharing ridership. In our case study, China has ambitions and plans to control air pollution in its cities. Therefore, scenarios can be developed based on their goals for air quality improvement, and hence to assess how modal substitution pattern could be affected if the goals were met. To begin with, a 20% air quality increase is proposed as a mid-term goal in our scenarios in accordance with the air pollution reduction target in China (Zhang, 2017). The central government has set a five-year plan (2012 to 2017) to decrease the air pollution levels in the country's top 3 city clusters (i.e. Beijing-Tianjin-Hebei cluster, the Yangtze cluster centred by Shanghai and the Pearl cluster centred by Guangzhou) by 25%, 20% and 15% respectively. Hence, the median target (20%) is selected as the reference for this study. Next, a 50% air quality increase is proposed as a long-term goal. It is based on the fact that coal burning accounts for 50%-70% of air pollution in the above mentioned 3 clusters (Wang, 2014). Thus, a 50% air quality increase is adopted to represent an optimistic "coal-free era" in the long-term.

To generate broader insights, measures for bike-sharing service improvement are also proposed. As per the model estimation results, reductions in travel cost and access time are introduced and joint with air quality improvement to create more scenarios for analysis. Table 4-7 shows the simulation results, while Table 4-8 shows the direct and cross-point elasticity.

Table 4-7 Scenarios and Modal Substitution Patterns

Scenarios		
Mid-term	M1	20% air quality increase
	M2	20% air quality increase + 20% bike-sharing travel cost reduction
	M3	20% air quality increase + 50% bike-sharing travel cost reduction
	M4	20% air quality increase + 50% bike-sharing travel cost reduction + 20% bike-sharing access time reduction
	M5	20% air quality increase + 50% bike-sharing travel cost reduction + 50% bike-sharing access time reduction
Long-term	L1	50% air quality increase
	L2	50% air quality increase + 20% bike-sharing travel cost reduction
	L3	50% air quality increase + 50% bike-sharing travel cost reduction
	L4	50% air quality increase + 50% bike-sharing travel cost reduction + 20% bike-sharing access time reduction
	L5	50% air quality increase + 50% bike-sharing travel cost reduction + 50% bike-sharing access time reduction

Modal Substitution Patterns							
		Bike-share	Walk	E-bike	Bus	Car-share	Car
	Baseline	21.5%	30.2%	9.2%	28.8%	2.4%	7.9%
Mid-term	M1	22.0%	30.9%	9.1%	28.7%	1.9%	7.4%
	M2	22.6%	30.7%	9.0%	28.5%	1.9%	7.4%
	M3	23.4%	30.4%	8.9%	28.1%	1.8%	7.4%
	M4	24.7%	29.8%	8.8%	27.7%	1.8%	7.2%
	M5	26.7%	28.9%	8.6%	27.0%	1.8%	7.0%
Long-term	L1	22.7%	31.7%	8.8%	28.7%	1.4%	6.7%
	L2	23.2%	31.5%	8.8%	28.5%	1.4%	6.6%
	L3	24.1%	31.2%	8.7%	28.1%	1.4%	6.5%
	L4	25.4%	30.6%	8.6%	27.6%	1.4%	6.4%
	L5	27.4%	29.7%	8.3%	26.9%	1.3%	6.3%

Table 4-8 Direct and Cross Point Elasticity

Choice probability of	Bike-sharing travel cost	Bike-sharing access time
Bike-sharing (direct)	- 0.118	- 0.274
Walk (cross)	0.038	0.084
Bus (cross)	0.035	0.072
Car (cross)	0.034	0.066

The key insights are identified as follows:

- Firstly, better air quality can indeed improve the demand for bike-sharing (Baseline to M1 and L1); meanwhile, the demand for walking also rises whereas private car usage drops. However, by comparing to the rest of scenarios (M2-M5 and L2-L5), it is easily noticed that air quality improvement is less effective than bike-sharing service improvement (e.g. access time saving, travel cost saving) in promoting bike-sharing ridership.

- Secondly, a saving in access time to bike-sharing parking spots appears to be more effective than saving in bike-sharing travel cost in short-dist trips. In M4 and M5 (or L4 and L5) when access time reduction starts to intervene, bike-sharing ridership rises more significantly than M2 and M3 (or L2 and L3). The elasticity analysis in Table 4-8 reflects the same fact that the probability of choosing bike-sharing is more elastic to a change in access time (-0.274) than a change in travel cost (-0.118).
- Finally, by looking through M2-M5 and L2-L5 (i.e. measures focusing on bike-sharing service improvement), it is seen that the increases in bike-sharing demand mostly come from the shrinking demand for walking and bus rather than private car. The cross elasticity values also reveal the same trend (Table 4-8). Such a discovery leads to an interesting choice in policy making: the improvement of bike-sharing service (e.g. access time saving, travel cost saving) is more effective than air quality improvement in promoting bike-sharing usage; however, the latter is on the other hand more useful in suppressing private car demand as the figures show. Hence, since all policy measures come with costs it should be policy makers' discretion to prioritise target and make use of the two options.

4.5 Conclusions

This study investigated the factors affecting mode choice behaviour in Taiyuan (China) with a focus on bike-sharing choice. Based on the combined SP and RP short-dist trip data, NL and Mixed NL models were developed to study the impacts of natural environmental conditions, trip and mode attributes as well as systematic taste heterogeneity on mode choices. In the end, the potential impacts of a number of policy options on bike-sharing's modal substitution pattern were analysed.

The mixed NL model well addressed the inter-alternative correlation between bus and car-sharing as well as the panel effect caused by repeated choice observations. The incorporation of RP data into SP data significantly increased the model performance and the credibility of model estimation results. The signs of coefficients are in general consistent between the SP alone models and the models using combined SP and RP data. Several vital insights were generated for bike-sharing choice. People would be more likely to use the service if air quality was better; the service users also favoured warmer weather and disliked rain; bike-sharing appeared to be a more popular choice in leisure trips rather than commute trips; lower travel cost and shorter access time to parking spots would encourage its ridership. Moreover, by comparing the results to the existing findings in developed countries, a significant difference was revealed concerning socio-economic factors. Bike-sharing choice was often significantly associated with particular socio-economic groups as shown in the literature. In this research by examining through systematic taste heterogeneity, none of the socio-economic groups significantly interacted with any factors affecting bike-sharing choice. The finding was however in line with the earlier study in Beijing (Campbell et al., 2016), in which the results also showed the users of bike-sharing service could arise anywhere from the social spectrum.

The policy impact analysis offered more intuitive information to policy makers. In short-dist trips, improving bike-sharing service itself (e.g. access time saving, travel cost saving) would be more effective than improving air quality for promoting bike-sharing usage. To take one step further, access time saving was found to be more effective than travel cost saving. Nevertheless, if suppressing private car usage was also a policy target, then air quality improvement could be reconsidered since it was more effective than bike-sharing service improvement which was more likely to bring down the demand for walking and bus rather than private car.

Overall, this study is one of the first works that explore air pollution’s impact on mode choice behaviour as well as factors affecting bike-sharing choice in a developing country. The findings could benefit policy making by revealing the effectiveness of different policy options, although how to deliver the proposed policy options, in reality, remains as a challenge to policy makers and such an issue is beyond the scope of this work. Cities with close characteristics to Taiyuan could benefit the most from the results and the insights. Researchers from developing countries could also make use of the methodologies in this research to study similar issues in their cases; especially in cities that have vast local and geographical differences to Taiyuan.

CHAPTER 5. THE MODAL SUBSTITUTION PATTERN FOR CAR-SHARING: SOURCES OF DEMAND

This chapter investigates the modal substitution pattern for car-sharing. Similar to Chapter 4, pooled SP/RP data is used, mixed NL mode choice models are developed and a scenario analysis is followed. However, we would now like to focus on mid-dist (2km to 5km) and long-dist (more than 5km) trips since in general car-sharing is not expected to be a competitive travel option when making short-dist trips due to the associated access and alighting time (Martinez et al., 2017). Such a focus is also a result after observing the relatively small number of short-dist car trips in both RP and SP cases (Table 4-1, Chapter 4). Thus, in particular, we would investigate under each of the two distance cases, the extent to which the demand for car-sharing would come, from private car and public transport, to offer a direct insight to the puzzle stressed by Jorge and Correia (2013). Policy makers can see the modal substitution pattern as a result of different measures that they could adopt to promote car-sharing usage, and meanwhile, policy options that could more effectively bring down private car usage will also be identified.

The chapter is structured as follows. Section 5.1 explains the data source, followed by the modelling framework in section 5.2. Section 5.3 presents the model estimation results and based on which a number of informative indicators (e.g. value of travel time savings, direct and cross point elasticity) are derived in section 5.4. A policy impact analysis and relevant discussion are provided in section 5.5. In the end, section 5.6 concludes the chapter.

5.1 Data

Similar to the previous chapter, SP data could suffer from not reflecting the exact circumstance in reality (Louviere et al., 2003), and thus we further refined the SP mode choice data by keeping only observations that were rigorously consistent with the participants' RP mode choice information, which was collected in the trip diary survey. Specifically, if someone made choices in the mid-dist SP scenarios but did not reveal any 2km-5km trips in his/her trip diary, these SP choices would be considered as less reliable and dropped out from the analysis. The same rule applies to long-dist trips. As a result, we have 3,698 individuals with 6,848 valid SP observations left for mid-dist trips and 6,317 individuals with 11,925 valid SP observations left for long-dist trips.

Table 5-1 displays the key statistics of the 3,698 and 6,317 individuals, alongside their SP mode choice patterns. The corresponding RP mode choices under the two distance cases are followed in Table 5-2 by having a slightly different set of alternatives (i.e. with private bike and no car-sharing, as discussed in Chapter 4). From both data sources, we can see when the trip gets longer, the demand for private car increases and the demand for bus, electric bike and bike-sharing all slightly decrease. Concerning socio-economic characteristics, the statistics of age and occupational status demonstrate that adults with fixed jobs constitute the main group in the sample, indicating that the sample has successfully captured regular commuters whose mode choice behaviours are highly important to urban planning and policy making.

Table 5-1 Sample Statistics and SP Modal Splits

		Mid-dist (N=3,698)	**Long-dist** (N=6,317)
Gender	Male	51%	52%
	Female	49%	48%
Age	under 18	7%	5%
	18-25	31%	25%
	26-35	27%	32%
	36-45	22%	26%
	46-59	11%	11%
	60 or above	2%	1%
Marital status	Single	45%	37%
	Married	55%	63%
Educational level	High school or below	27%	25%
	College	35%	33%
	Undergraduate	33%	36%
	Graduate and above	5%	6%
Occupational status	Fixed job	68%	76%

	Student	24%	16%
	Retired	2%	1%
	Self-employed or unemployed	6%	7%
Public transport card	Percentage of possession	74%	79%
Cycling capability	Health enough to cycle	95%	94%
Household monthly income (after tax)	Under ￥3000	34%	28%
	￥3000 -￥6000	38%	40%
	￥6000 -￥9000	15%	18%
	￥9000 -￥15000	8%	9%
	￥15000 -￥30000	3%	3%
	Over ￥30000	2%	1%
Household car	Percentage of possession	45%	55%
Household electric bike	Percentage of possession	46%	46%

SP modal splits in mid- and long-dist trips					
Car-share	**Car**	**Taxi**	**Bus**	**E-bike**	**Bike-share**
					Mid-dist: 6,848 obs.
19%	13%	8%	36%	12%	12%
					Long-dist: 11,925 obs.
19%	24%	9%	32%	9%	7%

Table 5-2 RP Modal Splits in Mid- and Long-dist Trips

Mid-dist (4,807 obs.)		**Long-dist (9,899 obs.)**	
Car*	16%	Car*	28%
Taxi	5%	Taxi	7%
Bus	46%	Bus	40%
E-bike	17%	E-bike	14%
Bike-share	11%	Bike-share	9%
Bike	5%	Bike	2%

* It is also revealed by the trip diary survey that the mid-dist car trips consist of 11% car driver trips and 5% car passenger trips; the long-dist car trips consist of 20% car driver trips and 8% car passenger trips.

5.2 Modelling Framework

The results in the previous chapter have demonstrated the good performance of a mixed NL framework, so that once again, this modelling technique is applied, and two models are separately developed to study the mid- and long-dist mode choice data. The mathematical formulation of a mixed NL structure is described again here:

The utility function for an alternative i ($i \in C_n$) chosen by an individual n ($n = 1,...,N$) at the t^{th} ($t = 1,...,T$) number of SP scenario is given by:

$$U_{int} = \sum_{k=1}^{K} \beta_k X_{intk} + \sigma_i \eta_{in} + \varepsilon_{int} \quad (8)$$

while the measurable part of the utility is defined as:

$$V_{int} = \sum_{k=1}^{K} \beta_k X_{intk} + \sigma_i \eta_{in} \quad (9)$$

where C_n is the choice set, U is the utility associated with a mode choice, X is the vector of explanatory variables and the normally distributed error component η with zero mean captures the panel effect. The estimated parameters are β_k and σ. V is the measurable utility and ε is the unobserved term i.i.d. Extreme Value and independent from η.

The choice probability functions are:

Choice of a nest (upper level):

$$P_{M_s nt} = \frac{e^{\lambda_s IV_{snt}}}{\sum_{z=1}^{Z} e^{\lambda_z IV_{znt}}} \quad (10)$$

Choice of an alternative inside a nest (lower level):

$$P_{int|M_s} = \frac{e^{V_{int}/\lambda_s}}{\sum_{j \in M_s} e^{V_{jnt}/\lambda_s}} \qquad (11)$$

General choice of an alternative:

$$P_{int} = P_{M_s nt} P_{int|M_s} \qquad (12)$$

where P is choice probability, M_s represents the nest s ($s = 1,...,z$), IV is the expected maximum utility for the choice of alternatives inside a nest, λ is the scale parameter measuring the different variances across nests.

The general choice probability function is integrated over η, gives (now P_{int} is fully denoted as the conditional probability $P_{nt}(i_t \mid X_{int}, \beta_k, \eta_{in}, C_n)$):

$$L_n(i \mid X_{in}, \beta_k, \sigma_i, C_n) = \int \prod_{t=1}^{T} P_{nt}(i_t \mid X_{int}, \beta_k, \eta_{in}, C_n) f(\eta_{in}) d\eta_{in} \qquad (13)$$

Log-likelihood function that needs to be maximized:

$$LL(\beta, \eta) = \sum_{n=1}^{N} \sum_{i \in C_n} y_{in} InL_n(i \mid X_{in}, \beta_k, \sigma_i, C_n) \qquad (14)$$

where y_{in} takes the value of 1 if an individual n chooses an alternative i and 0 otherwise.

The variables that were included in the final models are listed in Table 5-3. Each explanatory variable was tested by its effect on all mode choice utilities and the one which showed minimum effect (in terms of absolute value) was normalised to zero. Highly insignificant variables were removed from the utility functions to avoid type I error. Several issues are worth mentioning: Air pollution was presented in categorical measures to survey participants; however, the categories were defined based on the air quality index scheme as shown in Table 5-3. Thus, we modelled air pollution as a continuous variable, a generally preferred way of measurement in choice modelling (Ben-Akiva and Lerman, 1985; Moudon et al., 2005). Temperature was tested by a linear (continuous variable) and a curvilinear (dummy variable 1 for extreme temperature and 0 otherwise) relationship respectively for its effect on mode choice utilities; the former type of correlation was adopted due to higher t-statistics. Generic parameters on travel time and cost were tested against alternative specific parameters. The use of generic parameters reduced model fitness in terms of likelihood ratio test and adjusted rho-bar squared, and thus alternative specific parameters for travel time and cost were eventually applied. Systematic taste heterogeneity (i.e. how different socio-economic groups think of different attributes) has been a favourite way to study socio-economic impacts (Amador et al., 2005; Cherchi and Ortúzar, 2002; Cherchi and Ortúzar, 2011). Our final models adopted such a form also due to the resulted higher values on model fitness comparing to directly adding the socio-economic variables in utility functions. Moreover, after testing with the socio-economic variables in their original sub-grouping formats, we merged the sub-groups of each variable into two general groups (i.e. low and high) to more clearly manifest the impacts. In the end, availability conditions were considered in the mode choice models: 1. Car is available to households that own a car[24], 2. Electric bike is available to households that own an electric bike, and 3. Cycling is available to those who can cycle given their state of health. These conditions increased model validity by helping to explain the circumstances where someone did not choose a particular mode could be due to the mode was not an available option.

The above analysis was first applied on the mid- and long-dist SP datasets. Then we formed up a pooled dataset for each distance case by bringing in the respondents' RP trips conducted in the same distance range. The critical limitation of SP data is it only captures hypothetical choice behaviour which may be inconsistent with choices that would be made in real life (Louviere et al., 2003). The joint analysis of the two types of data could reduce the behavioural bias and many works have followed such a practice (Hensher and Bradley, 1993; Ben-Akiva et al., 1994; Bradley and Daly, 1997; Polydoropoulou and Ben-Akiva, 2001; Bhat and Sardesai, 2006; Cherchi and Ortúzar, 2011; Lavasani et al., 2017). In our case, although the RP data did not capture car-sharing choice as well as a few other variables (air pollution, temperature, parking cost and space, access time and app availability due to paper-based survey) it could still help with the rest parameter estimation and improve the overall model fitness. Thus, in each of the two distance cases, we conducted the mixed NL analysis on the pooled dataset in order to have a comparison to the model performance based on SP data. Different

[24] Possession of a driving license is not an availability condition in this case since we allow the choices of car and car-sharing to come from both drivers and passengers.

scaling factors were applied in the joint SP/RP model estimation to address the difference in the variances of the unobserved error terms across the two datasets. Since SP data is the primary source in this study, the RP utilities were scaled relative to it.

In the end, many hypotheses have been proposed prior to the modelling analysis including a few relevant to car-sharing: longer travel time and higher travel cost could both decrease the probability to choose car-sharing, longer walking time to car-sharing spots would also decrease the utility of using car-sharing service, whereas a smartphone based application would make car-sharing more appealing and more likely to be chosen.

Table 5-3 Explanatory Variables and Measurements

Variable	Measurement
Air pollution	air quality index (AQI) by taking the average value of each level (25 for excellent level '0-50', 75 for good level '51-100', 125 for light pollution '101-150', 175 for medium pollution '151-200', 250 for heavy pollution '201-300', 400 for terrible pollution 'above 300')
Rain	1 if weather is rainy, 0 if otherwise
Temperature	temperature in °C
Commute	1 if trip purpose is commute (i.e. work/education), 0 if otherwise
Travel cost	in RMB (￥)
Parking cost	in RMB (￥)/hour
Parking space	1 if available, 0 otherwise
Travel time	in min
Access time	in min, walking time to stations/parking spots
Waiting time	in min, waiting time at bus stop
App availability	1 if a smart phone application is available, 0 otherwise
Male	1 if gender is male, 0 if female
Lower age	1 if age is "under 18" or "18-25" or "26-35", 0 if "36-45" or "46-59" or "60 or above"

Lower income	1 if household monthly income is "under ￥3000" or "￥3000-￥6000" or "￥6000-￥9000", 0 if "￥9000-￥15000" or "￥15000-￥30000" or "over ￥30000"
Lower education	1 if educational level is "high school or below" or "college", 0 if "undergraduate" or "graduate and above"

5.3 Model Estimation Results

Table 5-4 and 5-5 present the mixed NL results, which were generated using PythonBiogeme (Bierlaire, 2016a). In both mid- and long-dist trips, the joint SP/RP model offers improved values in likelihood ratio test and adjusted rho-bar squared comparing to the model using only SP data. The choice behaviour as being revealed by SP and SP/RP datasets are very much consistent in terms of the observed signs of impact[25]. We, therefore, base our discussion only on the results of the joint SP/RP model for both distance cases.

Table 5-4 Mixed NL Results for Mid-dist Case

	SP data		**SP & RP data**	
	Coef.	**t-stat**	**Coef.**	**t-stat**
$\alpha_{carshare}$ (SP)	- 1.76	- 4.70	- 1.88	- 6.51
α_{car} (SP)	- 0.60	- 1.24	- 0.03	- 0.13
α_{taxi} (SP)	- 1.75	- 4.06	- 1.40	- 4.15
α_{bus} (SP)	- 0.18	- 0.43	0.12	0.45
$\alpha_{bikeshare}$ (SP)	4.18	9.62	3.41	11.19
$\alpha_{cardriver}$ (RP)	-	-	0.90	7.16
$\alpha_{carpassenger}$ (RP)	-	-	0.35	2.76
α_{taxi} (RP)	-	-	0.87	5.48

[25] The only exception is observed on the impact of trip purpose. When RP data is involved, bike-sharing is no longer a preferred mode for mid-dist commute trips while taxi and bus are no longer among the preferred modes for long-dist commute trips.

α_{bus} (RP)	-	-	1.17	7.62
α_{ebike} (RP)	-	-	0.68	4.07
α_{bike} (RP)	-	-	0.04	0.16
Natural environmental conditions				
Air pollution-carshare (SP)	0.0109	6.98	0.0089	7.42
Air pollution-car (SP)	0.0041	2.54	0.0026	2.64
Air pollution-taxi (SP)	0.0032	1.86*	0.0005	0.43**
Air pollution-bus (SP)	0.0009	0.59**	0.0008	0.76**
Air pollution-bikeshare (SP)	- 0.0243	- 11.12	- 0.0202	- 12.88
Rain-ebike (SP & RP)	- 1.02	- 3.49	- 0.45	- 4.31
Temperature-taxi (SP)	- 0.02	- 3.02	- 0.01	- 2.21
Temperature-ebike (SP)	0.05	4.58	0.03	4.07
Trip and mode attributes				
Commute-carshare (SP)	- 0.78	- 3.77	- 0.54	- 3.16
Commute-taxi (SP & RP)	- 1.39	- 5.92	- 0.28	- 4.82
Commute-ebike (SP & RP)	0.92	5.28	0.18	3.86
Commute-bikeshare (SP & RP)	0.61	3.25	- 0.06	- 1.40**
Travel cost-carshare (SP)	- 0.03	- 1.95*	- 0.04	- 2.86
Travel cost-car (SP & RP)	- 0.15	- 0.82**	- 0.07	- 2.33
Travel cost-taxi (SP & RP)	- 0.08	- 4.66	- 0.04	- 3.34
Travel cost-bus (SP & RP)	- 0.02	- 0.15**	- 0.02	- 2.21
Travel cost-bikeshare (SP & RP)	- 0.41	- 3.18	- 0.55	- 5.59
Parking cost-car (SP)	- 0.14	- 4.93	- 0.05	- 3.50
Parking space-car (SP)	0.17	0.91**	0.07	0.69**
Travel time-carshare (SP)	- 0.03	- 2.59	- 0.01	- 1.32**
Travel time-car (SP & RP)	- 0.02	- 0.76**	- 0.01	- 1.11**
Travel time-taxi (SP & RP)	- 0.01	- 0.07**	- 0.01	- 1.44**
Travel time-bus (SP & RP)	- 0.04	- 3.36	- 0.01	- 0.52**

Travel time-ebike (SP & RP)	- 0.05	- 3.09	- 0.02	- 1.62**
Travel time-bikeshare (SP & RP)	- 0.18	- 9.85	- 0.19	- 13.81
Travel time-bike (RP)	-	-	- 0.01	- 0.06**
Waiting time-bus (SP)	- 0.03	- 2.07	- 0.03	- 2.88
Access time-carshare (SP)	- 0.02	- 1.08**	- 0.04	- 2.49
Access time-bikeshare (SP)	- 0.37	- 10.45	- 0.24	- 10.91
App availability-carshare (SP)	0.35	3.23	0.36	3.79
App availability-taxi (SP)	0.36	2.18	0.28	2.04
App availability-bus (SP)	0.11	0.93**	0.14	1.77*
App availability-bikeshare (SP)	3.79	10.69	3.63	12.09
Systematic taste heterogeneity				
Air pollution * Male-bus (SP)	- 0.0028	- 4.15	- 0.0017	- 3.43
Air pollution * Lower age-taxi (SP)	0.0027	3.08	0.0032	3.83
Air pollution * Lower age-bus (SP)	0.0042	5.33	0.0029	5.20
Air pollution * Lower education-carshare (SP)	- 0.0040	- 4.03	- 0.0025	- 2.85
Air pollution * Lower education-taxi (SP)	- 0.0036	- 3.34	- 0.0008	- 1.13**
Commute * Lower education-carshare (SP)	- 0.54	- 2.47	- 0.38	- 1.98
Commute * Lower education-taxi (SP & RP)	- 0.53	- 2.02	- 0.09	- 1.08**
Inter-alternative correlation & Panel effect				
$\mu_{selfdriven}$ (SP)	1.93	8.17#	1.44	7.26#
$\sigma_{carshare}$ (SP & RP)	1.20	8.84	1.66	15.92
σ_{car} (SP & RP)	2.92	11.41	0.63	7.41
σ_{bus} (SP & RP)	1.95	18.13	0.89	13.40
σ_{ebike} (SP & RP)	2.53	12.61	1.35	12.50
$\sigma_{bikeshare}$ (SP & RP)	1.24	6.10	0.89	9.95
σ_{bike} (RP)	-	-	1.04	5.56
Scaling factor (RP)	-	-	7.65	10.03#

Number of observations	6848	11655
Initial log-likelihood	- 10738.4	- 15408.3
Final log-likelihood	- 8523.9	- 11342.9
Likelihood ratio test	4428.9	8130.7
Adjusted rho-bar squared	0.20	0.26

Note: * parameter values not meeting the 95% significance level

** parameter values not meeting the 90% significance level

t-test against base value of 1

Table 5-5 Mixed NL Results for Long-dist Case

	SP data		SP & RP data	
	Coef.	**t-stat**	**Coef.**	**t-stat**
$\alpha_{carshare}$ (SP)	- 3.45	- 5.46	- 3.36	- 10.52
α_{car} (SP)	- 1.12	- 1.95	- 1.29	- 5.61
α_{taxi} (SP)	- 1.00	- 1.86	- 0.68	- 3.48
α_{bus} (SP)	3.97	7.19	2.40	10.09
α_{ebike} (SP)	0.01	0.01	- 1.34	- 5.20
$\alpha_{cardriver}$ (RP)	-	-	- 2.75	- 16.97
$\alpha_{carpassenger}$ (RP)	-	-	- 3.10	- 18.64
α_{taxi} (RP)	-	-	- 1.73	- 14.36
α_{bus} (RP)	-	-	- 0.69	- 6.06
α_{ebike} (RP)	-	-	- 2.44	- 12.38
α_{bike} (RP)	-	-	- 1.17	- 8.10
Natural environmental conditions				
Air pollution-carshare (SP)	0.0102	15.90	0.0077	14.52

Air pollution-car (SP)	0.0102	9.39	0.0073	9.72
Air pollution-taxi (SP)	0.0067	13.25	0.0071	15.77
Air pollution-bikeshare (SP)	- 0.0254	- 6.25	- 0.0070	- 5.62
Rain-car (SP & RP)	0.36	1.54**	0.33	3.46
Rain-taxi (SP & RP)	0.33	2.06	0.30	4.50
Rain-bus (SP & RP)	0.24	1.91*	0.04	0.51**
Rain-ebike (SP & RP)	- 0.89	- 5.11	- 0.61	- 4.69
Rain-bikeshare (SP & RP)	- 1.03	- 3.67	- 0.15	- 1.90*
Temperature-carshare (SP)	- 0.06	- 6.26	- 0.04	- 5.10
Temperature-taxi (SP)	- 0.04	- 6.08	- 0.03	- 4.98
Temperature-bus (SP)	- 0.07	- 9.60	- 0.06	- 9.42
Temperature-bikeshare (SP)	0.05	3.83	0.01	0.24**
Trip and mode attributes				
Commute-carshare (SP)	1.84	9.63	0.98	7.01
Commute-taxi (SP & RP)	0.27	1.79*	- 0.63	- 11.78
Commute-bus (SP & RP)	0.03	0.18**	- 0.58	- 6.49
Commute-bikeshare (SP & RP)	- 2.94	- 5.76	- 0.96	- 13.35
Travel cost-carshare (SP)	- 0.03	- 3.26	- 0.02	- 1.36**
Travel cost-car (SP & RP)	- 0.02	- 0.34**	- 0.06	- 9.04
Travel cost-taxi (SP & RP)	- 0.05	- 5.53	- 0.04	- 12.95
Travel cost-bus (SP & RP)	- 0.96	- 12.59	- 0.32	- 7.00
Travel cost-bikeshare (SP & RP)	- 1.35	- 5.63	- 0.67	- 8.83
Parking cost-car (SP)	- 0.10	- 3.04	- 0.09	- 3.83
Parking space-car (SP)	0.69	2.88	0.19	1.35**
Travel time-carshare (SP)	- 0.08	- 7.06	- 0.03	- 3.53
Travel time-car (SP & RP)	- 0.05	- 1.88*	- 0.04	- 11.04
Travel time-taxi (SP & RP)	- 0.04	- 3.02	- 0.05	- 15.70
Travel time-bus (SP & RP)	- 0.01	- 1.91*	- 0.09	- 5.69
Travel time-ebike (SP & RP)	- 0.06	- 9.68	- 0.04	- 10.88

Travel time-bikeshare (SP & RP)	- 0.07	- 8.51	- 0.38	- 16.44
Travel time-bike (RP)	-	-	- 0.02	- 5.17
Waiting time-bus (SP)	- 0.08	- 6.10	- 0.15	- 12.68
Access time-carshare (SP)	- 0.06	- 4.34	- 0.04	- 3.81
Access time-bus (SP)	- 0.29	- 17.68	- 0.25	- 17.36
Access time-bikeshare (SP)	- 0.11	- 2.27	- 0.01	- 0.29**
App availability-carshare (SP)	1.79	8.33	1.49	10.73
App availability-taxi (SP)	0.20	1.95*	0.29	3.34
Systematic taste heterogeneity				
Air pollution * Male-bikeshare (SP)	0.0053	2.45	0.0019	2.12
Air pollution * Lower income-car (SP)	- 0.0024	- 2.94	- 0.0021	- 3.38
Air pollution * Lower education-car (SP)	- 0.0017	- 2.34	- 0.0009	- 1.69*
Temperature * Male-carshare (SP)	- 0.01	- 1.36**	- 0.01	- 0.90**
Temperature * Male-bus (SP)	- 0.01	- 3.18	- 0.01	- 3.32
Temperature * Lower age-carshare (SP)	0.03	5.30	0.02	4.81
Temperature * Lower age-taxi (SP)	0.03	5.89	0.02	5.29
Commute * Lower income-bus (SP & RP)	0.53	3.63	0.53	5.90
Commute * Lower education-carshare (SP)	- 0.22	- 2.33	- 0.18	- 2.50
Inter-alternative correlation & Panel effect				
$\mu_{sharingeconomy}$ (SP)	2.55	6.26#	1.75	5.31#
$\sigma_{carshare}$ (SP & RP)	1.44	12.53	0.97	7.67
σ_{car} (SP & RP)	4.10	21.15	2.52	21.11
σ_{bus} (SP & RP)	1.66	18.40	1.97	24.57
σ_{ebike} (SP & RP)	2.84	16.06	3.76	18.88
$\sigma_{bikeshare}$ (SP & RP)	3.74	9.19	1.16	10.55
σ_{bike} (RP)	-	-	0.02	0.27**
Scaling factor (RP)	-	-	2.68	19.37#

Number of observations	11925	21824
Initial log-likelihood	- 18938.3	- 35361.5
Final log-likelihood	- 14322.4	- 23925.7
Likelihood ratio test	9231.9	22871.5
Adjusted rho-bar squared	0.24	0.32

Note: * parameter values not meeting the 95% significance level

** parameter values not meeting the 90% significance level

t-test against base value of 1

In Table 5-4 and Table 5-5, the impacting factors are classified into three types: natural environmental conditions, trip and mode attributes and systematic taste heterogeneity. As far as natural environmental conditions, car-sharing and private car are the significantly preferred choices when air pollution level increases. This is possibly due to the sealed space and more protected environment they could offer to users who want to stay away from pollution. As a comparison, weather conditions are not that strongly associated with the choice of car or car-sharing. In mid-dist trips, neither of them is significantly affected by rain or temperature (results not presented due to high insignificance); however, in long-dist trips, car is preferred when there is rain and car-sharing is more likely to be chosen in colder temperature. The results potentially imply a correlation between weathers' effects and trip distance, such that when a trip becomes longer, travellers may start to care more about the weather conditions.

With regard to trip and mode attributes, travel time and cost both negatively affect the probabilities to choose car-sharing and car in mid- and long-dist trips. Both findings are consistent with microeconomic theory. However, not all parameter values appear to be significant, i.e. travel time's impact on both car and car-sharing in mid-dist trips and travel cost's impact on car-sharing in long-dist trips. More insights on significance level are discussed later alongside the estimation of VTTS. Next, the four mode-related attributes that were only captured by the SP survey [car parking cost (negative), car parking space (positive), car-sharing access time (negative) and car-sharing app availability (positive)] all have the expected impact signs to our hypothesis, although parking space is much less significant in affecting car choice in both distances. The results could bring some direct implications for policy making; specifically, reducing the walking time to car-sharing spot and introducing smartphone application to car-sharing service could both help improve the usage of car-sharing, while raising the parking cost would be useful in suppressing private car demand. At last, in mid-dist trips, car-sharing is revealed as a preferred mode for non-commute purposes; meanwhile, in long-dist trips, the service is preferred for commute use. Private car choice is not found with significant correlation with any of the trip purposes.

Systematic taste heterogeneity offers more in-depth insight on socio-economic impact. For a car-sharing alternative, a number of interaction terms are detected with significance. The lower education group is not keen on using car-sharing service even when air pollution levels are high, which could make the service more attractive. The lower age group seems to prefer car-sharing even when car-sharing becomes less appealing in warmer weather. The former discovery is statistically significant in the mid-dist case and the latter is in the long-dist case. Moreover, despite car-sharing is generally preferred for commute in long-dist trips and not preferred in mid-dist trips, the lower education group is, in particular, less likely to use the service for commute in both cases. Additionally, in the long-dist case, the interaction between temperature and gender group is also captured but presented with statistical insignificance. This is due to the effect was initially found significant in the NL structure; however, it became insignificant after the mixed NL structure incorporates panel effect which could better explain the model. As for private car alternative, no significant taste heterogeneity is discovered in mid-dist trips; in long-dist trips, the lower income and lower education groups would value less the increased utility of car resulted from increased air pollution level, which looks similar to what we found for car-sharing. As a summary, less wealthy and less educated people may be less likely to use car-sharing and private car; younger group seems to prefer car-sharing, however, this is only indicated by one significant interaction term; gender effect is negligible.

Factors affecting other mode choices are not discussed in detail given the scope of this work and readers are invited to see them directly from Table 5-4 and 5-5. Overall, all factors have the expected signs of impact, though a few of them appear statistically insignificant.

At last, inter-alternative correlation and panel effect are captured by the mixed NL structure of our models. Different nests are identified for mid- and long-dist trips. In the former case, the nest ‘self-driven automobile’ including car-sharing and car is found significant (Figure 5-1) while in the latter case, car-sharing and bike-sharing are found to have significant correlation under the nest ‘sharing economy’ (Figure 5-2). Both nests come from the SP part of the data. Other possibilities have also been tested such as car-sharing, car and taxi under ‘comfortable automobile’, car-sharing, taxi and bus under ‘shared automobile’, electric bike and bike-sharing under ‘two-wheeled vehicle’ as well as bike-sharing and bike under ‘active transport’ when RP data is also involved. However, none of these nests was found with significance[26]. It should also be noted that the nesting parameter μ is larger than 1 in all the models. Such a value range satisfies the specification requirement of nested logit (Hess et al., 2004; Ortúzar and Willumsen, 2011) where $\mu = 1/\lambda$[27]. For panel effect, it is estimated simultaneously by the SP part and the RP part in the pooled datasets, since both of which contain repeated choice observations from a single individual. The effect on all alternatives appears to be significant (note that taxi is normalised) except for the one on private bike in the long-dist case.

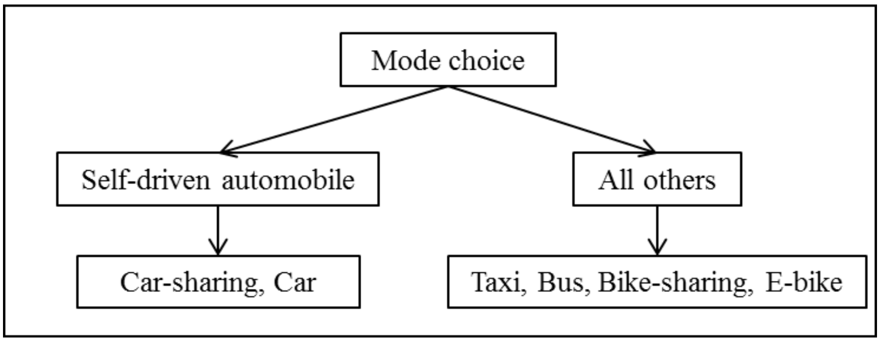

Figure 5-1 The NL Structure Detected in the Mid-dist Model

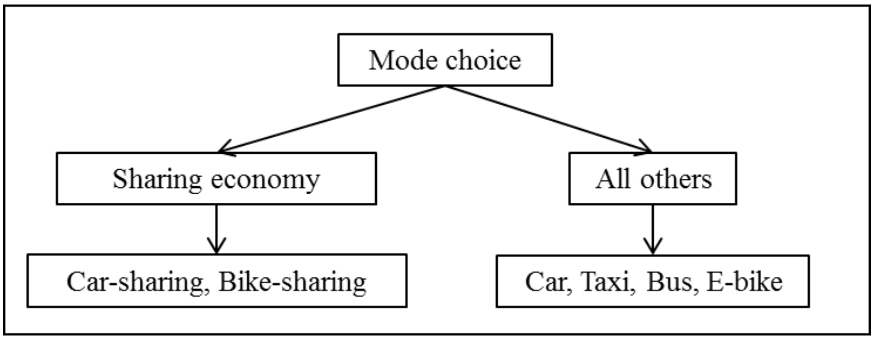

Figure 5-2 The NL Structure Detected in the Long-dist Model

[26] In fact, we found another nest (between car driver and car passenger) using only the RP data, where the t-statistic also shows significance; however, the nesting parameter μ has a value of 1.03 which is almost equivalent to an MNL specification. Thus, we discarded this nest by following the practice of Ortúzar and Willumsen (2011), in order to retain efficiency in model estimation.

[27] λ was defined earlier in Eq. 10 and Eq. 11.

5.4 Value of Time and Elasticity Indicators

By having the mode choice model results, VTTS for car-sharing, private car, taxi, bus and bike-sharing[28] are calculated. VTTS is estimated from models of discrete choice as the ratio of the marginal utility of travel time on the marginal utility of income. For linear-in-parameters utility specifications this ratio is simply the ratio of travel time on travel cost coefficient; in other words, it measures a substitution effect that how much people are willing to pay for enjoying a reduction in travel time.

Table 5-6 VTTS for Car-sharing, Car, Taxi, Bus and Bike-sharing

	Mid-dist	Long-dist
Car-sharing	￥22.0 ($3.3)/h	￥81.1 ($12.2)/h
Car	￥6.4 ($1.0)/h	￥43.0 ($6.4)/h
Taxi	￥20.7 ($3.1)/h	￥75.4 ($11.3)/h
Bus	￥21.0 ($3.2)/h	￥51.5 ($7.7)/h
Bike-sharing	￥20.5 ($3.1)/h	￥33.6 ($5.0)/h

The key impression from the results (Table 5-6) is that the VTTS values for all modes are higher in long-dist trips than in mid-dist trips. Many studies have found VTTS increasing with trip length (Wardman, 1998; Axhausen et al., 2008; Shires and De Jong, 2009) and such a finding is supported by microeconomic theory. In brief, marginal disutility increases as the journey becomes longer so that a travel time reduction in a longer trip is worth more. This also explains the observed increases in t-statistics of travel time's impact on all mode choices from the mid-dist case (Table 5-4) to the long-dist case (Table 5-5).

The comparison across modes offers additional insights. Firstly, for mid-dist trips, all the modes share similar VTTS except for car which value is lower than the rest. There are two possible effects that could jointly determine the estimated VTTS for a specific mode (Wardman, 1998; Mackie et al., 2003; Shires and De Jong, 2009). One is "user type effect", which means the users of some modes may have different socio-economic characteristics to the users of other modes, leading to potentially different VTTS values; for example, car users normally come from

[28] Electric bike does not involve a perceived travel cost.

higher income groups which could give a relatively high VTTS. The other is “mode specific effect”, such that VTTS may also depend on the perceived utility associated with the journey time spent on a mode; for example, car normally gives more pleasant travel experience in terms of the comfort, cleanliness and privacy it offers, so that the willingness to pay extra amount in order to save its journey time is often weaker than travelling with other modes. Thus, in our case, the lower VTTS for car could potentially imply the mode-specific effect overwhelms the user type effect (Shires and De Jong, 2009).

Next, the results also show that by moving from mid- to long-dist trips, the VTTS values for car-sharing, car and taxi increase much more aggressively compared to bus and bike-sharing (recall that VTTS increases with trip length). Such a difference is possibly a result of the aforementioned user type effect. As compared to bus and bike-sharing users, the users of car-sharing, car or taxi are found coming from higher education and income groups as per the results shown in Table 5-4 and 5-5. Evidence has widely been discovered that people having higher income or being more educated tend to have higher VTTS (Wardman, 1998; Jara-Diaz, 2003; Mackie et al., 2003; Axhausen et al., 2008; Trottenberg and Belenky, 2011). Thus, when the trip length increases as moving from the mid distance to long distance in this case, it might not be surprising to see the surge of VTTS values with respect to car-sharing, car and taxi which user groups would be more willing to pay extra in order to save travel time.

Finally, as a comparison, Wang and MacKenzie (2017) derived a VTTS value of $9.06/h for the car-sharing service in Seattle though different countries are likely to have different VTTS values (Shires and De Jong, 2009).

In addition, direct and cross point elasticity are calculated with respect to several key attributes of car-sharing and private car. They are car-sharing’s travel cost and access time in the mid-dist case; car-sharing’s travel time and access time in the long-dist case; private car’s travel cost and parking cost in both distances, given their significant impacts as being revealed by the models. “Direct” and “cross” refer to the impact of a change of an alternative’s attribute level on the choice probability of the same alternative and of the other alternative respectively (Ben-Akiva and Lerman, 1985). “Point” means elasticity is measured in terms of an infinitesimal level change of an attribute. The estimation procedure is referred to Bierlaire (2017) and the results are given in Table 5-7.

Table 5-7 Direct and Cross Point Elasticity

	Choice probability of	Direct		Cross	
Mid-dist	Car-sharing	- 0.197 (TC-carshare)	- 0.188 (AT-carshare)	0.049 (TC-car)	0.014 (PC-car)
	Car	- 0.370 (TC-car)	- 0.119 (PC-car)	0.035 (TC-carshare)	0.030 (AT-carshare)
Long-dist	Car-sharing	- 0.802 (TT-carshare)	- 0.253 (AT-carshare)	0.021 (TC-car)	0.035 (PC-car)
	Car	- 0.059 (TC-car)	- 0.086 (PC-car)	0.180 (TT-carshare)	0.058 (AT-carshare)

Note: "TC" is travel cost, "TT" is travel time, "AT" is access time, "PC" is parking cost

Some trends are clearly revealed:

- All elasticity values are smaller than one, which means the probabilities of choosing car-sharing and private car are relatively inelastic to the level change of a single attribute. This fits our expectation since mode choice utilities are determined by many attributes altogether with significance, and thus the effect of a single attribute is expected to be limited. Two recent studies (De Luca and Di Pace, 2015; Carteni et al., 2016), which also computed elasticity values for car-sharing and private car, revealed exactly the same range of values.
- Most of the cross elasticity values (except for changing car-sharing's travel time on the probability to choose private car in the long-dist case) are close to zero, implying that the probability of choosing a mode would depend more on its own attribute level changes rather than the attribute level changes of an alternative mode.

More specifically on direct elasticity,

- For car-sharing, first recall that studying the elasticity on travel cost in the mid-dist case and travel time in the long-dist case is due to their significant impacts as being revealed by the models. It is found that these two attributes are more effective than access time in affecting car-sharing choice probability in both distances.

- For private car, the choice probability is more elastic to attribute level changes in mid-dist trips than in long-dist trips. This is very much consistent with common perception as car usually is less willing to be substituted when the trip distance gets longer. To take a further look, in the mid-dist case, the choice probability is more elastic to a change in travel cost whereas, in the long-dist case, it is more elastic to a change in parking cost.

5.5 Policy Impact Analysis

So far, the results have indicated how individuals' choices would respond to the changes in attribute levels. Nevertheless, an elasticity analysis is still inadequate to help identify the effective ways for promoting car-sharing usage in real practice, especially when the possible degrees of policy intervention could be different across attributes given practical constraints. For instance, it is found in the mid-dist case that the probability of choosing private car is more elastic to a change in travel cost than parking cost. However, the degree that policies are able to adjust car travel cost would usually be smaller than adjusting parking cost. It is because car travel cost (i.e. fuel cost) heavily depends on market oil price whereas parking cost is often a rather local issue and less constrained for adjustment. Thus, which of these two attributes should be the policy focus remains unclear. Our scenario analysis in this section can help to answer such a type of question while revealing other critical insights for policy making. Specifically, we simulate in the SP environment[29] the modal substitution pattern under different policy options that can be implemented in reality. The simulation method is sample enumeration, based on the results derived from the pooled data using mixed NL models. The policy scenarios and corresponding modal splits are displayed in Table 5-8 for the mid-dist case and Table 5-9 for the long-dist case.

[29] The simulation analysis only aims to reveal how people make trade-offs across the attributes; it does not intend to forecast market demand in the real world.

Table 5-8 Scenarios and Modal Substitution Patterns for Mid-dist Case

Scenarios	
"Moderate"	A: car-sharing travel cost (-20%), car-sharing access time (-10%)
"Intermediate"	B1: car-sharing travel cost (-20%), car-sharing access time (-20%)
"Intermediate"	B2: car-sharing travel cost (-50%), car-sharing access time (-10%)
"Radical"	C: car-sharing travel cost (-50%), car-sharing access time (-20%)
"Intermediate"	B2 + [D: car travel cost (+10%), car parking cost (+20%)]
+	B2 + [E1: car travel cost (+10%), car parking cost (+50%)]
Complementary	B2 + [E2: car travel cost (+20%), car parking cost (+20%)]
Measures	B2 + [F: car travel cost (+20%), car parking cost (+50%)]

Modal Substitution Patterns

	Car-share	Car	Taxi	Bus	E-bike	Bike-share
Baseline	18.8%	13.2%	7.9%	36.2%	12.2%	11.7%
A	20.0%	13.1%	7.7%	35.6%	12.1%	11.5%
B1	20.4%	13.0%	7.7%	35.4%	12.0%	11.5%
B2	21.3%	12.9%	7.6%	34.9%	11.9%	11.4%
C	21.6%	12.9%	7.5%	34.7%	11.9%	11.4%
B2 + D	21.4%	12.2%	7.6%	35.3%	12.0%	11.5%
B2 + E1	21.5%	11.7%	7.7%	35.4%	12.1%	11.6%
B2 + E2	21.5%	11.7%	7.7%	35.4%	12.1%	11.6%
B2 + F	21.6%	11.3%	7.7%	35.6%	12.2%	11.6%

Table 5-9 Scenarios and Modal Substitution Patterns for Long-dist Case

Scenarios	
"Moderate"	A: car-sharing travel time (-10%), car-sharing access time (-10%)
"Intermediate"	B1: car-sharing travel time (-10%), car-sharing access time (-20%)
"Intermediate"	B2: car-sharing travel time (-20%), car-sharing access time (-10%)
"Radical"	C: car-sharing travel time (-20%), car-sharing access time (-20%)
"Intermediate"	B2 + [D: car travel cost (+10%), car parking cost (+20%)]
+	B2 + [E1: car travel cost (+10%), car parking cost (+50%)]
Complementary	B2 + [E2: car travel cost (+20%), car parking cost (+20%)]
Measures	B2 + [F: car travel cost (+20%), car parking cost (+50%)]

Modal Substitution Patterns

	Car-share	Car	Taxi	Bus	E-bike	Bike-share
Baseline	19.0%	23.9%	8.7%	31.0%	9.0%	8.4%
A	21.1%	23.3%	8.4%	30.0%	8.8%	8.4%
B1	21.6%	23.1%	8.3%	29.9%	8.7%	8.4%
B2	22.8%	22.8%	8.1%	29.4%	8.6%	8.3%
C	23.3%	22.6%	8.1%	29.2%	8.5%	8.3%
B2 + D	23.0%	22.2%	8.2%	29.6%	8.6%	8.4%
B2 + E1	23.2%	21.6%	8.3%	29.8%	8.7%	8.4%
B2 + E2	23.0%	22.1%	8.2%	29.6%	8.7%	8.4%
B2 + F	23.3%	21.5%	8.3%	29.8%	8.7%	8.4%

We first target on car-sharing demand promotion by setting up a moderate scenario, two intermediate scenarios and a radical scenario (A, B1, B2 and C). The policy options differ across distances as car-sharing choice is significantly associated with travel cost in the mid-dist case and with travel time in the long-dist case. The impact of access time is significant in both cases. The 20% and 50% travel cost reduction targets can be achieved by receiving subsidies from the public sector; however, a travel time reduction is more difficult to realise. One way to bring down car-sharing's journey time is allowing users to drive on "priority lanes", such as the driving permission for electric cars on bus lanes (BBC, 2016). However, the effect of such a measure cannot be easily predicted and thus, more conservative reduction targets for travel time (i.e. 10% and 20%) are adopted. Access time reduction also adopts relatively conservative targets since it usually requires an increase in the number of parking spots, which is a rather complex task for car-sharing operators.

The modal substitution pattern is different between the two distance cases. In mid-dist trips, car-sharing's market share increases 2.8% (18.8% to 21.6%) from the baseline to the radical scenario (C); in the long-dist case, the increase is 4.3% (19.0% to 23.3%). The difference implies that more people are willing to switch to car-sharing in long-dist trips and such a finding is in line with the discovery that car-sharing becomes more competitive as trips become longer (Martinez et al., 2017). With respect to the usage of other modes (compare the baseline still to C), bus shrinks 1.5% and car shrinks 0.3% in mid-dist trips while bus shrinks 1.8% and car shrinks 1.3% in long-dist trips[30]. The comparison among the figures reveals a challenge for the mid-dist case, i.e. private car usage is not reduced when car-sharing becomes more attractive and instead, bus usage is sacrificed much more. This is an outcome that government and urban planners may dislike. The finding suggests that at least for mid-dist trips, making car-sharing more competitive on its own is not sufficient; complementary policies are in absolute need for cutting down private car's demand.

Therefore, we develop another four scenarios (D, E1, E2 and F) which include policy options for raising private car's travel and parking costs. As we proposed earlier, adjusting car parking cost is possibly more flexible than adjusting car travel cost. Thus, 20% and 50% increase targets are applied to parking cost while 10% and 20% are applied to travel cost. These four scenarios are expected to join one of the intermediate scenarios B1 or B2 to create more effective and more practical policy packages. A and C are not any longer considered since one shows the limited effect on modal split changes and the other may be too radical in real practice. Eventually, B2 is preferred than B1 in both distances due to the effectiveness it shows on improving car-sharing's market share.

The combined scenarios can reveal broader insights. First of all, the increases in

[30] The findings on car correspond to the cross elasticity values. The probability to choose car is much more elastic to the changes in car-sharing's attributes in the long-dist case (0.180 is much higher than the rest).

car-sharing's market share (compare to the baseline) now come more from the falls in private car usage than in bus usage. For example, in the radical scenario B2+F, bus shrinks 0.6% and car shrinks 1.9% in mid-dist trips while bus shrinks 1.2% and car shrinks 2.4% in long-dist trips. Another discovery is on the effectiveness of the two car-attributes in reality. In mid-dist, raising car travel cost is a more effective measure than raising parking cost in suppressing car usage as per their direct elasticity values (Table 5-7). However, parking cost increase has higher policy flexibility than car travel cost increase (50% vs. 20%). Thus, in real practice, intervention can be radical with either of the two options given their equal effects on private car's market share in B2+E1 and B2+E2. As a contrast, in long-dist, a radical parking cost increase of 50% is more effective than a radical car travel cost increase of 20% (again, see B2+E1 and B2+E2) due to parking cost has both greater elasticity and higher policy flexibility than car travel cost.

To conclude, we summarise the key takeaways for policy making in bullet points:

- Our elasticity analysis identifies that people are less easy to switch away from private car when trip distance increases (the direct elasticity values on car travel and parking costs are greater for mid-dist trips than for long-dist trips). Thus, policy measures on raising car travel cost and parking cost should be prioritised for shorter trips to avoid inefficient use of resources (though the threshold/criterion for shorter and longer trips warrants more research).
- The above conclusion leads to two subsequent questions: if such policy measures are genuinely needed for shorter trips, and what the alternative solution could be to suppress private car demand for longer trips. Our policy impact analysis reveals the answers. In the mid-dist case, when car-sharing service is made more appealing, the increasing demand mainly comes from a shrinking demand for bus rather than for private car. Therefore, the policy measures on private car attributes are in absolute need and should be implemented alongside any car-sharing promotion policies. In the long-dist case, private car users are found much easier to switch to a better car-sharing service. Therefore, instead of the inelastic measures of raising the costs of using car, it is more effective to improve the attractiveness of car-sharing and make it as a practical substitute for private car.
- The effectiveness of various car-sharing promotion policies differs across distances.

In shorter trips, decreasing travel cost is more effective than travel time whereas in longer trips, decreasing travel time is more effective than travel cost. The finding fits well into microeconomic theory (Wardman, 1998; Axhausen et al., 2008; Shires and De Jong, 2009). Besides, any aggressive measures on access time reduction should be avoided especially when resources are constrained. It is instead preferred to reduce travel cost more aggressively in mid-dist case and travel time more aggressively in long-dist case.

- Back to the shorter trip case where policy measures on private car attributes are needed, we recommend that it is up to the discretion of policy makers to prioritise car travel cost increase or parking cost increase when trade-off needs to be made given any practical constraints. The former is in itself more effective in suppressing private car demand while the latter is expected to have more rooms for policy intervention.

5.6 Conclusions

This chapter studied the factors that could affect car-sharing choice and identified the effective policy options that could promote car-sharing usage while suppressing private car demand. We conducted at first a mode choice analysis by using combined SP and RP survey data collected in the case study city, Taiyuan, China. Then, based on the choice model results, several informative indicators were derived such as VTTS, direct and cross point elasticity. Finally, we studied the modal substitution pattern in the SP environment to evaluate the effectiveness of different policy options. The results and relevant insights were generated separately for mid-dist trips (2km to 5km) and long-dist trips (more than 5km) throughout the work.

Key findings are highlighted as follows. The model estimation results show people's car-sharing choice behaviour could differ by trip distance. In a cold weather, the attractiveness of car-sharing is found to increase with trip distance. When a trade-off needs to made between travel time and cost, car-sharing users would care more about travel cost savings in shorter trips and travel time savings in longer trips. The service is also preferred for conducting non-commute trips in the shorter trip case while it is strongly preferred for commute purpose instead in the longer trip case. For the VTTS that is subsequently derived, the value for car-sharing is estimated as \$3.3/h in mid-dist trips and \$12.2/h in long-dist trips. Such a value difference is in line with our current insight on VTTS which normally increases with trip length (Wardman, 1998; Axhausen et al., 2008; Shires and De Jong, 2009). Finally, for elasticity measures, the values of cross elasticity are generally smaller than direct elasticity. This means the probabilities to choose car-sharing and private car are more sensitive to the level changes of their own attributes rather than the other's attributes.

More critical insights are gained from the policy impact analysis. Raising the cost of car usage (e.g. via travel cost and parking cost) should be prioritised for shorter trips since car is more difficult to be substituted when the trip distance increases. In fact, shorter trips also need such direct measures to help suppress the demand for private car while promoting the demand for car-sharing; otherwise, the increasing demand for car-sharing would mainly come from bus users. On the contrary, longer trips would need an alternative and more effective solution to bring down private car usage and that is discovered as making car-sharing service more attractive to users so that it can serve as a viable substitute to private car. To promote car-sharing usage, the focus could be put more on saving the users' travel cost for shorter journeys and more on saving their travel time for longer journeys.

Overall, this research offered some direct insights on if more people choosing car-sharing "reduces the use of private vehicles or if, on the contrary, it reduces the number of public transport users" (Jorge and Correia, 2013). More importantly, the results and the evidence derived from the policy impact analysis can be taken away as useful guidance for car-sharing policy making. We welcome more studies on car-sharing choice to compare to the various critical findings in this research.

CHAPTER 6. THE INFLUENCE OF ATTITUDINAL FACTORS ON SHARED MOBILITY CHOICES

This chapter aims to study how personal attitudes (latent variables) could possibly affect bike-sharing and car-sharing choices. Meanwhile, given the potential importance of attitudinal influence on VTTS estimation (Abou-Zeid et al., 2010; Bahamonde-Birke et al., 2017), we would also like to disclose with empirical evidence, the extent to which such influence might be significant, especially when the interaction with travel time or cost is captured. The dataset that we will use for this part of the research consists of 3,486 individuals and their 6,381 commute trip observations from the SP survey (to ensure car-sharing choice can be captured). Three attitudinal variables examined are "Willingness to be a green traveller", "Satisfaction with cycling environment" and "Advocacy of car-sharing service".

Attitudinal information is usually analysed through ICLV models (Ben-Akiva et al., 2002; Walker and Ben-Akiva, 2002; Bolduc et al., 2005; Bolduc and Alvarez-Daziano, 2010). In general, the ICLV model provides an integrated modelling framework which consists of a latent variable model and a discrete choice model. The latent variable model studies the potential causes of latent variables (i.e. unobserved attitudinal factors) via a structural equation system and also analyses via a set of measurement equations the observed indicators through which latent variables are manifested. The discrete choice model evaluates mode choice utilities as usual but now taking into account the impacts of latent variables as well alongside other explanatory factors. This research follows such an ICLV modelling framework, and a nested logit discrete choice model is developed to relax the IIA property (i.e. independence of irrelevant alternatives).

Through a robust integrated modelling analysis, the impacts of personal attitudes on bike-sharing and car-sharing choices can be quantitatively revealed, provide a better understanding of shared mobility choice behaviour. The value of time analysis will disclose how much difference attitudes could make on VTTS estimates; in other words, this will tell whether different VTTS estimates are needed for travellers with differentiated attitudes.

The work is structured as follows. Section 6.1 describes in detail the sample data that will be analysed in the ICLV model. Section 6.2 explains the modelling framework and section

6.3 evaluates the model estimation results. Finally, section 6.4 concludes the chapter.

6.1 Data

Our preliminary data cleaning reduced the sample size to 9,499 individuals. However, since this research is more interested in commute trips and attitudinal information, the sample was further filtered by keeping only those SP observations where the trip purpose is commute and those individuals who responded to the questions about attitudes & perceptions in a valid manner (i.e. a tolerance threshold is applied on the number of patterned scores given to consecutive statements and if the scores have significant inconsistency among several comparable statements). Eventually, the final dataset for this research includes 3,486 individuals with 6,381 SP mode choice observations.

Table 6-1 presents the key descriptive statistics of the sample we use here and the mode choices in the labelled SP survey[31]. The commuters mainly consist of those aged between 26 and 45 (83%), and most of them are married (85%). Gender and educational level distributions are relatively equal where the number of males and females are close, and half of the sample has a university degree. There is a high possession rate of public transport card (87%) meaning that most of the commuters can access bus and bike-sharing services “barrier-free”. Finally, more than 60% of the respondents have a driving license and almost all respondents have good health to cycle (96%).

Table 6-1 Sample Descriptive Statistics

		N=3,486
Gender	Male	54%
	Female	46%
Age	under 18	-
	18-25	1%
	26-35	48%
	36-45	35%
	46-59	15%

[31] All distance cases included due to both bike-sharing and car-sharing choices are studied.

	60 or above	1%
Marital status	Single	15%
	Married	85%
Educational level	High school or below	22%
	College	29%
	Undergraduate	41%
	Graduate and above	8%
Driving license	Percentage of possession	64%
Public transport card	Percentage of possession	87%
Cycling capability	Healthy enough to cycle	96%
Household monthly income	Under ￥3000	21%
(after tax)	￥3000 -￥6000	42%
	￥6000 -￥9000	23%
	￥9000 -￥15000	10%
	￥15000 -￥30000	3%
	Over ￥30000	1%
Household car	Percentage of possession	56%
Household electric bike	Percentage of possession	44%

Commute Trip Modal Splits (6,381 SP obs.)						
Bike-share	Car-share	Bus	Taxi	Walk	E-bike	Car
11%	14%	27%	4%	12%	10%	22%

The latent construct of our ICLV model was determined using the collected attitudinal information. To reveal the potential latent variables and the best indicators through which the latent variables are manifested, a principal component analysis (Jolliffe, 2002) was conducted followed by a varimax rotation (Kaiser, 1958) to assess the factor loadings of all possibly relevant statements in the survey. Eventually, three latent variables came out with a sufficient number of supportive statements. Based on the information carried by the statements (measured using a 7-point Likert scale), we named the three latent variables as: “Willingness to be a green traveller” constructed based on five statements/indicators, “Satisfaction with cycling environment” based on four statements, and “Advocacy of car-sharing service” based on four statements. Their statistics are given in Figure 6-1, 6-2 and 6-3 respectively, displaying the percentages of the sampled individuals agreeing/disagreeing with different levels.

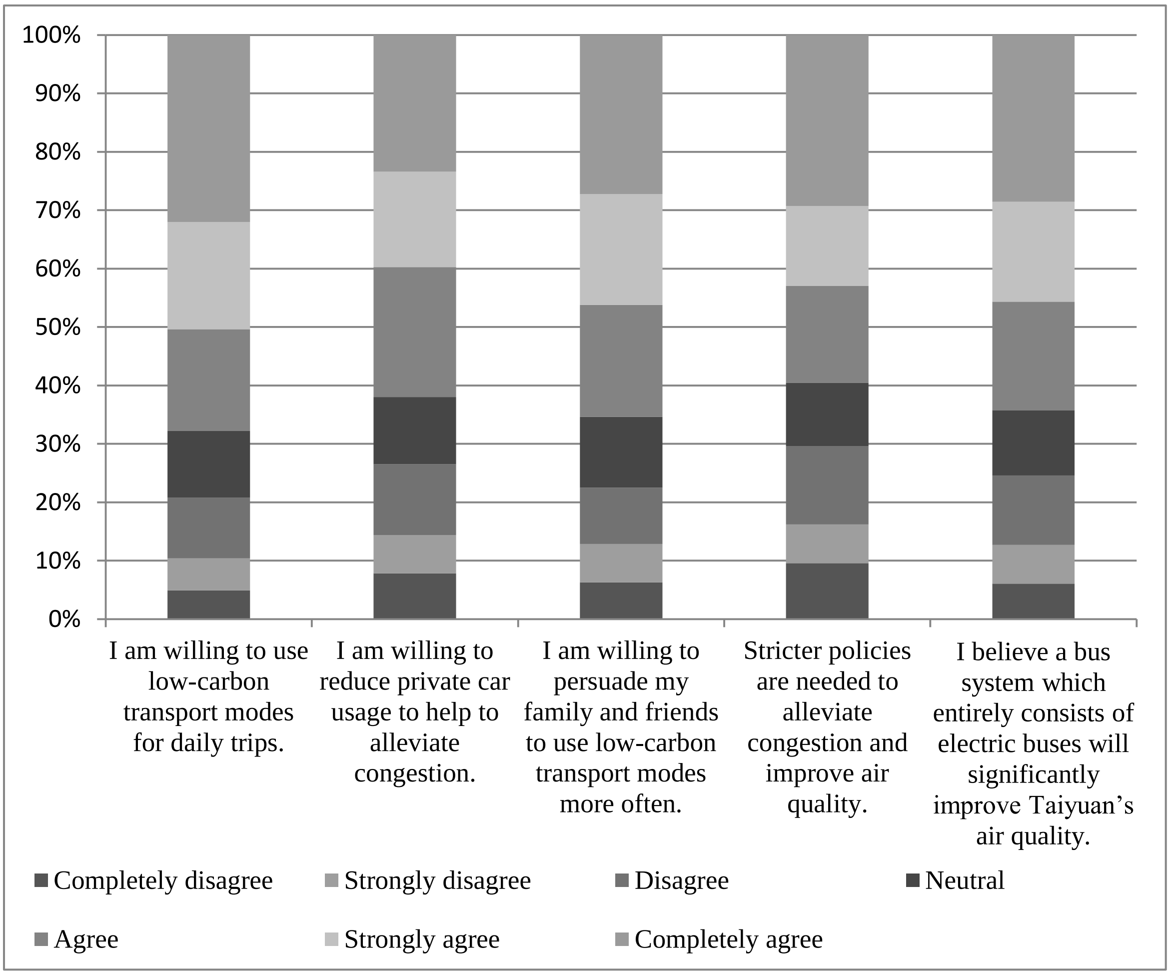

Figure 6-1 The Indicators of “Willingness to be a Green Traveller” (N = 3,486)

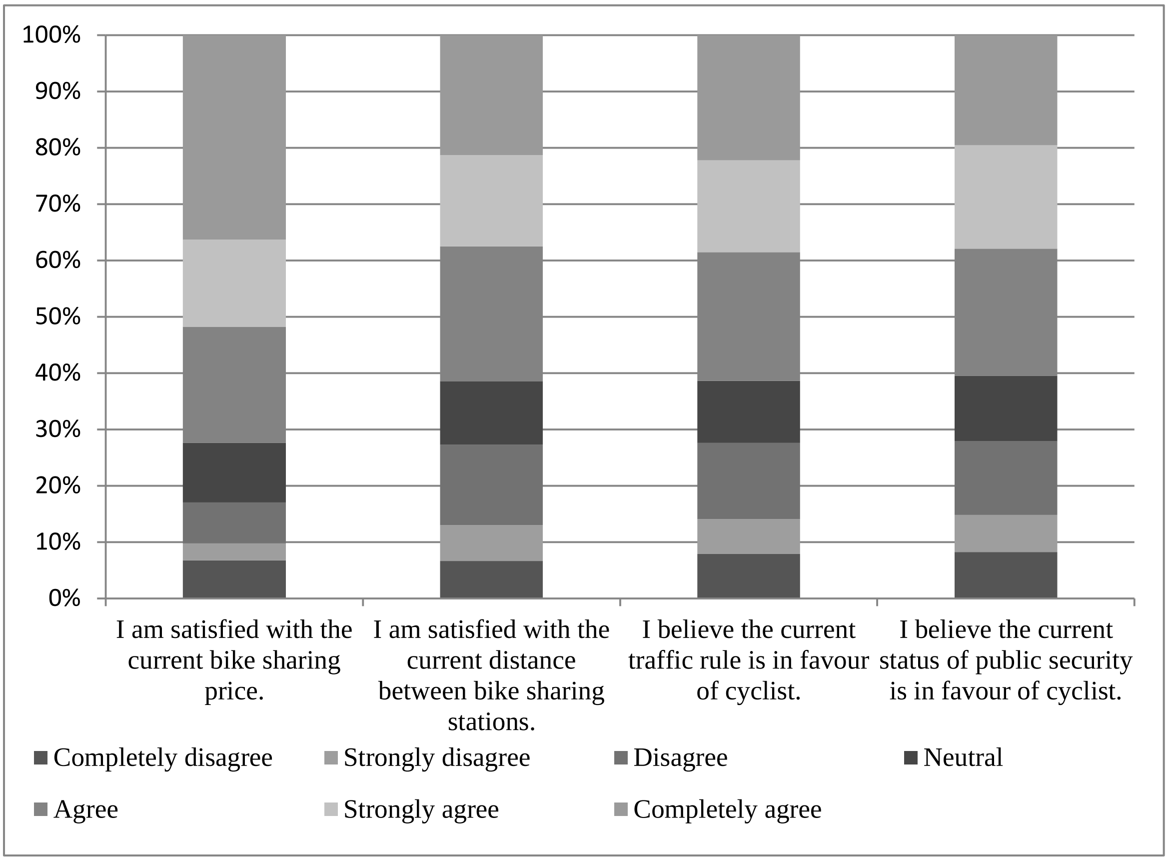

Figure 6-2 The Indicators of "Satisfaction with Cycling Environment" (N = 3,486)

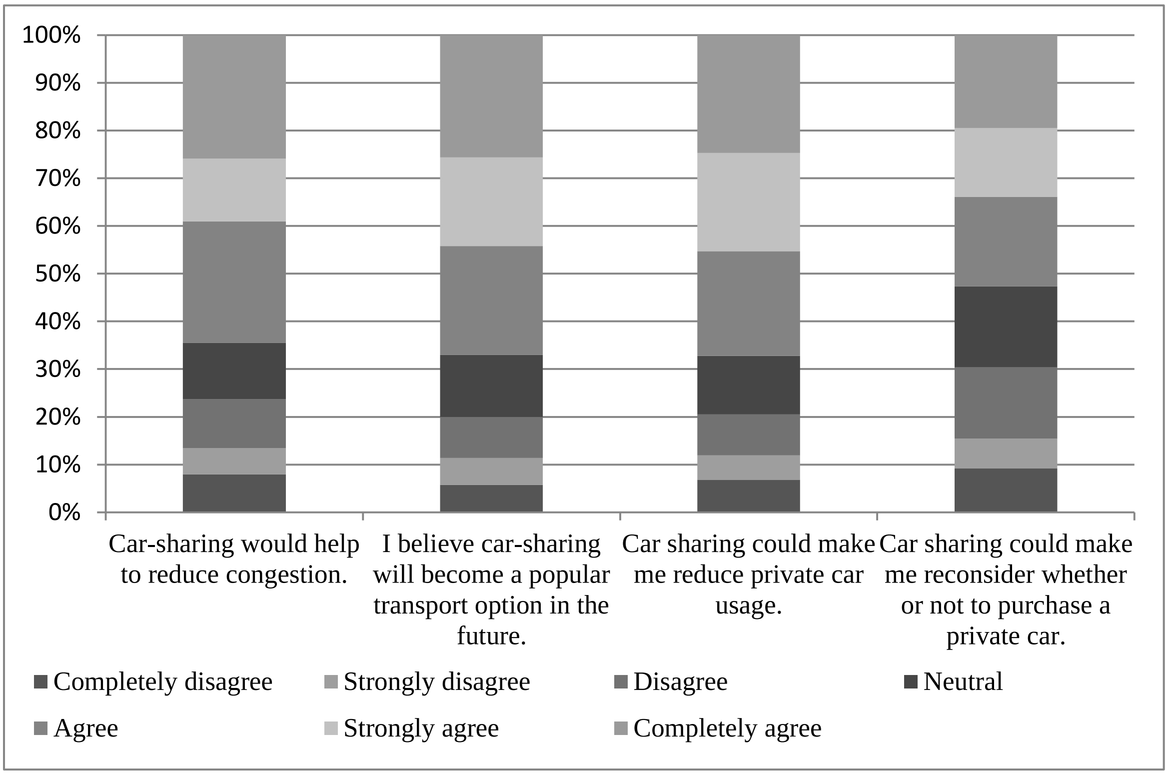

Figure 6-3 The Indicators of "Advocacy of Car-sharing Service" (N = 3,486)

In Figure 6-1, the detected five statements actually coincide with Taiyuan municipality's movement towards an eco-friendly transport system (see Chapter 3). In general, the sampled respondents seem to be supportive to such a vision by having more than 60% positive responses (i.e. "Agree", "Strongly agree" or "Completely agree") in all five statements. The details, however, do differentiate slightly. By comparing across the first three statements, we can see even if people are willing to use low-carbon transport for themselves and even persuade others, they could be less willing to sacrifice their private car usage. Similarly, when mentioning the word "policy", even if in general (the 4th statement), people tend to be more conservative in giving positive responses.

In Figure 6-2, the first two statements reflect the city's bike-sharing service standards with respect to price and station distance. The results show that commuters are mostly satisfied with the current price scheme by having nearly 40% of them completely agree with the statement "I am satisfied with the current bike-sharing price" and less than 20% expressed negative attitudes (i.e. "Disagree", "Strongly disagree" or "Completely disagree"). Unlike many cities in the world, the charging scheme that Taiyuan bike-sharing operator (Taiyuan Public Transport Holdings) adopts does not require a fixed/access fee each time. Users only need to pay based on the amount of time they spend (i.e. free in the first hour, ￥1/h for the next hour, ￥2/h for the next and ￥3/h for the rest of the day). Moreover, a user can return the bike to a docking station and get replaced with another one instantly to re-start the time count and avoid being charged. As for station distance, the current average distance between any two stations is smaller than 500 meters (Toutiao, 2017).

The latter two statements in Figure 6-2 reflect the indirect issues that bike-sharing users may consider. Firstly, the current traffic rules in Taiyuan have both pros and cons to cyclists. On the one hand, unlike the strict rules and punishments that car drivers have to bear, cyclists can travel much more freely. On the other hand, however, there are no individual green lights for "going straight" and "turning right" (vehicles travel on the right side in China). Hence, bicycles which go straight could have direct conflict with cars which turn right. Studies have also shown that cyclists could have significant safety concerns when cars were moving aside (Fishman et al., 2012; Paschalidis et al., 2016; Piatkowski et al., 2017; Romero et al., 2017). Secondly, perceptions on public security may also affect bike-sharing usage due to the fear of crime or the perceived sense of being unsafe could discourage travellers from using non-private modes (McCarthy et al., 2016). Nevertheless, it seems that Taiyuan municipality has created a generally satisfactory cycling environment since more than 60% of the sampled individuals give positive responses to both traffic rule and public security statements, as well as to the two statements on service standards.

Finally, Figure 6-3 illustrates an overall optimistic view of car-sharing service and its future. However, by comparing between “Car-sharing could make me reduce private car usage” and “Car-sharing could make me reconsider whether or not to purchase a private car”, it is undoubtedly noticed that respondents are more cautious in agreeing with the latter statement, demonstrating their differentiated perceptions towards using a car and owning a car. In other words, having a car is not only meant to meet transport demand, but is also likely to carry additional values which car-sharing might be less capable of providing.

Before we move to the modelling analysis, the following hypotheses are proposed to show in what ways we expect the latent variables could influence shared mobility choices:

- Commuters who are more willing to be a low-carbon traveller would be more likely to use bike-sharing and car-sharing;
- Commuters who are more satisfied with the cycling environment would be more likely to use bike-sharing;
- Commuters who are car-sharing advocates would be more likely to use car-sharing.

6.2 Modelling Framework

Before the latent construct is introduced, a nested logit model is developed to reveal the effects of different explanatory variables (attributes presented in the SP survey and socio-economic factors) on mode choices while taking into account inter-alternative correlation given the fact that alternatives were labelled in the SP survey and could possibly share unobserved attributes. The model is specified after several rounds of tests to drop out the variables with highly insignificant effects and to identify the appropriate forms of including variables in utility functions. In particular, systematic taste heterogeneity is captured by evaluating the interaction effects between socio-economic factors and SP attributes. Such a way of analysis has been increasingly adopted in discrete choice literature since it reveals whether the attributes would be differently perceived by different types of choice makers (Cherchi and Ortúzar, 2011; Ortúzar and Willumsen, 2011). Additionally, intra-person correlation among the observed mode choices was also assessed using a mixed logit structure (Cantillo et al., 2007); however, the parameter did not turn out significant and was thus excluded from the final model. This is possibly due to a large proportion of the sampled individuals only have one SP mode choice observation after passing through the data cleaning procedure as described in section 6.1 (i.e. we refined the sample by keeping only the SP observations where the trip purpose is commute). Table 6-2 provides a summary of the explanatory variables in the model and their measured values.

Next, to incorporate the latent variables (i.e. personal attitudes), we develop an ICLV model which consists of a latent variable model and a discrete choice model (Ben-Akiva et al., 2002; Walker and Ben-Akiva, 2002; Bolduc et al., 2005; Bolduc and Alvarez-Daziano, 2010). The former part evaluates the latent variables using a set of structural equations (Eq. 15) and a set of measurement equations (Eq. 16). The structural equations aim to identify the causes of the different attitudes among individuals and that will usually be their unique socio-economic characteristics. The measurement equations intend to establish a relationship between the indicators from survey results and personal attitudes; in other words, create a channel to observe/measure the latent variables. It is also noteworthy that the indicators are imported into our model under their original ordered format (i.e. 7-point Likert-scale) rather than via a continuous approximation. For the discrete choice model, we use the nested logit model that has been developed earlier and meanwhile introducing the latent variables via two specifications. One is to study their linear effects in the utility functions (Eq. 17) and the other is to study their interaction effects with travel time/cost (Eq. 18). As a result, we can find out how the VTTS estimation could be affected by the different model specifications. The latent variable model and the discrete choice model are simultaneously estimated using a maximum likelihood estimator. The simultaneous estimation jointly uses all the available information and thus can result in both unbiased and efficient parameter values (Raveau et al., 2010). The estimation is conducted in Pythonbiogeme; in order to accommodate three latent variables in a single ICLV model, monte-carlo integration is used instead of numerical integration (Bierlaire, 2016b). The complete modelling framework is described by Figure 6-4.

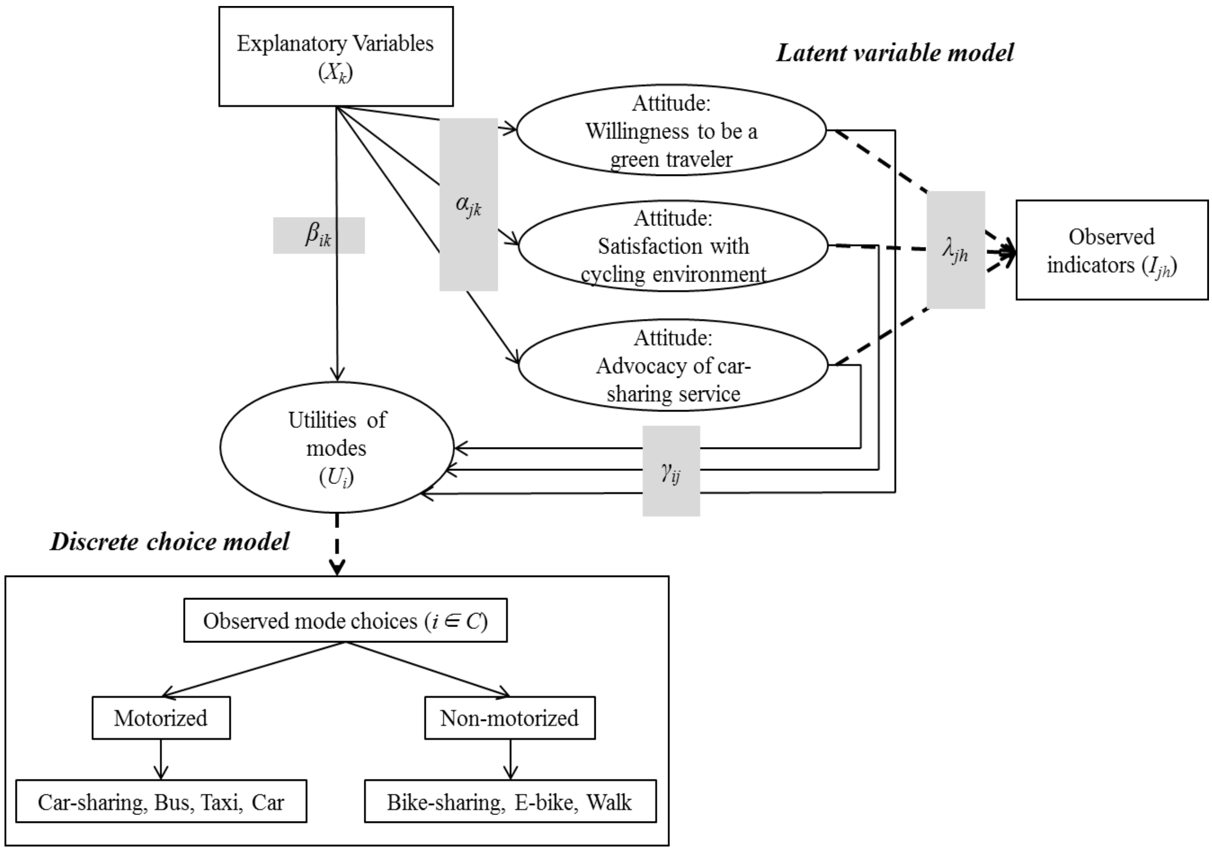

Figure 6-4 An ICLV Model with 3 Latent Variables and a Nested Logit Discrete Choice Model

The mathematical presentation of the modelling framework is given as follows:

Structural equation (latent variable model):

$$ATT_j = \mathrm{A}_j + \sum_{k=1}^{K} \alpha_{jk} X_k + \sigma_j \omega_{jn} \tag{15}$$

Measurement equation (latent variable model):

$$I_{jh} = \Lambda_{jh} + \lambda_{jh} ATT_j + \sigma_{jh} \upsilon_{jhn} \tag{16}$$

where ATT_j is the vector of attitudinal factors, X_k is the vector of explanatory variables and α_{jk} is the vector of estimated coefficients (A_j is the vector of intercepts). I_{jh} is the vector of indicators through which the attitudinal factors are manifested and their effects on the indicators are revealed by the parameter vector λ_{jh} (Λ_{jh} is the vector of intercepts). ω_{jn} and υ_{jhn} are the error components normally distributed across individuals with mean 0 and variance 1, $\sim N(0,1)$, and σ_j and σ_{jh} are their effects (standard deviation) respectively.

Utility function (discrete choice model):

$$U_i = \mathrm{B}_i + \sum_{k=1}^{K} \beta_{ik} X_k + \sum_{j=1}^{J} \gamma_{ij} ATT_j + \varepsilon_i \qquad (17)$$

$$U_i = \mathrm{B}_i + \sum_{k=1}^{K} \beta_{ik} X_k + \sum_{j=1}^{J} \sum_{k=1}^{K} \gamma_{ij} ATT_j X_k + \varepsilon_i \qquad (18)$$

where U_i is the utility associated with an alternative mode, X_k is the vector of explanatory variables and any form of interactions among them (e.g. systematic taste heterogeneity), and β_{ik} is the vector of estimated coefficients (B_i is the vector of alternative specific constants). The effects of attitudinal factors are revealed by the parameter vector γ_{ij}. ε_i is the error component i.i.d. extreme value distributed.

Table 6-2 Explanatory Variables and Measurements

Variable	Measurement
Air pollution	air quality index (AQI) by taking the average value of each level (25 for excellent level '0-50', 75 for good level '51-100', 125 for light pollution '101-150', 175 for medium pollution '151-200', 250 for heavy pollution '201-300', 400 for terrible pollution 'above 300')
Rain	1 if weather is rainy, 0 if otherwise
Temperature	temperature in °C
Travel cost	in RMB (￥)
Travel time	in min
Access time	in min, walking time to stations/parking spots
Wait time	In min, waiting time at bus stop
App availability	1 if a smart phone application is available, 0 otherwise
Gender (female)	1 if gender is female, 0 if male
Age (under 35)	1 if age is in the lower half categories in the survey (i.e. "under 18" or "18-25" or "26-35"), 0 if in upper half (i.e.

	“36-45” or “46-59” or “60 or above”)
Household income (below ￥9,000)	1 if household monthly income is in the lower half categories in the survey (i.e. “under ￥3000” or “￥3000-￥6000” or “￥6000-￥9000”), 0 if in upper half (i.e. “￥9000-￥15000” or “￥15000-￥30000” or “over ￥30000”)
Educational level (not have a degree)	1 if educational level is in the lower half categories in the survey (i.e. “high school or below” or “college”), 0 if in upper half (i.e. “undergraduate” or “graduate and above”)

6.3 Results

6.3.1 Latent Variable Model

Table 6-3 presents the results of the latent variable model. For the structural equations, we assessed the effects of a variety of socio-economic factors on personal attitudes, including gender, age, household income, educational level, marital status and job types. The first four are detected with their significant associations with at least one latent variable while the last two do not demonstrate any significant effects (and thus dropped out). It is found that gender and age could significantly affect all three personal attitudes. Specifically, female commuters are more willing to travel with green modes and tend to be more favourable towards car-sharing, but meanwhile, they are less likely to be satisfied with the cycling environment in the city. For the age effect, the younger generation (under 35) are found to hold relatively negative attitudes across all three cases. The other two factors, household income and educational level, the former seems not affecting the willingness to be a green traveller, while the latter does not affect the satisfaction with cycling environment. Nevertheless, it is also revealed that those who are less wealthy could be more likely to be satisfied with cycling environment and those who are less educated could be less willing to be a green traveller; in addition, both groups are found to be less favourable towards car-sharing. Generally speaking, most of the discovered impacts can be interpreted intuitively. For example, it is as expected that female travellers are more sensitive to the surrounding issues when they cycle and thus more difficult to be satisfied; wealthier people are more likely to use car and therefore tend to advocate a car-sharing service; and those who are more educated are usually more aware of environmental issues and hence more willing to adopt a green travel style. In contrast, the interpretation of age effect should be treated with caution, especially by observing a negative relationship (with a large t-statistic) between the younger generation and advocacy of car-sharing service, which is a relatively surprising result since car-sharing users tend to young as per the findings in some earlier studies (Becker et al., 2017; Dias et al., 2017; Prieto et al., 2017). Further research would be needed to explore any intrinsic factors that might result in such an outcome.

With regard to the measurement equations, the results show that all the indicators are positively associated with the three latent variables, which are in line with our expectations. In other words, the more the respondents hold positive attitudes (i.e. willing to be a green traveller, satisfied with cycling environment and advocate car-sharing service), the more they agree with the selected statements in the survey. For each latent variable, the parameters of one of the indicators are normalised to the base values as per the model specification requirement (Bierlaire, 2016b).

Table 6-3 Results: Latent Variable Model

Structural equation		
	coefficient	**t-statistic**
Willingness to be a green traveller		
A_{green}	1.32	23.15
Gender (female)	0.74	13.90
Age (under 35)	- 0.13	- 2.45
Educational level (not have a degree)	- 0.22	- 4.19
σ_{green}	2.07	56.22
Satisfaction with cycling environment		
A_{cycle}	- 0.47	- 5.88
Gender (female)	- 0.34	- 6.57
Age (under 35)	- 0.25	- 4.82

Household income (below ￥9,000)	1.78	22.05
σ_{cycle}	2.07	49.70
Advocacy of car-sharing service		
$\mathrm{A}_{carshare}$	2.08	23.73
Gender (female)	0.67	12.72
Age (under 35)	- 0.89	- 15.54
Household income (below ￥9,000)	- 0.38	- 5.15
Educational level (not have a degree)	- 0.84	- 14.68
$\sigma_{carshare}$	2.18	54.77
Measurement equation		
	coefficient	**t-statistic**
Willingness to be a green traveller		
Λ_{green1}	0.24	9.45
Λ_{green2}	- 0.25	- 9.31
Λ_{green3}	0	-
Λ_{green4}	0.11	2.79
Λ_{green5}	0.40	12.16
λ_{green1} (I am willing to use low-carbon transport modes for daily trips.)	0.99	69.99
λ_{green2} (I am willing to reduce private car usage to help to alleviate congestion.)	0.95	66.40
λ_{green3} (I am willing to persuade my family and friends to use low-carbon transport modes more often.)	1	-
λ_{green4} (Stricter policies are needed to alleviate congestion and improve air quality.)	0.82	43.12

λ_{green5} (I believe a bus system which entirely consists of electric buses will significantly improve Taiyuan's air quality.)	0.71	44.83
σ_{green1}	0.96	43.81
σ_{green2}	1.16	53.84
σ_{green3}	1	-
σ_{green4}	2.09	57.40
σ_{green5}	1.75	57.90
Satisfaction with cycling environment		
Λ_{cycle1}	1.12	29.64
Λ_{cycle2}	0.32	11.29
Λ_{cycle3}	0.12	4.69
Λ_{cycle4}	0	-
λ_{cycle1} (I am satisfied with the current bike sharing price.)	0.79	37.62
λ_{cycle2} (I am satisfied with the current distance between bike sharing stations.)	0.64	39.35
λ_{cycle3} (I believe the current traffic rule is in favour of cyclist.)	0.95	57.42
λ_{cycle4} (I believe the current status of public security is in favour of cyclist.)	1	-
σ_{cycle1}	2.15	52.94
σ_{cycle2}	1.80	57.61
σ_{cycle3}	1.35	49.69
σ_{cycle4}	1	-
Advocacy of car-sharing service		

$\Lambda_{carshare1}$	- 0.21	- 8.11
$\Lambda_{carshare2}$	0.01	0.20*
$\Lambda_{carshare3}$	0	-
$\Lambda_{carshare4}$	- 0.33	- 10.91
$\lambda_{carshare1}$ (Car-sharing would help to reduce congestion.)	1.01	66.24
$\lambda_{carshare2}$ (I believe car-sharing will become a popular transport option in the future.)	1.01	75.61
$\lambda_{carshare3}$ (Car sharing could make me reduce private car usage.)	1	-
$\lambda_{carshare4}$ (Car sharing could make me reconsider whether or not to purchase a private car.)	0.77	50.71
$\sigma_{carshare1}$	1.16	52.15
$\sigma_{carshare2}$	0.77	38.55
$\sigma_{carshare3}$	1	-
$\sigma_{carshare4}$	1.68	62.36

* parameter values not meeting the 95% significance level

6.3.2 Discrete Choice Model

The results from three different mode choice models are compared in Table 6-4. The first column gives the nested logit mode choice model without adding the latent variables. Inter-alternative correlation appears to be significant since the sampled commuters are found to consider between motorized and non-motorised options first before making a specific mode choice. Besides, the nesting parameter μ is greater than 1, which complies with the model specification requirement (Hess et al., 2004; Ortúzar and Willumsen, 2011). The shared mobility, bike-sharing and car-sharing alternatives, could be influenced by a variety of factors. Among different natural environmental conditions, air pollution is found to affect the choice of these two alternatives oppositely, and that is an increase in air pollution level would decrease the utility of using bike-sharing while making car-sharing a more appealing option. By also observing the negative impact on walk choice and positive impacts on taxi and car choices, it is possible to argue that air pollution would make travellers prefer modes that have a closed space (car-sharing etc.) rather than those with more exposure (bike-sharing etc.). The other two natural environmental conditions, rainy weather and temperature, are not found with significant impacts on commuters' shared mobility choices.

For trip and mode attributes, as we have expected, travel time and cost are both negatively correlated with bike-sharing and car-sharing usage. In addition, an available smart phone application would increase the probability to choose car-sharing while no significant impact is detected for its correlation with bike-sharing choice. The difference is possibly due to the different levels of familiarity (and thus different degrees of app dependence) with the two services, especially given that bike-sharing has been extensively used in the city for many years whereas to date car-sharing is still not a widely available travel option. Systematic taste heterogeneity is also captured by detecting the significant interaction effects between some attributes above and socio-economic variables. In particular, details are obtained with respect to the age effect on bike-sharing choice. Although both air pollution and travel cost are negatively correlated with bike-sharing usage, different age groups may value these effects differently and in our case that is the younger commuters (under 35) would be more anxious towards the negative impact of air pollution while worrying less about travel cost.

For car-sharing choice, the only interaction effect that turns out significant is between educational level and travel cost where less educated commuters have weaker preference than more educated commuters, while an increase in travel cost would further push those less educated away from choosing car-sharing. At last, factors affecting other mode choices are also available for readers to check, though they will not be discussed in detail given our focus on the two shared mobility services. Overall, all factors have the expected impact signs.

The second and third columns present the model estimation results when the latent variables are involved. As expected, the model fitness improves. For the linear effects of latent variables, it is found that a more positive attitude towards "Willingness to be a green traveller" could significantly increase the probability of choosing bike-sharing and walk to commute, while making car less likely to be chosen. Nevertheless, car-sharing choice is not found to be significantly affected by such an attitude. One possible explanation is that the city of Taiyuan did not have any operated car-sharing schemes when the survey took place in 2015 and people were probably not aware whether the service vehicles would be powered by clean energy or traditional fossil fuel; thus, it is likely that car-sharing was not perceived as a low-carbon travel option among many survey respondents.

The other two personal attitudes, "Satisfaction with cycling environment" and "Advocacy of car-sharing service", do have the results that are in line with our hypotheses, i.e. people that are more satisfied with the cycling environment would be more likely to choose bike-sharing and those who are car-sharing advocates would prefer to use car-sharing for commute. It is also noteworthy that car-sharing advocates may be less likely to use car given the observed negative impact sign, though the result is not as significant as those discussed above (we decided to present this parameter since the t-statistic demonstrated high significance when testing alone the effect of "Advocacy of car-sharing service", and the 95% significance no longer held when adding all three latent variables in the model). As for the interaction effects of latent variables, the impact signs are similar to which in the linear effect model but the taste heterogeneity on travel time and travel cost is now captured. Most of the interaction effects that are discovered with significance are between the attitudes and travel time, except for car, which instead has travel cost associated with more significant taste heterogeneity by commuters with differentiated attitudes. As for bike-sharing and car-sharing, those with more positive attitudes towards "Willingness to be a green traveller" and "Satisfaction with cycling environment" are found less uncomfortable with longer bike-sharing travel time, and similarly, car-sharing advocates could more easily accept longer car-sharing travel time.

Table 6-4 Results: Discrete Choice Model

	Without LVs		With LVs – linear effect		With LVs – interaction effect	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
$\alpha_{bikeshare}$	1.06	7.48	0.64	4.44	1.20	7.95
$\alpha_{carshare}$	- 0.87	- 5.09	- 1.04	- 5.34	- 0.95	- 5.29
α_{bus}	1.27	7.20	1.21	7.10	1.35	7.50
α_{taxi}	- 1.35	- 5.08	- 1.46	- 5.22	- 1.45	- 5.21
α_{walk}	1.18	3.83	0.87	2.79	1.25	4.02
α_{ebike}	0.71	5.05	0.63	4.70	0.77	5.29
α_{car}	0	-	0	-	0	-
Natural environmental conditions						
Air pollution-bikeshare	- 0.0028	- 4.34	- 0.0031	- 4.75	- 0.0031	- 4.76
Air pollution-carshare	0.0026	5.81	0.0027	5.85	0.0028	6.03
Air pollution-taxi	0.0027	5.13	0.0028	5.13	0.0029	5.25
Air pollution-walk	- 0.0023	- 4.07	- 0.0022	- 4.03	- 0.0022	- 4.01
Air pollution-car	0.0019	5.70	0.0021	5.79	0.0021	5.85
Rain-bus	0.28	3.39	0.30	3.40	0.32	3.49
Rain-taxi	0.53	3.79	0.56	3.83	0.59	3.89
Rain-walk	- 0.46	- 3.29	- 0.46	- 3.24	- 0.44	- 3.07
Rain-ebike	- 0.61	- 5.03	- 0.59	- 4.79	- 0.57	- 4.60
Rain-car	0.34	3.60	0.35	3.58	0.37	3.63
Temperature-bus	- 0.01	- 3.83	- 0.01	- 3.82	- 0.01	- 3.75
Trip and mode attributes						
Travel cost-bikeshare	- 0.332	- 3.24	- 0.297	- 2.87	- 0.269	- 2.59
Travel cost-carshare	- 0.016	- 2.70	- 0.015	- 2.62	- 0.017	- 2.68
Travel cost-bus	- 0.373	- 5.05	- 0.386	- 5.02	- 0.402	- 5.13

Travel cost-taxi	- 0.018	- 2.11	- 0.019	- 2.13	- 0.019	- 2.04
Travel cost-car	- 0.001	- 0.03*	- 0.001	- 0.08*	- 0.017	- 1.20*
Travel time-bikeshare	- 0.041	- 13.48	- 0.042	- 13.72	- 0.054	- 14.14
Travel time-carshare	- 0.007	- 3.27	- 0.008	- 3.40	- 0.009	- 3.52
Travel time-bus	- 0.015	- 3.82	- 0.016	- 3.92	- 0.016	- 3.86
Travel time-taxi	- 0.007	- 0.56*	- 0.006	- 0.47*	- 0.007	- 0.52*
Travel time-walk	- 0.010	- 0.54*	- 0.009	- 0.47*	- 0.002	- 0.08*
Travel time-ebike	- 0.038	- 5.15	- 0.039	- 5.26	- 0.039	- 5.16
Travel time-car	- 0.001	- 0.35*	- 0.001	- 0.38*	- 0.001	- 0.18*
Access time-bus	- 0.05	- 5.80	- 0.05	- 5.81	- 0.05	- 5.84
Wait time-bus	- 0.01	- 2.84	- 0.01	- 2.75	- 0.01	- 2.59
App availability-carshare	0.17	2.56	0.18	2.65	0.19	2.68
Systematic taste heterogeneity						
Gender (female) * Travel time-bus	0.006	3.60	0.006	3.44	0.006	3.53
Age (under 35) * Air pollution-bikeshare	- 0.004	- 4.93	- 0.004	- 4.68	- 0.004	- 4.72
Age (under 35) * Air pollution-walk	- 0.002	- 3.42	- 0.002	- 3.23	- 0.002	- 3.21
Age (under 35) * Temperature-bus	- 0.014	- 3.41	- 0.014	- 3.47	- 0.016	- 3.56
Age (under 35) * Travel cost-bikeshare	0.354	3.18	0.359	3.18	0.354	3.13
Age (under 35) * Travel time-bus	0.007	2.73	0.007	2.75	0.007	2.82
Age (under 35) * Travel time-ebike	- 0.010	- 2.86	- 0.010	- 2.88	- 0.010	- 2.84
Household income (below ￥9,000) * Travel cost-bus	0.128	2.65	0.138	2.75	0.146	2.77

Household income (below ￥9,000) * Travel time-ebike	0.016	2.32	0.016	2.35	0.016	2.33
Educational level (not have a degree) * Travel cost-carshare	- 0.010	- 3.28	- 0.009	- 2.92	- 0.009	- 2.93
Educational level (not have a degree) * Travel cost-car	- 0.018	- 3.05	- 0.022	- 3.36	- 0.024	- 3.41
Latent variables (personal attitudes)						
Green travel-bikeshare			0.173	7.00		
Green travel-walk			0.139	4.80		
Green travel-car			- 0.060	- 3.71		
Cycle satisfaction-bikeshare			0.052	2.27		
Car-sharing advocacy-carshare			0.038	2.65		
Car-sharing advocacy-car			- 0.021	- 1.62*		
Green travel * Travel time-bikeshare					0.004	5.60
Green travel * Travel time-walk					0.006	3.32
Green travel * Travel cost-car					- 0.006	- 3.21
Cycle satisfaction * Travel time-bikeshare					0.002	2.48
Car-sharing advocacy * Travel time-carshare					0.001	2.57
Car-sharing advocacy * Travel cost-car					- 0.002	- 1.44*
Inter-alternative correlation & Model fitness						
$\mu_{motorized}$	1.72	6.07#	1.68	6.11#	1.58	6.32#
$\overline{\rho}^2$	0.18		0.21		0.21	

* parameter values not meeting the 95% significance level

t-test against base value of 1

6.3.3 Value of Time

Recalling the arguments that taste heterogeneity, as a result of individuals' differentiated attitudes, could be taken into account for more realistic VTTS estimation, this research intends to offer comparable evidence to the earlier result in Abou-Zeid et al. (2010), of the extent to which personal attitudes could have an influence on the estimated VTTS values. Table 6-5 displays the VTTS estimates for the two shared mobility services resulted from our three mode choice models; 1. without the latent variables, 2. latent variables entered linearly in the utility functions and 3. latent variables' interaction effects with travel time/cost are captured so that the value will be integrated over all individuals in order to calculate the societal VTTS.

It is easily observed that VTTS for both bike-sharing and car-sharing would increase when having personal attitudes in the model, especially when the taste heterogeneity on travel time is captured. Although such an increasing trend is consistent with several earlier findings that more restrictive models tend to underestimate the value of time (Hensher, 2001a; Hensher, 2001b; Amador et al., 2005), it should be noted that over-estimation could also be the case sometimes depending on the chosen variables, functional form and the nature of data, as explained by Amador et al. (2005). Moreover, for both bike-sharing and car-sharing, we found VTTS could increase by around 40% from the model specification without the latent variables to the specification capturing their interaction effects with travel time. As discussed in the literature review (section 2.3), such a figure is consistent to the detected amount of increase in several other works when allowing the taste of travel time to vary randomly (Algers et al., 1998; Hensher, 2001a; Amador et al., 2005), and is clearly larger than the amount revealed by Abou-Zeid et al. (2010), i.e. around 7%, derived from a group of individuals who share close attitudes.

Table 6-5 Value of Travel Time Savings across Models

	Without LVs	**With LVs – linear effect**	**With LVs – interaction effect**
Bike-sharing	￥7.4 ($1.1)/h	￥8.5 ($1.3)/h	￥10.3 ($1.5)/h
Car-sharing	￥26.3 ($3.9)/h	￥31.7 ($4.8)/h	￥37.8 ($5.7)/h

Overall, VTTS is an important indicator that is often used to guide the design of pricing policies for travel demand management. The above results would imply a need to derive different

VTTS for travellers with differentiated attitudes since the value could vary substantially when people have distinct tastes towards travel time/cost. We hereby generate another set of results trying to indicate how much the difference could be between those having relatively positive attitudes and negative attitudes. In the model that captures interaction effects, the taste of bike-sharing travel time could be affected by both "Willingness to be a green traveller" and "Satisfaction with cycling environment". Therefore, we use the results from structural equations to select individuals whose socio-economic characteristics are all positively correlated with the two attitudes to formulate a group representing those having a positive attitude in general, and vice versa a group for those having a negative attitude. For car-sharing travel time taste that could be affected by "Advocacy of car-sharing service", the same procedure applies to formulate the two contrasting groups. Table 6-6 shows the findings. It is revealed that VTTS among those holding a relatively negative attitude could be 20% and 40% higher respectively for bike-sharing and car-sharing than those holding a relatively positive attitude, which, in terms of intuition means that those who are more comfortable with the travel time spent on the two shared mobility services would have a lower willingness to pay for travel time savings.

The plots in Figure 6-5 and 6-6 present the fact in a more explicit way. As an alternative approach to above, we could use the observed indicator values from measurement equations to group the individuals with differentiated attitudes. Specifically, we calculate for each individual an average score they gave in the survey to the indicators, for each of the three latent attitudes. This process could put individuals into six groups, i.e. whose average score is between "1 and 2", "2 and 3", "3 and 4", "4 and 5" , "5 and 6", "6 and 7" (recall that 7-point Likert scale is used in our survey), as a way to represent the different levels of attitudes. In general, for all the three latent variables, we see VTTS decreases as people hold an increasingly positive attitude. By comparing the results to Table 6-6, we notice the range (or the spread) of VTTS becomes smaller when grouping the individuals by the indicator values from measurement equations. Such a difference is more or less expected due to the better approach to split attitudinal groups is via using the explanatory variables from structural equations (Vij and Walker, 2016), which could more effectively represent the different levels of attitudes, and in turn, more clearly demonstrate the VTTS spreads, compared to using measurement equations. Besides, this may also help explain the observed 'noise', i.e. for "Satisfaction with cycling environment", the VTTS revealed for the group [6,7] is however higher than the value for the group [5,6], as shown in Figure 6-5.

Table 6-6 VTTS by Structural Equation Groups

	Being positive towards "green travel" + "cycle satisfaction"	Being negative towards "green travel" + "cycle satisfaction"
Bike-sharing	￥9.6 ($1.4)/h	￥11.3 ($1.7)/h
	Being positive towards "car-sharing advocacy"	**Being negative towards "car-sharing advocacy"**
Car-sharing	￥31.7 ($4.8)/h	￥45.5 ($6.8)/h

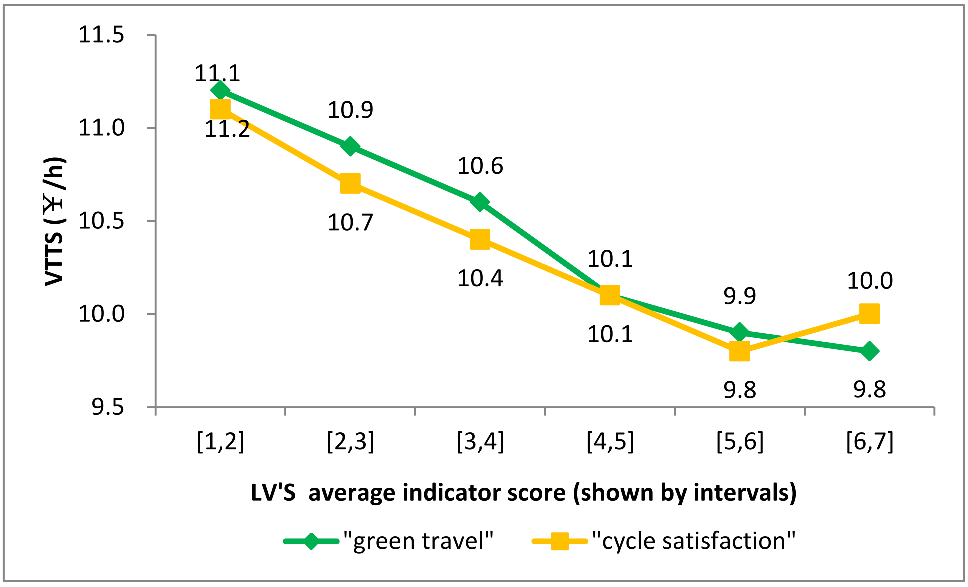

Figure 6-5 VTTS for Bike-sharing by Measurement Equation Groups

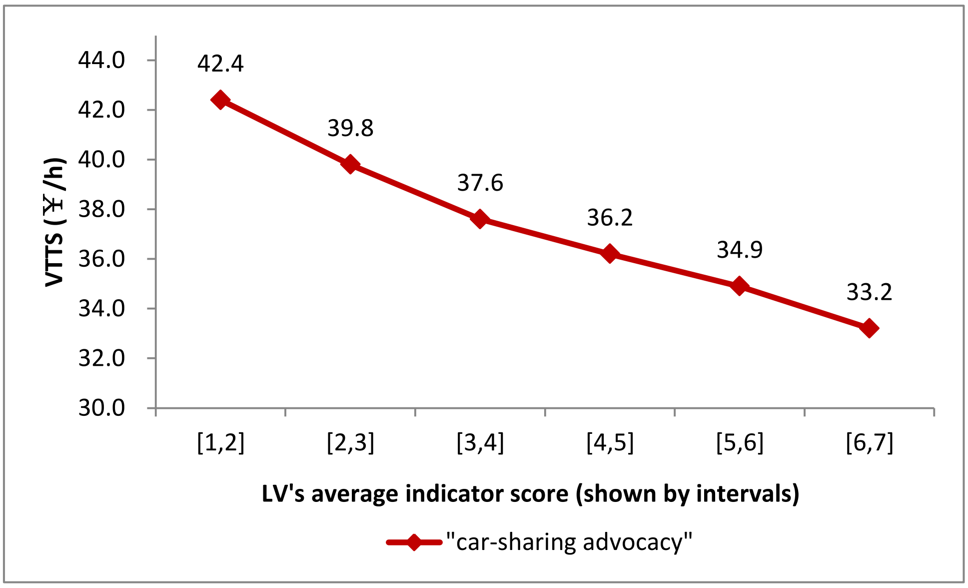

Figure 6-6 VTTS for Car-sharing by Measurement Equation Groups

As a conclusion, the need to look at and disclose the corresponding VTTS for commuters with differentiated attitudes is highlighted in this research; otherwise, a single and over-simplified measure of VTTS across population could be misleading and potentially bias any pricing policies for effective travel demand management. However, it should be noted that the analysis of value of time in this research aims mainly to offer an indication demonstrating the extent to which personal attitudes could have an influence on the estimated values. A more accurate derivation of VTTS for practical application would need to involve studies of many other factors such as trip distance (Wardman, 1998; Axhausen et al., 2008), specific local context (Shires and De Jong, 2009), demographics (Jara-Diaz, 2003; Mackie et al., 2003; Trottenberg and Belenky, 2011) and other potential individual heterogeneity (Bastin et al., 2010).

6.4 Conclusions

This work studies how the usage of shared mobility services could be influenced by personal attitudes. An ICLV modelling framework is adopted to explore the effects of three attitudinal factors on bike-sharing and car-sharing choices, while simultaneously investigating the potential causes associated with each of the attitudes. A group of Chinese commuters' SP mode choice data is collected for the analysis. It is found that the probability to choose bike-sharing for a commute trip could be positively affected by the attitudes towards "Willingness to be a green traveller" and "Satisfaction with cycling environment" and car-sharing choice is positively correlated with the attitude towards "Advocacy of car-sharing service". Moreover, by taking into account the interaction effects between the attitudinal factors and travel time of the two shared mobility services, a significant difference is discovered on the estimated VTTS comparing to the case of not having the attitudinal factors in the model or adding the attitudinal factors linearly in utility functions. The finding highlights the possibility to derive different VTTS for travellers with differentiated attitudes, as the tastes towards travel time spent could vary substantially. In other words, for practical application, a single measure of VTTS across population should not be preferred, in order to avoid biased pricing policies for travel demand management.

Although the work offers the state-of-the-art evidence of the extent to which personal attitudes could have an influence on the value of time estimation, several strategies could be adopted by future research to disclose more benefits of mode choice analyses involving latent variables. The work of Bahamonde-Birke et al. (2017) distinguished between the concepts of ‘attitude’ and ‘perception’, and a critical difference between the two is attitudes are often explained by socio-economic characteristics whereas perceptions are usually formulated based on mode-related attributes. Due to data constraints, we worked with three attitudinal factors in this research; however, studying perceptual factors in a mode choice analysis could potentially bring more practical values (Chorus and Kroesen, 2014), i.e. by having measures that could alter mode-related attributes and in turn affecting perceptions, mode choice behaviour and modal substitution pattern could be shifted towards a socially desirable outcome. Another critical challenge encountered by many ICLV studies (including this work) with a simultaneous model estimation structure and relying on maximum simulated likelihood inference approach is the extremely lengthy computation time, especially when multiple latent variables are involved. Bhat and Dubey (2014) proposed an alternative inference approach, maximum approximate composite marginal likelihood, to shorten model estimation time since the dimensionality of integration in the likelihood function will be independent to the number of latent variables and will require no more than bivariate normal cumulative distribution function to be evaluated for likelihood maximization (Bhat, 2011). So far, the application of such a new strategy is only compatible with specific modelling tool (i.e. GAUSS programming language) and would require complex coding inputs. Nonetheless, it is still a feasible alternative approach for future studies to consider, especially when there is a need to handle a broader range of attitudinal and perceptual factors.

CHAPTER 7. CONTROLLING CAR USAGE FROM A HABITUAL PERSPECTIVE

In the earlier chapters, we tried to reveal any efforts that could be made at a tactical level for promoting shared mobility usage while suppressing the demand for private car. Now we would like to search for additional inspirations, as complements to the insights gained earlier, for what other aspects could be looked at to control private car usage.

Recall that choice behaviour could be habitual, and the habitual changes of mode choice can be triggered by a variety of life course events. As such, although it is probably desirable to see a switch away from using car following the occurrences of some life events, meanwhile, switching to car is also a possible outcome and in fact, several results have indicated that switching from non-car modes to car was more frequently observed than the opposite (Oakil et al., 2011; Clark et al., 2016a). Such a puzzle could pose an additional challenge to travel demand management and it is crucial if efforts could be made to hold back the mode switches to car; since otherwise, once car is picked up and over time its usage becomes habitual, it would be even more difficult to alter the mode choice behaviour (Ouellette and Wood, 1998).

This research aims to offer some direct insights to a query related to such a puzzle (i.e. given the presence of life course events that could result in the mode switches from non-car modes to car, what could be the counter-measures to hold back such a change) by conducting a mode switching analysis. A retrospective mode choice survey was launched to collect the citizens' regular commute mode information in 2006, 2008, 2010 and 2012 (totally four observation periods). A variety of life status data in the corresponding observation periods was also collected. A binary logit regression model is developed first to study the mode switching behaviour from car to non-car modes followed by a set of “mirror models” which evaluate the mode switches from different non-car modes to car. The mirror models could reveal any differences in mode switching behaviour among different non-car mode users, and hence more targeted policy implications could be derived.

The remainder of the chapter is structured as follows. The next section provides the information about the retrospective survey and the descriptions of life course events and observed mode switching patterns. The details of the model formulation follow. The model estimation results come next and a discussion of policy implications is presented in the end.

7.1 Data

This research uses the retrospective survey data to study the effects of life course events on mode switching behaviour. Earlier chapters have extracted rather large-scale samples for their modelling analyses; however, for the retrospective part, the number of responses that we keep in the final sample is limited. This is due to 1. the difficulty in recalling past information in a retrospective survey (Peters, 1988; Lillard and Waite, 1989) so that a lot of missing values do exist and the corresponding observations are removed, and 2. we applied many other criteria to make sure the selected data is credible enough to enter the analysis, for instance, a person included in the final sample should have full observations across all four periods and become a resident in the city at least before the first observation period, etc. Relevant information has been gathered in the survey to ensure those criteria can be fulfilled. Eventually, we have 1,799 individual respondents with their all four-period commute mode choices (7,196 observations in total) ready to be used in the mode switching analysis. Some key information of this sample is presented in Table 7-1.

Table 7-1 Sample Descriptive Statistics

		N=1,799 in each year			
		2006	**2008**	**2010**	**2012**
Gender	Male	53%	53%	53%	53%
	Female	47%	47%	47%	47%
Household monthly income (after tax, in CNY)*	Below ￥3k	44%	40%	35%	31%
	￥3k -￥6k	38%	40%	42%	44%
	Above ￥6k	18%	20%	23%	25%
Home & Work place	Both in central districts	29%	28%	27%	27%
	Either or both in outer districts	71%	72%	73%	73%
Marital status	Single	39%	32%	24%	16%
	Married	61%	68%	76%	84%

Number of children	None	62%	57%	47%	38%
(under 12)	At least one	38%	43%	53%	62%
Employment status	Have a fixed job	72%	77%	80%	84%
	Self-employed or student	28%	23%	20%	16%
Commute distance	Within 2km	17%	17%	16%	16%
	2km to 5km	20%	20%	18%	17%
	Beyond 5km	63%	63%	66%	67%
Household car	percentage of possession	34%	38%	45%	50%
Household e-bike	percentage of possession	46%	48%	49%	50%
Household bike	percentage of possession	68%	68%	68%	68%
Commute mode	Car	17%	20%	25%	29%
choice	Bus	27%	27%	25%	23%
	E-bike	17%	16%	15%	14%
	Bike	23%	22%	21%	20%
	Walk	15%	14%	13%	13%
	Taxi	1%	1%	1%	1%
Note: age information is missing from the retrospective survey					

The sample is almost equally composed of male and female commuters. Age information is not collected in the retrospective survey. Household income has gradually increased over time. The proportion of people who both live and work in the central districts of Taiyuan city (there are 6 districts in Taiyuan and 2 are perceived as the central districts in the past decade) has remained stable. We found from the data that this is not due to the approximately the same number of people moving in/out, but simply because most respondents in the sample have stayed within the central/outer district boundary. Many people got married, had a child and got a fixed job during our study period. The distribution of commute distances is relatively stable over time; however, this time, it is revealed from data that such stability is caused by the occurrences of both commute distance increases and decreases, not because people have their home and work place locations unchanged (though, as mentioned earlier, most of them still stayed within the boundary of central/outer district). There is an increasing possession rate of car by household over time, while the possession rates of electric bike and bike remained similar across the different periods. By looking back the 2015 sample statistics in previous chapters, electric bike ownership has remained high (i.e. around 50%) throughout our entire survey periods. This is very much consistent to the whole picture of China, which has had a higher adoption rate of electric bike for a decade compared to other parts of the world (Cherry, 2010; 2013). Meanwhile, bike ownership has dropped substantially from 2012 to 2015, which reflects the aforementioned influence of the continuous expansion of the city's bike-sharing program. Regarding the commute mode choices, car usage has been through a continuous increase from 2006 to 2012; by looking at the rest of modes, we can see the increasing demand for car came from bus, electric bike, bike and walk journeys. Meanwhile, taxi was rarely chosen for regular commute trips and its share remained low in all four periods.

Table 7-2 and 7-3 provide more specific statistics for a mode switching analysis with respect to life course event occurrences. In Table 7-2, we identified five critical life course events that could result in mode switching behaviour; these are: "Get married", "Have a child", "Get a fixed job", "Increase of household income" and "Commute distance change". Over the entire study period (2006-2012), the percentages of respondents who got married, had a child and got a fixed job are 28%, 24% and 12% respectively. The latter two figures (24% and 12%) are consistent with the statistics in Table 7-1 where the number of people having at least one child increased from 38% in 2006 to 62% in 2012, and having a fixed job increased from 72% in 2006 to 84% in 2012. However, 28% of participants who got married, is 5% higher than the yearly marriage statistics (from 61% in 2006 to 84% in 2012). The difference implies 5% people may have got divorced but such a life course event will not be studied in our models given its low occurrence rate. The survey captures monthly household income in six levels: below ￥3k, ￥3k -￥6k, ￥6k -￥9k, ￥9k -￥15k, ￥15k -￥30k and above ￥30k. A jump to a higher household income level is another event that might make people reconsider their mode choice decisions. 26% of the sampled individuals have been through at least once such an income increase over the entire study period. Finally, commute distance change is broken down to two sub-cases, where 22% have experienced a distance increase, and 14% have experienced a distance decrease.

Table 7-2 Life Course Event Occurrences on Individuals over the Study Period (2006-2012)

Life course event	% individuals been through the listed life course events (N=1,799)
Got married	28%
Had a child	24%
Got a fixed job	12%
Increase of household income (at least once)#*	26%
Commute distance increased (at least once)*	22%
Commute distance decreased (at least once)*	14%

Household monthly income is measured in six levels in the survey: below ￥3k, ￥3k -￥6k, ￥6k -￥9k, ￥9k -￥15k, ￥15k -￥30k, above ￥30k

* Events that could occur more than once over the entire study period (2006-2012) in the given sample

To reveal the mode switching pattern, we convert the original sample data into a different format. Initially, each respondent has four mode choice observations from the four periods (2006, 2008, 2010 and 2012) respectively. Then, we formulate paired observations by capturing the mode choices in a precedent period and the period followed. As such, each respondent now has three paired observations (2006/2008, 2008/2010 and 2010/2012) to display any mode switching behaviour. Table 7-3 offers an overview of the mode switching pattern over the entire study period (2006-2012). About 90% paired observations which had car as the commute mode in the precedent period, still had car chosen in the period followed. As a comparison, for bus, electric bike, bike and walk that were chosen in the precedent period, the percentages of paired observations which had the same modes chosen in the following period were lower, though all of the percentages were still above 80%. Thus, there was slightly stronger adherence to car usage than to using the rest of modes. Besides, it is noteworthy that car is always the most popular alternative, when people would like to switch away from bus, electric bike, bike and walk in the period followed.

Table 7-3 Mode Switching Pattern over the Entire Study Period (2006-2012)

Precedent period	**The following period**					
	Car	Bus	E-bike	Bike	Walk	Taxi
Car	89.5%	5.4%	0.9%	2.2%	1.9%	0.2%
Bus	11.1%	83.2%	1.7%	2.2%	1.5%	0.3%
E-bike	6.4%	2.7%	84.9%	5.8%	0.2%	0%
Bike	6.1%	4.3%	2.4%	86.0%	1.0%	0.1%
Walk	6.0%	3.8%	1.0%	1.0%	88.2%	0%

Note: we do not analyse the sticking to/switching away behaviour when having taxi in the precedent period due to the very limited observations of having taxi as a regular commute mode (see also the “Commute mode choice” in Table 7-1)

7.2 Modelling Framework

Based on the data structure displayed in Table 7-3, we put the paired observations into five sub-datasets in which the commute mode choice in the precedent period is car, bus, electric bike, bike and walk respectively. These are the datasets that will be used in our mode switching analysis.

A binary logit regression model is developed at first to investigate the mode switching behaviour from car (precedent period) to non-car (the following period). Broader insights could be obtained if the “non-car” alternative can be decomposed into the actual modes that are chosen in the following period (e.g. car-bus, car-electric bike…) and hence perform a multinomial logit regression. However, there are very limited mode switching events in this working dataset (i.e. the first row of Table 7-3), and as a result, our modelling attempt with multinomial logit regression encountered a convergence issue. Eventually, a binary approach is adopted (see Oakil et al., 2011; Clark et al., 2016a).

Next, a set of “mirror models” are developed to study the mode switching behaviour from bus to car, electric bike to car, bike to car and walk to car. There are two considerations behind such a practice: 1. It is important to distinguish and verify if a factor that could induce a mode switch, for instance, car to non-car, is due to preferring a non-car alternative or simply preferring a switch of mode. This is the information that must be clearly revealed to avoid ineffective or even erroneous policy measures that could be developed from the modelling results (i.e. if a factor induces a mode switch from car to non-car is however due to “preferring switch”, in other words, this factor will have the same impact sign on non-car to car switch, then any policies designed around this factor and aim to encourage a car to non-car switch may at the same time result in a mode switch from non-car to car). Hence, these mirror models will help to check if a factor’s impact on various mode switches to car is opposite or in the same direction to its impact on mode switch from car in the earlier model, and thus distinguish between “preferring mode” and “preferring switch” to better inform policy making. 2. Another benefit of a set of mirror models is that the differences in mode switching behaviour among different mode users can be revealed, i.e. a factor may only have a significant impact on some mode users and may be completely irrelevant to others. In other words, different and more targeted policy implications can be obtained when there is a need to persuade different non-car mode users not to switch to car as a regular commute mode.

Again, either binary or multinomial logit regression can be applied to set up the mirror models. Taking the bus user model as an example, the binary specification will classify the paired choice observations into two categories: bus to car and bus to non-car, while the multinomial specification can handle more alternatives by for example further splitting the above “bus to non-car” into “bus to bus” (the majority) and “bus to the rest” (though only a tiny proportion). We tested both specifications and the most important part “bus to car” shared the same results in terms of factors’ impacts on such a choice. Thus, we adopt the binary specifications for all the mirror models in order to simplify the result presentation while not losing any valid information and model explanatory power.

The variables that are used to explain the mode switching behaviour include life course events (dynamic) and socio-economic factors (static). The life course events are those presented in Table 7-2; besides, for commute distance change (both increase and decrease), we generate three sub-groups, i.e. (change by) less than 2km, 2km to 5km and more than 5km to explicitly assess how different degrees of distance change in an urban context would possibly affect mode switches. All life course events are studied with their impacts on mode switch observations in the same years. Oakil et al. (2011) also explored lead (one year before) and lag (one year after) effects of life course events in their mode switching models. However, we do not incorporate such effects in the analysis given the 2-year observation interval in our data which means the lead and lag effects are likely to be trivial. Three socio-economic factors are studied; gender, household income and home & work place (see Table 7-1). Mode switch availability conditions are also applied to the models, and they appear as that car, electric bike and bike can be chosen as regular commute modes only if an individual's household owns those vehicles.

Finally, given the fact that an individual often has more than one paired observations in the datasets, a standard logit mixture approach (McFadden and Train, 2000; Hensher and Greene, 2003) is applied to all models to account for any potential intra-person correlation. Eq. 19 presents the mathematical form of our mixed logit model. Model estimations are performed in BisonBiogeme (Bierlaire, 2003).

$$U_{in} = \sum_{k=1}^{K} \beta_k X_{ink} + \sigma_i \eta_{in} + \varepsilon_{in} \qquad (19)$$

where U is the utility associated with a mode choice, i is the choice alternative, n is the individual choice maker, X is the factor of explanatory variables and β is the estimated parameter. The intra-person correlation is captured by the error component η, and the impact is denoted by the standard deviation σ. ε is the error component i.i.d. Extreme Value and independent from η.

7.3 Results

Table 7-4 and 7-5 display the modelling results of mode switching from car and to car respectively. As an overview, the log-likelihood and the adjusted rho-square values imply a fairly good level of fitness of all the models. The parameter measuring intra-person correlation also has universal significance confirming the presence of individual-specific attribute which did post an unobserved effect on mode switching behaviour.

7.3.1 Model Estimation Results

In Table 7-4, with respect to the mode switching behaviour from car to non-car, almost all variables exhibit significant effects, except the life course event of having a child, which has a negative impact sign and is the only variable not meeting the 90% significance level. For the rest of life course events, getting married and encountering an increase of the household income also manifest a negative effect, which means both events are less likely to induce a shift to using non-car modes for regular commute. In comparison, positive effects on a switch from car to non-car are observed with the event of getting a fixed job and all the three cases of a commute distance decrease (i.e. by < 2km, by 2-5km and by > 5km). For the socio-economic factors, males and commuters from wealthier households would prefer to stick with car, rather than picking up any alternatives; however, if both the home and work place are inside the central districts of the city, people might be more willing to switch their commute modes away from car.

Table 7-4 Mixed Binary Logit Regression Result: Mode Switch from Car to non-Car

	coefficient	**t-statistic**
(The alternative: "car to car" is normalised to the base)		
Constant	- 2.48	- 12.27
Intra-person correlation (standard error)	1.76	6.50
Static variables (socio-economic factors)		
Gender (male)	- 1.64	- 6.15
Household monthly income (Above ￥6k)	- 0.50	- 1.94
Home & Work place (both central districts)	2.39	9.07
Dynamic variables (life course events)		
Got married	- 1.64	- 1.82
Had a child	- 1.22	- 1.40*
Got a fixed job	2.97	5.22
Increase of household income	- 2.17	- 2.64
Commute distance decreased by < 2km	3.66	3.28
Commute distance decreased by 2-5km	2.73	3.09
Commute distance decreased by > 5km	4.40	8.50
Model performance		
Number of obs.	1,110	

Initial log-likelihood	- 769.39
Final log-likelihood	- 251.10
$\bar{\rho}^2$	0.66
* Parameter does not meet the 90% significance level	

So far, we only described some facts of the modelling results without further elaboration. This is because a single model studying only the car to non-car mode switching behaviour cannot firmly tell whether the factors' impacts are due to "preferring mode" (i.e. different utilities on car and non-car modes) or "preferring switch" (i.e. different utilities on embracing changes and living with status-quo). Thus, we now introduce the results of the mirror models in order to further unveil the mode switching behaviour.

Table 7-5 shows the parameter values in the mirror models. Unlike the earlier "car to non-car" model in which most variables exhibit significant effects, there are many more insignificant variables in each of the four mirror models and are thus dropped out to avoid any model convergence problem. However, despite that part, the remaining significant variables do display consistency regarding their impact signs across the different mirror models and the analyses below will demonstrate whether these effects are due to "preferring mode" or simply "preferring switch".

Table 7-5 Mixed Binary Logit Regression Results: Mode Switches to Car

	Bus to car		**E-bike to car**		**Bike to car**		**Walk to car**	
	coef.	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**	**coef.**	**t-stat**
(In each model, the alternative: "not switch to car" is always normalised to the base)								
Constant	- 2.24	- 10.58	- 0.74	- 2.55	- 2.74	- 8.44	- 4.88	- 4.32
Intra-person correlation (standard error)	1.45	4.30	1.93	6.27	0.84	3.15	2.11	7.74
Static variables (socio-economic factors)								
Gender (male)	-	-	- 3.90	- 3.74	- 1.68	- 2.93	- 4.17	- 3.42
Household monthly income (Above ￥6k)	0.90	3.10	-	-	1.27	2.50	3.99	3.42

Home & Work place (both central districts)	- 1.09	- 3.24	- 2.79	- 3.30	-	-	-	-
Dynamic variables (life course events)								
Got married	-	-	2.63	3.08	2.81	4.45	7.23	4.78
Had a child	2.14	5.78	-	-	-	-	-	-
Got a fixed job	-	-	-	-	-	-	4.95	2.85
Increase of household income	2.35	6.89	2.96	3.13	1.89	2.89	2.76	2.23
Commute distance increased by < 2km	-	-	-	-	-	-	4.69	3.04
Commute distance increased by 2-5km	-	-	5.49	2.29	4.19	3.83	-	- #
Commute distance increased by > 5km	2.23	3.93	2.52	1.95	3.18	4.05	-	- #
Model performance								
Number of obs.	1,446		862		1,173		768	
Initial log-likelihood	- 362.52		- 114.37		- 225.97		- 175.37	
Final log-likelihood	- 175.88		- 52.80		- 72.33		- 23.53	
$\bar{\rho}^2$	0.50		0.48		0.65		0.83	

Note: insignificant variables are dropped out since there are many of them in each model and including them can lead to model convergence problems

Those two variables in the “walk to car” model have no displayed values; not due to the effects are insignificant, but they have limited number of occurrences in the data and cannot be properly modelled

Preferring Mode

Several life course events are associated with mode preference. “Got married” could significantly affect the mode switches from electric bike, bike and walk to car where bus to car is the only model in which the significance is lost. By comparing these positive impact signs with the negative impact sign in the earlier model, it can be identified that getting married is likely to make people start moving away from non-car modes to using car for regular commute; while if car users get married, they would possibly prefer sticking with car without switching to any non-car alternatives. The same conclusion can be made for having a child and encountering an increase of household income, where both events also have positive effects on the mode switches to car in the mirror models, and the effects are opposite to those in the earlier model, where negative signs are observed. However, it should be noticed that having a child is only significant in inducing bus users to switch to car, whereas a surge in household income has a universally significant effect in all four mirror models. Another life course event that belongs to “preferring mode” rather than “preferring switch” is the change of commute distance. Different degrees of commute distance increases are positively associated with the mode switches to car in the mirror models, whereas a mode switch from car to non-car in the earlier model is positively associated with commute distance decreases.

For socio-economic factors in the mirror models and the earlier “car to non-car” model, opposite impact signs are found on monthly household income and home and work place location, which means both of these factors are associated with mode preference. Specifically, car commuters with higher household income would like to stick with car usage, and non-car commuters with higher household income would prefer switching to car. For those settled themselves in the central districts, they are more willing to accept a mode switch from car to non-car, while the switch from non-car to car turns out as a less appealing option.

Preferring Switch

Only one life course event and one socio-economic factor seem to be associated with such a type of behaviour. In the earlier model, getting a fixed job could lead to a mode switch from car to non-car; in the mirror models, the effect also has a positive impact sign, though it is significant only in the walk to car model. The implication would be that getting a fixed job (i.e. from self-employed or student) may induce a switch of commute mode. However, both switching to and away from car could occur, possibly depending on the more specific travel needs which cannot be identified from the available information in our survey. Similarly, male commuters are found with negative impact signs throughout the earlier “car to non-car” model and the subsequent mirror models which could imply their relatively strong “reluctant to switch” characteristic compared to female commuters.

7.3.2 Discussions and Policy Implications

Like many travel behavioural studies, the modelling outputs could offer a bunch of insights to enrich the current literature. However, to what extent the insights could actually be taken away to inform policy making is always sceptical since in many cases the findings cannot be transferred into practical application due to various constraints. Thus, next, we will discuss each of the key factors in our models and evaluate their potentials in helping design policies with an objective to keep commuters away from car use.

Getting Married

There could be various reasons explaining why such an event would possibly induce a mode switch to car. For example, due to a car purchase activity which occurs frequently by getting married and thus resulting in an easy car access (Clark et al., 2016b), or due to a need to save commute journey time when starting to undertake additional family roles and as such switch to car given its faster speed, etc. In fact, the latter hypothesis could possibly reflect the results of our mirror models, in which getting married would make the users of electric bike, bike and walk switch to car, whereas its effect on bus users, who are probably more satisfied with the mobility of their status-quo mode, did not reveal any significance. Such a result could offer an opportunity for policy intervention. Although we cannot halt the mode switch to car by manipulating the occurrences of life course events, policy making could potentially step in from a tactical angle by encouraging the mode switch to bus. As such, when the users of electric bike, bike and walk get married, they could find their travel needs can also be satisfied by switching to bus. A very common policy practice to serve such a type of objective is the Voluntary Travel Behaviour Change (VTBC) strategy (Brög et al., 2009; Stopher et al., 2009), which usually consists of informational and marketing efforts to encourage a behavioural change (Clark et al., 2016a), for example in our case could be providing special rewards to new customers starting to use bus, in order to attract the regular electric bike, bike and walk commuters.

Having a Child

Recall that the event does not have a significant effect on the mode switching behaviour from car to non-car modes; however, a positive and significant effect is observed in one of the switching to car models. Oakil et al. (2011) also had a similar discovery and one explanation they proposed was, having a child would lead to stronger demand for travel flexibility, e.g. for baby's regular check-up or day care drop off and pick up, which is something car can offer. Moreover, further insight could be revealed by comparing across the mirror model results. Having a child is only significant in inducing bus and not the rest of mode users to switch to car, which implies that flexibility may not be the only concern in such a circumstance. The stronger willingness of bus users to choose car might be due to the dislike of public transport environment when travelling with baby in their commute trips (for drop-off and pick-up). Hence, encouraging new parents who used to commute by bus to switch to those non-car travel options could be a policy pursuit. For instance, subsidies could be offered to new parents for their purchases of cycling tools (e.g. e-bike or bike).

Getting a Fixed Job

Given the finding that employment status change could lead to both switching to and away from car, we prefer not to derive any policy implications at this stage until further research unveils the intrinsic factors that might result in such an outcome. Distance could be one of those factors after observing the significant impacts of commute distance changes on mode switching behaviour in our models (their policy implications will be discussed shortly). However, we did not study the potential interaction between the change of employment status and the changes of commute distance since there are not enough observations in the datasets. Besides, other intrinsic factors may exist and need to be investigated as well.

Increase of Household Income

This is the only factor that has a universally significant effect in all four mirror models. However, from a practical perspective, the results also imply none of the four modes can be a competitive alternative to car when commuters become wealthier and therefore the room for policy intervention would be limited.

Changing Commute Distance

An increase in commute distance could make non-car mode users start to prefer car; however, different non-car mode users would be affected by different degrees of increase. Bus users tend to switch to car only if the distance increase is large (by more than 5km); the two cycling mode users tend to switch to car under a smaller threshold (by 2km to 5km); finally, commuters on foot can switch to car even when there is a relatively small degree of increase (by less than 2km). It seems that such a trend is in line with the travel speed of each non-car mode. As for the implications for policy making, bus users could potentially stay with bus, if for example they can be rewarded for making long-distance bus journeys. One solution is introducing a flat or even a diminishing bus pricing scheme with respect to journey distance so that the incurred longer travel time by bus comparing to which by car can be compensated in terms of a cost-saving, though whether the implementation is feasible or whether any side-effects would arise should be carefully studied by relevant research. By having a commute distance increase, persuading cyclists and on-foot commuters to stay with their original mode choices would be a trickier task since many more pain-points will get involved, e.g. physical fitness, comfort and safety concerns, which cannot be easily addressed by policy intervention. Thus, from a practical perspective, it might be more effective to encourage a mode switch to bus, for example via the aforementioned VTBC strategy by offering new-customer rewards to the cyclists and on-foot commuters who are willing to make a switch. Besides, for the two bicycle modes in particular, efforts could also be made towards the integration with public transport system (e.g. carrying foldable bikes on bus / placing bikes on the attached racks, both measures have already been adopted by many cities across the globe), which may offer another solution to handle a commute distance increase.

Socio-economic Factors

The three socio-economic factors in this research are studied regarding their linear effects on mode switching behaviour. A more sophisticated approach would be evaluating their interaction effects with life course events to better reveal the mode switching pattern, i.e. whether a socio-economic group would be affected more/less by a particular life course event and hence more realistic policy implications can be obtained (Scheiner, 2014). However, due to our data constraints that the number of interaction observations is very limited, only linear effects can be properly modelled. In fact, the data constraints by only having a small number of observations on life events or mode switch occurrences seem to be a universal issue given its presence in earlier studies as well (Oakil et al., 2011; Clark et al., 2016a; Klinger, 2017). Future work that can overcome such a data challenge could potentially be of significant contribution to mode switching research; meanwhile, a broader range of socio-economic factors, such as age, educational level and household size, could also be explored when relevant data is collected.

7.4 Conclusions

This work offered a mode switching analysis using a retrospective survey data. The impacts of a variety of life course events were investigated and the corresponding implications for policy making were discussed. The survey data had a panel structure by capturing a group of Chinese citizens' main commute mode choices in four observation periods. A mixed binary logit regression model was developed at first to study the mode switching behaviour from car to non-car modes between a precedent period and the period followed. A set of "mirror models" were developed next to reveal the mode switches from each of the non-car modes to car. The mirror models also had a binary structure with the logit mixture to capture intra-person correlation.

It was revealed that getting married, having a child and encountering an increase of household income could induce a mode switch from non-car modes to car, while car users who experienced these life course events would prefer sticking to car as their regular commute mode. Similarly, an increase in commute distance would make people more likely to switch to car, whereas a decrease would make people switch away from car. The only event that is not associated with a clear mode preference is getting in a fixed job, which could result in both switching to and away from car, and further research would be needed to explore any intrinsic factors that might result in such an outcome.

Moreover, the mirror models also revealed the differences in mode switching behaviour among different non-car mode users, and corresponding policy implications were subsequently derived. To prevent the commuters using electric bike, bike and walk from switching to car when they get married, it could be useful to encourage the mode switches to bus which may also be able to satisfy their travel needs, since the bus commuters who get married are not found with the same level of desire to switch to car. Possible informational and marketing measures could be introduced to facilitate such a mode switch to bus. In comparison, bus users would be more willing to pick up car when they have a child, whereas the rest of non-car mode users seemed to be indifferent to such a switch towards car when experiencing child birth. Thus, measures could step in to encourage an opposite switch this time (i.e. bus to cycles or walk) via, for example, subsidies to new parents for their purchases of bikes and bike-related equipment. Another event that could lead to useful policy implications was a commute distance change. Bus commuters would switch to car only if the distance increase is large (by more than 5km); e-bike and bike users would switch to car under a smaller threshold (by 2km to 5km); commuters on foot could switch to car even when there was a small increase (by less than 2km). As a result, a rewarding scheme would probably be needed for undertaking long-distance bus journeys to prevent bus users from switching to car. Meanwhile, persuading cyclists and on-foot commuters to switch to bus rather than staying with their status-quo choices would also be recommended, since an increase in distance could result in more pain-points that cannot be easily addressed by policy intervention (e.g. physical fitness, comfort and safety concerns). Finally, when discussing these policy implications, attempts were also made to provide possible explanations for the differences in mode switching behaviour among different non-car mode users (i.e. why an event could have a significant effect on some mode users and not on the others). However, they are still at a hypothetical level and this would also be an opportunity to build up further research.

Several socio-economic factors were also studied. In particular, males were found to be more reluctant to make a switch to other available travel options (either from car to non- car and from non-car to car) comparing to females. However, due to data constraints, any interaction effects between socio-economic factors and life course events were not modelled. This is an area that should be studied in the future in order to acquire more targeted policy implications.

Besides, not only with socio-economic factors, life course events per se could also be inter-connected across each other. For example, the event of receiving a fixed job may occur simultaneously with a commute distance change, as in the case of this work. Such an effect could be disclosed once more life event observations become available (i.e. through more waves of longitudinal data, or more individuals in a larger sample), so that a good number of interacted events can be captured and modelled. Another strategy is to isolate any potentially correlated events by extracting a subset of observed cases to explicitly study their independent effects, e.g. via developing different groups of models or implementing a sensitivity test (see Clark et al., 2016), which could be explored by future research with a specific interest in such a topic.

CHAPTER 8. CONCLUSIONS

In this chapter, we would like to make some concluding remarks for the thesis. We will start by reviewing the work completed in each of the individual chapters to show how the earlier proposed research questions have been answered. Next, the focus will be put on a comparison between the results obtained in this thesis and the results from existing literature for developed countries. Then, based upon the findings we have gained in this work, an overall evaluation will be made on the contributions and wider implications of this research to the real world. In the end, we will review some key limitations associated with the data and the analysis methods used. Moreover, while talking through all these subjects and issues, opportunities for moving forward and pathways for conducting future studies will also be discussed.

8.1 A Quick Review of the Work

This thesis delivered a mode choice study with specific attention being put on the fast-developing shared mobility services, and in particular on bike-sharing and car-sharing. In the beginning, four important knowledge gaps plus a general lack of understanding on mode choice behaviour in developing countries were recognised and discussed, which helped to set up the context for this research. Hence, we proposed four research questions which we aim to provide answers through this work, to better understand how to encourage the use of shared mobility services in the developing world, while in the meantime to effectively control private car usage.

We conducted four chapters of research, each with a specific research objective, to answer the aforementioned questions. Chapter 4 and 5 studied the factors that could affect the mode choices of bike-sharing and car-sharing respectively, and their corresponding modal substitution patterns. In Chapter 4, the results revealed, in particular, the significant negative impact of air pollution on choosing bike-sharing as the travel mode. Nevertheless, via a policy impact analysis which revealed the modal substitution pattern (Table 4-7), it was found that improving air quality was actually less effective in promoting bike-sharing ridership than making some direct improvements on bike-sharing service (e.g. through access time saving, travel cost saving), though the measure could still be effective in helping reduce the dependence on using private car for short-distance trips. Besides, we developed both NL and mixed NL mode choice models using an SP alone dataset, as well as a pooled SP/RP dataset to find out which model specification and which dataset would possibly lead to the most robust results. Eventually, the mixed NL model based on the pooled SP/RP data turned up with the best performance, which also offered guidance for the model development in Chapter 5 regarding car-sharing choice.

In Chapter 5, by using pooled SP/RP datasets, two mixed NL mode choice models were developed to study car-sharing choices under mid-dist and long-dist trip cases accordingly, and to explore if the results differ by distance. With a core objective of promoting car-sharing while suppressing private car usage, some critical insights for policy making were obtained via a policy impact analysis (Table 5-8 and 5-9) and the derivation of several behavioural indicators (e.g. VTTS, direct and cross point elasticity). It was found that raising the cost of private car usage (travel cost, parking cost) should be prioritised for shorter trips since car would be more difficult to be substituted when trip distance increased. Shorter trips also need such direct measures to help suppress the demand for private car when promoting a car-sharing service; otherwise, car-sharing would attract more bus users instead. Longer trips (within the city radius) need a more effective solution to bring down private car usage, and that was discovered as making car-sharing service more appealing so that it could serve as a viable substitute for private car.

For more information on any differences of the factors’ impacts on shared mobility choices between the case in a developing country and developed world, we leave it to the next section 8.2 for a more detailed discussion.

Regarding the third research question, Chapter 6 brought in attitudinal effects on the choices of using bike-sharing and car-sharing services. Specifically, we adopted an ICLV modelling framework to explore the effects of three attitudinal factors on bike-sharing and car-sharing choices, while simultaneously investigating the causes associated with each of the attitudes. A group of commuters’ SP mode choice data was used. It was found that the probability of choosing bike-sharing could be positively affected by the attitudes towards “Willingness to be a green traveller” and “Satisfaction with cycling environment”; while car-sharing choice was positively correlated with the attitude towards “Advocacy of car-sharing service”. By taking into account the interaction effects between the attitudinal factors and travel time of the two services, a significant difference was discovered on the estimated VTTS comparing to the case of not having attitudinal factors in the model or adding attitudinal factors linearly in utility functions. The findings highlighted the need to derive different VTTS for travellers with differentiated attitudes, as the tastes towards travel time spent could vary substantially (Table 6-6; Figure 6-5 and 6-6).

Chapter 7 addressed the last research question on the habitual-level policy opportunities for controlling private car usage. Retrospective commute mode choice data over four observation periods (2006, 2008, 2010, 2012) were collected to analyse individuals' habitual mode choice changes. Binary ML models were developed to study first the mode switching behaviour from car to non-car modes and then the mode switches from each of the non-car modes to car. It was found that different non-car mode users do have different mode switching behaviour by observing their distinct reactions to life course events, especially towards getting married, having the first child and different degrees of commute distance change. A thorough discussion on how to make use of these results to serve policy design was provided in the end.

8.2 Comparisons between Developing and Developed Countries

Some earlier studies have revealed the difference in travel behaviours across different case study locations (Barnes and Krizek, 2005; Tang et al., 2011; Maurer, 2012; Kamargianni, 2015; Faghih-Imani et al., 2017); however, these studies focused on areas in developed countries. As such, it is insightful to explore if there are any differences in travel behaviour between the developing and the developed world in general. By reviewing the factors that have been investigated in the previous chapters and their effects on shared mobility and other mode choices, we see that most of the factors demonstrate consistent effects to those already identified in the existing literature for developed countries. These broadly include a variety of natural environmental conditions as well as trip and mode attributes. Nevertheless, a key difference did emerge from our results, and that is about the impact of socio-economic factors.

Such a type of factors would usually pose a significant influence on mode choice and other forms of travel behaviour; however, it was not the result in this work. When specifying mode choice models in earlier chapters, we analysed systematic taste heterogeneity rather than the traditional linear effect of socio-economic factors. This is due to insignificant coefficient values were extensively observed when including the variables linearly in utility functions, while systematic taste heterogeneity substantially increased the overall model fitness. Eventually, as our results in Chapter 4, 5 and 6 have shown, several socio-economic factors demonstrated their effects on mode choice behaviour by significantly interacting with a few other attributes; but meanwhile, there were far more interaction effects that have turned out as insignificant and were thus dropped out from model estimation and presentation.

One explanation, as we mentioned in the survey design in Chapter 3, could be that our sampled respondents occasionally shared close socio-economic characteristics (e.g. those with similar ages, educational background and income levels when they were from the same work place). As a result, when the variations across individuals are limited, it is possible that we could find the influence from the socio-economic side less significant.

However, this may not be the whole case, as a few more results from developing countries (though mostly from China as well) have also shown the links between socio-economic characteristics and mode choice behaviour are weak, which may imply a behavioural difference between the developed and developing countries. For instance, we discovered in Chapter 4 the choice of bike-sharing was not significantly correlated with any of the socio-economic factors either linearly or via the form of systematic taste heterogeneity. The finding is very much consistent to which from a case study in Beijing, China (Campbell et al., 2016), as the authors also showed in their mode choice analyses the users of bike-sharing service could arise anywhere from the social spectrum, rather than from any specific demographic groups. Besides, there has been more evidence coming up. Another case study in Beijing looked at the general commute mode choices among teenagers going to schools (Li and Zhao, 2015). They studied a variety of socio-economic factors at both individual and household levels, and the model outputs revealed that for trips within 3km some effects were insignificant while for longer trips (over 3km) most of the socio-economic factors appeared to be insignificant. Feng et al. (2017) also discovered very close findings via a case study in Nanjing, China. The work proposed a relatively novel conclusion such that the impact of ‘classic’ socio-demographics on travel behaviour would diminish over time after they modelled a set of repeated cross-sectional survey data from different years. The authors made a further attempt trying to interpret why nowadays in China, it is more likely to see socio-economic factors being redundant in directly explaining people’s travel behaviour. Since the interpretation may not only serve the case of China, but possibly also the wider developing world, we would like to quote this part from the article in order to deliver a full idea:

> “*Apparently, people could have more opportunities including growing financial resources, more specialised destinations and transport mode choices to choose from due to economic growth, spatial transformations and heavy investment in public transport and therefore more diversified travel behaviour are observed. In the wake of more and more individualised and affluent societal contexts in current China, the objective socio-demographic factors, like gender, age and education, seem eminently possible to lose weight as determinants of travel behaviour while the influences of lifestyles and preferences or, to put it more generally, the subjective side of travel behaviour, which has long been neglected in transport studies are expected to become more and more prominent.*” (p.8)

Putting it in other words, developing countries such as China and others have been embracing a much faster pace of development and changes nowadays, compared to countries from the developed world. Hence, not only could the subjective side of lifestyles and preferences increasingly affect travel behaviour (Feng et al., 2017), but also the fast-changing urban contexts, transport service supplies and operations as well as the policies and measures released by governments and transport operators could all heavily influence the environment and surrounding conditions that people would rely upon to make any behavioural decisions. As such, the effects of socio-economic factors could easily become less significant, or, at least, less likely to be observed and captured.

Nevertheless, we should still be critical to such a view even though the findings from several earlier works, and including this thesis, suggested the same fact. First of all, even if individuals’ lifestyles and preferences may play a more important role in determining people’s travel behaviour, what could explain the different lifestyles and preferences may still come back to individuals’ socio-economic characteristics. We have identified such a type of correlation when studying the attitudinal influence in Chapter 6, i.e. in the structural equations, several socio-economic factors including gender, age, educational level and household income were found to be the key determinants that could explain the different attitudes among individuals. Another noteworthy fact is that although the aforementioned studies indicate the universal insignificance of socio-economic effects on mode choice behaviour, there are other studies suggesting the impact of different socio-economic factors could vary case by case as per their findings from mode choice studies in a number of different developing countries including China, India, South East Asia and the Arab world (Elias et al., 2015; Le Loo et al., 2015; Munshi, 2016; Shen et al., 2016; Ji et al., 2017; Sun et al., 2017; Wu and Hong, 2017). Therefore, even though the aforementioned rapid changes and trends of development do widely hold in today's developing countries and can intuitively explain the insignificant socio-economic influence (Feng et al., 2017), a macro-level conclusion suggesting a general difference between the developing and the developed world must be treated with caution. The question to what extent travel behaviour could be associated with socio-economic factors, is shown by this work and the others as context-sensitive indeed; but if there could be any rather common behaviours among people in developing countries would require more research; especially given, the still, very limited number of mode choice studies in the broad developing world.

8.3 Contributions and Wider Implications

First of all, the findings in the thesis can help fulfil several knowledge gaps to the current mode choice literature. To our knowledge, it is one of the first works (alongside Campbell et al., 2016) that disclosed and confirmed the effect that air pollution could have on mode choice behaviour. In particular, it quantitatively revealed the extent to which an improvement of air quality could be able to boost the demand for using bike-sharing when comparing to the standard measures focusing on upgrading the attributes of bike-sharing service. The thesis also provided in-depth evidence regarding the sources that the demand for car-sharing would potentially come from. Specifically, the results were found to vary substantially by trip distance, i.e. the service would be more easily to attract private car users in longer trips, and such a trend could also give feedback to a recent finding that the competitiveness of car-sharing would increase with trip length (Martinez et al., 2017). Moreover, the study enriched the current literature on how shared mobility choices could be correlated with choice makers' own attitudes, while also demonstrating the importance of taking into account individuals' differentiated attitudes in VTTS estimation. Furthermore, the work extended the results on habitual mode switching behaviour from few earlier binary analyses, i.e. car to non-car and non-car to car (Oakil et al., 2011; Clark et al., 2016a), by further revealing the different mode switching behaviour from several different non-car mode user groups. Overall, all these fresh findings could help improve our current understanding of people’s mode choice behaviour.

Next, based upon the detailed policy insights that have already been discussed in each of the individual chapters, we would like to explore here any wider implications of the findings and insights for the real world. The correlation between air pollution and mode choice behaviour could theoretically imply a “virtuous circle” that we proposed earlier (i.e. better air quality could result in higher demand for using non-motorized transport, and higher non-motorized transport usage could further reduce air pollution). If so, there could be extra societal benefits by controlling the air pollutants from industrial and other sectors, as it would indirectly help to encourage the demand for using bike-sharing and other non-motorized travel options. In fact, what happened in the city of Beijing during the last year inspired us for coming up with such a thought. Beijing has been well-known for its extremely severe urban air pollution problem for over two decades at least. Interestingly, the air quality drastically improved in 2017 (BBC, 2018; Telegraph, 2018), even though some moderate improvements could be seen from a few years before. Two incidents also occurred in the same year. Hundreds of factories in Beijing and in 27 cities nearby were forced to shut down, suspend or curtail production; an unsustainable but strongest-ever government action in this kind, in order to quickly eliminate air pollution in the capital (BBC, 2018). Meanwhile, Beijing’s bike-sharing usage exploded to a wild scale in 2017 since some big bike-sharing companies, such as Mobike and Ofo, entered the city in 2015 (Campbell, 2018). Although, without scientific proof, we cannot tell to what extent has the air pollution reduction helped to boost the bike-sharing usage and to what extent the bike-sharing trips has further contributed to air quality improvement, it at least raised an interesting case for looking into such a potential “virtuous circle”. Further research would be welcome to provide more in-depth insights.

Car-sharing, at the moment, is not widely used in China and other developing countries, but the service is expected to grow rapidly (Dhingra and Stanich, 2014; Carrigan, 2015; Alam, 2016) and as our findings have shown, it could potentially bring down private car usage, if appropriate policy measures could steer from aside. However, the findings could lead to a further question that when private car users find car-sharing appealing to travel with, will they scrap or give away their own cars? This is a rather important issue because short-term travel decisions sometimes can be conditional on long-term travel decisions (Ben-Akiva and Bierlaire, 1999), such as the adverse effect of owning a car on the preference of using car-sharing to make a trip (Celsor and Millard-Ball, 2007; Le Vine et al., 2014; Ciari et al., 2016). Hence, as long as car ownership remains unchanged, there could be doubts around if the car-sharing supporting policies at a tactical level would have stable or long-term effects. Although optimistic results have been found regarding car-sharing’s contribution in helping reduce car ownership (Cervero et al., 2007; Loose, 2010; Martin and Shaheen, 2010; Martin et al., 2010; Mishra et al., 2015; Bondorová and Archer, 2017; Vij, 2017), debates are still there such as people are found reluctant to change car ownership while enjoying using shared car services at the same time (Kim et al., 2015), or the ownership change is heavily conditional on how frequent people use car-sharing (Le Vine and Polak, 2017). Besides, as our research extended the focus and discussion to the broad developing world, to what extent these results from developed countries could hold or change may still require further investigations.

Moreover, the car-sharing choice analysis has raised implications for VTTS estimates, followed by an ICLV modelling analysis in the subsequent chapter trying to disclose more insights on the variations of VTTS among individuals with differentiated personal attitudes. One issue is worth to be noticed in those VTTS calculations; most of the mode choice studies that wish to obtain value of time related measures normally would adopt a generic parameter across all alternatives for estimating travel cost’s effect on mode choices. This is due to the standard way to calculate VTTS would need the measurement of marginal utility of income, and one could use its ‘minus’ instead, i.e. the coefficient of travel cost in the context of mode choice analysis. Hence, a generic travel cost coefficient can serve as a consistent representation of income. However, in mode choice studies, an alternative-specific measurement of travel cost’s effect is also a common practice, which was adopted throughout this thesis as it outperformed the specification with the use of a generic parameter in all of our models, and the VTTS estimates were obtained accordingly. Although, under this way of calculation, VTTS may no longer be suitable for project appraisals which need a unitary travel cost (or in turn, income) measurement to derive the expected monetised benefits to society, the values calculated using our strategies can potentially be more accurate in supporting policy designs at an operational level. Travel mode operators are normally interested in understanding how much individuals would be willing to afford a travel cost increase for each unit of their travel time saved, and hence making adjustments on prices and levels of service offered. Both strategies (generic & alternative-specific) could generate the results; however, in many cases, a generic travel cost parameter could compromise model performance by not revealing its potentially differentiated effects on different alternatives. As a result, for transport service operators which are more cared about the substitution pattern between the two factors, VTTS that takes into account alternative-specific effects of travel cost and time could potentially be of greater values by reflecting travellers' mode choice behaviour in a more accurate way. In fact, there have been practices performing VTTS estimation using alternative-specific travel cost coefficients instead (Polydoropoulou et al., 2013; Kamargianni et al., 2015), and more attention could be made in future on the evaluation of such a strategy in supporting operational policy designs and hence test our hypothesis.

In the very end, the work attempted to provide complementary insights from another perspective on how to reduce private car usage. Since life course events were found being able to trigger the habitual mode switches to/from car, it would be worth asking further that if there could be other types of events (i.e. not 'intrinsic' as those directly related to individuals) also having such effects, and more importantly, bringing more policy insights. By making hypotheses broadly, many substantial changes such as those in land use, in transport network and other built environment conditions, in transport service accessibility and even any persistent changes in an area's general weather conditions, may all possibly result in changes in mode choice habits. In fact, if studies can capture some of these 'extrinsic' events in mode switching analyses, we expect there could even be more rooms for policy design. It is especially the case for developing countries, where the built environments, transport supplies and a lot other contextual aspects are currently in massive and rapid transitions and reforms. As such, interventions could have more opportunities to step in and hence pose an influence on people's mode choice habits. Moreover, when evaluating those 'extrinsic' events, their potential interactions with, not only the socio-economic factors but also the 'intrinsic' events (i.e. life course events), should be taken care of. For example, if a public transit station/stop was opened to use, car users who lived nearby might or might not switch to this public transport service, possibly depending on if they had children recently or if there were changes in their employment and income status, etc. More research would be needed to shed light on the expected interactions among these events.

Overall, in this thesis, we aimed to offer some insights on how shared mobility, in particular bike-sharing and car-sharing, could potentially affect modal split pattern, which is a key component in transport demand forecast. However, a further question we could ask is, when shared mobility services continue to expand and are more extensively used in the future, could this have an impact on some other aspects, such as trip generation and distribution, in transport demand forecast. This is a subject that also lacks research at the moment, although we could more or less expect some ways of influence. For example, for the number of trips generated in a region, on the one hand shared mobility services could largely enhance the general transport accessibility (e.g. through providing shared car/bike stations or service spots, which could further connect to public transport), while on the other hand they may help reduce vehicle ownership as per some earlier reviewed evidence; both of which are frequently observed trip generation factors (Jamal, 2017), although one may have a boosting effect (general accessibility) while the other having a suppressing effect (vehicle ownership). Overall, future research could be brought in to explore the wider impact of shared mobility, especially when we have a mixed expectation such as in the above example, in order to provide clearer evidence and hence to better inform the demand forecast.

8.4 Limitations on Data and Analysis Method

We have occasionally touched upon some of these technical-level limitations throughout the earlier writing of individual chapters. Nevertheless, a summary is provided here for an overall discussion of some key limitations associated with the data and analysis methods used to conduct this research.

Regarding the survey design and data collection, several issues have come across, and improvements could be considered when future studies come around. SP choice experiment is an important source of data for works that are interested in evaluating the effects of new alternatives and new attributes which are about to be brought into the market (such as car-sharing in our case). A good design of an SP survey could often help improve the efficiency in choice model estimation. We applied the orthogonal design for this case study as it has been a robust and widely used approach for many years. However, we have also mentioned that the various forms of efficient designs, which are commonly regarded as the state-of-the-art techniques nowadays, were not applied in our survey given the constraints we had on project cost (i.e. more advanced software such as Ngene is usually needed to handle an efficient design). Future SP surveys could evaluate whether or not using efficient designs would be feasible on their own practices; especially the so far most advanced Bayesian efficient design, which, on the one hand, allows random variation when assigning prior values to the parameters to be estimated, but on the other hand, requires much greater computational efforts compared to other simpler efficient designs (ChoiceMetrics, 2018). Nevertheless, there are some latest arguments coming up as well, questioning how much those efficient designs may benefit a choice analysis even comparing to the traditional orthogonal and random designs; flexibility could be allowed in choosing the different design techniques as the effects on model estimation could vary case by case (Walker et al., 2018).

Apart from the method of an SP survey design, the elements inside, such as what alternatives and what attributes could be included, may also be improved from our current case. We noticed the opportunity at a later stage after the data collection. In particular, there are two important elements which we missed, but are expected to bring along useful insights if they could be captured by similar research in the future. Firstly, we did not include ride-hailing as an alternative mode in the SP choice set. At the time of our survey, there were severe debates in Taiyuan, alongside many other cities in China, on if the emerging ride-hailing services such as DiDi should be banned, after receiving massive protests from taxi drivers. In fact, the ban was activated in Taiyuan in just a couple of months (Mo, 2016). Therefore, we excluded ride-hailing from our SP survey due to both its small market share back then (the service just started to operate) and the uncertainty around how long the service could survive under government pressures. However, later, bans had been eventually removed in Chinese cities and the service has been developing fast since then. It is therefore crucial for future research to include ride-hailing as an alternative, when designing similar SP surveys for developing countries, as such a service may significantly affect people's preferences on other modes, given its continuously increasing demand nowadays. Secondly, in the current SP survey design, we assigned smartphone-based application as an individually available attribute to some transport services (e.g. bus, taxi, bike-sharing and car-sharing). These mode-specific attributes were then analysed in mode choice models, and the results indicated a generally significant effect of app availability on the preferences of different modes. Such a finding may bring in another issue that is worth to be considered. As the mode-specific smartphone-based applications could attract people to use the corresponding transport services, will a multimodal service app be a valuable contribution to the market? This is something that could be studied by SP surveys in the future, via including a multimodal service app as a general attribute related to each of the alternative modes in a choice set (even for walking, e.g. through providing routing and travel time information, as many journey planners do nowadays), to test its effect on mode choice behaviour, which could be of greater value to the market.

Moreover, by thinking of combing the SP data with RP mode choice data, another research that could be worth doing in similar types of work is to forecast the modal split changes in a real-world context, for example, how the entry of car-sharing would affect the current modal split pattern in Taiyuan, which could provide more direct insights to help design the relevant demand management policies. Our studies in Chapter 4 and Chapter 5 offered an opportunity for doing such an analysis. However, a critical barrier that we have encountered is the availability of modal split data at a city level in the case of Taiyuan. Since the data is not open to the public, we cannot verify to what extent the collected RP trip diary data would reflect the exact modal split pattern in Taiyuan. As a result, it would be highly uncertain if a demand forecast in the RP environment would contribute much in supporting policy designs in the real practice. Meanwhile, this is also why the earlier analyses relied mostly on the use of SP data as it collected a more extensive range of attributes that could be investigated, while only using the RP data as a complementary input.

With regard to the remaining part of the survey, some information was also inadequately gathered and more or less posed an influence on the amount of research we can deliver in this work. For instance, in Chapter 6, we extracted and studied three attitudinal factors from the statements scored by our survey respondents. However, recall in the earlier conclusions that perceptions are generally better for policy use as they are mode-specific and could more easily react to policy measures altering mode-related attributes (Chorus and Kroesen, 2014;

Bahamonde-Birke et al., 2017). Therefore, it would be worth including more perceptual statements in future studies to derive more practical implications for policy making. A few statements in our survey were designed to capture people's perceptions of specific travel modes. However, the actual responses we collected from the sample eventually, did not allow the factor analysis to formulate any significant perceptual factors that could be studied.

Another part of our research that suffered from a lack of collected information is the retrospective survey. It could be more insightful to study the interaction effects between life course events and socio-economic characteristics. As such, it can reveal the extent to which different socio-economic groups would react to a particular life course event and hence more targeted measures can be introduced to affect their different mode switching behaviour. Unfortunately, the number of interacted observations in our sample was too small to support such an analysis, though data limitation has appeared to be a rather common challenge among today's mode switching studies (Oakil et al., 2011; Clark et al., 2016a; Klinger, 2017). Hence, in general, any future works that could gather a good number of observations on life course events and mode switch occurrences would potentially be of significant contribution to the research in this field.

As for the modelling side, one common challenge in discrete choice modelling when the complex model construct is involved, would be the lengthy modal estimation time; possibly taking days or even weeks with the standard computation devices that most modellers could have access to. This is especially the case in Chapter 6 where we developed an ICLV model with three latent variables and a simultaneous model estimation structure. In particular, the model also involves the use of a logit kernel as well as a maximum simulated likelihood inference approach; both of which are the standard practices and have been widely applied in studies on similar topics. However, an alternative way to specify an ICLV model may be considered in the future, and that is to develop an ICLV model using a probit-kernel and also performs the estimation using a new inference approach, namely maximum approximate composite marginal likelihood. Such an approach has been proposed by Bhat and Dubey (2014), where they applied both techniques to a typical ICLV framework (i.e. there is only a single nominal variable which is the choice set), and was further generalized for broader applications by Bhat (2015) in which the techniques were ready to be applied to a framework that jointly handles mixed types of dependent variables (i.e. multiple nominal, ordinal, count and continuous variables). The new inference approach they proposed may significantly shorten the model estimation time, since it requires no more than bivariate normal cumulative distribution function to be evaluated for likelihood maximisation (Bhat, 2011). Meanwhile, the dimensionality of integration in the likelihood function is independent to the number of latent variables, which could also help ease the workload when importing three or more attitudinal factors to the model (Kamargianni et al., 2015). Moreover, unlike the logit-kernel, a probit-kernel would offer a more flexible covariance structure of error terms without exhibiting the IIA property (i.e. independence of irrelative alternatives), which brings it potential to directly account for any inter-alternative correlations, instead of the need to introduce a nested model structure as we adopted in this research. It should also be pointed out that the maximum approximate composite marginal likelihood inference approach usually works more smoothly with a probit-kernel since additional computation efforts would be needed if estimating with a logit kernel, which requires a normal scale mixture representation for the extreme value error terms (Bhat, 2011). We have attempted to apply both techniques and based upon which to perform the estimation of our ICLV model. However, it would require relatively complex coding inputs in a unique programming environment (GAUSS) and also appeared as less capable in handling the 7-point Likert-scale indicators (as we have in our data) when specifying the measurement equations in the latent variable model. Eventually, we followed the conventional strategies, even though they cost an extremely long computational time during the model estimation.

8.5 Embracing the Future: A Last Bit of Thinking

The discussions above have shed light on where to move forward and on some of the opportunities for conducting further research; either through exploring a broader range of issues or improving the research design per se. However, a final remark we would like to make is regarding how this study can fit itself in the future era. In other words, if similar research is carried out in the coming decade, what new features and what new implications could possibly be attached to the work.

The era we live in at the moment is flooded with innovations and technological advancements. As we foresee, there are several aspects from this work, could interact with a number of hot topics in today's transport sector, such as the use of mobile phone or call detail record data to retrieve travel information, the role of virtual reality in SP choice experiment design, the emerging concept of Mobility-as-a-Service and the upcoming autonomous vehicle era.

Instead of the traditional survey approach that actively collects individuals' travel information, e.g. by filling a trip diary, the passively-generated mobile phone data could potentially offer more precision on the information collected and a larger volume of observations to be studied (Chen et al., 2016). Although people may question that transport activities are not directly revealed by mobile phone data, strategies have been developed to help derive this information, e.g. by asking mobile phone users to report and verify their transport activities (Matyas and Kamargianni, 2018a) or by systematic data inference approaches (Alexander et al., 2015; Toole et al., 2015; Jiang et al., 2017). Hence, we do expect the RP data used in future mode choice research to come more frequently from mobile phone, rather than the traditional trip diary record. As far as we know, China, as a country from the developing world, has planned for a massive use of mobile phone data in future travel demand forecast for several big city clusters. In order to access the data, an advantage that developing countries possibly have at the moment, compared to developed countries, is that data privacy is less concerned when collecting individuals' mobile phone data. However, this also indicates the need to take care of issues around data protection, before mobile phone data can become a standard practice and completely replace trip diary surveys.

The way of how SP data is collected could also vastly change in the future. When people are invited to participate in an SP choice experiment, they may not correctly perceive a choice situation that is presented to them using descriptive texts. This is why sometimes we could see inconsistent choice behaviour lying between SP and RP data. Attempts have been made for example by using graphical presentations instead of descriptive texts to visualise a choice situation, and as such to help people better understand the choice situation that they are put in (e.g. Kamargianni and Polydoropoulou, 2013). However, these strategies can still be difficult in handling people's misperceptions on elements which never yet exist; this can either be new attributes that could be added to the current alternatives, or new alternatives that are about to be introduced in the market. Fortunately, given the technology burst, an increasingly popular concept may help solve the issue, and that is called virtual reality. It is not difficult to imagine how it looks like when people are making choices in an SP experiment by wearing virtual reality devices. In particular, people can now have a visualised and clearer idea on those elements which never yet exist, and hence more likely to make a fully informed choice. Recently, such a practice has started to be tested and the preliminary results do indicate significant improvements in people's perceptions, showing a promising future for integrating virtual reality and SP choice experiments (Farooq et al., 2018).

Mobility-as-a-Service has been a widely discussed subject in last years. It offers a model that brings together mobility service providers and individual travellers who can now seamlessly plan, access and pay for mobility through a single platform (Kamargianni et al., 2018). A core product that Mobility-as-a-Service is expected to offer is the different service plans, which bundle mobility services in different ways, e.g. there could be different amount of usage of each mobility service in different plans, so that customers can choose which one plan to subscribe as per their travel needs and preferences (Matyas and Kamargianni, 2018b). In the future, this could imply an increasing demand for research on customers' mode use preferences, especially the preferences towards shared mobility services, which are likely to be the key offerings in a service plan. Hence, when the era of Mobility-as-a-Service comes, the results and insights that we gained from this work could still be of great use, for example, in helping the design of Mobility-as-a-Service plans.

Besides Mobility-as-a-Service, the fast development of autonomous vehicles could lead us to another possibly upcoming era. However, there are conflict views regarding in what ways autonomous vehicles would change our current travel behaviour. Although the vehicles can certainly be integrated into car-sharing and public transport systems, there are also concerns around what if autonomous vehicles made private cars a more appealing travel option (Röhrleef et al., 2015). In fact, given such a context, the work we have done in this thesis could potentially be of greater values. This is because our topic is about how to make shared mobility services more preferred by travellers, in order to pull them away from using private cars. As such, if efforts could be made today to persuade more car users to take up shared mobility or even public transport service, then over time as the mode choice becomes a habit, we would be more likely to embrace an era of autonomous vehicles by having people traveling in automated car-sharing and public transport systems, rather than seeing roads flooded with private automated cars.

All in all, a discussion around how this study may interact with the above issues is simply inspired by seeing the burst of technologies in today’s world. There could be other issues involved as we move forward and see more innovations coming up.

APPENDIX A: An Example Questionnaire

UCL ENERGY INSTITUTE

SXTI Planning Institute of City and Comprehensive Transportation

Taiyuan Citizens' Transport Mode Choice Survey

（Anonymous）

- The questionnaire is suitable for all Taiyuan citizens.
- The questionnaire has six sections, please follow the instructions.
- The data will be used for academic purposes only.

Questionnaire No. ______
Date: 2015/___/___

Section 1: Personal Information

----

1. Gender: __

2. Age: ☐ Under 18 ☐ 18~25 ☐ 26~35 ☐ 36~45 ☐ 46~59 ☐ 60 and above

3. Which year did you come and settle down in Taiyuan? ____

4. What is your marital status? ☐ Single ☐ Married

5. How many children do you have? __

6. What is your education level?
☐ High school and below ☐ College ☐ Undergraduate ☐ Graduate and above

7. What is your occupation?
☐ Public servant ☐ Enterprise staff ☐ Service personnel ☐ Worker
☐ Teacher ☐ Military service ☐ Student ☐ Retired ☐ Farmer ☐ Others

8. Are you doing any part-time jobs? ☐ Yes ☐ No

9. Do you have an occupation where driving is the sole function of the job, please indicate (if not, please go to question 10).
☐ Bus driver ☐ Taxi driver ☐ Truck driver
☐ Emergency or patrol vehicle driver (e.g. ambulance, police car)
☐ Service driver (e.g. work for public or private sector) ☐ Delivery vehicle driver

10. Do you hold a driving license? ☐ Yes ☐ No
If you have a license, do you have a readily available car whenever you want to drive?
☐ Yes ☐ No

11. Do you own a Taiyuan public transport card? ☐ Yes ☐ No

12. Do you use a smartphone? ☐ Yes ☐ No
If yes, what functions below do you use? (can be multiple)
☐ Orientation ☐ Route Planning ☐ Calling Taxi ☐ Checking Real-time Bus Information
☐ Checking Real-time Bike Sharing Information

13. Do you consider yourself as capable of cycling given your current health status (including any issues due to old age)? ☐ Yes ☐ No

14. Please provide the street names of both your work place address: ________ and your home address: ________
(It would be used only to assess the accessibility of transport modes.)

Section 2: Household Information

"Household" refers to the family that currently you live in for daily life

1. What is your house tenure type?

☐ Owned outright ☐ Owned with mortgage ☐ Rented ☐ Other (please specify) ________

2. What is your monthly household income (after tax)?

(As with all your replies, your response will be treated in confidence. This question is asked only for studying income effect on mode choice.)

☐ Under ￥3,000 ☐ ￥3,000 -￥6,000 ☐ ￥6,000 -￥9,000 ☐ ￥9,000 -￥15,000 ☐ ￥15,000 -￥30,000 ☐ Over ￥30,000

3. Which of the below transport tools are owned by your household at the moment? (can be multiple)

☐ Car (If yes, number of cars: ___)

☐ Electric bike (If yes, number of electric bikes: ___)

☐ Bike (If yes, number of bikes: ___)

☐ Other (please specify both tool type and number) ________

4. Follow the question above, please fill in the form below if your household owns one or more cars.

	Fuel type	Fuel cost per month	Overnight parking place	Parking cost per month (excluding overnight)	Car age	Current odometer number	Engine displace-ment
Car 1	☐ 93# ☐ 97# ☐ Diesel ☐ Gas ☐ Others	___rmb	☐Charged car park (￥__ per month) ☐Charged street parking (￥__ per month) ☐Free parking	_______rmb	_______year	_____km	☐ Under 1 ☐ 1.0-1.2 ☐ 1.3-1.5 ☐ 1.6-2.0 ☐ 2.1-3.0 ☐ Over 3.0
Car 2	☐ 93# ☐ 97# ☐ Diesel ☐ Gas ☐ Others	___rmb	☐Charged car park (￥__ per month) ☐Charged street parking (￥__ per month) ☐Free parking	_______rmb	_______year	_____km	☐ Under 1 ☐ 1.0-1.2 ☐ 1.3-1.5 ☐ 1.6-2.0 ☐ 2.1-3.0 ☐ Over 3.0
Car 3	☐ 93# ☐ 97# ☐ Diesel ☐ Gas ☐ Others	___rmb	☐Charged car park (￥__ per month) ☐Charged street parking (￥__ per month) ☐Free parking	_______rmb	_______year	_____km	☐ Under 1 ☐ 1.0-1.2 ☐ 1.3-1.5 ☐ 1.6-2.0 ☐ 2.1-3.0 ☐ Over 3.0

Section 3: Trip Dairy

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1. Please read the example below, then recall and fill in the form with your trip yesterday if it is a weekday (if not, please recall the last weekday).

Trip purpose	**Stage**	**Departure time (24h)**	**Origin**	**Destination**	**Transport mode**	**Duration (min)**	**Travel cost (￥, for taxi, bus, bike share)**
work	1	*7:00*	*home*	*bus stop*	*walk*	*5*	*0*
	2	*7:10*	*bus stop*	*bus stop*	*bus*	*25*	*1*
	3	*7:35*	*bus stop*	*work place*	*walk*	*1*	*0*
	4						
lunch	1	*12:00*	*work place*	*bike station*	*walk*	*1*	*0*
	2	*12:01*	*bike station*	*bike station*	*bike share*	*10*	*0*
	3	*12:11*	*bike station*	*restaurant*	*walk*	*2*	*0*
	4						
work	1	*13:20*	*restaurant*	*bike station*	*walk*	*2*	*0*
	2	*13:22*	*bike station*	*bike station*	*bike share*	*10*	*0*
	3	*13:32*	*bike station*	*work place*	*walk*	*1*	*0*
	4						
dinner	1	*18:00*	*work place*	*restaurant*	*taxi*	*15*	*16*
	2						
	3						
	4						
return home	1	*20:30*	*restaurant*	*home*	*car passenger*	*20*	*0*
	2						
	3						
	4						

Now please fill in the form with your own trip dairy:

Trip purpose	**Stage**	**Departure time (24h)**	**Origin**	**Destination**	**Transport mode**	**Duration (min)**	**Travel cost (￥, for taxi, bus, bike share)**
	1						
	2						
	3						
	4						
	1						
	2						

	3							
	4							
	1							
	2							
	3							
	4							
	1							
	2							
	3							
	4							
	1							
	2							
	3							
	4							

2. Do you consider your trip yesterday typical (i.e. occurs in most days in a week)?
☐ Yes (if yes, how many days of a week __ / 7) ☐ No

3. How long away on foot is the nearest bus stop from: your home __ min & **your work place: ___**min

4. How long away on foot is the nearest bike sharing docking station from: your home __ min & **your work place: ___**min

5. How many times in average do you use bus (one-way trips) a week? __ times

6. **How many times in average do you use your own bicycle (one-way trips) a week? __** times

7. How many times in average do you use bike sharing (one-way trips) a week? __ times

8. What difficulties have you encountered while using Taiyuan bike sharing? (can be multiple)

☐ No bikes available at station
☐ Cannot return bike at station due to full capacity
☐ Cannot find a station or station too far away when looking for a ride
☐ Cannot find a station or station too far away when looking for a return
☐ Forget to bring the public transport card
☐ Lose the public transport card
☐ Device default at station
☐ Bike component broken
☐ A single card cannot be used by multiple people at the same time
☐ Others______________________

Section 4: Attitudes and Perceptions

Please indicate the level of your agreement with each of the statements below (1=Completely disagree, 2=Strongly disagree, 3=Disagree, 4=Neutral, 5=Agree, 6=Strongly agree, 7=Completely agree).

Part 1: Environment & Air pollution

	1	2	3	4	5	6	7
I am aware about the climate change issues.							
I am worried about the climate change issues.							
I am worried about air pollution in Taiyuan.							
I am willing to use low-carbon transport modes for daily trips.							
I am willing to reduce private car usage to help to alleviate congestion.							
I am willing to persuade my family and friends to use low-carbon transport modes more often.							
Congestion charging zones is a promising measure for reducing congestion.							
Stricter policies are needed to alleviate congestion and improve air quality.							

Part 2: Bus

	1	2	3	4	5	6	7
I am satisfied with the current bus ticket price.							
I am satisfied with the current distance between bus stops.							
Bus is a convenient transport mode for me.							
I believe a bus system which entirely consists of electric buses will significantly improve Taiyuan's air quality.							
I consciously use the bus over a private vehicle to protect the environment.							
I avoid using bus as it is congested.							
More money should be invested on bus transport network to improve service standard.							
I believe that better integration between bus stops and bike-sharing stations is needed.							
Most of my family members use buses for their primary trips (i.e. work, education).							
Most of my close friends use buses for their primary trips (i.e. work, education).							
When more close friends use buses, it would make buses							

more attractive to me.							

Part 3: Bicycles and Bike Sharing

	1	2	3	4	5	6	7
I am satisfied with the current bike sharing price.							
I am satisfied with the current distance between bike sharing stations.							
I believe cycling is a good physical exercise.							
I believe the current traffic rule is in favour of cyclist.							
I believe the current status of public security is in favour of cyclist.							
I feel unsafe while cycling anyway.							
I always use bike or walk for short distance trips.							
I avoid cycling when the air pollution level is high.							
Most of my family members use bicycles for their primary trips (i.e. work, education).							
Most of my close friends use bicycles for their primary trips (i.e. work, education).							
When more close friends use bike sharing, it would make bike sharing more attractive to me.							

Part 4: Car Sharing

(Car sharing is similar to the current bike sharing; users can pick up a car at fixed stations or any parking spots on road; users will use mobile app to book, locate, unlock and start the vehicle and make payment.)

	1	2	3	4	5	6	7
Car-sharing would help to reduce congestion.							
I believe car-sharing will become a popular transport option in the future.							
Car sharing could make me reduce private car usage.							
Car sharing could make me reconsider whether or not to purchase a private car.							
Car is a sign of prestige for me.							
I am satisfied with my current main transport mode.							
I am interested to know more information when there is a new transport mode available.							

Section 5: A Retrospective Survey

Recall the year 2006, 2008, 2010 and 2012, then please fill in the form below.

	2006	2008	2010	2012
Marital status	☐ Single ☐ Married	☐ Single ☐ Married	☐ Single ☐ Married	☐ Single ☐ Married
Occupation	☐ Full-time ☐ Self-employ ☐ Student ☐ Retired ☐ Unemployed	☐ Full-time ☐ Self-employ ☐ Student ☐ Retired ☐ Unemployed	☐ Full-time ☐ Self-employ ☐ Student ☐ Retired ☐ Unemployed	☐ Full-time ☐ Self-employ ☐ Student ☐ Retired ☐ Unemployed
Number of children	________	________	________	________
Work/education district	☐ Yingze ☐ Xinghualing ☐ Wanbailin ☐ Jiancaoping ☐ Jinyuan ☐ Xiaodian ☐ Other_____	☐ Yingze ☐ Xinghualing ☐ Wanbailin ☐ Jiancaoping ☐ Jinyuan ☐ Xiaodian ☐ Other_____	☐ Yingze ☐ Xinghualing ☐ Wanbailin ☐ Jiancaoping ☐ Jinyuan ☐ Xiaodian ☐ Other_____	☐ Yingze ☐ Xinghualing ☐ Wanbailin ☐ Jiancaoping ☐ Jinyuan ☐ Xiaodian ☐ Other_____
Home district	☐ Yingze ☐ Xinghualing ☐ wanbailin ☐ Jiancaoping ☐ Jinyuan ☐ Xiaodian ☐ Other_____	☐ Yingze ☐ Xinghualing ☐ wanbailin ☐ Jiancaoping ☐ Jinyuan ☐ Xiaodian ☐ Other_____	☐ Yingze ☐ Xinghualing ☐ wanbailin ☐ Jiancaoping ☐ Jinyuan ☐ Xiaodian ☐ Other_____	☐ Yingze ☐ Xinghualing ☐ wanbailin ☐ Jiancaoping ☐ Jinyuan ☐ Xiaodian ☐ Other_____
Monthly after-tax household income (“household” refers to the family that you lived in for daily life)	☐ Under 3000 ☐ 3000-6000 ☐ 6000-9000 ☐ 9000-15000 ☐ 15000-30000 ☐ Over 30000	☐ Under 3000 ☐ 3000-6000 ☐ 6000-9000 ☐ 9000-15000 ☐ 15000-30000 ☐ Over 30000	☐ Under 3000 ☐ 3000-6000 ☐ 6000-9000 ☐ 9000-15000 ☐ 15000-30000 ☐ Over 30000	☐ Under 3000 ☐ 3000-6000 ☐ 6000-9000 ☐ 9000-15000 ☐ 15000-30000 ☐ Over 30000
No. of household owned car	________	________	________	________
No. of household owned e-bike	________	________	________	________
No. of household owned bike	________	________	________	________
What transport mode did you normally use for your trip to work/education?	☐ Car ☐ Bus ☐ E-bike ☐ Bike ☐ Walk ☐ Taxi	☐ Car ☐ Bus ☐ E-bike ☐ Bike ☐ Walk ☐ Taxi	☐ Car ☐ Bus ☐ E-bike ☐ Bike ☐ Walk ☐ Taxi	☐ Car ☐ Bus ☐ E-bike ☐ Bike ☐ Walk ☐ Taxi
Duration of one-way trip to work/education?	________min	________min	________min	________min

Section 6: Scenarios

Please select the transport mode that you would use to travel in each of the scenarios below (single choice & tick in the bottom row in each scenario).

(Car sharing is similar to the current bike sharing; users can pick up a car at fixed stations or any parking spots on road; users will use mobile app to book, locate, unlock and start the vehicle and make payment.)

Scenario 1: Travel within 2km, to work/education, sunny day, 10°C, with light pollution

	Car	**E-bike**	**Bus**	**Car share**	**Bike share**	**Walk**
	Drive 3 min	Ride 5 min	Drive 5 min	Drive 7 min	Ride 8 min	Walk 20 min
	Fuel ￥1.2		Ticket ￥1	Cost ￥3	Cost ￥0	
	Easy to park car					
	Parking ￥5/h					
			Walk 5 min to station	Walk 5 min to station	Walk 2 min to station	
			Every 2 min			
			With app	With app	With app	
Your choice (please tick)						

Scenario 2: Travel within 2km, to shopping, snowy day, -10°C, with excellent air quality

	Car	**E-bike**	**Bus**	**Car share**	**Bike share**	**Walk**
	Drive 7 min	Ride 5 min	Drive 12 min	Drive 7 min	Ride 8 min	Walk 15 min
	Fuel ￥1.6		Ticket ￥1	Cost ￥1	Cost ￥1	
	Hard to park car					
	Parking ￥5/h					
			Walk 5 min to station	Walk 10 min to station	Walk 5 min to station	
			Every 2 min			
			With app	With app	Without app	
Your choice (please tick)						

Scenario 3: Travel within 2-5km, to leisure, sunny day, 20°C, with excellent air quality

	Car	**E-bike**	**Bus**	**Taxi**	**Car share**	**Bike share**
	Drive 15 min	Ride 20 min	Drive 20 min	Drive 10 min	Drive 20 min	Ride 30 min
	Fuel ￥3		Ticket ￥1	Cost ￥18	Cost ￥8	Cost ￥0
	Hard to park car					
	Parking ￥5/h					
			Walk 10 min to station		Walk 15 min to station	Walk 2 min to station
			Every 5 min			
			Without app	With app	With app	With app
Your choice (please tick)						

Scenario 4: Travel within 2-5km, to work/education, sunny day, 5°C, with terrible pollution

	Car	**E-bike**	**Bus**	**Taxi**	**Car share**	**Bike share**
	Drive 25 min	Ride 20 min	Drive 30 min	Drive 25 min	Drive 25 min	Ride 30 min
	Fuel ￥3.5		Ticket ￥1	Cost ￥30	Cost ￥10	Cost ￥0
	Hard to park car					
	Parking ￥8/h					
			Walk 5 min to station		Walk 5 min to station	Walk 2 min to station
			Every 5 min			
			Without app	With app	With app	Without app
Your choice (please tick)						

Scenario 5: Travel more than 5km, to work/education, rainy day, 10°C, with terrible pollution

	Car	E-bike	Bus	Taxi	Car share	Bike share
	Drive 40 min	Ride 60 min	Drive 60 min	Drive 30 min	Drive 40 min	Ride 90 min
	Fuel ￥18		Ticke￥0.5	Cost ￥40	Cost ￥15	Cost ￥2
	Easy to park car					
	Parking ￥5/h					
			Walk 5 min to station		Walk 5 min to station	Walk 5 min to station
			Every 2 min			
			Without app	Without app	Without app	Without app
Your choice (please tick)						

Scenario 6: Travel more than 5km, to work/education, rainy day, 30°C, with good air quality

	Car	E-bike	Bus	Taxi	Car share	Bike share
	Drive 20 min	Ride 20 min	Drive 30 min	Drive 30 min	Drive 25 min	Ride 60 min
	Fuel ￥5		Ticket ￥2	Cost ￥25	Cost ￥20	Cost￥1.5
	Easy to park car					
	Parking ￥2/h					
			Walk 10 min to station		Walk 5 min to station	Walk 2 min to station
			Every 5 min			
			With app	Without app	With app	With app
Your choice (please tick)						

The survey ends here. We will held one more survey in the winter (a very short survey, only contains the trip diary part) to compare any mode choice differences of Taiyuan citizens between summer and winter. If you wish to help us with the short winter survey, please leave your name (optional) for further contact. Your name (optional): __________, we appreciate your support.

APPENDIX B: Studying Air Pollution's Impact on Mode Choice Behaviour via A Seasonality Analysis[32]

The link between air pollution and transport sector has been widely recognized for a long period of time (Colvile et al., 2001). Urban transport has become an increasingly important source of air pollution due to the surge in the use of motorized vehicles, especially during the last 20 years in developing countries after the rapid economic growth and urbanization (Lefèvre, 2009; Vasconcellos, 2013; Cheng et al., 2015). Today, developing countries are still suffering significantly from severe and frequent air pollution problems. The traditional approach to tackle the problem is through improving fuel products and vehicle technologies to directly cut down pollutants (Faiz and Sturm, 2000; Gwilliam et al., 2004; Guttikunda and Mohan, 2014). Besides, reducing motorized vehicle usage via promoting non-motorized transport modes has also become a popular solution nowadays in developing countries (Hidalgo and Huizenga, 2013). In fact, there are a large number of researches involving mode choice behaviour analysis, which have effectively supported the policy making in improving the demand for non-motorized transport.

Nevertheless, current policies on improving air quality and encouraging the take-up of non-motorized transport are often separated. In other words, it has still been a "one-way approach" that non-motorized transport is seen as a solution to improve air quality. However, whether better air quality could improve the willingness to use non-motorized transport remains veiled. So far, the impact of air pollution on mode choice behaviour is rarely explored due to most of the existing mode choice studies are based on the cases in developed countries, which in general have relatively limited air pollution concerns. However, capturing air pollution's impact has great implication for developing countries. If evidence can be found to unveil the impact, the current "one-way approach" would become an old fashion and instead a "virtuous circle" could be created (i.e. better air quality could result in higher demand for non-motorized transport, and more non-motorized transport usage could further reduce air pollution). As a result, developing countries may be more incentivized to work on air pollution reduction from other sources (e.g.

[32] See a published version at: https://doi.org/10.3141/2634-15

industrial, residential and business sectors) in order to exploit the extra gains in urban transport.

Moreover, air quality in developing countries was recently found to have significant seasonal differences (Jiang et al., 2014; Rich, 2015). For instance in China, through a study involving 110 cities, air pollution was found to be smallest in summer and most severe in winter due to winter's low-frequency rainfall and high energy consumption (Jiang et al., 2014). Thus, it is possible to capture the impact of air pollution on mode choice behaviour via a seasonality analysis. Besides, it has been discovered that factors affecting mode choice behaviour could have different impacts across seasons when natural-environment conditions were different (Kamargianni, 2016). Therefore, in this work, a seasonality analysis will not only help revealing air pollution's impact, but will also provide in-depth understanding of other factors' impact changes across different natural-environment conditions.

Overall, this research aims to provide policy makers with the evidence of air pollution's impact on urban transport mode choice behaviour; in particular to find out whether non-motorized transport (i.e. private biking, walk, and bike-sharing) will be more popular when having better air quality. Meanwhile, other factors such as trip and socio-economic characteristics are also covered in the analysis. RP travel behaviour data are collected in two seasons and two discrete mode choice models are developed respectively.

Two rounds of travel behaviour survey were launched in the case study city Taiyuan, one in summer 2015 and one in winter 2015-2016. The goal is to study how the mode choice behaviour of the same individual changes under different air quality levels. Eventually, 492 Taiyuan citizens provided valid one-day travel information in both rounds. The city has dramatic natural-environment differences in summer and winter in terms of both weather condition and air quality. Usually, there is moderate weather as well as clean air in summer comparing with freezing temperature and poor air quality in winter. Therefore, the case is not only suitable to study air pollution's impact, but also offers a clear difference in natural-environment condition for revealing the impact changes of trip and socio-economic characteristics. In addition, Taiyuan has one of the most successful bike-sharing schemes in China (Song, 2015), giving the city great potential to promote non-motorized transport.

This research will inspire the policy making in air pollution reduction by exploring a new path using air pollution's reciprocal effect on travel behavioural change. Moreover, the seasonality analysis will offer in-depth understanding of factors' impact changes when having different natural-environment conditions. Furthermore, since the case study is based on a Chinese city, this research will particularly be a useful reference to policy makers from China as well as other developing countries.

For the remainder of this work, section B.1 describes the data collection and characteristics of the data. Section B.2 explains how the models are specified followed by an interpretation on the model estimation results in section B.3. Finally, section B.4 concludes the research.

B.1 Data

Two rounds of questionnaire survey were conducted, one in summer (August and September 2015) and one in winter (December, January, and February 2015-2016). Among the aforementioned 9,499 individuals who provided valid questionnaire responses in the summer survey, 706 individuals agreed to continue the participation in the winter survey. In winter 2016, the 706 individuals were asked to fill a paper questionnaire which only contains the trip diary survey and eventually 492 of them provided valid responses.

This work uses only the RP travel behaviour data collected from the same 492 individuals in both seasons. As such, any seasonality effects of the same factors on mode choice behaviour can be more clearly revealed. By comparing this smaller sample with the main sample of 9,499 individuals (Table B-1), it is found that the most key characteristics of the smaller sample are close to the main; there are only a few notable differences. More females are included in the smaller sample. More young professionals (i.e. aged between 26 and 35) are captured while the percentage of elder professionals (i.e. aged between 36 and 45) decreases. There are also larger proportions of driving license and public transport card holders, as well as those having private cars, electric bikes and bikes in households. Besides, all other indicators are almost the same between the two samples. Meanwhile, both samples show a high possession rate of public transport card meaning that most of the sampled individuals can access bus and bike-sharing services "barrier-free". Almost all respondents state that they are healthy enough to cycle which ensures that bike and bike-sharing can be feasible choices in the survey. Finally, the occupational status (i.e. nearly 80% are fixed-job individuals) shows that both samples have successfully captured regular commuters whose mode choice behaviours are the mostly concerned in urban planning and policy-making. Overall, the smaller sample with 492 individuals is valid for data analysis without incurring significant bias.

In addition to the questionnaire survey, daily air pollution and weather condition data for the corresponding travel days in the summer and winter surveys were collected from China's Ministry of Environment Protection (Ministry of Environment Protection, 2016) and Shanxi Meteorology (Shanxi Meteorology, 2016). Air pollution is measured by a continuous variable, air quality index (AQI), the primary air pollution indicator used in China. Weather conditions are measured by a continuous variable °C temperature and three dummy variables showing if the day is rainy, snowy or neither. Moreover, as there is one uniform AQI for a single day, it will be identically applied to all trip observations on the same day. However, temperature can change significantly during different periods in a day. Therefore, to more accurately measure the temperature impact on mode choice behaviour, different temperatures will be applied to different trip observations according to their departure time. In particular, by considering Taiyuan's daily temperature change pattern, we assume trips departing during 11 am to 4 pm are associated with the maximum daily temperature, trips from 8 pm to 7 am in the next day are associated with the minimum daily temperature, and the average temperature is applied to the trips departing in the rest periods.

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

Table B-1 Sample Descriptive Statistics

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

Household car	Percentage of possession	48%	59%
Household electric bike	Percentage of possession	42%	48%
Household bike	Percentage of possession	51%	58%

Table B-2 Key Statistics from Summer and Winter Surveys

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

B.2 Modelling Framework

Two MNL mode choice models are developed based on the data collected in the two different seasons. MNL model is widely used to study discrete choice behaviour (Ben-Akiva and Lerman, 1985). Random utility theory underpins the model such that a choice made by an individual is based on his/her perceived utility generated by that choice and the utility associated with each choice is determined by its attributes, choice maker's characteristics, and other explanatory variables.

Since one of the objectives is to capture if factors' impacts could be different when having different natural-environment conditions, the two MNL models are assigned the same explanatory variables in order to compare the results (see Equations 20 to 27). For instance, air pollution and temperature impacts are taken into account; however, rain and snow are excluded as they are only relevant to one season.

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

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

Three categorical socio-economic variables are also considered for their impacts on mode choice behaviour; including gender, age, and household income (see Table B-1). However, when testing the impacts of age and income, the pilot results show each of their subgroups has minor effect on mode choices. As a result, the subgroups of age and income are merged into two general groups (i.e. lower half and higher half) in order to more clearly demonstrate their impacts.

Finally, availability conditions to the transport mode alternatives should be imposed for each individual. These conditions will increase model validity by helping explain the circumstances such as someone did not choose an alternative mode for an observed trip could be due to the fact that the mode was an unavailable option. As a result, the availability conditions are specified as follows:

- "Car driver" is available to the individuals who have driving licenses and at least one car in their households;
- "Car passenger" is available to all individuals;
- "Bus" is available to all individuals;
- "Electric bike" is available to the individuals who have at least one electric bike in their households;
- "Bike" is available to the individuals who are healthy enough to cycle and have at least one bike in their households;
- "Bike-sharing" is available to the individuals who are healthy enough to cycle;
- "Walk" is available to all individuals;
- "Taxi" is available to all individuals.

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

$$U_{cardri} = \alpha_{cardri} + \beta_{work1} * WORK + \beta_{tem1} * TEM + \beta_{pol1} * POLLUTION$$
$$+ \beta_{cardritt} * CARDRITT + \beta_{cardritc} * CARDRITC + \beta_{male1} * MALE \quad (20)$$
$$+ \beta_{age1} * AGELOW + \beta_{inc1} * INCLOW + \varepsilon_{cardri}$$

$$U_{carpass} = \alpha_{carpass} + \beta_{edu2} * EDU + \beta_{carpasstt} * CARPASSTT + \beta_{male2} * MALE$$
$$+ \beta_{age2} * AGELOW + \beta_{inc2} * INCLOW + \varepsilon_{carpass} \quad (21)$$

$$U_{bus} = \alpha_{bus} + \beta_{work3} * WORK + \beta_{edu3} * EDU + \beta_{tem3} * TEM + \beta_{pol3} * POLLUTION$$
$$+ \beta_{bustt} * BUSTT + \beta_{bustc} * BUSTC + \beta_{male3} * MALE + \beta_{age3} * AGELOW \quad (22)$$
$$+ \beta_{inc3} * INCLOW + \varepsilon_{bus}$$

$$U_{ebike} = \alpha_{ebike} + \beta_{work4} * WORK + \beta_{tem4} * TEM + \beta_{pol4} * POLLUTION + \beta_{ebikett} * EBIKETT$$
$$+ \beta_{male4} * MALE + \beta_{age4} * AGELOW + \beta_{inc4} * INCLOW + \varepsilon_{ebike} \quad (23)$$

$$U_{bike} = \alpha_{bike} + \beta_{work5} * WORK + \beta_{edu5} * EDU + \beta_{tem5} * TEM + \beta_{pol5} * POLLUTION$$
$$+ \beta_{bikett} * BIKETT + \beta_{male5} * MALE + \beta_{age5} * AGELOW + \beta_{inc5} * INCLOW + \varepsilon_{bike} \quad (24)$$

$$U_{bikesh} = \alpha_{bikesh} + \beta_{work6} * WORK + \beta_{edu6} * EDU + \beta_{tem6} * TEM + \beta_{pol6} * POLLUTION$$
$$+ \beta_{bikeshtt} * BIKESHTT + \beta_{male6} * MALE + \beta_{age6} * AGELOW \quad (25)$$
$$+ \beta_{inc6} * INCLOW + \varepsilon_{bikesh}$$

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

(26)

$$U_{taxi} = \beta_{work8} * WORK + \beta_{tem8} * TEM + \beta_{pol8} * POLLUTION + \beta_{taxitt} * TAXITT$$
$$+ \beta_{taxitc} * TAXITC + \varepsilon_{taxi} \quad (27)$$

Where:

WORK = 1 if trip purpose is work-related, 0 if otherwise;

EDU = 1 if trip purpose is education-related, 0 if otherwise;

TEM = °C temperature (continuous);

POLLUTION = air quality index (continuous);

CARDRITT = travel time by car driver (in min);

CARPASSTT = travel time by car passenger (in min);

BUSTT = travel time by bus (in min);

EBIKETT = travel time by electric bike (in min);

BIKETT = travel time by bike (in min);

BIKESHTT = travel time by bike-sharing (in min);

WALKTT = travel time by walk (in min);

TAXITT = travel time by taxi (in min);

CARDRITC = travel cost by car driver (in ￥);

BUSTC = travel cost by bus (in ￥);

TAXITC = travel cost by taxi (in ￥);

MALE = 1 if gender is male, 0 if female;

AGELOW = 1 if age is under or equal to 35, 0 if above 35

INCLOW = 1 if household monthly income is under or equal to ￥9000, 0 if more than ￥9000;

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

B.3 Results

Table B-3 presents the model estimation results for summer and winter observations. The differences between the results in the two seasons are specifically identified. It is expected from earlier research that an increase in air pollution level could discourage the use of more “exposed” modes, for example, all cycling-related modes and walk, and encourage the take-up of more “protected” modes such as car, bus, and taxi (Li and Kamargianni, 2016).

On the one hand, the winter results are in line with such earlier findings. It is observed with high significance that bike, bike-sharing, and walk are not preferred when air pollution level increases; instead travellers will switch to car, bus, taxi and electric bike. The only different finding is the choice of electric bike, which is positively correlated with air pollution level in the winter results and however found a negative correlation in the earlier research. The phenomenon could possibly be explained by the commonly observed inconsistent behaviour between RP observations and SP experimental results (Ben-Akiva and Lerman, 1985; Louviere et al., 2003), such that a traveller may still have to use the privately owned electric bike in a polluting day in real life though this may not be a preferred choice in a hypothesized polluting scenario.

On the other hand, given much better air quality, the summer model shows more disordered results in terms of air pollution’s impact. For instance, the three non-motorized modes are even found to have inconsistent impact signs (i.e. air pollution negatively correlated with walk but positively correlated with bike and bike-sharing). The results indicate that air pollution increases the perceived utilities of the cycling modes from a modelling perspective. However, the main cause is in fact that when the general air quality is good in summer, a traveller may be insensitive to a change in air pollution statistics and therefore a cycling decision can still be made even if air quality degrades from “perfect” to “very good”. In other words, air pollution now becomes a less important concern comparing to other factors. Overall, the results from the two seasonal models imply that severe air pollution can significantly discourage the usage of all non-motorized transport modes (bike, bike-sharing, and walk); however, when air pollution becomes moderate, a change in air pollution level does not have a significant impact on mode choice behaviour.

Temperature is the other natural-environment factor studied in this research besides air pollution. Similarly, the seasonal comparison reveals that mode choices will be affected differently when having different temperature levels. The summer results show that an increase in temperature will make a variety of modes relatively popular when comparing to taxi, which is a strictly less preferred option under higher temperature in summer. This may be due to the strong local perception that it is uncertain to receive adequate air condition treatment from taxi drivers. In winter, a temperature increase is positively associated with the choices towards bike-sharing, electric bike and car and negatively associated with walk, bike, bus and taxi. Such relatively abnormal finding may be a special phenomenon of the case study; nevertheless, more local evidence is needed to better interpret this result.

Two different trip purposes are studied. For travellers going to work, the results in both seasons show that when the parameter of car passenger choice is normalized to zero, taxi is the only mode choice that will not be chosen and all other alternative modes are found to have positive correlations with work-related purposes. Meanwhile, car passenger, bus, bike, bike-sharing, and walk are all the potential choices for travellers with education-related purposes given their positive impact signs in both seasons. Overall, the results imply that trip purpose is a factor that could consistently affect mode choice behaviour across different air quality and weather conditions.

Travel time and travel cost are important attributes in affecting mode choice behaviour.

For travel time, the winter model found the expected negative relationship with most of the mode choices (except for car passenger and taxi, which will be explained shortly), which means the utility associated with each mode will decrease when it takes a longer time to arrive at the destination. In comparison, a number of impact signs turn out as positive in the summer model including the impacts on car choice, bus choice and electric bike choice (as well as the choices of car passenger and taxi as in the winter model). Such sign changes could be caused by the better natural-environment conditions (i.e. better air quality and warmer weather) in the summer period so that longer travel time may not result in significant comfort/utility loss. In other words, the travel time saving may not be as important as in the winter period. However, it must be noticed that travel time impacts on non-motorized transport choices such as bike, bike-sharing and walk are always negative throughout summer and winter. Such consistent behaviour could be due to the relatively low mobility power and the resulted longer travel time of non-motorized transport so that a further increase in travel time is always less preferred by travellers despite natural-environment conditions. In contrast, the positive impact signs of car passenger and taxi choices throughout the two seasons could be explained by the fact that they are both passenger transport and unlike bus, they do not have any exclusive lanes. Thus, when making a mode choice decision before travelling, the decision maker does not have the same level of prior knowledge on travel time as other self-driven modes. As for travel cost, the impacts on the three mode choices have consistent signs in summer and winter. Higher costs will reduce the demand towards bus and taxi; however, car cost is positively associated with its mode choice. The key reason is that in a RP survey, many drivers do not have perfect knowledge on the cost of car driving (i.e. the fuel cost). Therefore, the travel cost of car may not be precisely taken into account by individuals in choice making.

At last, an important discovery is that the effects of all three socio-economic variables (i.e. gender, age and income) are completely dominated by other factors' impacts according to their low significance on all modes across the two seasons. However, some trends are still worth noting. More females will choose car passenger, bus, bike-sharing and walk as the travel modes in summer; whereas in winter females will only prefer to be car drivers. The elderly age group is found to have a positive relationship with using bike-sharing in summer; they will not choose it anymore in winter. Similarly, in summer wealthier people are open to all mode options except for electric bike, which is more preferred by the lower income group. However, in winter, car driver and car passenger are the only options preferred by wealthier people. Overall, the results of gender, age and income impacts could indicate the existence of seasonal influence, such that females, elderly and wealthier people are found more sensitive to worse air quality and lower temperature. Nevertheless, they are not the influential factors on mode choice behaviour as compared to others.

Table B-3 Summer and Winter Model Estimation Results

	Summer		**Winter**	
	coefficient	**t-statistic**	**coefficient**	**t-statistic**
α_{cardri}	- 9.57	- 2.75	1.89	1.46
Work-car driver	1.49	4.77	0.67	2.77
Temperature-car driver	0.08	2.79	0.02	1.16
Air pollution-car driver	0.018	2.69	0.015	5.63
Travel time-car driver	0.02	1.10	- 0.03	- 0.97
Travel cost-car driver	0.19	4.41	0.12	2.66
Male-car driver	0.06	0.08	- 0.23	- 0.47
Age (lower)-car driver	- 0.12	- 0.16	- 0.40	- 0.81
Income (lower)-car driver	- 1.81	- 0.99	- 0.45	- 0.65
$\alpha_{carpass}$	- 6.86	- 1.99	3.24	2.74
Education-car passenger	1.14	3.30	1.51	4.89
Travel time-car passenger	0.07	3.44	0.005	0.17
Male-car passenger	- 0.30	- 0.45	0.62	1.40
Age (lower)-car passenger	- 0.44	- 0.59	- 0.06	- 0.13
Income (lower)-car passenger	- 2.40	- 1.33	- 0.52	- 0.80
α_{bus}	- 5.18	- 1.49	43.40	0.79
Work-bus	0.85	2.86	0.27	0.93
Education-bus	1.42	4.63	1.16	2.95
Temperature-bus	0.03	1.01	- 0.04	- 1.99

Air pollution-bus	0.013	2.09	0.0002	0.06
Travel time-bus	0.003	0.32	- 0.12	- 6.86
Travel cost-bus	- 2.69	- 6.00	- 37.90	- 0.69
Male-bus	- 0.71	- 1.06	0.10	0.21
Age (lower)-bus	- 0.53	- 0.72	- 0.44	- 0.87
Income (lower)-bus	- 0.87	- 0.48	0.32	0.45
α_{ebike}	- 16.90	- 0.75	- 8.26	- 0.15
Work-ebike	0.84	2.51	0.17	0.60
Temperature-ebike	0.09	2.90	0.01	0.48
Air pollution-ebike	- 0.002	- 0.21	0.003	1.35
Travel time-ebike	0.04	1.76	- 0.02	- 0.94
Male-ebike	0.44	0.65	1.22	2.54
Age (lower)-ebike	- 0.005	- 0.01	- 0.29	- 0.56
Income (lower)-ebike	6.74	0.30	10.90	0.20
α_{bike}	- 4.96	- 1.41	7.88	5.23
Work-bike	0.83	2.22	0.48	1.25
Education-bike	0.83	1.94	0.92	1.69
Temperature-bike	0.03	0.74	- 0.06	- 2.25
Air pollution-bike	0.016	1.85	- 0.009	- 2.63
Travel time-bike	- 0.12	- 7.12	- 0.21	- 8.26
Male-bike	0.14	0.20	0.07	0.13
Age (lower)-bike	- 0.21	- 0.27	- 0.01	- 0.01
Income (lower)-bike	- 1.68	- 0.91	0.87	1.05
α_{bikesh}	- 9.06	- 2.57	14.50	7.97
Work-bike share	0.40	1.02	1.05	2.37
Education-bike share	1.77	4.67	0.67	1.01
Temperature-bike share	0.13	4.02	0.04	1.07
Air pollution-bike share	0.017	2.20	- 0.058	- 6.71

Travel time-bike share	- 0.07	- 4.81	- 0.24	- 7.42
Male-bike share	- 0.66	- 0.94	0.73	1.18
Age (lower)-bike share	- 0.51	- 0.67	0.41	0.65
Income (lower)-bike share	- 1.11	- 0.60	0.32	0.34
α_{walk}	1.60	0.44	14.60	9.21
Work-walk	0.75	1.54	0.31	0.77
Education-walk	1.53	2.93	1.45	2.56
Temperature-walk	0.03	0.70	- 0.06	- 2.02
Air pollution-walk	- 0.001	- 0.13	- 0.018	- 5.12
Travel time-walk	- 0.24	- 15.03	- 0.31	- 14.54
Male-walk	- 0.74	- 0.99	0.08	0.15
Age (lower)-walk	0.12	0.14	0.38	0.64
Income (lower)-walk	- 1.29	- 0.69	1.02	1.31
Work-taxi	- 1.23	- 0.81	- 0.0001	- 0.00
Temperature-taxi	- 0.38	- 2.60	- 0.07	- 1.65
Air pollution-taxi	- 0.013	- 0.55	0.003	0.65
Travel time-taxi	0.57	7.62	0.03	0.61
Travel cost-taxi	- 0.81	- 7.81	- 0.02	- 0.29
Number of observations	1797		1722	
Initial log-likelihood	- 3323.4		- 3189.3	
Final log-likelihood	- 1400.2		- 1173.0	
Likelihood ratio test	3846.4		4032.6	
$\bar{\rho}^2$	0.559		0.612	

B.4 Conclusions

The work studies the factors that may affect urban transport mode choice behaviour in a developing country. It significantly advances the knowledge boundary in the research community, and to our knowledge, it is the first study investigating the impact of air pollution on mode choice behaviour. Two seasonal MNL models are built to reveal any differences in the factors' impacts under distinctive natural-environment conditions. Some implications for policy making could be drawn to help more effectively promote the demand for non-motorized transport.

This research suggests that cleaning the air and promoting non-motorized transport must be tackled simultaneously due to their inter-dependence. It is possible to have a "virtuous circle" that not only an increase in the use of non-motorized transport would help improve air quality, but by having better air quality those non-motorized modes would also be increasingly attractive to travellers. Policy consideration could, therefore, be placed on the air pollution reduction in industrial, residential and business sectors, which could, in turn, lead to further air quality improvement in urban transport. However, cost and benefit analysis will be required to assess the feasibility of such "virtuous circle" in real practice, especially given the finding that air pollution's impact will diminish as it drops to lower levels. In addition, females, elderly and wealthier people, i.e. those who are found in the seasonality analysis to be more sensitive to a change in natural-environment conditions, are in particular expected to use more non-motorized transport when air quality improves.

Nevertheless, commuters, who conduct regular trips for work and education purposes, have relatively inelastic demand for non-motorized transport across air quality and weather condition changes. A similar finding is also associated with travel time, which has strong negative impact on non-motorized transport usage in both seasons. The results imply that policies directly addressing trip purpose and travel time must be considered despite natural-environment conditions. For instance, policies could focus on satisfying commuters' stable demand for bike-sharing especially in the areas where workplaces and schools are concentrated. Measures can include increasing the number of docking stations or adopt more flexible bike return policies during peak time (e.g. portable card scanning machine can be used to record bike usage data so that bikes can be returned to and assembled by a staff in addition to docking stations). Besides, the travel time of using bike-sharing could be reduced by introducing electric bikes to the existing bike-sharing schemes as a way to enhance bike-sharing mobility and meanwhile without causing air pollution.

In the end, this research also reveals an important distinction between findings in developing and developed countries. In this study, socio-economic characteristics (i.e. gender, age, and income) hardly have significant impacts on any mode choices, although many impact changes are observed across seasons. However in developed countries, socio-economic characteristics were usually identified to have strong correlations with mode choice behaviour (Shafizadeh and Niemeier, 1997; Rodríguez and Joo, 2004; Moudon et al., 2005; Parkin et al., 2008; Zahran et al., 2008; Baker, 2009; Akar, et al., 2013; Ricci, 2015; Wang et al., 2015; Faghih-Imani et al., 2017). The finding implies that policies should focus more on factors that have more significant impacts (e.g. air pollution, trip purpose and travel time) than socio-economic groups, in order to effectively promote travel behavioural changes. Nevertheless, more mode choice studies are needed in developing countries to further compare the findings.

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