Smartphone-based Mobility Mapping and Perceived Air Quality Evaluation in Beijing

by

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Abstract

Recently, the rapid development of smartphone technologies has brought new opportunities for the citizen travel survey. Based on a survey performed using a smartphone app, Moves, in Beijing, China, this thesis discusses the survey design and implementation process as well as the mobility analysis methods. The survey was launched in January 2016. This thesis is based on data from 258 subjects.

The air quality is monitored through several objective measures. However, citizens’ subjective feelings have rarely been investigated. This thesis develops the Perceived Air Quality (PAQ) measure that captures the sensory reactions to air pollution. The PAQ data are collected through questionnaires, which are part of the travel survey. A strong correlation is found between daily average PAQ and AQI, indicating that the PAQ could become a meaningful indicator for air quality. However, the strong correlation only exists in the aggregated level.

Finally, the thesis evaluates the association between travel behavior and air quality. Travel behavior is measured by number of trips, number of non-motorized trips, percentage of non-motorized trips, total distance traveled and total travel time. The air quality is measured by AQI and PAQ. The Random Effect regression models show that the association between travel behavior and air quality is pretty weak. It indicates that currently not many Beijing residents are taking air quality as a crucial factor when making travel decisions.

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## Contents

Chapter 1 Introduction ............................................................................................................. 13
  1.1 Motivation ....................................................................................................................... 16  
    1.1.1 Travel Survey Method Improvement ........................................................................ 17  
    1.1.2 Understanding Travel Demand ............................................................................... 17  
    1.1.3 Adapting the Transportation Services to Meet the Demands .................................. 18  
  1.2 Research Objectives and Approach ................................................................................ 19  
  1.3 Thesis Framework and Organization .............................................................................. 21

Chapter 2 Literature Review .................................................................................................. 23
  2.1 Advanced Travel Survey Method .................................................................................. 23  
    2.1.1 Travel Survey Method Development ....................................................................... 23  
    2.1.2 Smartphone-based Travel Survey .......................................................................... 25  
  2.2 Air Pollution and Air Quality Measurement ................................................................... 26  
    2.2.1 Air Pollution in China ............................................................................................. 26  
    2.2.2 Air Quality Measurement ....................................................................................... 27  
  2.3 Air Pollution and Travel Behavior .................................................................................. 30

Chapter 3 Survey Design and Implementation ...................................................................... 33
  3.1 Choosing the Right App. ............................................................................................... 33  
    3.1.1 Moves ..................................................................................................................... 37  
  3.2 Survey Framework and Implementation ......................................................................... 38  
  3.3 Sample Recruitment and Composition .......................................................................... 40
  3.4 Entry and Exit Questionnaires ....................................................................................... 44  
    3.4.1 Entry Questionnaire ............................................................................................... 44  
    3.4.2 Exit Questionnaire ................................................................................................. 46
  3.5 Travel Survey .................................................................................................................. 47  
    3.5.1 Moves Data Collection and Description ................................................................... 47  
    3.5.2 Memory-based Self-reported Travel Survey ........................................................... 50
  3.6 Perceived Air Quality Survey .......................................................................................... 51  
  3.7 Lessons From Survey Design And Implementation ....................................................... 53  
    3.7.1 Smartphone-Based Travel Survey .......................................................................... 53  
    3.7.2 Special Situations in China ..................................................................................... 54

Chapter 4 Mobility Analysis .................................................................................................. 57
  4.1 Moves Data Used in this Chapter .................................................................................. 58
  4.2 Location Clustering ......................................................................................................... 59  
    4.2.1 Spatial Clustering Method ...................................................................................... 60
    4.2.2 Clustering Results ................................................................................................. 61
4.3 Home and Workplace Location Detection ........................................ 62
   4.3.1 Method .................................................................................. 63
   4.3.2 Home location inference ......................................................... 64
   4.3.3 Workplace location inference ................................................ 66
4.4 Trip inference .................................................................................. 66
4.5 Commuting Trips Identification ....................................................... 69
4.6 Matching Moves data with survey data ........................................... 70
4.7 Summary ....................................................................................... 72

Chapter 5 Air Quality Evaluation .......................................................... 75
5.1 Perceived Air Quality Survey Results .............................................. 75
   5.1.1 Home-Work-Commute Spatial Variation .................................. 78
   5.1.2 Temporal Variance ................................................................. 79
   5.1.3 Ratings By The Air Pollution Sensitive Subgroup ..................... 80
5.2 Objective Air Quality Measurement ................................................. 81
   5.2.1 Spatial Variation of Different Measures .................................... 82
   5.2.2 Temporal Variation of Different Measures ................................. 84
5.3 Relate Perceived Air Quality and Objective Air Quality Measurements ... 85
   5.3.1 Correlation Between PAQ And Objective Air Quality Measurements 86
   5.3.2 Person-to-Person Variance ....................................................... 89
5.4 Discussion ...................................................................................... 91
   5.4.1 Effectiveness and Limitations of the PAQ Measure .................... 91
   5.4.2 Combining PAQ and the Objective Measurements ................... 92

Chapter 6 Air Quality and Travel Behavior ............................................. 95
6.1 Variables and Data ......................................................................... 95
6.2 AQI as the Indicator for Air Quality ............................................... 98
   6.2.1 Hypotheses ............................................................................ 98
   6.2.2 Model Estimation and Interpretation ...................................... 98
6.3 PAQ as the Indicator for Air Quality .............................................. 101
   6.3.1 Hypotheses ............................................................................ 101
   6.3.2 Model Estimation and Interpretation ...................................... 102
6.4 Discussion ...................................................................................... 106
   6.4.1 Model Evaluation and Limitations ......................................... 106
   6.4.2 Beijing Residents’ Response to Air Pollution ......................... 107

Chapter 7 Conclusion ........................................................................... 109
7.1 Summary ....................................................................................... 109
   7.1.1 Smartphone-based Travel Survey Method ............................... 110
   7.1.2 Perceived Air Quality Measure .............................................. 111
   7.1.3 Association between Air Quality and Travel Behavior ............. 113
7.2 Limitations and Future Work .......................................................... 113
7.2.1 Smartphone-based Travel Survey Method .................................................. 114
7.2.2 Perceived Air Quality Measure ..................................................................... 115
7.2.3 Association between Air Quality and Travel Behavior ................................. 116
Bibliography ............................................................................................................. 117
Appendix I: Entry Questionnaire ........................................................................... 121
Appendix II: Travel Diary ....................................................................................... 129
Appendix III: PAQ Questionnaire ............................................................................ 133
Appendix IV: Exit Questionnaire ............................................................................ 135
List of Figures

Figure 1-1 Combine Several Data Sources to Generate More Accurate Inference ................................. 15
Figure 1-2 Motivation Pyramid ........................................................................................................... 17
Figure 1-3 Research Framework ......................................................................................................... 22
Figure 2-1 Acceptability Scale, Odor Intensity Scale, And Irritation Scale. ............ 29
Figure 2-2 Indoor Climate and Feeling Scales ...................................................................................... 30
Figure 3-1 Moves Icon and User Interface......................................................................................... 37
Figure 3-2 Process of Data Authorization and Access ................................................................. 38
Figure 3-3 Survey Framework ........................................................................................................... 39
Figure 3-4 The Flow of Participant Invitation, Dropping Out, and Participation ......................... 42
Figure 3-5 Data Structure of the Moves Daily Summary ............................................................... 49
Figure 3-6 Different Trip Notation .................................................................................................... 50
Figure 3-7 The User Burden Curve Of Different Travel Survey Methods ......................... 54
Figure 4-1 Two Close Frequently Visited Place in a Residential Area .................................. 59
Figure 4-2 Decrease of Number of Clusters as Epsilon Increases (Only Show Users with More than 100 Initial Locations) .................................................. 61
Figure 4-3 Distribution of Number of Clusters per Subject ............................................................ 62
Figure 4-4 Distribution of Number of Overnight Stay Places ..................................................... 66
Figure 4-5 Travel Mode Re-Categorization ...................................................................................... 68
Figure 4-6 Distribution of Number of Trips per Day ......................................................................... 68
Figure 4-7 Example of Matching the Moves Trip and The Survey Trip ......................... 71
Figure 4-8 Trip Time (Left) and Mode (Right) Matching Results at Different Thresholds in Different Directions ................................................................................. 72
Figure 5-1 Number of Subjects Taking the PAQ Survey in Beijing Each Day ...... 76
Figure 5-2 Average PAQ Rating of Each Day ............................................................................... 77
Figure 5-3 The Distribution of Sensory Ratings ............................................................................. 77
Figure 5-4 The Temporal Variance of PAQ Rating of The Home, Workplace, and Worst Stop During Commuting Trip for Each User ........................................ 80
Figure 5-5 Daily Average PAQ of the Sensitive Group and Insensitive Group ........... 81
Figure 5-6 Location of the 35 Air Quality Monitoring Stations in Beijing .................. 82
Figure 5-7 Spatial Variation of Daily Averages of Different Air Pollutants ................ 83
Figure 5-8 Daily Variation of Average Air Pollutant Density ................................................... 84
Figure 5-9 Correlation between PAQ and Objective Measurements ............................... 86
Figure 5-10 Variance Of PAQ Ratings From Different Subjects Within Same AQI Categories ......................................................................................................................... 91
List of Tables

Table 1.1 Pros And Cons Of Different Data Sources.......................................................... 14
Table 3.1 Mobility Tracking Apps Comparison................................................................. 35
Table 3.2 Comparison between Moves and Slife............................................................... 36
Table 3.3 Socioeconomic Feature Distribution of the Sample........................................... 43
Table 3.4 Sample Attrition Rate and Reasons ................................................................. 44
Table 4.1 Travel Mode Split According to Moves Data..................................................... 69
Table 4.2 Trip Time and Mode Matching Results at Different Thresholds............ 72
Table 5.1 The Intra-Personal Home-Work-Commute PAQ Variance ...................... 78
Table 5.2 Spatial Variation of the Concentration of Air Pollutants ......................... 84
Table 5.3 Day-to-Day Standard Deviation of All Air Pollutants ............................... 85
Table 5.4 Correlation between Air Pollutants and AQI ................................................. 85
Table 5.5 Correlation Coefficient between PAQ and Air Pollutants ....................... 87
Table 5.6 Major Sensory Effects of Air Pollutants......................................................... 87
Table 5.7 Correlation Coefficient between Sensory Ratings and Pollutant Concentrations ....................................................................................................................... 88
Table 5.8 Relationship between Pollutant Concentrations and PAQ Ratings for Each Subject .................................................................................................................. 89
Table 5.9 AQI Ranges....................................................................................................... 90
Table 5.10 Correlation between Air Quality Measures and Pollutant Concentrations .......................................................................................................................... 92
Table 6.1 Variables in the Regression Model ................................................................. 97
Table 6.2 Estimation Results with AQI as the Air Quality Measure ....................... 100
Table 6.3 Estimation Results with PAQ as the Air Quality Measure ....................... 103
Chapter 1

Introduction

Technological advances have had substantial effects in the realm of travel surveys. In the recent years, thanks to its ubiquitousness, built-in GPS function, powerful computing capacity, as well as the easy and flexible user interface, the smartphone is becoming an increasingly popular and promising travel survey tool. Over the past years, various academic projects have proved the feasibility of using the smartphone to collect travel data. Now there are even public agencies trying to leverage the smartphone to perform the household travel survey. For instance, a smartphone-based seven-day household travel diary was conducted for the Madison County Council of Governments (MCCOG) in Anderson, Indiana and the Federal Highway Administration (FHWA) Office of Planning and Office of Transportation Policy Studies in the US (Greene et. al., 2016). With mature implementation and data processing methods, the smartphone-based travel survey could be extended to various levels of transportation agencies, and has the potential of obtaining abundant and accurate travel data with low costs.

The smartphone-based travel survey becomes more powerful when combined with other travel data sources. Let’s compare three major travel data sources. The first one is the questionnaire-based travel survey, which usually asks the respondent to report their socioeconomic characteristics as well as the trip time, mode, destination and purpose of a typical day. The second one is the public transit card data, which contains automatically collected card transactions with location and time stamps. It collects a huge amount of data at minimal marginal cost. The third one is the smartphone-based travel data. The three data sources overlap with each other in certain areas, and each has its own pros and cons. Table 1.1 summarizes which data
is covered by which data source: black dot means covered and circle means not covered. The questionnaire-based travel survey has the potential of covering every detail of a trip in the questions, including the starting and ending time and location, travel mode, and trip purpose. The transit card data is restricted to describe the transit rides only. The smartphone-based survey can easily capture the track points and time stamps along a trip, though the data requires further processing to generate meaningful trips. Travel mode can be inferred with certain accuracy nowadays, but trip purpose cannot be easily inferred yet.

The above discussion, however, is only theoretical. In reality, what we really get always deviates from the theoretical situation. This is especially true with the questionnaire-based travel survey. Due to inaccurate memory and intentional leaving out trips to reduce report burden, the trips reported is usually a subset of all the trips actually made. Also, it is likely that the reported starting and ending time will have errors. In comparison, the travel mode and trip purpose are more likely to be truthful. The transit card data could be misleading in the way that one could have multiple cards, or several people could share one card. Also, occasionally one may pay with cash so the trip is missing from the dataset. The smartphone-based survey becomes vulnerable when the phone is out of battery or left behind.

Table 1.1 Pros And Cons Of Different Data Sources

<table>
<thead>
<tr>
<th></th>
<th>Non-motorized trips</th>
<th>Public transit trips</th>
<th>Car/taxi trips</th>
<th>Train/airplane long-distance trips</th>
<th>Activity type at destination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Questionnaire-based Travel Survey</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>Transit Card Data</td>
<td>○</td>
<td>●</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Smartphone Data</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>○</td>
</tr>
</tbody>
</table>

● captured ○ not captured

Although none of the three data sources is perfect in matching the ground truth, a proper data fusion may take us closer to the ground truth than any single data source does, since each data source has its own advantages. Let’s look at an example as shown in Figure 1-1. Suppose that a complete trajectory is home – walking – bus stop – bus – bus stop – walking – work – walking – shopping – taxi – home. The
questionnaire-based travel survey, transit card data, and smartphone-based travel survey will each have a different representation of the ground truth. The travel survey is likely to cover the main locations (home and workplace) and main trips (bus trip and taxi trip), but miss the walking trips and the small stop for shopping. The transit card data accurately records the on and off time and location of the bus trip. The smartphone is likely to record every detail of the trip, but is not sure about the motorized travel modes and location types (whether home, workplace, or a shop). These three representations are displayed in Figure 1-1 as the top three records. If we combine the three data sources by merging the top three records together to get the inferred trajectory (the fourth record in figure 1-1), we can see that now we almost have every detail of the trip, except for the activity type in the shopping stop in this example. The point is, although the inferred trajectory by data fusion may still not be the exact ground truth, it could bring a significant improvement from the travel survey status quo.

![Figure 1-1 Combine Several Data Sources to Generate More Accurate Inference](image)

Given that the smartphone-based travel survey is promising to advance the travel survey method, now the challenge lies in how to improve the smartphone-based travel survey in terms of survey design, implementation and data analysis, to make it more mature and ready for practice. This thesis describes the design and implementation of a smartphone-based survey in Beijing, China, discusses the lessons learned in the survey design and implementation, explores the data processing and analysis methods, and compares the smartphone-collected data against travel survey data.

Another key topic of the thesis is travel behavior and air quality. Due to excessive
fossil fuel burn in the transportation sector, heating sector, and related production industries, big cities in China are experiencing increasingly heavy air pollution in recent years. The air pollution causes severe health concerns. In the short term, residents exposed to heavy air pollution may feel respiratory discomfort. In the long term, air pollution could lead to increased risk of disease and mortality. From the residents’ perspective, one rarely has the capacity to reduce the air pollution of a city per se, but can only try to reduce one’s own exposure to the pollutants. Given a heavily polluted day, possible ways to reduce exposure to air pollution includes changing travel time, mode and route, or even cancelling less important trips. If such travel behavior changes indeed happen according to air quality, then the travel demand distribution on heavily polluted days is expected to be different from that of clear days.

This thesis explores the relationship between travel behavior and the air quality. The air quality data come from two data sources. The first one is Beijing Municipal Environmental Monitoring Center (BMEMC). The 35 air quality monitoring stations in Beijing constantly measure the concentration of 6 major air pollutants and Air Quality Index (AQI) and reports the result to a publicly accessible database every hour every day. The second data source is that we ask the subjects to report a perceived air quality (PAQ) rating in the survey every day. The PAQ rating is a metric developed in this thesis. It’s adapted from a PAQ system for measuring indoor air quality. Different from the objective pollutant density measurement, the PAQ measures how people feel about the overall air quality as well as specific sensory feelings. This thesis will first assess the objective air quality measurements in Beijing and the participants’ PAQ ratings, and then compare the objective and subjective measurements, and finally relate the air quality data to the travel behavior changes.

1.1 Motivation

There are several motivations for performing this research. The motivations are progressively going deeper, from method-oriented to phenomenon-oriented to problem-solving-oriented, as described in Figure 1-2.
1.1.1 Travel Survey Method Improvement

The direct motivation for performing the smartphone-based travel survey is to accumulate experiences and lessons to make the survey method more mature. As discussed in the previous section, the smartphone-based travel survey is a promising survey tool, but not many studies have been performed in the world to generate a widely accepted method from survey design to data analysis. The existing studies are mostly from European, American, and Australian cities, which may not be completely applicable to the developing counties. In China, there have been very few smartphone-based travel surveys in the past. Given that China has many special situations, including huge population, heavy traffic in big cities like Beijing, big income and lifestyle gap in different socioeconomic groups and so forth, we believe it is meaningful to try out the smartphone-based survey in China as one of the pilot studies. The experience will be valuable for similar studies in the future.

1.1.2 Understanding Travel Demand

The motivation of pursuing a better travel survey method is to better understand the travel demand with the collected data. The smartphone-based travel survey and its combination with other data sources could bring a lot more details about the travel demand than the previous methods.

Firstly, it has the potential of describing the static travel demand of a typical day.
from door to door, covering almost every mode and trip leg. For example, compared with other data sources, it is more convenient to record the routes of walking trips and cycling trips with the smartphone. If we accompany the trajectory data with questionnaires on the walking and cycling experience, we would get great data about city walkability and cycling environment much more easily than with traditional survey. It also provides great data for public transit trips. The last mile problem has been a cliché for public transit services, but few studies have shown the details of the last mile trips. Now with the smartphone data, it becomes possible to take a closer look at the actual distance and travel mode of the last mile for each of the public transit stops. A lot more important details about the transit trips can be revealed, including number of transfers needed to complete a transit trip, connecting distance and waiting time, and so forth. Compared with the public transit card data, the smartphone data completes the picture by filling the non-transit gaps.

Moreover, due to the low marginal cost of collecting multi-day data, the smartphone-based travel survey could capture the dynamics in travel demand. There are many variables that could affect travel demand, among which air quality is an important but seldom discussed one. This thesis covers travel data and air quality data for a period long enough to examine the interaction in between. Besides air quality, there are many more dynamics that can be analyzed in the same manner. For example, Beijing has the odd-and-even license plate policy, so that residents cannot drive the same car everyday. Then what are the alternatives to the car-owners when they cannot drive? The multi-day mobility tracking could give the answer. Also, by tracking for a longer period, special transportation behaviors rather than an over-generalized typical travel pattern begin to emerge, like travel patterns when there is a big event in the city, during national holidays, when there is bad weather, or when a certain transportation policy takes effect (e.g. when the highway is free of charge instead of tolled).

1.1.3 Adapting the Transportation Services to Meet the Demands

It is important for the public agencies and scholars to understand the travel demand and its dynamics, since it is the basis to adapt the existing transportation services and policies to better serve the public. The static travel demand can help with
regular transportation supply adaptation. For example, from the full OD matrix of the public transit trips, we can identify severe last mile problem or complicated transfers, which could be indicators for lack of feeder system or bad transit network design. Knowledge about the travel demand dynamics can help the public agency cope with special occasions. For example, suppose that we find that when the air pollution is severe, people shift from walking or cycling commutes to public transit to reduce exposure to the pollutants. Then when there is a forecast for heavy pollution, the public transit agency should be prepared for a higher passenger volume. This is equally true for other dynamics such as bad weather, big city events and so forth.

1.2 Research Objectives and Approach

In line with the motivations described above, this thesis focuses on performing a smartphone-based travel survey and exploring the relationship between travel behavior and air quality. Specifically, there are the following four objectives.

1. Design and implement a smartphone-based travel survey seeking to identify pitfalls and obstacles as well as develop solutions to them.

2. Explore initial data processing methods and data fusion possibilities to enhance the smartphone-based travel survey method.

3. Develop a measure of perceived air quality describing the air quality from the perspective of residents’ subjective feelings. Compare it against objective measurements.

4. Evaluate the association between daily travel behaviors and air quality.

These objectives are addressed through performing a daily mobility pattern and perceived air quality survey in Beijing and the following data analysis. This thesis is based on the MIT ESI: Clearer Skies in Beijing project. The on-going project aims at collecting mobility and perceived air quality data from 1,000 residents in Beijing. Due to time constraints, this thesis only analyzes data from 258 subjects. For each subject, smartphone-recorded travel trajectory, self-reported travel diary, perceived
air quality evaluation, and personal background information are collected.

To address the first objective, a thorough process from survey design to implementation is conducted, including local survey market research, tracking app performance test and selection, trajectory data access and storage setup, questionnaire design, recruitment strategy design, pilot survey, and formal survey implementation. Throughout the process many problems were encountered. Those problems that we believe could be commonly faced by similar practices are recorded in detail. Corresponding reflections, trade-offs, and solutions are also discussed.

To address the second objective, this thesis uses data from 258 participants as a sample, to demonstrate the features of the raw smartphone-recorded trajectory data. To make the trip and stop data meaningful in terms of transportation research analysis, a spatial clustering of the stops is performed to reduce the total number of stops. Trip segments and trips are re-generated based on rules. Home and workplace location of each user are detected using rule-based models, and thus identifying the commuting trips. An initial attempt on data fusion is performed by matching the smartphone-identified trips to the self-reported trips.

To address the third objective, an outdoor PAQ measure is developed, based on past indoor PAQ measures and outdoor environment characteristics. During the survey period, subjects report the outdoor PAQ for three spots every day: around home, around the workplace, and worst spot during commuting. To evaluate the outdoor PAQ measure, the spatial and temporal air quality variations revealed by the PAQ ratings are compared against that revealed by the objective measurements. The correlation between the PAQ ratings and objective measurements is examined both in the aggregated level and individual level. To address the person-to-person variation in making PAQ ratings, the PAQ ratings made by sensitive and insensitive subgroups are compared. How different people respond to the same Air Quality Index (AQI) category is also examined.

To address the fourth objective, a dataset is constructed by linking the daily travel data and the air quality data. In the dataset, each row represents a day. The columns are variables, including socioeconomic characteristics, air quality measurements,
weekday, as well as travel behavior measures. The travel behavior is measured by 5 variables, namely number of trips per day, number of non-motorized trips per day, percentage of non-motorized trips per day, distance travelled per day, and total travel time per day. With this dataset, several regression models are built to test how the different aspects of travel behavior are affected by air quality, personal characteristics, and working constraints.

1.3 Thesis Framework and Organization

Figure 1-3 illustrates the research framework. On one hand, the smartphone-based travel method is practiced from survey design to data analysis, with a smartphone app called Moves. The collected travel data is analyzed and compared with traditional memory-based self-reported survey data to understand their pros and cons as well as promote travel survey method improvement. On the other hand, the outdoor PAQ measure is developed to collect subjective air quality data along the survey. The PAQ ratings are compared against the objective air quality measurements collected by the official air quality monitor stations in Beijing. Based on the comparison, evaluation of the PAQ measure as well as the relationship between PAQ and objective measures are presented. Finally, the two threads are combined together, to answer the question of what is the relationship between air quality and travel behavior.
The organization of this thesis is as follows. Chapter 2 summarizes the background of this research, including the evolution of the travel survey, recent progress on the smartphone-based travel survey, air pollution status in China, air pollution measurements, and existing studies on the association between air pollution and travel behavior. Chapter 3 describes the details of the survey design and implementation, and presents the data used by this thesis. Chapter 4 presents the processing of the smartphone-collected trajectory data, including initial data cleaning, home and workplace location detection, trip identification, travel sequence construction, as well as the comparison between smartphone-identified trips and self-reported trips. Chapter 5 summarizes and compares the air quality evaluation from objective and subjective measurements. Chapter 6 evaluates the association between travel behavior and air quality. Finally, Chapter 7 presents the concluding remarks of this thesis.
Chapter 2

Literature Review

This chapter details the background and motivations for performing this research. Section 2.1 shows that technology advance has always been an important impetus to update the travel survey method. As one of the most cutting-edge method, the smartphone-assisted survey method has been proved of its feasibility by various field experiments, but still needs more studies to make the method mature. Besides, the existing practices are mostly from the developed countries. There are very few past practices in China, which is where this research locates. Section 2.2 describes how the air pollution is becoming increasingly severe in China and how the air quality is being measured currently. Section 2.3 relates the air quality level to travel behavior. Past studies have shown that the exposure to air pollutants could be reduced by carefully selected travel plans, including time, routes, and travel mode. Hence, it is reasonable to expect an interaction between the travel behavior and air quality.

2.1 Advanced Travel Survey Method

2.1.1 Travel Survey Method Development

Travel survey is an important input for developing models that assist urban and transportation planning as well as policy formulation. Scholars pay close attention to methods of collecting more detailed and accurate travel survey data. Due to technology advances, the travel survey method has been improving over time to fulfill the goal of obtaining data with higher quality with lower cost.
Traditionally, the travel survey is done face-to-face and records with paper and pencil. Such method is very costly and potentially dangerous to the investigator especially in some areas of the country. Therefore, mail surveys and telephone surveys gradually replaced the face-to-face interview. After the internet becomes popular, subjects are allowed to answer the questions in a webpage, and the data will be automatically collected for the researcher. Moreover, the answers to some questions can be prepared for the respondent to select from, such as trip purpose and travel mode. In this way, the burden of both the respondent and the data analyst are reduced. However, no matter how the communication method changes, the survey data come from the respondent’s perception, which is subjective, not accurate, and can be manipulated or avoided.

The emergence of Global Positioning System (GPS) devices solves the problem of non-response and misreporting to some degree. GPS studies first appeared in the late 1990s (Wagner, 1997). Initially, GPS devices were attached to cars. Later on, hand-held devices were used to capture all modes of travel (Wolf, 2004). According to some studies, compared with GPS records, paper-based travel diaries under-report about 20–30% of trips (Bricka & Bhat, 2006; Stopher & Greaves, 2009; Stopher & Shen, 2011; Wolf, 2000). GPS records also improve the accuracy of reported trip times, locations, and paths, and reduce respondent burden. However, GPS has its own problems. Compared with traditional survey, it cannot answer questions of travel mode and travel purpose. Besides, there are problems of increased budget from purchasing the GPS device, unstable signal in certain areas, and difficulties in GPS data processing.

Mobile phones can also track the subject with GPS signals. Compared with dedicated GPS devices, mobile phone GPS location data is not as dense and accurate, but mobile phone has the advantage of taking data from more sources such as Global System for Mobile Communications (GSM) and Call Detail Record (CDR) data. The location accuracy of mobile phone data is also pretty satisfactory. Also, Using personal mobile phones avoids the problem of assigning and recycling GPS devices to the participants, thus reduces survey cost. Initial mobile phone assisted surveys were implemented in the mid-2000s Asakura and Hato (2004) were among the earliest to show fundamental concepts and methodologies of using mobile communication instruments for tracking individual travel behaviour in urban space. The characteristics of the tracking method using cellular phone is discussed in detail. Afterwards, Ohmori et al. (2006) developed a
GPS mobile-phone-based activity diary survey system and a GPS-equipped PDA-based activity diary survey system. Gonzalez, Marta C., Cesar A. Hidalgo, and Albert-Laszlo Barabasi (2008) explored the temporal-spatial pattern of trajectories recorded by cellphone, and clustered the subjects into different types based on the data.

The recent advance and popularity of smartphones is leading to the next travel survey method update. In the last five years, smartphones become increasingly popular. In the United States, smartphone users grow from 62.6 million in 2010 to 171 million in 2014, and are expected to continue increasing (Statista, 2015). Now more than half of the US population are smartphone users. Compared with regular mobile phone, smartphone is more powerful in data computing. With certain learning algorithm, some smartphone apps can infer travel mode and travel purpose. Moreover, there are apps dedicated to assist the travel data collection. Such apps not only track GPS locations, but also provide prompted recall services to collect non-location data, such as filling background questionnaire, asking for travel mode, activity type, assessment of the current travel experience, and so forth. With the interactive interface, it is convenient for the user to verify the data on the phone. Cottrill, Caitlin, et al. (2013) developed the Future Mobility Survey (FMS) for travel data collection in Singapore, which is a smartphone-based prompted recall travel survey that aims to support data collection initiatives for transport-modeling purposes. Berger, Martin, and Mario Platzer (2015) with the app SmartMo, Geurs, Karst T., et al. (2015) with the app MoveSmarter are also researches in the same kind. Such studies show that the smartphone-based travel survey is well feasible in the practiced countries, and the method is promising in collecting more detailed and accurate data at a lower cost than the traditional methods.

2.1.2 Smartphone-based Travel Survey

Till today, smartphone-based travel survey has already been practiced in many cities, especially in the U.S. and European countries. Though still not the most commonly adopted travel survey method by public agencies, it is by no means novel to the academia. Scholars are now turning to the specific aspects of the method to make it more robust, in terms of sampling, movement and stop detection, location detection, travel mode detection, activity detection and so forth.
Montini, Lara, et al. (2015) and Pereira, Francisco, et al. (2013) conducted travel survey using dedicated GPS devices and smartphones at the same time to compare their performance. Pereira, Francisco, et al. (2013) Safi, Hamid, et al. (2015), and Maruyama, Takuya, et al. (2015) discuss issues in the design and implementation of smartphone-based survey, including hardware framework design, battery depletion, participant involvement, sample bias, and privacy concerns. Such discussions accumulate experiences and lessons learned from the initial attempts, laying the foundation for more mature and comprehensive practices in the future. Another category of in-depth research focuses on data processing. Based on the raw spatial-temporal individual data, substantial literature discusses algorithms to obtain meaningful locations, trips, travel modes, and activity types (Chen, Jingmin, and Michel Bierlaire, 2015; Zhao, Fang, et al. 2015, etc.). The details of such methods will be reviewed in Chapter 4 before introducing the methods used to process data in this thesis.

Despite the enthusiastic practices and analyses on smartphone-based travel survey in the world, there remain few such practices in China. There are a few studies that use mobile phone GSM data or call/text communication data to construct the OD matrix (Hu et. al, 2013; Yang et. al, 2015). Such data are accessed in bulk with individual data records remain anonymous, thus is difficult to be compared against or linked with other data, such as socioeconomic characteristics and self-reported travel surveys. Very few studies carry out a smartphone-based travel survey on a particular set of subjects. Yang et. al (2015) performed a smartphone-based travel survey in Shanghai, and compared the data against self-reported travel survey. Meanwhile, China has huge amount of smartphone users. In 2014, there are 482.7 million smartphone users in China (Statista, 2016), which is 35% of the population, and the number is expected to continue to grow in the following years. With such a large smartphone user pool, it is promising to test out the feasibility of using the smartphone-based travel survey as an alternative to the traditional travel survey method.

2.2 Air Pollution and Air Quality Measurement

2.2.1 Air Pollution in China

In the past decades, China has undergone rapid economic growth. The annual
growth rate of the gross domestic product (GDP) in China was nearly 10% in the recent years. The economic growth highly depends on energy consumption, which then lead to air pollution. China became the largest global energy consumer in 2011 and is the world’s second-largest oil consumer (US Energy Information Administration, 2015). Coal accounts for 66% of the total energy consumption, and emissions from coal combustion are the major anthropogenic contributors to air pollution in Chinese cities (Chan and Yao, 2008; US Energy Information Administration, 2015).

The air pollution causes a severe health concern. One of the major air pollutants in Chinese cities is the small particulate matter (PM). Studies show that short-term exposure to particulate matter has been linked to adverse health effects, including increased mortality, increased rates of hospital admissions and emergency department visits, exacerbation of chronic respiratory conditions, and decreased lung function (Chen et al. 2011). Other major pollutants in Chinese cities include SO2, NO2, O3, and CO (Beijing Municipal Environmental Monitoring Center, 2015).

### 2.2.2 Air Quality Measurement

The traditional way of measuring and analyzing air quality is through objective measurements, including density of various pollutants and visibility. There are six principal pollutants, or core pollutants, as addressed by The United States Environmental Protection Agency (EPA). They are Carbon Monoxide, Nitrogen Dioxide, Ozone, Particulate Matter 2.5, Particulate Matter 10, and Sulfur Dioxide. To make the air quality level more intuitive, there is also the Air Quality Index (AQI), which is calculated based on the principal pollutants. AQI runs from 0 to 500. The higher the AQI value, the greater the level of air pollution and the greater the health concerns. The function to calculate AQI is as follows:

\[
I_p = \left[ \frac{(I_{hi} - I_{low})}{(BP_{hi} - BP_{low})} \right] (C_p - BP_{low}) + I_{low},
\]

where \( I_p \) is the AQI of the pollutant; \( C_p \) is the rounded concentration of pollutant \( p \); \( BP_{hi} \) is the breakpoint greater or equal to \( C_p \); \( BP_{low} \) is the breakpoint less than or equal to \( C_p \); \( I_{hi} \) is the AQI corresponding to \( BP_{hi} \); \( I_{low} \) is the AQI corresponding to \( BP_{low} \). (US EPA, 2015)
Note that the above function is calculated based on the concentration of a specific pollutant. The US Beijing Embassy only monitors PM2.5 and thus the AQI reported by it is based on the concentration of PM2.5 only. The AQI data used in this thesis is from Beijing Municipal Environmental Monitoring Center, which calculated the AQI of all the six air pollutants, and report the highest AQI as the daily AQI.

Most of the current research on air pollution in China takes the perspective of analyzing such objective measurements. Some studies analyze the trends of pollutants concentration (Zhang, Renjian, et al., 2013, Yang, F., et al., 2011) or visibility (Chang & Liu, 2009, Deng et. al. 2008) over time. Some studies explore origins of the pollutants (Zheng & Smith, 2007, Yan & Crookes, 2010). Some studies explore the health impacts caused by certain pollutants (Tie, Wu, & Brasseur, 2009). The objective measurements are convenient to collect, easy to interpret, and can be mapped to subjective feelings.

Another perspective is to measure subjective feelings. After all, we care about the air quality because it affects feelings and health. The final goal of air quality control is for people to feel good. In this sense, the subjective measurement is a direct measurement to evaluate the air quality. Additionally, we can compare the subjective measurement with the objective measurements on various pollutants, to see how different pollutants affect different aspects of feelings. Of course, there are disadvantages about subjective measurement. For one thing, human feeling is not perfectly accurate. It could vary even when the objective air quality stays the same. Also, different people could have significantly different feeling on the same environment. It could be very hard to interpret and compare the subjective measurement across individual or even intra-individual. With the disadvantages said, the subjective measurement is still meaningful, and is collected in this thesis.

In the literature, the subjective measurement of air quality is referred to as perceived air quality (PAQ). The perceived air quality is people’s sensatory feelings towards the air quality. It is usually measured together with sick building syndrome (SBS) symptoms to evaluate the indoor air quality. The most widely used measurement is developed by Wargocki et al. (1999), based on earlier works by
Gunnarsen and Fanger (1992), Yaglou (1955), Yaglou et al. (1936), and Wyon (1994). It first asks the acceptability of the overall air quality in a continuous scale. The subject has to make a clear distinction between the acceptable and unacceptable perceived air quality. The odor and irritation intensity are assessed in a 6-level scale, from nothing to overpowering odor/irritation (Figure 2-1). It also asks about the indoor climate and feelings, on a continuous scale or from 0 to 100 (Figure 2-2). Usually the percentage of subjects dissatisfied (PD) is calculated to assess the overall PAQ in an environment.

Figure 2-1 Acceptability Scale, Odor Intensity Scale, And Irritation Scale.
Figure 2-2 Indoor Climate and Feeling Scales

The PAQ measurement used in this thesis is developed based on the above measurement. Details are in Chapter 3, Data Collection and Description.

2.3 Air Pollution and Travel Behavior

For many residents, they are most exposed to the air pollution when making daily trips. There is abundant literature discussing how exposure to air pollution during trips can be affected by mode choice, route choice and travel time.

- Mode choice and air pollution exposure
  Kaur and Nieuwenhuijsen (2008) finds that travel mode is a statistically significant determinant of personal exposure to PM2.5, ultrafine particle counts, and CO. Briggs et. al. (2008) shows that exposure to particle air pollution while walking is greatly higher than those while driving, since the filtration system in the car helps to prevent ingress of particles. Tsai et. al. (2008) reports similar
results.

• Route choice and air pollution exposure
Hertel et. al. (2007) proves that a proper selection of route through the urban area may significantly reduce the air pollution exposure. The study compares biking on different routes, as well as biking and riding the bus. The results show that the accumulated air pollution exposure for the low exposure route is between 10% and 30% lower for the primary pollutants (NOx and CO). The bus is generally following highly trafficked streets, and the accumulated exposure along the bus route is therefore between 79% and 115% higher than the high exposure bicycle route. Thai et. al. (2008) finds that land use and proximity to traffic significantly affect exposure to particle air pollution along designated bicycle routes. Specifically, while concentration of PM2.5 is found to be relatively spatially uniform over the length of the study route, PM10 shows a more heterogeneous spatial distribution. Construction sites and areas susceptible to the suspension of road dust have higher concentrations of coarse particles. Ultrafine particles were also heterogeneously distributed in space, with areas with heavy traffic volumes having the highest concentrations. Kaur and Nieuwenhuijsen (2008) finds that traffic count explains little of the variability in the PM2.5 concentrations, but it has a greater influence on ultrafine particle count and CO concentrations.

• Travel time and air pollution exposure
Hertel et. al. (2007) shows that travelling outside the rush hour time periods reduces the accumulated exposure between 10% and 30% for the primary pollutants, and between 5% and 20% for the secondary pollutants.

Since studies show that properly selected travel mode, trip route, and trip time can significantly reduce exposure to air pollution, it is reasonable to expect that people actually adjust their travel plan in real life, especially on heavily polluted days in heavily polluted cities like Beijing. However, to the best of our knowledge, no literature exist that describes the travel behavior response, like changing from biking to bus or avoid peak hour travel, to reduce exposure to air pollution. With the smartphone-based travel survey collecting multi-day travel data, now there is chance to explore this relationship with real data.
Chapter 3
Survey Design and Implementation

This chapter discusses the survey design and implementation process. This study collects two types of data: Beijing residents’ daily trajectories and air quality evaluations. The two data sets are collected in the same period of time to reveal the association in between. The trajectories are collected through a smartphone-based travel survey. For a subset of the survey days, the subjects fill out a travel diary based on memory. The subjective air quality evaluations are collected through daily questionnaires accompanying the travel survey. The official objective air quality evaluations are obtained from the official database provided by Beijing Municipal Environmental Monitoring Center (BMEMC).

In line with the research objective of practicing the smartphone-based travel survey method in China in hope of identifying pitfalls and obstacles as well as developing solutions to them, the thorough process from survey design to implementation is recorded and discussed in this chapter. Section 3.1 discusses how to choose the right app for the purpose of smartphone-based travel survey. Section 3.2 presents survey implementation details. Section 3.3 describes sample recruitment strategy and the socioeconomic feature distribution. Section 3.4 presents the design of questionnaires, travel data collection method, and PAQ survey design. The chapter ends with a summary discussing lessons learnt in the process.

3.1 Choosing the Right App

A major advantage of the smartphone over the basic mobile phone is that there are
apps, which allow convenient data collection, storage, presentation on the screen for easy user interaction and even initial raw data processing. Collecting the trajectory data from a trajectory-tracking app is probably the most convenient way of retrieving the data from a smartphone.

There are many such apps out there in the market. It is important to choose, or design in some occasions, the right app with right features. The apps are built for various purposes, and thus have different features. For the study of daily trajectory tracking, some features are indispensible, while others may add burden to the user so we would rather not have them. From the perspective of this research, the following features are important:

- **Automatic trajectory tracking.** It would be preferable if an app automatically tracks the location or trajectory 24 hours a day. It should not prompt users to start or end tracking. The user will just leave the app alone and the app should quietly do the entire job. Some apps are designed to track only a period of movement. They often have an obvious START button, and track only after the button is pressed, until the user presses STOP. Technically such apps can also do the job for our study, but add to the user burden, and the timer running on the screen is pretty disturbing.

- **Travel mode recognition.** Some apps can infer travel mode based on speed and acceleration. For a travel survey, such a feature is clearly preferable. It is a pity that currently even the best app in the market can only distinguish walking, running, biking, and motorized transportation, but cannot distinguish among the many motorized transportation modes. An alternative is asking the user to label the travel mode on their own, which is adopted by some smartphone-based travel studies. The drawback is adding burden to the user, so it becomes a trade-off between user burden and more accurate data.

- **Battery drain.** Too much battery drain could reduce users’ willingness to use the app or participate in the survey. Some apps allow the user to turn off tracking temporarily for battery saving. Such a feature could be a double-edged sword. If the user is instructed properly, it could be useful for occasions when the user is staying in a place for a long time (e.g. working in an office) and needs
to save the battery, so that the battery could be used to capture more important data (e.g. the work to home commuting trip). Without proper instruction or data quality control, the feature could lead to intentionally reduced data reporting from the user. Some apps slow down GPS collection rates automatically when the phone is stationary for a period of time to reduce battery drain. The side effect is that it may lose the beginning period of the next trip.

**Data export.** It is essential that the app provides a way to export the data as location coordinates, trajectory track points, and labels including timestamps, travel modes and so forth. Preferable data structures include json, geojson, csv, and the alike. Compared with bulk export from the app company's server at the end of the survey, daily export through an API is preferable, since in this way the data quality of each user could be monitored every day. When problems occur, early identification is crucial to fix the problem on time and avoid disputes and loss.

**Stability in China.** Some western apps fail to function properly in China. The reasons are various. Some apps cannot align the GPS location and the map properly. Some apps cannot communicate with the server due to Google service failure in China. Some apps only work well on iPhones. Chinese domestic apps tend to be more stable and work for all kinds of phones.

Based on the above criteria, a comparison of relevant apps is listed in Table 3.1.

<table>
<thead>
<tr>
<th>APP Name</th>
<th>Automatic tracking</th>
<th>Travel mode recognition</th>
<th>Low battery drain</th>
<th>Data export</th>
<th>Stable in China</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moves</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>○</td>
</tr>
<tr>
<td>Slife</td>
<td>●</td>
<td>●</td>
<td>○</td>
<td>○</td>
<td>●</td>
</tr>
<tr>
<td>Gudong</td>
<td>○</td>
<td>○</td>
<td>●</td>
<td>○</td>
<td>●</td>
</tr>
<tr>
<td>Endomondo</td>
<td>○</td>
<td>○</td>
<td>●</td>
<td>○</td>
<td>●</td>
</tr>
<tr>
<td>Run Keeper</td>
<td>○</td>
<td>○</td>
<td>●</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Lemeng</td>
<td>○</td>
<td>○</td>
<td>●</td>
<td>○</td>
<td>●</td>
</tr>
<tr>
<td>Yidong GPS</td>
<td>○</td>
<td>○</td>
<td>●</td>
<td>○</td>
<td>●</td>
</tr>
</tbody>
</table>

●: Yes, ○: No
Based on the comparison in Table 3.1, Moves and Slife are the two most promising apps. A final comparison between them (Table 3.2) shows that the key trade-off is among location accuracy, user pool, and data export method. (Whether the tracking feature can be turned off or not is not a key feature for choosing the app.) The location-offset problem is caused by the difference between the universal projection system and the unique China-only projection system. It causes an offset when mapping the trajectory to the base map as a presentation on the smartphone screen. Though disturbing, it is not a fatal error that cannot be fixed. The problem can be solved by mapping the coordinates to a proper base map or applying a projection transfer algorithm. A major limitation of Moves is that it only functions properly on iPhones. By the time the survey was launched, Moves released a new version that only functioned on iOS 9.0 and later, which further limited the user pool. The major advantage of Moves is that it has a stable and ready API that allows easy data access from the third party, like us the researchers. There is no such API available from Slife, so the data can only be obtained by bulk data export directly from the Slife server. As discussed previously, daily data quality monitoring is very important for obtaining high quality data. It is risky to see the data only after the whole survey is completed. Under such consideration, the final choice of app in this research is Moves.

Table 3.2 Comparison between Moves and Slife

<table>
<thead>
<tr>
<th>Same</th>
<th>Moves</th>
<th>Slife</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Automatic location tracking</td>
<td>• Automatic Location tracking*</td>
</tr>
<tr>
<td></td>
<td>• Inferred travel mode</td>
<td>• Inferred travel mode**</td>
</tr>
<tr>
<td></td>
<td>• Starting/ending time</td>
<td>• Starting/ending time</td>
</tr>
<tr>
<td></td>
<td>• JSON format data</td>
<td>• JSON format data</td>
</tr>
<tr>
<td></td>
<td>• Reasonable battery drain</td>
<td>• Reasonable battery drain</td>
</tr>
<tr>
<td>Difference</td>
<td>• Location offset</td>
<td>• Location accurate</td>
</tr>
<tr>
<td></td>
<td>• iPhone only in China</td>
<td>• Includes Android users</td>
</tr>
<tr>
<td></td>
<td>• API for the 3rd party to access data</td>
<td>• No API available</td>
</tr>
<tr>
<td></td>
<td>• Can be turned off</td>
<td>• Cannot be turned off</td>
</tr>
</tbody>
</table>

* The tracking point frequency is lower in Slife.
** The travel mode inference in Slife is not as accurate as in Moves.
3.1.1 Moves

Moves (Figure 3-1) is a smartphone app for iPhone and Android phones. It automatically records every movement of the user during the whole day. The tracking function is always on, unless the user chooses to stop it. The travel mode is differentiated into walking, cycling, and other transportation trips. The app consumes battery power. With typical phone use, a smartphone running Moves should have enough battery power to last all day. The optional Battery Saving Mode in Moves for iPhone claims to save up to 40% of battery.

The user can review the daily movement as a storyline, where it shows where, when, and how much the user moves. The routes also show up on a map, so the spatial pattern is more straightforward. The user can click on a location or a route to edit it. The user is able to name a location as home, work, or other destination, change the travel mode of a trip, or delete a location or trip.

![Figure 3-1 Moves Icon and User Interface](image)

Moves has an API that allows easy access to a large amount of users’ data, upon the users’ authorization. It works in the following 2-step process. First, the third party, namely the researcher, sends out an email to the users asking for permission to get information about their daily trajectories. Second, once the researcher gets the permission, the researcher can communicate to the Moves server to retrieve the
3.2 Survey Framework and Implementation

A Beijing local survey company was hired to implement the whole survey. The responsibility of the survey company includes recruiting subjects, instructing the subjects to install and use Moves, distributing questionnaires, monitoring the data quality, and distributing the compensation.

There are two phases of this survey study. The first phase is a one-week pilot survey aimed at recruiting 100 subjects. The main purpose of the pilot survey is to test the process including subject recruitment, app installation, quality of data flow from the subject to our server, questionnaire design, and so forth. The second phase is the formal survey. Each participant spends at least two weeks in the survey. Besides the entry and exit questionnaire that collects the socioeconomic features, relevant backgrounds and self-evaluations, the participant will install Moves and keep it running for 14 days. During the 14 days, the participant will answer a PAQ questionnaire each day. Moreover, in the last 4 days of the 14 days, the participant will fill out a travel diary that describes all the trips that he made in the day. All the participants need not start and end the survey at the same date. The survey proceeds on a rolling basis across 3 months. Participants come and go according to their own schedule. Figure 3-3 describes the framework of the whole survey.
All the questionnaires and travel diaries are online forms on the survey company's own platform. The participants will receive a link to the webpages and fill them out online. The details of these questionnaires and surveys are discussed in section 3.4 to 3.6.

To ensure the quality of travel data, we set a data quality standard. A qualified day is defined as a day with length of data flow longer than or equal to 10 hours, where regular nighttime (11pm to 7am next day) does not count. In this way, it is highly likely that the majority of trips are captured. A qualified sample is defined as a subject who provides data of longer than or equal to 12 qualified days. If a sample cannot provide as many as 12 qualified days in 14 days, he or she is welcome to extend the survey period until the standards are met.

Since there are data quality standards, a quality monitoring system is important to make sure that problems are identified and solved in time. We do not want to see the situation where due to technical issues or misunderstanding, the user believes he is sending out data every day but the server does not get the data, and we only realize the problem in the last day of survey. To avoid this, a report on how many hours each user is providing data each day is generated automatically every day. The survey company keeps track of this report, and helps users solve problems, or let them quit the survey if the problem cannot be solved.
When a participant has successfully provided all the data meeting the standards, he or she will receive a cash payment of 120 Yuan (around 18 USD) from the survey company. The participant will also get the direction of how to delete the app to prevent providing future personal data to us.

3.3 Sample Recruitment and Composition

The sample recruitment was initiated from the sample pool of the survey company, which contains around 100,000 people in Beijing. However, as the survey moved on, we found that it is very difficult to recruit 1,000 subjects just from the pool due to various obstacles. Therefore, the recruitment strategy was adjusted to multiple-source sampling.

The major obstacle of recruiting subjects is the technical problem. On Android phones, Moves requires Google Play Service to function properly. However, in China, the Google Play System does not have legal status. Google Play and its affiliated apps including Google Play Service are removed from Android phones in China, and there are no official versions of such apps available online for self-installation. There do exist several unofficial Google Play System installers online, but they are not stable and only work for certain Android phone brands and modes. Hence, Android users are not eligible for the survey. Moves is not available for Windows phones, which means we can only recruit iPhone users. In China, iPhone users took roughly 25% of all the smartphone users in 2015 (Statista, 2016). Although this percentage could be higher in big cities like Beijing, restricting the subjects to iPhone users still makes our potential sample pool much smaller. To make things worse, there are further technical barriers. Moves requires iOS 9.0 or later to function properly on iPhone. Users of iPhone 5 or earlier versions are generally unwilling or unable to upgrade to iOS 9.0. This further narrows down the sample pool to a fraction of iPhone users.

Some potential participants refuse to take the survey upon invitation. One major reason is that the survey takes much time while the payment is not especially attractive. The most time consuming part is setting up Moves data authorization and filling out the travel diary for 4 days. Another major reason is privacy concerns. Since the survey collects the complete travel routes and activity locations, some
users feel unsecure about their privacy, although we already declared data will be anonymous and for research purpose only.

For those who are eligible and willing to participate in the survey, some turn out to be unable to provide Moves data. As explained in section 3.1.1, the user needs to send authorization information to the project server, which is located outside China. Mainly due to bad network connection, the user often needs to repeat the authorization process several times before the project server successfully receives the authorization information. The foreign language (English) in the process and unfamiliarity of smartphone usage makes the process even more confusing to certain users. Some users managed to grant authorization, but just cannot provide stable data flow to our server, due to bad network connection, weak GPS signals, or some unknown reasons. Such participants will have to drop out from the survey.

To summarize, the amount of actual participants shrinks sharply from the amount of potential participants due to above reasons. Figure 3-4 depicts this flow of participation and dropping out. To make the recruitment process smoother, after the pilot survey, we adjusted the sample recruitment strategy. After the pilot survey is completed, we accumulated dozens of Moves users. For them, the troublesome Moves data authorization part is already done, and their daily routine is already disclosed to us. Therefore, the marginal cost of continuing to participate the formal survey is less. Hence, we welcome the participants from pilot study to move on to the formal survey. Second, we encourage the existing participants to introduce their acquaintances to participate in the survey and instruct them the authorization process. For one thing, when introduced by an acquaintance, people tend to be more trustful and cooperative to the survey. Moreover, compared with online tutorial of the authorization process, face-to-face instruction is much more effective. The potential defect is the snowball effect. If a large portion of the participants are invited by existing participants, especially if the initial participants are not randomly selected, we will end up with a very biased sample. We try to avoid such unfavorable condition by limit the number of referrals. Third, the recruiting information is spread to people outside the sample pool of the survey company through Weibo (Chinese version Twitter) and relevant environment protection organizations.
Up to March 14th 2016, the study recruited 301 participants (43 from pilot and 258 from formal survey). The socioeconomic feature distribution is as listed in Table 3.3. There is noticeable unbalance in gender and age. Female counts for almost 75% of the whole sample size. In terms of age, nearly 90% of the sample are below 35. Such unbalance is accompanied with a relatively large proportion of students (17.61%). The unbalance is caused by the survey design and budget limit. Given the money incentive of 120 Yuan (around 18 USD) per 2 weeks, many potential subjects find the survey to be burdensome. Young people especially students tend to have lower value of time plus feel less burdensome playing with the smartphone. Female are generally more patient than male to go through the sometimes troublesome data access authorization process. Since the survey is till ongoing, the unbalance will be treated in the following recruitment process. Plan is made to increase the incentive from 120 Yuan (around 18 USD) to 140 Yuan (around 22 USD) per 2 weeks.
Table 3.3 Socioeconomic Feature Distribution of the Sample

<table>
<thead>
<tr>
<th>Socioeconomic characteristics</th>
<th>Number of subjects</th>
<th>Ratio</th>
<th>Beijing Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>gender</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>male</td>
<td>77</td>
<td>25.58%</td>
<td>50.55%</td>
</tr>
<tr>
<td>female</td>
<td>224</td>
<td>74.42%</td>
<td>49.45%</td>
</tr>
<tr>
<td><strong>age</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Under21</td>
<td>28</td>
<td>9.30%</td>
<td>31.8%</td>
</tr>
<tr>
<td>21to25</td>
<td>78</td>
<td>25.91%</td>
<td></td>
</tr>
<tr>
<td>26to30</td>
<td>94</td>
<td>31.23%</td>
<td></td>
</tr>
<tr>
<td>31to35</td>
<td>67</td>
<td>22.26%</td>
<td>47.2%</td>
</tr>
<tr>
<td>36to40</td>
<td>20</td>
<td>6.64%</td>
<td></td>
</tr>
<tr>
<td>41to50</td>
<td>14</td>
<td>4.65%</td>
<td></td>
</tr>
<tr>
<td>51to60</td>
<td>0</td>
<td>0.00%</td>
<td>11.3%</td>
</tr>
<tr>
<td>Above60</td>
<td>0</td>
<td>0.00%</td>
<td>9.6%</td>
</tr>
<tr>
<td><strong>Employment status</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>fully employed with fixed working time</td>
<td>177</td>
<td>58.80%</td>
<td>N/A</td>
</tr>
<tr>
<td>fully employed with free working time</td>
<td>31</td>
<td>10.30%</td>
<td></td>
</tr>
<tr>
<td>fully employed with regular shifts</td>
<td>11</td>
<td>3.65%</td>
<td></td>
</tr>
<tr>
<td>have multiple jobs or working locations</td>
<td>9</td>
<td>2.99%</td>
<td></td>
</tr>
<tr>
<td>not employed/ work from home/ freelance</td>
<td>18</td>
<td>5.98%</td>
<td></td>
</tr>
<tr>
<td>student</td>
<td>53</td>
<td>17.61%</td>
<td></td>
</tr>
<tr>
<td>retired</td>
<td>0</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>other</td>
<td>2</td>
<td>0.66%</td>
<td></td>
</tr>
<tr>
<td><strong>Hukou status</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beijing Hukou</td>
<td>191</td>
<td>63.46%</td>
<td>60%</td>
</tr>
<tr>
<td>non-Beijing hukou</td>
<td>110</td>
<td>36.54%</td>
<td>40%</td>
</tr>
</tbody>
</table>

To recruit the 258 subjects in the formal survey, the dropping rates at different phases are recorded as Table 4.3. The information of the survey is distributed to more than 26,000 iPhone users in Beijing, among which more than 1,200 people (4.62%) showed interest to participate. More than 70% of those who showed initial interest downloaded Moves successfully, but after that, only 36.28% of them completed the data access authorization process. After the authorization is done, more than 80% of the subjects completed the whole survey with qualified data. This dropping out patterns reveals the key barriers in the recruitment process. The first
barrier is that iPhone users tend to have higher value of time than the whole average level, according to the survey company's past experience and recruiting results. So less people show interest in trading their privacy and time for a limited amount of money. Then for people who are willing to participate, the major barrier is completing the authorization process.

Table 3.4 Sample Attrition Rate and Reasons

<table>
<thead>
<tr>
<th>Phase of Survey</th>
<th>Number of subjects</th>
<th>Percentage going to next phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Received invitation (iPhone users)</td>
<td>26000+</td>
<td>4.62%</td>
</tr>
<tr>
<td>Showed interest</td>
<td>1200+</td>
<td>71.67%</td>
</tr>
<tr>
<td>Downloaded Moves</td>
<td>860+</td>
<td>36.28%</td>
</tr>
<tr>
<td>Authorized Data Access</td>
<td>312</td>
<td>82.69%</td>
</tr>
<tr>
<td>Completed whole survey</td>
<td>258</td>
<td>-</td>
</tr>
</tbody>
</table>

To control the snowball effect, the initial participants and participants invited in by existing participants are labeled. Out of the 258 subjects who completed the formal survey, 239 subjects are recruited by the survey company and 19 subjects are introduced by existing users. There should be minimal snowball effect.

3.4 Entry and Exit Questionnaires

3.4.1 Entry Questionnaire

The entry questionnaire is designed to capture the following characteristics.

a) Socioeconomic characteristics

The travel pattern may vary according to socioeconomic characteristics. We collect basic socioeconomic characteristics including age, gender, and Hukou. Hukou is a unique characteristic for Beijing residents. People may live and work in Beijing, but without a Beijing Hukou. As of 2014, around 40% of Beijing
residents are without Beijing Hukou (Beijing Statistics, 2015). Without Beijing Hukou, people may be restricted in important life choices such as purchasing an apartment or sending kids to school. Therefore, their life and travel patterns may be different from Beijing Hukou residents.

b) Lifestyle

Though we will get the travel routes and location data from Moves, we still need other facts of the participants to make sense of the data. We collect lifestyle features, including employment status and residence status, to help us understand, or to some degree verify, the data. The employment status is categorized by working time, such as whether the participant is employed, whether the working time is flexible, and whether there is a regular shift. This characteristic helps us understand the commuting pattern. The residence status asks what other family members live together with the participants. It helps us identify the role of the participant in the family and then further infer his or her duties and activities.

c) Mode choice

We want to have some knowledge of how the travel choices are made. Whether the travel is made because there is no other choice, or out of utility maximization from a range of choices, can make a huge difference for us to understand the travel behavior. In the lifestyle questions we try to deal with this issue from the trip generation and time choice side. By asking mode choices, we deal with it from the travel mode side.

We ask how many cars and bikes are easily accessible for the participant. This is by no means a comprehensive mode choice survey, but provides some basic sense of the issue.

d) Smartphone familiarity

Since the travel routes and location data are collected by the smartphone, we want to have some sense of how familiar the participants are with using
smartphone. For data quality reason, skilled smartphone users are more likely to solve small app glitches, respond to app prompts correctly, make proper phone settings and so forth, therefore generating data of higher quality. Another reason is that the approach of smartphone-based travel survey excludes certain groups of people, namely non-smartphone-users and not-so-good smartphone users. We should be aware of the issue and identify which groups of people are most represented in this approach.

To measure the smartphone familiarity, we ask people their phone brand, the length of time of using the current phone and on average length of time of using one same phone. The brands are grouped according to different potential customers. iPhone and Samsung are by themselves. There are other groups representing regular domestic brands, regular foreign brands, and domestic creative brands. The frequency of changing phones could be another indicator for smartphone obsession. Some people may use expensive phones only for the friendly interface and stability. They may not enjoy play with the functions and settings of the phone. Such users are not likely to update the phone as technologies advance. Thus, we separate them from smartphone fans by looking at the frequency of changing phones.

e) Air quality sensitivity

In this study, we measure the air quality with people's subjective perception. A potential problem is that people may have different perceptions with identical air quality. The different perceptions may come from physiological reasons or psychology reasons. To capture such differences, we ask whether people see themselves as more sensitive to air pollution, whether they check air quality indexes and reports frequently (so that they may have a different reference point), and how they evaluate the current Beijing air quality condition.

3.4.2 Exit Questionnaire

The exit questionnaire is designed to fulfill the following purposes.
a) Evaluation of the accuracy of Moves.

Overall, Moves is pretty accurate in location and travel detection. However, we still want to get the assessment from the participants in this study specifically to exclude the small probability event that Moves is performing badly during this period. Participants are asked to rate the performance of Moves. If the rate is low, they are further asked to rate the performance in different aspects.

b) Re-contact Information, in case we want to continue the study in the future to gain panel data.

c) Beijing public transit card information. Though we cannot access the Beijing public transit data yet, we would like to leave a chance for future study. It would be important to compare the Moves record and transit trips tracked by the Beijing transit system.

d) Open question of other feedbacks.

3.5 Travel Survey

3.5.1 Moves Data Collection and Description

Moves provides various information about one’s daily travel. The full information and the data structure is as Figure 3-5. The key information includes starting and ending time as well as location of a trip or stay, inferred travel mode, and place labels (only if the user chooses to label). The inferred travel mode includes walking, biking, running, and transport. Motorized travel modes, like car, bus or subway, are all put into one category, transport.

Moves stores data in JSON arrays. By the end of each day, a data summary is generated for each user. The summary consists of date, last update date, a summary of trips by different modes, and segments. The most important information is in segments. A segment is a period of time during which the user is moving or staying. Accordingly, there is the move segment and place segment. Normally, the move
segment and place segment shows up one after another, but there are also rare cases when two segments of a same kind shows up in a row. There is a third kind of segment, off segment. It indicates that Moves tracking had stopped for some reason. A move segment could consist of one or more trips. A trip is of a single mode, while a move segment could consist of several trips of different modes. For example, there could be a move segment consisting of a walk trip, followed with a transport trip, and then another walk trip, which is the typical scenario when one is taking public transit.
Figure 3-5 Data Structure of the Moves Daily Summary
The notation of trips and segments adopted by Moves does not conform to what is usually used in the academia. To avoid confusion, from now on, we will define a short single mode movement as a trip segment, while a long distance movement with meaningful origins and destinations as a trip. The Moves notation and the notation adopted in this thesis are illustrated in Figure 3-6.

![Figure 3-6 Different Trip Notation](image)

(Move notation; right: notation adopted in this thesis)

Moves determines stay in a very cautious way. If the user is waiting for the red light at a crossing for 3 minutes, it could be detected as a stay. There is no way for the user to determine the threshold. Thus, future consolidation of trips is necessary, which is discussed in Chapter 4.

### 3.5.2 Memory-based Self-reported Travel Survey

In the last four days of the 2-week survey period, the subject fills out a self-reported travel survey each day. The self-reported travel survey is supposed to be purely based on memory, just as what people do in traditional non-trajectory data assisted surveys. We advise the subjects not to refer to the Moves record when they fill the survey, but since the subjects fill out the survey by themselves, we do not really have control over it.

The self-reported survey includes date of the reported day, starting time and location, ending time and location, travel mode, and trip purpose for each trip the subject made on that day. The locations are in word description. The travel mode and trip purpose are coded categories that the subject can choose from. They are adapted from the London Travel Demand Survey (LTDS). The full survey is available
in the appendix.

The purpose of collecting self-reported travel survey data is two-fold. First, we hope to compare it with the Moves data, and study the gap between the two data sources. Many scholars already addressed this issue. What this thesis provide is another case study where the data from the two sources are from exactly the same subjects in the same period. The second objective, is to provide labels, or ground truth, for those trips that are both captured by Moves and the self-reported travel survey. As already discussed, Moves does not provide activity type, and the inferred travel mode is crude. Suppose that the subjects do not fake data, then the reported travel mode and trip purpose could become labels for the Moves trips. Though not every Moves trip will be matched with a self-reported trip, the ones that do match will hopefully be enough to develop supervised learning on travel mode and trip purpose detection.

3.6 Perceived Air Quality Survey

As stated in Chapter 2, there is already a widely used perceived air quality measure for the indoor air evaluation. In this study we focus on the outdoor environment. Based on the current measure, taking into account the outdoor air quality features, we develop a Perceived Air Quality measure for outdoor air quality evaluation.

The current measurement system consists of one general question plus several specific questions, as follows:

a) Overall judgment of the air quality: how acceptable or unacceptable;

b) Rate the overall odour and irritation level;

c) Describe the environment (humidity, lighting, etc.) on a scale;

d) Describe the personal feeling (irritation reaction, mental status, etc.) on a scale.

We adopt this basic format of one general question plus several specific questions. The general question is the same: how acceptable or unacceptable the air quality is.
The specific questions are adjusted to better suite the outdoor environment. First, we add the air haziness level. The indoor environment is often too small to have the problem of haziness, but outdoors haziness is one of the most important and obvious indicators. Second, we remove the indoor environment questions such as the lighting of the room. Third, we consolidate the specific questions into categories. The final measure has two parts:

a) Overall judgment of the air quality: how acceptable or unacceptable

b) Specific questions: rate the haziness, odor, irritation, and headache/dizziness level.

The final Perceived Air Quality Survey is available in the Appendix.

To reduce burden of the participants, we allow a participant to skip the specific questions if he or she believes the general air quality is acceptable, or to say with no significant problem. See appendix for the perceived air quality survey.

The participants are asked to evaluate the air quality in this way for their home area, work place, and along the commuting trip each day during the 2-week survey. The commuting trip air quality evaluation is not very straightforward. For one thing, the trip could be pretty long so that the air quality varies. To deal with this problem, we ask the participants to rate a spot on their commuting trip that has the worst air quality and identify that spot. For another thing, some participants may take a subway and thus avoid part of the over ground air. There is not really a solution to this problem, and we will look at the part where the participant is actually exposed in the outdoor air only.

There is one factor that has potential influence on the subjective perceived air quality, which is people’s expectation. The air pollution problem has been around for years and many Beijing residents are quite familiar or even used to it. They may refer to an air quality report and expect a very hazy day, but if the day turns out to be not so bad, they may perceive the day as acceptable. To account for this factor, we ask the participants to indicate how often and in what way do they check out air quality reports. We will try to find a way to incorporate people’s potential bias
caused by such expectations.

3.7 Lessons From Survey Design And Implementation

The previous sections have presented the ideas behind the survey design and the implementation details. Under such ideas and implementation guidelines, the survey has been successful by and large. This section discusses some additional things that are learnt in this process, including unexpected difficulties, newly discovered phenomenon, and faulty designs, in hope of shedding some light for future similar practices.

3.7.1 Smartphone-Based Travel Survey

Compared with traditional survey methods, the smartphone-based travel survey is more like an experiment, which involves lots of technical details and tests. A pilot study is crucial to test whether the app works and whether the data flow is smooth.

Compared with traditional survey methods, a unique characteristic of the smartphone-based travel survey is that the entry barrier for the participant is relatively high, but once on track, the marginal cost of providing additional data is minimal. Taking Moves as an example, to participate in the survey, the subject needs to download the app, get familiar with how it works, follow steps to grant authorization for the researcher to access the data, and perhaps learn to label the home and workplace location in the first few days. After all the above work is done, the subject barely needs to do anything in order to provide data for an additional day or even week or month, except for living with some battery drain. Compared with the questionnaire survey where the subject takes the same effort to fill out a survey of same length everyday, or the GPS logger survey where the subject needs to carry the logger around everyday, the user burden curve here is clearly very different (Figure 3-7). The implication of such a user burden curve is that the smartphone-based travel survey is especially suitable for collecting panel data. Given the purpose is to collect panel data, it is cheaper to collect data for a long time with fewer subjects than to collect data for a short time with a very large sample size.
A trade-off that the researcher needs to think through is to what extent to burden the user with adding labels. The smartphone-based travel survey collects huge amount of data. Many interesting details may hide in the big data, waiting to be discovered in later data analysis. Since the information dig may require machine learning, it would be greatly preferable to have some ground truth to train the algorithm. Important labels include home location, workplace location, detailed travel mode, and activity type at a place. Adding labels adds to the user burden, especially adding non-repetitive labels like the activity type, which may vary everyday. It is up to the researcher to decide what labels are most important. A middle course is to require all the labels for some of the days. For example, while Moves collects data continuously for a month, ask the user to label all the details of the trips and activities for only a week. Then it is possible to develop models based on supervised learning from the labeled sub dataset, and then apply the model to label the rest of the data.

3.7.2 Special Situations in China

The previous lessons can be generally applied to smartphone-based travel surveys. There are also lessons that occur because of some special situations of China.

Section 3.1 already mentioned that some western apps fail to function properly in China. For example, Moves does not work on Android phones in China, since it
requires connection to the Google Play Services, which is not available in China. Excluding the Android users lead to extra difficulty in recruitment, since the iPhone users tend to have higher value of time and privacy concerns. Additionally, due to the Great Firewall (GFW) of China, even though Moves works on iPhones, sometimes it fails to connect to the server, which is located outside China.

The process of downloading Moves, getting familiar with how it works, and the data access authorization process is particularly difficult for many Chinese citizens. It often takes around 10 days for the survey company and the subject to communicate to each other before they complete the above jobs. Although very detailed instructions with screenshots are provided to the subjects, many still find it hard to complete the authorization at first attempt. The reasons include poor Internet connection to the Moves server, English language barrier, and unfamiliarity with the smartphone. After several failures, the subject may lose patience and quit the survey. Shifting from written instructions to face-to-face instructions can make the process much more smooth.
Chapter 4

Mobility Analysis

As discussed in Chapter 3, instead of presenting the raw GPS trajectory, Moves applies certain inference methods to the raw GPS data, generating a meaningful travel structure of locations, trips, and inferred travel modes. Such inference is very similar to what researchers do to interpret the raw GPS data. However, the inference by Moves tends to be cautious and preserves details. In terms of place identification, slightly deviating locations could be labeled as two places. In terms of trip identification, small trips, which may be as short as a hundred meters, taking only a few minutes are kept in the data. For a trajectory-tracking app, there is no problem with such a cautious strategy. For a travel survey study, however, sometimes it is helpful to remove some details in order to see the big picture.

This chapter discusses methods to prepare the Moves data to construct daily mobility patterns. Section 4.1 introduces the data used in this chapter. Section 4.2 describes the spatial clustering process to limit the amount of important places, through an algorithm called density-based spatial clustering of applications with noise (DBSCAN). With the clustering results, Section 4.3 identifies the home and workplace locations through rule-based methods. Section 4.4 re-defines trip segments and trips by setting certain stop thresholds. Commuting trips are identified by associating the trip origins/destinations to the identified home and workplace locations. Finally, Section 4.5 compares the Moves trips with the self-reported trips and explores the possibilities of learning more trip details through data fusion.
4.1 Moves Data Used in this Chapter

The survey was launched in early January 2016 and is expected to continue until June 2016. The long coverage leads to the fact that many special occasions are included in the survey period. Chinese Lunar New Year is included in this period (February 8th). The national holiday is from February 7th to 13th. For students, the winter vacation overlaps with this holiday, but lasts longer before and after. The exact date varies according to school. During this fuzzy period, the largest national annual commute happens, and the lifestyle changes dramatically. Instead of taking regular commuting trips everyday, people may just stay home all day long, or go to the other extreme of making constant travelling in a remote tourism city. Such a special period could be very interesting for transportation research, and proves the point that one advantage of the smartphone-based travel survey is that it captures the dynamics of mobility demands by covering special events. However, for the purpose of this thesis, the subset data of this period may disturb the analysis. For example, the next section tries to detect the home and workplace location. For a family that is travelling in Japan for a week, constantly changing dwelling locations and not working at all, it is just impossible to detect the home or workplace location. Therefore, some subjects are removed before performing the analysis in this part.

To avoid the irregular travel patterns, this chapter only considers a subset of all the subjects. The selection rule is that the subject must have 7 or more qualified days excluding the holiday period. A qualified day is defined as a day during which the subject reports Moves data for longer than 10 hours (excluding night time, which is defined as before 7 a.m. or after 11 p.m.). The holiday period is defined as February 1st to February 14th, covering the national holiday week and one week before it, considering that for many Chinese people the lifestyle already changes by early February. This is because some companies have longer Lunar New Year vacation as a benefit, some people choose to take the annual vacation during this time, and so forth. It is the period when many Chinese people believe it is time to stop working and celebrate. For college students, the holiday is even longer than this period, but no further exclusion criteria is made for them. The final number of subjects that meet the criteria is 256.
4.2 Location Clustering

Moves collects location data when the user is staying in a place. Each place of stay is assigned with a unique place ID. Only locations with exactly the same coordinates are assigned with one same ID.

Due to signal drifting and within-building movement, when one is staying in a place for a long time, we often see multiple GPS locations around the place. It is a general problem for all GPS-based location tracking projects. The Moves data show a similar but slightly different pattern. For frequently visited places, what is often seen is a major place with highest frequency of visit accompanied by several less frequently visited but very close places (Figure 4-1). The deviating places is not as many as a typical GPS location pattern, so it is most likely that Moves has already performed a spatial clustering with the raw location data, and reassigned locations that are clustered to the same group with the same coordinates. Only Moves’s clustering algorithm has more rigorous criteria to retain its data precision, thus resulting in more location then what is meaningful to identify important locations. How Moves performs the clustering is unknown. This section performs a spatial clustering on the Moves places to further reduce the number of places, in hope of revealing the true location of important places.

Figure 4-1 Two Close Frequently Visited Place in a Residential Area.
Numbers on the location indicates visit frequency. Very likely it results from coordinates variance while staying in one same location.
4.2.1 Spatial Clustering Method

There have be substantial discussion on the methods of performing spatial data clustering in the academic field. Major types of spatial clustering method include partitioning algorithms, hierarchical algorithms, density-based algorithms, and model-based algorithms. They each have pros and cons and are suitable for different cases. Our case has several features. First, it is difficult to decide the optimal number of clusters a prior. Second, we do not care much about the hierarchy relationship among places. Third, it is feasible to set distance threshold and cluster size a prior. With the above features, density-based algorithm is the most suitable for our data. Among the density-based algorithms, density-based spatial clustering of applications with noise (DBSCAN) is a robust and popularly used algorithm. In this thesis, we use the DBSCAN algorithm in R to cluster the place data.

There are two parameters in the DBSCAN algorithm: minPts and epsilon. MinPts is the number of close neighbors one point should have to become a cluster. Say minPts is set to be 5. If there are 4 or fewer points close to each other, while they are far away from other points, they will be considered as outliers and excluded from the clustering result. In our case, we set minPts as 1, for two reasons. First, GPS location drifting is not a severe problem. We do not see obviously false locations, so there is no reason to delete any location. Second, the purpose of performing location clustering is to identify the primary locations (home, workplace, etc.) in the next step. Keeping the less frequently visited places does no harm to our purpose. It is safer to carry on information than to dump it when we are not sure. The second parameter, epsilon, specifies how close points should be to each other to be considered as reachable. Compared with minPts, this parameter is not so easy to decide. If epsilon is too large, we will over cluster points, which means actually separate locations will be clustered as one same location. For example, if one goes to a restaurant right next door to home, we may cluster them together and lose the dinning activity and trips. On the other hand, if the epsilon is too small, we fail to achieve the goal of clustering locations that actually belong to the same place. As we already discussed, if the workplace is large, a small epsilon will still see the locations in the workplace as separate. Intuitively, something from 20 to 100 meters seems to be a reasonable epsilon, but that is still a big range. To make the decision, we sketch
out how the number of clusters decreases as epsilon increases (Figure 4-2). We hope to find a turning point where the number of clusters drops sharply, but there is no such obvious point from the figure. Finally, based on experience and previous literature, we decide to use 50m as the criteria.

![Figure 4-2 Decrease of Number of Clusters as Epsilon Increases (Only Show Users with More than 100 Initial Locations).](image)

The cluster is performed per user rather than on all the locations in the data set. For each user, we find all the locations visited in the survey period and perform the DBSCAN clustering. Then for each cluster, the centroid of the locations weighted by the times visited is calculated. The centroid will replace all the actual locations, and the times and duration visited will be the sum of times and duration visited for all the locations in this cluster.

### 4.2.2 Clustering Results

Based on the method described above, the spatial clustering is performed for the 256 subjects. The number of clusters for each subject range from 10 to 187. The distribution of number of clusters for each subject is as Figure 4-3. Most subjects have 30 to 50 location clusters. Considering that the survey takes a long period, and
that the places could be restaurants, shops, bus transfer stops, or even waiting for a red light, this number of location clusters during 2 more weeks is reasonable.

![Distribution of number of clusters](image)

Figure 4-3 Distribution of Number of Clusters per Subject

### 4.3 Home and Workplace Location Detection

Home and workplace detection is important for constructing and understanding daily travel patterns. Home and workplace are the two most important trip origins/destinations for most people. Normally, one starts a day's trip from home and ends back at home. We can identify one of the most important types of trips, commuting trips, once the home and workplace locations are known.

For this thesis, there is another important reason for detecting home and workplace locations. The participants are required to rate the air quality around their home and workplace. However, most of the participants are not willing to share their home and workplace location explicitly. Therefore, there is a need to infer these places from their travel diary in order to match the perceived air quality to the map.
This section tries to detect the home and workplace from the data. As described in last section, a spatial clustering is performed on the original Moves places to reveal the important places. Now the remaining task is to find out the home and workplace from these places.

4.3.1 Method

There is substantial literature discussing how to detect home and workplace locations based on GPS data and Call Detail Record (CDR) data, from several different perspectives. One perspective is to match trip end locations to land use types to derive trip purposes, and good agreement was reported for “go to home” and “go to work” trips (Wolf et al. 2001). Another perspective is statistical inference, such as Bayesian frameworks (Hurtubia et al. 2009; Moiseeva et al. 2010) and decision trees (McGowen and McNally 2007; Reumers et al. 2013). A combination of the approaches proposed in Schönfelder et al. (2003) with probabilistic multinomial Logit models was proposed in Chen et al. (2010). A framework for activity recognition using Relational Markov Networks was proposed in Liao et al. (2005).

There are also simpler and more intuitive methods. Phithakkitnukoon et al. (2012) estimate the home location as the location for which the user has the highest level of call activity during nighttime hours. Similarly, a work location is estimated as the cell tower location with the highest call activities during normal business hours. Kung et al. (2014) adopted a very similar method. The daytime and nighttime locations in which the user spends the maximum dwell time are detected as workplace and home, as long as such location accounts for more than 50% of the total observed daytime and nighttime dwell-times in the user’s travel portfolio. If such places do not exist for a user, the user is disregarded.

Given our dataset and research objectives, we adopt a rather simple home and workplace detection method, similar to what Phithakkitnukoon et al. (2012) and Kung et al. (2014) have demonstrated. For each user, we find all the places where he stays overnight. Of all these places, the one that hosts the most overnight stays is estimated to be the home location. Then, we identify the place where one stays for the longest accumulated time in the daytime (10am to 6pm) in all weekdays, except
for home. This place is estimated to be the workplace.

The above method is very intuitive, and seems more like a definition than an inference, but suited well for our data and study objectives. The advanced statistical inference methods (e.g. Bayesian inference or decision trees) are powerful for inferring multiple labeled activity types, including but not limited to home and workplaces. In our dataset, we only have home labels from some participants and no labels at all for other activity types. Moreover, as we will see in next section, the home labels that we have are not very satisfactory, so that we cannot and should not find an estimate that perfectly fits to the labels. This makes all supervised learning methods less ideal. Compared with the land use map matching method, we have multi-week travel trajectories of each user, and the home and workplace stand out from other locations pretty obviously for most subjects, in terms of frequency of visit, duration of stay, and so forth. So we do not have to go through the complexities of finding the land use match just for detecting home and workplace location.

The methods adopted in this thesis work well for the research objective of constructing daily travel patterns. We are interested in the home and workplace locations because of their trip generating features. Namely, home is important because it is usually the starting and ending point of a day's trips. The workplace is important because of its repetitive and longtime occurrence as one's destination. If some other places fit in such criteria better, we would be interested in those places instead. For example, someone may identify his hometown in another city as home, while identifies the place that he stays everyday in Beijing as a dorm. In such case, we actually want to detect the location of the dorm rather than the home. Similarly for the workplace identification, if someone is retired and goes to a senior's activity center everyday, we treat this center as the most important destination rather than workplace. In this way, the methods adopted in this thesis directly serve our needs.

4.3.2 Home location inference

Of the 256 subjects, 70 labeled the home location in Moves. So we first test our method of home location detection on this labeled sub dataset. We use two measures to evaluate the accuracy of the detection: false positive rate and false
negative rate. False positive is when we detect a place as home while the user does not label it so. False negative is when we detect a place as non-home while the user labels it as home. Generally, if the detection criteria is loose, there will be a high false positive rate and a low false negative rate. If the detection criteria is strict, there will be a high false negative rate and a low false positive rate. We want to try our best to keep both rates low.

With the home detection method described in the previous section, the false positive rate is 0.3000 and the false negative rate is 0.3143. Such numbers are not specifically low, but after looking at the falsely detected cases we decide not to care too much about the numbers. The false positive or negative cases fall into the following three categories. First, there are mislabels. There are cases where the user labels one place as home, yet he never sleeps there across the survey period. In the same time, there is another place that very much looks like a home. Since the entry questionnaire asks about the work time pattern (whether often on nigh shift), we can easily screen out those who actually work at night. After excluding these subjects, in such cases, we decide the user just labeled the wrong place. Second, some label the home location that is meaningful in the social context but not in the daily mobility context, for example those who label the hometown location which is in another city instead of Beijing. Third, some people have multiple homes/places to stay overnight, and labels one of them as home, but not the one that hosts the most overnight stays. In such case, we still believe our way of estimating the home location is more meaningful in the daily mobility context. We keep the estimated home location, but also mark other places that host overnight stays frequently.

Then we apply the home detection method to the whole dataset of 256 subjects. Figure 4-4 shows the distribution of the number of overnight stay places. Most people have 1 or 2 places to stay overnight. The number of subjects having more places to stay overnight decreases rapidly as the number of places increases. The number of overnight stay places could be as high as 14 in our dataset.
Figure 4-4 Distribution of Number of Overnight Stay Places

4.3.3 Workplace location inference

In order to detect the work place location, the trip records on Saturdays and Sundays are removed from the dataset, because people tend not to go to work on weekends.

The workplace is defined as the place where people stay for the longest time, except for home, in the daytime. Daytime is defined as 10am to 6pm. From the data, we see that this period is when most people go out and (most probably) work during the day. Such definition of workplace is flexible for multiple groups of people. For regular employed ones, this is the major workplace. For students, this is school. For unemployed or retired people, this is the place they visit most frequently.

4.4 Trip inference

Moves uses a minimal threshold to determine stops, or in other words break trips or trip segments. The interval between trips or trip segments could be as short as a minute. Such short stops could be someone stopping for a text message or waiting for a red light. Such small stops are not very helpful in revealing the travel pattern. How to select a threshold to remove the small stops is a problem commonly faced by
many GPS-based trajectory interpretation studies. In literature, the most widely used threshold for the duration of a stop is 5 minutes (Welbourne, Evan, et al. 2005; Fan, Yingling, et al. 2013) and 10 minutes (Daniel Ashbrook and Thad Starner, 2003; Biagioni, James, et al. 2011). Stops shorter then the threshold are removed, connecting the before and after trips. Shorter threshold will preserve more details while longer threshold will get rid of more unimportant stops.

This thesis takes two steps to remove small stops. First, if the successive trips are of the same mode and the interval is shorter than 10 minutes, then the stop is removed and the successive trips are joined together. This step mainly cleans the trip segments. (Of course, if a trip only consists of one mode, then the trip only has one segment, so there is no difference between trip and trip segment.) Considering the relative long red light waiting time and slow traffic flow during peak hours in Beijing, 10 minutes is selected as the threshold rather than 5 minutes. Afterwards, if the interval between successive trips is shorter than 30 minutes, whether the mode of the trips are the same or not, the stop is removed and the successive trips are joined together. This step connects trip segments together to form trips. For example, if one walks to the bus stop, waits for the bus for 5 minutes, and then takes the bus to the destination, then the walking trip and the bus trip will not be connected together in the first step, but will be connected in the second step. The choice of 30 minutes is arbitrary. According to the author’s experience, it could well take 10 to 20 minutes to wait for a bus or taxi to come in Beijing. Additionally, a stay shorter than 30 minutes is not very likely to be an important trip, so will not be considered in this thesis.

In Moves, only trip segments are assigned with a travel mode. When the trip segments are connected to form trips, a new system of travel mode is developed to describe the trips (Figure 4-5). If all the trip segments are of the same mode, then keep the mode. If there are multiple modes including transport, then the trip is labeled as transport mix. If there are multiple modes, not including transport but including cycling, then the trip is labeled as cycling mix.
After the above stop-removing rules are applied to the Moves data, a new set of trips is generated. On most occasions a subject would make two trips per day (Figure 4-6). The frequency decreases sharply as the number of trips per day increases.

The mode share of all the trips is shown in Table 4.1. Walking trips count for 26.74% of all the trips. Cycling and cycling mix together count for nearly 5% of all the trips. Pure motorized trips count for 16.48% of all the trips. Transport mix, namely motorized trips accompanied by walking or cycling trips take the largest part (52.05%).
Table 4.1 Travel Mode Split According to Moves Data

<table>
<thead>
<tr>
<th>Travel mode</th>
<th>Number of trips</th>
<th>Percentage of trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walking</td>
<td>5425</td>
<td>26.75%</td>
</tr>
<tr>
<td>Cycling</td>
<td>704</td>
<td>3.47%</td>
</tr>
<tr>
<td>Cycling Mix</td>
<td>253</td>
<td>1.25%</td>
</tr>
<tr>
<td>Transport</td>
<td>3342</td>
<td>16.48%</td>
</tr>
<tr>
<td>Transport Mix</td>
<td>10554</td>
<td>52.05%</td>
</tr>
</tbody>
</table>

4.5 Commuting Trips Identification

Now that the home and workplace locations have been detected and that the daily trips have been constructed, the next step is to identify commuting trips. The method is straightforward. If the origin and destination of a trip is home and the workplace, regardless of the direction, the trip is identified as a commuting trip.

Out of the 4570 weekdays in the dataset, 4562 commuting trips are identified. Assuming that there are two commuting trips per subject per weekday, only half of the target number of working trips is achieved. Many reasons could lead to reduced number of identified commuting trips. Based on the definition of the commuting trip as a trip from home to workplace or the other way around, if one stays at a friend’s place for one night, then two commuting trips will be missing (one night commuting towards the friend’s place and one commuting from the friend’s place in the next morning). In this dataset, indeed many subjects have more than one place to stay overnight. Since only one of the places is labeled as home, there would be many days when the commuting trip starts from a non-home place and thus will not be identified. Similarly, if one has several workplace locations, the trips to and from the secondary workplaces will be missing. Another common situation is that there is a stop in between home and workplace, especially during the night commuting. Some people stop for dinner on the way home. If the stop is longer than 30 minutes, the stop is kept in the record and no direct commuting from workplace to home will be seen. Additionally, not all the subjects are regularly employed workers with fixed working hours. Students and freelance workers do not have regular commuting trips. Specifically for this research, ground truth for the home and workplace
location is not available, so wrongly detected home and workplace locations will also lead to missing commuting trips.

4.6 Matching Moves data with survey data

In 4 days of the 2-week survey period, the subject fills out a memory-based travel diary. This section presents how the Moves data and the self-reported survey data match to each other in terms of number of trips, trip starting and ending time, as well as trip mode.

The total number of trips reported by survey is fewer than what Moves records. On average, Moves reports 1.8 times more trips than the self-reported survey does. The Moves trips and survey trips are matched to each other one by one. A straightforward matching method is applied: if the absolute value of the difference of the starting time of two trips is smaller than the threshold, then the two trips are matched. The larger the threshold, the more matches will be found. The matching is performed in two directions. First, each of the trips reported by the survey is compared to the Moves trips in that day, to check whether there is a match. Then, for the days when a travel diary is filled, the Moves trips are compared to the self-reported trips to check whether there is a match. Figure 4-7 shows an example of trip matching. The duration of the reported trips in both sources are drawn in parallel. In this example day, Moves recognizes 4 trips while the subject reports 2 trips. Comparing the starting time of the trips, survey trip 1 can be matched to Moves trip 1. Survey trip 2 can be matched to Moves trip 2. Moves trip 3 and Moves trip 4 are not reflected by the survey. Thus, for this case, 100% of the survey trips are matched to Moves trips, while 50% Moves trips are matched to survey trips.
Figure 4-7 Example of Matching the Moves Trip and The Survey Trip  
(User Id = 0648)

After the trip matching is completed, for the matched trips, check whether the self-reported travel mode is the same with the travel mode inferred by Moves. Notice that the self-reported travel mode is more detailed than the Moves modes. To make the comparison, the travel modes are categorized into walking, cycling, and transportation to make them comparable to the Moves data.

There is a potential problem with the matching method described above. The survey trips come directly from the survey reported by the subjects. If the subject reports every detail of trip, then the survey trips are actually trip segments. On the other hand, the Moves trips have already consolidated the trip segments. Thus, the Moves trips and survey trips may not be perfectly comparable. This is especially important for the mode-matching step. For example, if the subject walks to the bus stop before taking the bus and reports the walking trip truthfully, then the walking trip is likely to be matched with the bus trip captured by Moves (since the walking trip segment and bus trip segment are combined). Then there will be a conflict when matching the trip mode. In the future the survey trips should be examined and consolidated when necessary.

The matching results are shown in Table 4.2 and Figure 4-8. As the threshold increases from 20 minutes to 60 minutes, the percentage of matched trips in both directions increase. There is a big gap between the two matching directions. For
example, when the threshold is 60 minutes, more than 75% of the trips reported by
the survey can be matched to a Moves trip, while only 43% of the Moves trips can be
matched to a survey trip. This is because Moves reports more trips than the survey
does. Among the matched trips, the percentage of matched travel modes does not
vary much according to the threshold or the matching direction. The matching rate
is very stable around 85%.

Table 4.2 Trip Time and Mode Matching Results at Different Thresholds

<table>
<thead>
<tr>
<th>Threshold to determine a match</th>
<th>Starting time match</th>
<th>Travel mode match</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Match Survey data to Moves data</td>
<td>Match Moves data to Survey Data</td>
</tr>
<tr>
<td>20min</td>
<td>63.11%</td>
<td>37.29%</td>
</tr>
<tr>
<td>30min</td>
<td>68.60%</td>
<td>39.65%</td>
</tr>
<tr>
<td>40min</td>
<td>71.63%</td>
<td>40.89%</td>
</tr>
<tr>
<td>50min</td>
<td>74.10%</td>
<td>42.03%</td>
</tr>
<tr>
<td>60min</td>
<td>75.87%</td>
<td>43.10%</td>
</tr>
</tbody>
</table>

Figure 4-8 Trip Time (Left) and Mode (Right) Matching Results at Different
Thresholds in Different Directions.

Dashed line is for matching survey data to Moves data. Solid line is for matching Moves
data to survey data.

4.7 Summary

Compared with the memory-based self-reported survey, the smartphone-based
travel survey captures more details and covers a larger scale. People tend to report major and regular stops and trips only, while the smartphone tracks almost every movement. Such feature has both pros and cons. The advantage is that the big data allows more opportunity in transportation research. The researcher can examine travels as small as a public transit transfer, as well as travels as big as inter-city travels. The disadvantage is that it introduces more noises. The researcher has to choose a research scale, and data of other scales need to be cleared before analyzing the travel behavior.

The last section of this chapter indicates that there is possibility in data fusion. The matching method used in this chapter can be improved in multiple ways. After a refined matching, the extra information provided by the survey data, including trip purpose and detailed travel mode, can be labeled to the Moves trips. Such labels can be used for Moves data inference. In this way, the Moves data become more powerful than it currently is. Besides the data fusion between Moves data and survey data demonstrated in this chapter, there are also other data sources suitable for data fusion, including public transit AVL, AFC, road network and so forth.
Chapter 5
Air Quality Evaluation

This chapter evaluates the air quality in Beijing with objective measures as well as the subjective measures developed by this thesis. This chapter aims at two objectives. First, understand the air pollution scenario in Beijing, including the concentration of various major pollutants, the variation of the pollutants spatially and temporally, as well as the subjective feelings to the pollution level and variation. Second, understand how the Perceived Air Quality (PAQ) measure responds to the objective measurements, its usefulness and limitations.

Section 5.1 presents the results from the PAQ survey. Section 5.2 describes the air quality in Beijing during the survey period with the official objective measures. Section 5.3 relates the subjective measures to the objective measures. Section 5.4 evaluates the PAQ measure by discussing its usefulness and limitations.

5.1 Perceived Air Quality Survey Results

The subject fills out a PAQ questionnaire each day during the survey period. The questionnaire asks the subject to evaluate the air quality around home, around workplace, and the most heavily polluted spot during the commuting route of the day. The evaluation is based on a 1 to 6 rank, respectively representing very bad, bad, just unacceptable, just acceptable, good, and very good. If the rating for a place is equal or under 3, meaning the air quality is bad, then a more specific question pops up. The specific question asks the subject to evaluate the level of air haziness, irritation, bad odor, and headache or dizziness. The evaluation is based on a 1 to 4 rank, respectively representing very bad, bad, just noticeable, and not at all. The details of the survey framework and questionnaire design can be found in Chapter 3.
Some subjects go outside Beijing during the survey period and thus evaluate the local air quality in that day. For the analysis in this part, only evaluations for Beijing are considered. The number of subjects filling out the PAQ questionnaire on each day is plotted as Figure 5-1. Since subjects come and go on a rolling basis according to their own time schedule, instead of a certain number of subjects form a batch sharing the same entering and quitting time, the number of subjects on each day varies.

![Figure 5-1 Number of Subjects Taking the PAQ Survey in Beijing Each Day](image)

Due to the uneven number of subjects per day, an overall average of the PAQ ratings of the whole dataset will be distorted, since the days with more subjects will have a higher weight. To avoid this problem and get an overall impression of the PAQ rating in Beijing, the ratings made by various subjects are first averaged per day. The daily PAQ averages for all places are plotted as Figure 5-2. Then the mean and standard deviation of the daily means are calculated. There still is the problem that when there are few subjects, the subjects over-represent the population. This problem exists for days before January 15th, when there are less than 50 subjects per day.

The mean of the daily PAQ averages is 4.68. The standard deviation is 0.82. Based on this result, the PAQ in Beijing falls to the positive side overall, with a moderate variance across days.
For all the days that have negative PAQ ratings, the detailed sensory ratings are summarized in Figure 5-3. Recall that lower ranks indicate that the problem is more severe. Figure 5-3 shows that air haziness is the most severe problem, followed by irritation, bad odor, and feelings of headache or dizziness.
5.1.1 Home-Work-Commute Spatial Variation

The spatial resolution of the PAQ rating is low in the individual level, since only three locations of Beijing city are evaluated (around home, around work, and worst spot during commuting trip). To understand the spatial variance based on this dataset, the maximum PAQ difference among the three spots for each day of evaluation is calculated. For example, if a user rates the PAQ as 1, 1, 1 for the three spots for a day, then the maximum PAQ difference is 0. If a user rates the PAQ as 2, 1, 4 for the three spots for a day, then the maximum PAQ difference is 3. The result of all the days is displayed as Table 5.1. Out of 7977 days, in 6646 days (83.31%) the user believes the PAQ is the same for the three spots. Almost all the time (97.55%) the user believes that the max PAQ difference is less than 2. In 7588 days (95.12%) the user believes the PAQs of the three spots are in the same category, namely all bad (below 4) or good (above 3). The mean standard deviation of the three PAQ ratings of all the days is 0.11. To summarize, most people in most days report that the spatial difference of PAQ is minimal.

<table>
<thead>
<tr>
<th>Max PAQ difference</th>
<th>Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>6646</td>
<td>83.31%</td>
</tr>
<tr>
<td>1</td>
<td>1136</td>
<td>14.24%</td>
</tr>
<tr>
<td>2</td>
<td>166</td>
<td>2.08%</td>
</tr>
<tr>
<td>3</td>
<td>26</td>
<td>0.33%</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0.01%</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>0.03%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>7977</strong></td>
<td></td>
</tr>
</tbody>
</table>

It has been considered to compare all the PAQ ratings of the same day made by different users, but not performed. The PAQ rating is a subjective measurement, meaning that each individual may have different criteria. Thus, the absolute PAQ rating from two users may not be comparable. The PAQ difference due to inter-personal difference may be as large as that due to air quality difference. If we have a large number of people rating the same place, then the average rating may
become comparable. Given our situation, where there are only around a hundred people per day making the ratings for a huge city like Beijing, the number of people rating the same spot is too few to generate a comparable averaged result. Therefore, performing a variance analysis over all the users will be too inaccurate to reveal meaningful information.

5.1.2 Temporal Variance

To evaluate the day-to-day PAQ variance, the following steps are taken. For each subject who stayed at least 7 days in Beijing during the survey period, find all the PAQ ratings that he made during the survey for each of the three spots. Then each user has three PAQ rating sequences along all the days that he has been taking the survey, respectively for home, workplace, and the worst spot during the commuting trip. The standard deviations of the three sequences are calculated. Then the three standard deviations of all the subjects are plotted in Figure 5-4. In Figure 5-4, the subjects are arranged so that the standard deviation of the ratings for around home is increasing.

The distribution of the standard deviations of all the subjects resembles a normal distribution. Most subjects are concentrated around the center while a small number of subjects go to tails in both sides. For the majority of subjects, the standard deviation is between 0.7 and 1.7. Compared with the spatial variance, where the standard deviation is 0.11, the temporal variance is much larger.

Figure 5-4 also shows a strong correlation among the standard deviation of all three spots. A subject with high standard deviation for the home ratings is likely to have high standard deviation for the workplace ratings as well as commuting trip ratings. This pattern is consistent with the minimal spatial PAQ variance. Since the three PAQ rating sequences are mostly the same, it is reasonable to see three similar standard deviations.
5.1.3 Ratings By The Air Pollution Sensitive Subgroup

Since PAQ is a subjective measurement, we are curious to see how people respond differently according to their own characteristics. A straightforward label is whether one is sensitive to air pollution. The hypothesis is that those who are sensitive to air pollution are more likely to differentiate heavily polluted days and clear days.

The subjects report whether they have respiratory diseases or are more sensitive to air pollution in the questionnaire. Such subjects are put into the sensitive subgroup. 23.74% of all the subjects are in the sensitive subgroup. For each day, the average PAQ rating made by all the sensitive people and the insensitive people are calculated respectively. The result is shown in Figure 5-5. The figure shows that in the PAQ peaks, namely when the air quality is better, the average rating from the sensitive subgroup tends to be higher. In the PAQ valleys, namely when the air quality is worse, the average rating from the sensitive subgroup tends to be lower. The standard deviation of the ratings of all the days from the sensitive subgroup is 0.8617, while that from the insensitive subgroup is 0.7026. The larger standard deviation from the sensitive subgroup indicates that sensitive subgroup is more
likely to give extreme ratings. The analysis result echoes the hypothesis that the sensitive group does differentiate the good days and bad days more clearly than the insensitive subgroup.

![Graph showing PAQ of sensitive and insensitive groups](image)

Figure 5-5 Daily Average PAQ of the Sensitive Group and Insensitive Group

### 5.2 Objective Air Quality Measurement

The objective air quality measurement comes from Beijing Municipal Environmental Monitoring Center (BMEMC). The data is available to public online\(^1\). The measurement includes hourly AQI, PM2.5, PM10, SO\(_2\), NO\(_2\), O\(_3\) and CO for everyday from 2014 to now, and the data is updated everyday. There are 35 monitoring stations in Beijing, as shown in Figure 5-6. The locations of the stations are carefully selected so that the inner city and urban area are both covered. There are stations that are located at normally less polluted area to serve as control points, as well as stations that are located besides traffic arteries to capture the heavy pollution. Overall, this dataset should be able to describe the pollutant concentration and distribution objectively.

Note that the AQI calculation method adopted by BMEMC is different from that adopted by the US Embassy. The US Embassy only measures PM2.5 concentration

\(^1\) [http://beijingair.sinaapp.com/](http://beijingair.sinaapp.com/)
and calculates the AQI based on it. BMEMC measures all six pollutant concentrations and calculate the AQI for each pollutant. Then the highest AQI is selected as the final AQI. This calculation method indicates that the AQI is not a comprehensive measure for air quality, but best describes the most significant pollutant.

![Figure 5-6 Location of the 35 Air Quality Monitoring Stations in Beijing](image)

In order to compare with the PAQ data, the objective air quality measurements from January 1 2016 to March 13 2016 are downloaded for analysis in this section.

5.2.1 Spatial Variation of Different Measures

Similar to the PAQ result analysis, we first evaluate the spatial variation of the objective measures. The analysis is done for each of the objective measurements respectively. Notice that they may have different scales and units. AQI is a unit-free number ranging from 0 to hundreds. All the air pollutants, except for CO, are measured by the concentration in the air in the unit of microgram per cubic meter. CO is measured in the unit of milligram per cubic meter, which should multiply 1000 to make it comparable to the concentration of other pollutants.

First, for each of the 35 stations, the average objective measurements over all the
days are calculated (Figure 5-7). As described above, the stations are grouped into 4 categories to capture the air quality in different areas. Stations 1 to 12 are located in inner urban area. Stations 13 to 23 are located in suburban area. Stations 24 to 30 are located in less-polluted area. Stations 31 to 35 are located near traffic arteries. The between category variance is larger, while the within category variance is smaller.

![Figure 5-7 Spatial Variation of Daily Averages of Different Air Pollutants](image)

The standard deviation of the data shown in Figure 5-7 is available in Table 5.2. SO₂ has the smallest variation. CO has the largest variation since its concentration is the highest among all pollutants. It’s not even in the same order of magnitudes.

The method described above smoothes away the day-to-day variation, since one station just has one number representing the overall level of all the days. To address the problem, another measure is calculated. First, the standard deviation of all the stations on each day is calculated. Then, the standard deviations of all the days are averaged, to generate the second row of Table 5.2. In this way, the measure becomes around twice as large, but the relative variation degree of different pollutants stays the same.
Table 5.2 Spatial Variation of the Concentration of Air Pollutants

<table>
<thead>
<tr>
<th></th>
<th>PM2.5</th>
<th>PM10</th>
<th>NO₂</th>
<th>O₃</th>
<th>SO₂</th>
<th>CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard deviation of all-day average values</td>
<td>20.04</td>
<td>21.05</td>
<td>13.87</td>
<td>8.97</td>
<td>6.11</td>
<td>477.11</td>
</tr>
<tr>
<td>Average over daily standard deviations</td>
<td>45.72</td>
<td>54.11</td>
<td>25.58</td>
<td>22.53</td>
<td>14.05</td>
<td>1037.96</td>
</tr>
</tbody>
</table>

5.2.2 Temporal Variation of Different Measures

To evaluate the day-to-day variation of the objective measurements, the average objective measurement over all stations is calculated for each day (Figure 5-8). There seems to be a periodic pattern for the concentration of pollutants. Judging from Figure 5-8, the period ranges from 3 or 4 days to a week or longer. The standard deviations of the daily concentration of the various pollutants are listed in Table 5.3. The first row shows standard deviation of the daily average data. The second row shows the average standard deviation of each station. Similar with the spatial variation, SO₂ shows the smallest variation while CO shows the largest variation, which is related to their absolute concentration level. The temporal standard deviation is generally larger than the spatial standard deviation, which echoes with the result from the PAQ rating variation analysis.

Figure 5-8 Daily Variation of Average Air Pollutant Density
Table 5.3 Day-to-Day Standard Deviation of All Air Pollutants

<table>
<thead>
<tr>
<th></th>
<th>PM2.5</th>
<th>PM10</th>
<th>NO$_2$</th>
<th>O$_3$</th>
<th>SO$_2$</th>
<th>CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day-to-day standard deviation</td>
<td>69.35</td>
<td>78.67</td>
<td>26.54</td>
<td>17.52</td>
<td>14.06</td>
<td>1048.18</td>
</tr>
<tr>
<td>Average day-to-day standard deviation over all stations</td>
<td>87.71</td>
<td>95.74</td>
<td>34.36</td>
<td>27.34</td>
<td>20.74</td>
<td>1425.49</td>
</tr>
</tbody>
</table>

There is a strong correlation between the concentration of different air pollutants. Table 5.4 shows a pairwise correlation coefficient between the pollutant concentrations along the survey period. It shows that the concentration of all the pollutants are positively correlated to each other, except for O$_3$, PM2.5, PM10, NO$_2$, and CO are especially closely correlated to each other. The AQI is most strongly correlated to PM2.5 and PM10, indicating that currently in Beijing PM2.5 and PM10 are the major pollutants.

Table 5.4 Correlation between Air Pollutants and AQI

<table>
<thead>
<tr>
<th></th>
<th>PM2.5</th>
<th>PM10</th>
<th>NO$_2$</th>
<th>O$_3$</th>
<th>SO$_2$</th>
<th>CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM10</td>
<td>0.9197</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NO$_2$</td>
<td>0.8720</td>
<td>0.7511</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O$_3$</td>
<td>-0.7129</td>
<td>-0.6068</td>
<td>-0.8837</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO$_2$</td>
<td>0.7666</td>
<td>0.6628</td>
<td>0.8251</td>
<td>-0.7821</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO</td>
<td>0.9092</td>
<td>0.7899</td>
<td>0.9450</td>
<td>-0.8714</td>
<td>0.8178</td>
<td></td>
</tr>
<tr>
<td>AQI</td>
<td>0.8857</td>
<td>0.9168</td>
<td>0.6755</td>
<td>-0.5429</td>
<td>0.5709</td>
<td>0.7551</td>
</tr>
</tbody>
</table>

5.3 Relate Perceived Air Quality and Objective Air Quality Measurements

The above analysis examines the data from the two sources separately. More details are revealed when the data from the two sources are put together. This section describes several issues raised in this way.
5.3.1 Correlation Between PAQ And Objective Air Quality Measurements

It has been shown that both the PAQ and objective air quality measurements display spatial variation and a stronger temporal variation. Then the questions lies in whether the variations from the two sources echo with each other. This question is important because if PAQ is random and barely related to the pollutants, then there is little sense measuring it as an indicator for air quality. It has to be related in someway.

Figure 5-9 compares the day-to-day variation of PAQ and objective measurements. To make the comparison meaningful, only the days when there are more than 20 subjects making the PAQ ratings are selected, which is every day from January 14 to March 14. The figure shows an obvious correlation between PAQ and most objective measurements. The correlation coefficients between PAQ and the objective measurements are listed in Table 5.5. PAQ is most closely related to AQI, PM2.5, PM10, and CO. Such strong correlation corresponds to the fact that the concentrations of these pollutants are the highest. The sign of correlation is negative for all pollutants other than O3, which corresponds to our expectation, since higher pollutant concentration and lower PAQ both point to worse air quality.

![Figure 5-9 Correlation between PAQ and Objective Measurements](image-url)
Table 5.5 Correlation Coefficient between PAQ and Air Pollutants

<table>
<thead>
<tr>
<th></th>
<th>AQI</th>
<th>PM2.5</th>
<th>PM10</th>
<th>NO₂</th>
<th>O₃</th>
<th>SO₂</th>
<th>CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAQ</td>
<td>-0.8397</td>
<td>-0.8310</td>
<td>-0.8103</td>
<td>-0.7683</td>
<td>0.7391</td>
<td>-0.6502</td>
<td>-0.8266</td>
</tr>
</tbody>
</table>

More specifically, we examine how the sensory ratings are related to the different pollutants. Table 5.6 lists the pollutants’ major sensory effects. The particulate matter (PM2.5 and PM10) is a complex mixture of solid particles and liquid droplets found in the air. It affects air haziness because its diameter is about that of wavelength of visible light. It scatters light, thus reducing the visibility and amount of light reaching the ground. Its certain components also lead to irritation. O₃ has bad odor, and causes irritation as well as headache and dizziness. SO₂ and NO₂ also have bad order, and mainly affect the respiratory tract.

Table 5.6 Major Sensory Effects of Air Pollutants

<table>
<thead>
<tr>
<th></th>
<th>Air haziness</th>
<th>Irritation</th>
<th>Bad odor</th>
<th>Headache/dizziness</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM2.5/PM10</td>
<td>●</td>
<td>●</td>
<td></td>
<td>□</td>
</tr>
<tr>
<td>CO</td>
<td></td>
<td></td>
<td></td>
<td>□</td>
</tr>
<tr>
<td>NO₂</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
</tr>
<tr>
<td>O₃</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td></td>
</tr>
<tr>
<td>SO₂</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Adapted from United States Environmental Protection Agency*

To evaluate the association between the sensory ratings and the pollutant concentrations, all the days rated as bad by some subjects (thus having the sensory ratings) are selected for this analysis. The sensory ratings are the averages of the ratings made by all subjects on that day. The pollutant concentrations are also daily averages. Table 5.7 summarizes the correlation coefficients. Notice that the statistical correlation does not indicate causal relationship. For example, even if pollutant A does not influence a certain sensory feeling from the chemical perspective, it may still exhibit a correlation with the feeling, because there is a strong correlation between the concentration of A and of B while B is the pollutant that actually causes the feeling. Since in our dataset there is a strong pairwise correlation between the pollutant concentrations, we cannot really isolate the individual effects of the pollutants. Some relationships seem to support Table 5.6. For example, PM2.5 and PM10 are strongly correlated with haziness and irritation,
while weakly correlated with bad odor and headache/dizziness; CO almost has no correlation with bad odor; the correlation between headache/dizziness and O3 is relatively stronger. But hardly any causal relationship can be drawn from them.

Table 5.7 Correlation Coefficient between Sensory Ratings and Pollutant Concentrations

<table>
<thead>
<tr>
<th></th>
<th>PM2.5</th>
<th>PM10</th>
<th>CO</th>
<th>NO₂</th>
<th>O₃</th>
<th>SO₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haziness</td>
<td>-0.4737</td>
<td>-0.5034</td>
<td>-0.4208</td>
<td>-0.3756</td>
<td>0.3311</td>
<td>-0.293</td>
</tr>
<tr>
<td>Irritation</td>
<td>-0.312</td>
<td>-0.2889</td>
<td>-0.2537</td>
<td>-0.2513</td>
<td>0.1909</td>
<td>-0.2095</td>
</tr>
<tr>
<td>Bad odor</td>
<td>-0.0449</td>
<td>-0.0486</td>
<td>-0.0077</td>
<td>-0.0436</td>
<td>-0.0642</td>
<td>0.0577</td>
</tr>
<tr>
<td>Headache/dizziness</td>
<td>-0.0102</td>
<td>-0.028</td>
<td>0.0266</td>
<td>-0.0329</td>
<td>-0.0847</td>
<td>0.1031</td>
</tr>
</tbody>
</table>

The above analysis on the correlation between PAQ and objective air quality measurements are in the aggregated level. The next table of graphs shows the individual responses. In Table 5.8, each graph examines one pollutant. The x-axis is the concentration of the pollutant. The y-axis is the PAQ rating. Each fine line in the graph represents the pollutant concentration – PAQ rating value pairs from one subject. For example, a downward going line in the CO graph means for this specific subject, the higher the concentration of CO, the lower he rates the air quality. Judging from the graph, although the overall trend corresponds to the expectation, which is already reflected by the correlation analysis, the behavior of individuals is not as regular. Many individual lines do not have a consistent slope. That is to say, as the concentration of a pollutant increases, the PAQ rating goes up and down irregularly.
Table 5.8 Relationship between Pollutant Concentrations and PAQ Ratings for Each Subject

5.3.2 Person-to-Person Variance

Section 5.1.3 already examined how the sensitive and insensitive subgroup rates the air quality differently in the aggregated level. Now that the objective measurements are available, it is interesting to see how different subjects rate the PAQ when the air quality is the same based on objective measurements.

Here we use the AQI as the objective measure to decide the air quality level. AQI is divided into six categories as Table 5.9. For each category, find all the days with the
AQI fitting into it, and then find the subjects making PAQ ratings for those days. The result is plotted in Figure 5-10. The x-axis is the AQI categories. The PAQ ratings of all the subjects in all the days with the respective AQI category are plotted as a boxplot.

Table 5.9 AQI Ranges

<table>
<thead>
<tr>
<th>AQI category</th>
<th>AQI Value Range</th>
<th>Level of Health Concern</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0 to 50</td>
<td>Good</td>
</tr>
<tr>
<td>2</td>
<td>51 to 100</td>
<td>Moderate</td>
</tr>
<tr>
<td>3</td>
<td>100 to 150</td>
<td>Unhealthy for Sensitive Groups</td>
</tr>
<tr>
<td>4</td>
<td>151 to 200</td>
<td>Unhealthy</td>
</tr>
<tr>
<td>5</td>
<td>201 to 300</td>
<td>Very Unhealthy</td>
</tr>
<tr>
<td>6</td>
<td>301 to 500</td>
<td>Hazardous</td>
</tr>
</tbody>
</table>

Adapted from US Environmental Protection Agency (2016)

Figure 5-10 shows that no matter how good or bad the air quality of a day is, there will always be subjects rating at all levels, indicating a significant person-to-person variance. The variance is larger when the air quality is worse, which means people are more likely to rate a bad day as good then to rate a good day as bad.

The underlying reasons could be various. One possibility is that the reference point is different. The air quality of the previous day could be an important reference point. After a heavily polluted day, a moderately polluted day may seem to be good. The reference point could also be individual-specific. Since the air pollution problem has become very salient over the recent years, some people have accepted the heavily polluted scenario as the default setting. Thus, even when there is a polluted day, those people may compare it with the heavily polluted default and conclude that the reality is not that bad. However, when the day is clear, everybody will just say it is a good day, no matter what the default setting is a normal or polluted day. Another possibility is that some subjects may deliberately lie about their feelings to avoid more questions. As described in Chapter 3, the PAQ questionnaire is designed in the way that only when the overall rating for a spot is bad (from 1 to 3) will the following specific sensory questions pop up. The initial idea is to reduce burden for the subjects. After all, if the subject believes that the air quality is good, there is
probably nothing to complain about the sensory discomforts. However, it is possible that subjects falsely report good PAQ ratings to avoid the sensory questions.

Figure 5-10 also hints a non-linear relationship between PAQ and AQI. The PAQ rating may respond more acutely when the AQI is worse, which makes sense intuitively. There could be a more sophisticated model to depict the relationship between PAQ and AQI, which takes into account the non-linear relationship, dependency of PAQ on previous air quality, and individual-specific reference point. This model is not explored in this thesis, but could be meaningful for future research.

![Figure 5-10 Variance Of PAQ Ratings From Different Subjects Within Same AQI Categories](image)

5.4 Discussion

5.4.1 Effectiveness and Limitations of the PAQ Measure

Since the PAQ rating system is developed in this thesis, we want to examine how effective it is in indicating the air quality as well as its limitations. Based on the analysis results in this chapter, several conclusions can be drawn here.
First, the PAQ rating is correlated to the objective measurements, especially the AQI index (correlation coefficient is -0.8397). Considering that the PAQ survey is very short and takes only a minute to complete, it is highly unlikely that the subjects first check the AQI before filling out the survey. If so, then the PAQ is truly related to AQI, and thus can be used as a fairly good alternative to AQI when the AQI is not available. The sensory ratings, however, are not so closely related to the concentrations of specific air pollutants. This is probably because the human sensory system is not accurate enough to differentiate the small variations of the pollutant concentrations. Therefore, the PAQ measure can only give an overall rating of the air quality, but not the specific pollutant levels.

Second, compared with AQI, the PAQ rating balances various pollutants better. Table 5.10 lists the correlation coefficient between the two measures and the air pollutant concentrations. The correlation coefficients between PAQ and the pollutants are more similar. In comparison, AQI represents certain pollutants better while fits not so well with others.

<table>
<thead>
<tr>
<th></th>
<th>PM2.5</th>
<th>PM10</th>
<th>NO2</th>
<th>O3</th>
<th>SO2</th>
<th>CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAQ</td>
<td>-0.8310</td>
<td>-0.8103</td>
<td>-0.7683</td>
<td>0.7391</td>
<td>-0.6502</td>
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<td>0.6755</td>
<td>-0.5429</td>
<td>0.5709</td>
<td>0.7551</td>
</tr>
</tbody>
</table>

Third, PAQ has a major limitation, which is that it behaves well only in aggregated level. Table 5.8 and Figure 5-10 both shows how different individuals respond differently to the same objective measurement. To make things worse, Table 5.8 shows that many individuals do not make consistent ratings. That means even if the ratings come from the same person, they may not be comparable. To solve the problem, there must be a fair number of people making PAQ ratings for the same place at the same time, to generate a meaningful average PAQ result.

### 5.4.2 Combining PAQ and the Objective Measurements

There are only 35 air quality monitor stations in Beijing right now. The stations are
dispersed in the vast area of Beijing, causing a very low spatial resolution of the air quality measure. The cost of building and maintain such stations is very expensive. An air quality monitor station usually needs a certain size of land, non-trivial money (about 200,000 USD for construction and 30,000 USD per year for maintenance), and human resources to regularly take care of it (Zheng, 2013).

Given that the PAQ rating (at least in the aggregated level) is promising to provide meaningful information on air quality, it has the potential to become a crowdsourcing air quality information source. Residents in the city can all report the PAQ for their own location and check the average PAQ at another location reported by other people. If enough people are in the project, the spatial and temporal resolution of the PAQ ratings will both be very high. It could even become a real-time report. In addition, even though the PAQ rating itself can hardly provide detailed data on the specific pollutant concentrations, with certain inference algorithm and other data input, it can help infer those concentrations. Again it will help increase the spatial resolution of the air quality measurements greatly.
Chapter 6
Air Quality and Travel Behavior

After constructing the daily trips in Chapter 4 and evaluating the air quality with multiple measures in Chapter 5, this chapter evaluates the association between air quality and travel behavior through regression analysis.

Ten models are built in this Chapter. Five of them use AQI as the air quality measure, each with a different travel behavior measure as the independent variable. The other five of them use PAQ as the air quality measure, again each with a different travel behavior measure as the independent variable. Section 6.1 introduces the variables and data used for the regression models. Section 6.2 presents the models that use AQI as the air quality measure. Section 6.3 presents the models that use PAQ as the air quality measure. Section 6.4 discusses the results and limitations of the models.

6.1 Variables and Data

Travel behavior can be measured in several ways. This chapter examines travel behavior with five measures: number of trips per day, number of non-motorized trips per day, percentage of non-motorized trips per day, total distance traveled per day, as well as total travel time per day. The travel behavior data comes from the Moves data, given that it covers more trips than the memory-based self-reported travel survey does.

Air quality is the major independent variable, which is measured with AQI and PAQ. The two measures are highly correlated. Therefore, they enter the regression model separately. There are several other independent variables besides air quality,
namely the socioeconomic characteristics, several subgroup labels concerning air quality, as well as the day in the week. User subgroup labels include whether the user is sensitive to air pollution, has flexible working hours, or attentive to air quality. Such data come from the entry questionnaire. Those who report to have respiratory disease or feel more sensitive to air pollution are labeled as sensitive. Those who report to have flexible working hours, retired, or students are labeled as flexible. Those who report to check the air quality index at least once a day from the smartphone app, website, news or other sources are labeled as attentive. These features are in the model because they could affect the perception of air quality or the travel decision. One who is more sensitive to air pollution is more motivated to reduce exposure to air pollution. One who has flexible working hours is more capable of making trip adjustments. One who is attentive to air quality is likely to put air quality into consideration when making decisions, including travel decisions. The day of a week may place constraints on travels therefore is also in the model. All the variables are summarized in Table 6.1.

The socioeconomic features enter the model as dummy variables. The baseline for gender is female. The baseline for age is 20 years old and younger. The baseline for Hukou status is non-Beijing Hukou. The baseline for number of accessible cars and bikes are both zero.

The independent variables will enter the regression model not only by themselves but also in interaction terms, as described by Function 6.1. The interaction terms capture the effect of how non-air-quality features influence the way people respond to the air quality through travel behaviors. For example, say that the dependent variable is number of trips per day and that the air quality is measured with AQI. If the coefficient of both AQI and AQI*sensitive are negative, it means that people tend to make fewer trips when the AQI goes up (air quality is worse), and this tendency is even stronger for the sensitive people.
Table 6.1 Variables in the Regression Model

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Independent Variable</th>
<th>Day of week</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel behavior</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of trips per day</td>
<td>AQI</td>
<td>Subgroup</td>
</tr>
<tr>
<td>Number of non-motorized trips per day</td>
<td>PAQ</td>
<td>Age</td>
</tr>
<tr>
<td>Percentage of non-motorized trips per day</td>
<td>Hukou status</td>
<td>Subgroup</td>
</tr>
<tr>
<td>Total distance travelled per day</td>
<td>Number of accessible cars</td>
<td>Subgroup</td>
</tr>
<tr>
<td>Total travel time per day</td>
<td>Number of accessible bikes</td>
<td>Subgroup</td>
</tr>
<tr>
<td></td>
<td>Number of accessible cars</td>
<td></td>
</tr>
</tbody>
</table>

Travel behavior $\sim AQ + socioeconomic features + subgroup + day of week + AQ \times socioeconomic features + AQ \times subgroup + AQ \times day of week$

(Function 6.1)

Some data records from the whole Moves dataset are removed before estimating the models. First, the days when the total traveled distance is longer than 150km, which is the diameter of Beijing city, are removed, considering that we are interested in the intra-city level trip decisions. Second, the days when the total traveled distance is shorter than 500m are removed, considering that on these days the subject has minimal exposure to the air pollution. Third, the commuting trips are removed, considering that the commuting trips are rather inelastic. It’s very hard for most people to cancel or change commuting travel plans no matter the air quality. Fourth, the initial analysis shows that a Thursday (February 25th) has particular low number of trips with unexplained reasons. This day is removed from the dataset as an outlier.

Therefore, we got an unbalanced panel data to enter the regression models. The plm package in R is used to perform the regression analysis in this chapter. The random
effect model, rather than the fixed effect model, is selected to count for the inter-subject difference, for the following reasons. First, Hausman tests show that the random effect model is more appropriate. Second, the fixed effect model does not work well when there is little intra-subject variation compared with inter-subject variation, which is the case in our data. Third, the random effect model is more appropriate when the subjects can be seen as a sample from a larger pool, which is the case in our data.

6.2 AQI as the Indicator for Air Quality

6.2.1 Hypotheses

The hypothesis is that when the AQI goes up, indicating that the air quality is worse, people would reduce number of trips, number of non-motorized trips, percentage of non-motorized trips, total distance traveled, as well as total travel time. Therefore, the coefficient of AQI in all five models should be negative. However, there may be one complication when the dependent variable is total travel time. When the air quality is very bad, the traffic tends to be congested, thus slowing down the ground transportations. If this is the case, then when the AQI goes up, the total travel time could also go up. Thus, the effect of AQI on total travel time is compound.

The interaction terms between subgroups and AQI are expected to be negative, since these subgroups of people are expected to be more willing to as well as capable of adjusting their travel plans. Being in the subgroup is expected to enhance AQI’s negative influence on the selected travel behaviors.

The interaction terms between AQI and non-Sunday days are expected to be positive, cancelling out people’s response to the air quality, since there should be more travel constraints on non-Sunday days.

6.2.2 Model Estimation and Interpretation

The estimation results of the five models are listed in Table 6.2.
of the estimation results are as follows.

- The independent variables listed here play a minor role in determining the travel behavior, which is reflected by the small adjusted R-squares of all five models. There are other more important factors that determine the travel behavior.

- The AQI is significant only in determining total distance traveled and total travel time, yet the signs of the coefficients are both different from expected.

- The interactions between sensitive and AQI are positive in Model 1 and Model 4, with positive signs. Given that the coefficients for AQI in these two models are also positive, being sensitive enhances people’s response to the air quality, but in a different direction from the expectation. Flexible and attentive are not significant in the interactions.

- The interactions between AQI and Tuesday through Saturday are significantly positive in Model 3, and the magnitude is comparable to the coefficient of AQI. Adding them together would cancel the effect of AQI out. It indicates that the negative effect of AQI on non-motorized trip only exists for Sundays and Mondays. This partially agree with our expectation, since Sundays generally have less travel constrains.

- The interactions between Beijing Hukou and AQI are significant in Model 4 and Model 5 with negative signs. The interactions between age and AQI are not significant. The interactions between number of accessible cars/bikes and AQI are significant in some models.

- Some non-air-quality variables are significant. For example, compared with Sunday, people make more non-commuting trips, especially motorized trips, and travel for a longer time on Saturdays. The weekdays are not significantly different from Sunday. Compared with female, male travel more, make more motorized trips, and travel for longer distance and time. Interestingly, those who can access 3 or more cars significantly travel more, while those who can access more bikes significantly travel less.
Table 6.2 Estimation Results with AQI as the Air Quality Measure

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>y = number of trips</td>
<td>y = non-motorized trips</td>
<td>y = non-motorized trips</td>
<td>y = total distance traveled (m)</td>
<td>y = total travel time (s)</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>2.1464***</td>
<td>1.3968***</td>
<td>0.5406***</td>
<td>10358.29</td>
<td>2484.95+</td>
</tr>
<tr>
<td>AQI</td>
<td>-0.0019</td>
<td>-0.0016</td>
<td>-0.001</td>
<td>87.26+</td>
<td>18.81*</td>
</tr>
<tr>
<td>Monday</td>
<td>-0.1947</td>
<td>0.1282</td>
<td>0.0506</td>
<td>-6644.79</td>
<td>-146.46</td>
</tr>
<tr>
<td>Tuesday</td>
<td>0.1798</td>
<td>0.218</td>
<td>0.0042</td>
<td>991.92</td>
<td>533.85</td>
</tr>
<tr>
<td>Wednesday</td>
<td>0.1472</td>
<td>0.1217</td>
<td>-0.0458</td>
<td>-676.84</td>
<td>901.97</td>
</tr>
<tr>
<td>Thursday</td>
<td>-0.1047</td>
<td>0.2541</td>
<td>0.0344</td>
<td>-5285.39</td>
<td>-81.07</td>
</tr>
<tr>
<td>Friday</td>
<td>-0.0001</td>
<td>0.2162</td>
<td>0.0309</td>
<td>-859.31</td>
<td>967.53</td>
</tr>
<tr>
<td>Saturday</td>
<td>0.3916*</td>
<td>0.0343</td>
<td>-0.1007*</td>
<td>4879.86</td>
<td>1641.31*</td>
</tr>
<tr>
<td>Sensitive</td>
<td>-0.2023</td>
<td>0.026</td>
<td>0.0691+</td>
<td>-6278.13+</td>
<td>-155.38</td>
</tr>
<tr>
<td>Flexible</td>
<td>0.2363</td>
<td>0.1179</td>
<td>0.0214</td>
<td>404.59</td>
<td>176.12</td>
</tr>
<tr>
<td>Attentive</td>
<td>-0.0724</td>
<td>-0.0814</td>
<td>-0.0036</td>
<td>5690.44+</td>
<td>502.72</td>
</tr>
<tr>
<td>Male</td>
<td>0.2727*</td>
<td>-0.146</td>
<td>-0.0639+</td>
<td>12980.03***</td>
<td>1675.02**</td>
</tr>
<tr>
<td>Beijing Hukou</td>
<td>0.3649**</td>
<td>0.0951</td>
<td>-0.0179</td>
<td>4579.96</td>
<td>1044.93*</td>
</tr>
<tr>
<td>Age 21-25</td>
<td>0.2077</td>
<td>-0.5216*</td>
<td>-0.1324+</td>
<td>14278.81*</td>
<td>1531.26</td>
</tr>
<tr>
<td>Age 26-30</td>
<td>0.4042</td>
<td>-0.3509</td>
<td>-0.1183+</td>
<td>14901.16*</td>
<td>2227.43*</td>
</tr>
<tr>
<td>Age 31-35</td>
<td>0.7321**</td>
<td>-0.1296</td>
<td>-0.1076</td>
<td>13507.08*</td>
<td>1796.54+</td>
</tr>
<tr>
<td>Age 36-40</td>
<td>0.272</td>
<td>-0.4761+</td>
<td>-0.1422+</td>
<td>9328.15</td>
<td>1442.1</td>
</tr>
<tr>
<td>Age 41-45</td>
<td>0.1862</td>
<td>-0.1371</td>
<td>-0.0518</td>
<td>6366.19</td>
<td>1784.52</td>
</tr>
<tr>
<td>Car = 1</td>
<td>0.0507</td>
<td>-0.1906</td>
<td>-0.0354</td>
<td>866.82</td>
<td>184.06</td>
</tr>
<tr>
<td>Car = 2</td>
<td>0.276</td>
<td>-0.2263</td>
<td>-0.082+</td>
<td>6889.51</td>
<td>156.45</td>
</tr>
<tr>
<td>Car = 3 or more</td>
<td>1.3059***</td>
<td>-0.0785</td>
<td>-0.0666</td>
<td>23601.55*</td>
<td>1715.36</td>
</tr>
<tr>
<td>Bike = 1</td>
<td>-0.1421</td>
<td>-0.0216</td>
<td>0.0066</td>
<td>-1042.62</td>
<td>-239.49</td>
</tr>
<tr>
<td>Bike = 2</td>
<td>-0.2986+</td>
<td>-0.1168</td>
<td>0.0149</td>
<td>-2644.25</td>
<td>15.82</td>
</tr>
<tr>
<td>Bike = 3 or more</td>
<td>-0.704**</td>
<td>-0.3604+</td>
<td>-0.0663</td>
<td>-8214.53</td>
<td>-1192.92</td>
</tr>
<tr>
<td>AQI:Monday</td>
<td>-0.001</td>
<td>0.0008</td>
<td>0.0007</td>
<td>-71.76</td>
<td>-11.28</td>
</tr>
<tr>
<td>AQI:Tuesday</td>
<td>-0.0022</td>
<td>0.0008</td>
<td>0.0014+</td>
<td>-108.13</td>
<td>-8.95</td>
</tr>
<tr>
<td>AQI:Wednesday</td>
<td>-0.0027</td>
<td>0.001</td>
<td>0.0015**</td>
<td>-70.93</td>
<td>-14.62+</td>
</tr>
<tr>
<td>AQI:Thursday</td>
<td>-0.0017</td>
<td>0.0008</td>
<td>0.0012*</td>
<td>-79.1+</td>
<td>-11.7</td>
</tr>
<tr>
<td>AQI:Friday</td>
<td>-0.0016</td>
<td>-0.0001</td>
<td>0.0009+</td>
<td>-60.3</td>
<td>-12.22+</td>
</tr>
<tr>
<td>AQI:Saturday</td>
<td>-0.0013</td>
<td>0.0008</td>
<td>0.0012*</td>
<td>-62.38</td>
<td>-8.9</td>
</tr>
<tr>
<td>AQI:Sensitive</td>
<td>0.0013+</td>
<td>0.0005</td>
<td>-0.0001</td>
<td>27.4+</td>
<td>3.03</td>
</tr>
<tr>
<td>AQI:Flexible</td>
<td>-0.0009</td>
<td>-0.0005</td>
<td>-0.0001</td>
<td>16.92</td>
<td>0.53</td>
</tr>
<tr>
<td>AQI:Attentive</td>
<td>0.0000</td>
<td>-0.0001</td>
<td>-0.0001</td>
<td>-8.39</td>
<td>-1.43</td>
</tr>
</tbody>
</table>
### 6.3 PAQ as the Indicator for Air Quality

#### 6.3.1 Hypotheses

Compared with AQI, the interaction between PAQ and air quality is more complicated. On one hand, similar with AQI, we expect that when the PAQ goes down, indicating that the air quality is worse, people would reduce number of trips, number of non-motorized trips, percentage of non-motorized trips, total distance traveled, as well as total travel time. Therefore, the coefficient of PAQ in all five models should be positive. However, on the other hand, the PAQ is the personal subjective feeling about air quality. Unlike AQI, PAQ could be easily affected by the level of exposure to the air pollution. Therefore, those who make more trips, more non-motorized trips, travel for a longer distance and time may rate PAQ as lower just because they are more exposed to the pollution. If this is the case, then the coefficient of PAQ in all five models should be negative. Thus, the relationship between PAQ and the dependent variables becomes compound due to the two-way causality problem. Similarly, there is no simple intuitive way to predict the sign of the interaction terms.

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
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<th></th>
<th></th>
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<tbody>
<tr>
<td>AQI:Male</td>
<td>0.0002</td>
<td>0.0000</td>
<td>-0.0001</td>
<td>-0.89</td>
<td>0.3</td>
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<tr>
<td>AQI:Beijing Hukou</td>
<td>-0.0002</td>
<td>0.0000</td>
<td>0.0000</td>
<td>-29.33*</td>
<td>-3.92+</td>
</tr>
<tr>
<td>AQI:Age21-25</td>
<td>-0.0003</td>
<td>0.0007</td>
<td>0.0000</td>
<td>-20.8</td>
<td>-4.99</td>
</tr>
<tr>
<td>AQI:Age26-30</td>
<td>-0.0007</td>
<td>0.0005</td>
<td>0.0001</td>
<td>-22.88</td>
<td>-3.53</td>
</tr>
<tr>
<td>AQI:Age31-35</td>
<td>-0.0019</td>
<td>-0.0005</td>
<td>0.0000</td>
<td>-27.5</td>
<td>-7.59</td>
</tr>
<tr>
<td>AQI:Age36-40</td>
<td>0.0001</td>
<td>0.0007</td>
<td>0.0002</td>
<td>11.55</td>
<td>-1.15</td>
</tr>
<tr>
<td>AQI:Age41-45</td>
<td>-0.0001</td>
<td>0.0003</td>
<td>0.0002</td>
<td>-3.24</td>
<td>-3.08</td>
</tr>
<tr>
<td>AQI:Car = 1</td>
<td>0.0002</td>
<td>0.0001</td>
<td>-0.0002</td>
<td>6.16</td>
<td>-1.14</td>
</tr>
<tr>
<td>AQI:Car = 2</td>
<td>0.0002</td>
<td>0.0006</td>
<td>0.0000</td>
<td>-15.6</td>
<td>-0.74</td>
</tr>
<tr>
<td>AQI:Car = 3+</td>
<td>-0.0028</td>
<td>-0.0031*</td>
<td>-0.0009+</td>
<td>-26.88</td>
<td>3.6</td>
</tr>
<tr>
<td>AQI:Bike = 1</td>
<td>0.0011</td>
<td>0.0007</td>
<td>0.0001</td>
<td>28.15+</td>
<td>4.7+</td>
</tr>
<tr>
<td>AQI:Bike = 2</td>
<td>-0.0003</td>
<td>0.0008</td>
<td>0.0003</td>
<td>5.34</td>
<td>-0.28</td>
</tr>
<tr>
<td>AQI:Bike = 3+</td>
<td>0.001</td>
<td>0.0022*</td>
<td>0.0007*</td>
<td>22.78</td>
<td>0.74</td>
</tr>
<tr>
<td>Adjusted R-Squared</td>
<td>0.0625</td>
<td>0.0265</td>
<td>0.0484</td>
<td>0.05</td>
<td>0.0475</td>
</tr>
</tbody>
</table>

Significance codes: ‘***’ under 0.001; ‘**’ under 0.01; ‘*’ under 0.05; ‘.’ under 0.1

Unbalanced Panel: n=218, T=1-42, N=3284
Due to time constraints, the two-way causality issue is not dealt with through model specification. We still apply the previous model format in this section.

### 6.3.2 Model Estimation and Interpretation

In this section, the PAQ ratings are used as the air quality measure. Both the overall rating and specific sensory ratings are entered into the models. Notice that higher PAQ indicates that the air quality is better, while higher sensory rating indicates that the sensory discomfort is more severe, thus the air quality is worse.

The estimation results of the five models are listed in Table 6.3. The interpretations of the estimation results are as follows.

- The independent variables listed here play a minor role in determining the travel behavior, which is reflected by the small adjusted R-squares of all five models. There are other more important factors that determine the travel behavior.

- The over all PAQ rating is not significant in any model. Haziness and irritation are not significant in any model either. Odor is significant in all models but Model 6. The coefficient is positive in Model 7 and Model 8, negative in Model 9 and Model 10. It indicates that worse odor is related to more number as well as percentage of non-motorized trips, while shorter travel distance and time. Headache/dizziness is significant only in Model 8, and the coefficient is negative, indicating that more severe headache/dizziness is related to lower non-motorized trip percentage.

- The interaction term of PAQ*weekend is significant in Model 9 with negative coefficient, enhancing the negative coefficient of PAQ. The interaction term of PAQ*male is significant in Model 7, Model 8, and Model 9. The interaction term of PAQ*Beijing Hukou is significant in Model 9 and Model 10, both positive.

- The interaction terms of haziness are largely insignificant, except for its interaction with 2 accessible cars. The interaction terms of irritation are also largely insignificant, with two exceptions significant at 0.05 level. The
interaction terms of headache/dizziness are also largely insignificant. It indicates that either haziness, irritation and headache/dizziness almost have no influence on people’s travel decisions, or the two-way causality issues cancels out the influence here.

- The interactions of odor and different age groups are all significant for Model 8, Model 9, and Model 10. The signs of the coefficients are all different from that of odor in the respective model, while the magnitude makes them almost cancel out. It indicates that the positive relationship between odor and non-motorized trip percentage as well as the negative relationship between odor and travel distance/time are only significant for people 20 years old and younger.

- Some non-air-quality variables are significant in the models. For example, on weekends people make less non-motorized trips and travel longer distance and time. Male tends to make less non-motorized trips and travel longer distance and time. Theses findings are similar with the previous section. The correlation between number of cars/bikes and travel behavior is not as significant in this set of models.

Table 6.3 Estimation Results with PAQ as the Air Quality Measure

<table>
<thead>
<tr>
<th></th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
<th>Model 10</th>
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<tbody>
<tr>
<td>y = number of trips</td>
<td>1.7013</td>
<td>0.4324</td>
<td>0.4646</td>
<td>27756.33</td>
<td>11253.68+</td>
</tr>
<tr>
<td>PAQ</td>
<td>-0.1035</td>
<td>0.0009</td>
<td>-0.0136</td>
<td>-2467.1</td>
<td>-1007.83</td>
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<tr>
<td>Haziness</td>
<td>-0.0689</td>
<td>-0.6643</td>
<td>-0.176</td>
<td>360.44</td>
<td>-479.18</td>
</tr>
<tr>
<td>Irritation</td>
<td>1.1998</td>
<td>0.3957</td>
<td>-0.2372</td>
<td>22503.54</td>
<td>2138.48</td>
</tr>
<tr>
<td>Odor</td>
<td>-1.7724</td>
<td>1.7262+</td>
<td>1.1822***</td>
<td>-49834.+</td>
<td>-8018.68+</td>
</tr>
<tr>
<td>headache/dizziness</td>
<td>1.5532</td>
<td>-0.4266</td>
<td>-0.6137+</td>
<td>22440.19</td>
<td>3989.12</td>
</tr>
<tr>
<td>Sensitive</td>
<td>-0.3585</td>
<td>-0.2255</td>
<td>-0.0675</td>
<td>-22583.96</td>
<td>-3169.</td>
</tr>
<tr>
<td>Flexible</td>
<td>0.2245</td>
<td>-0.1383</td>
<td>-0.0378</td>
<td>-4440.75</td>
<td>31.32</td>
</tr>
<tr>
<td>Attentive</td>
<td>0.5455</td>
<td>0.5075</td>
<td>0.1459</td>
<td>-2286.05</td>
<td>-745.39</td>
</tr>
<tr>
<td>Is weekend</td>
<td>-0.25</td>
<td>-0.8303*</td>
<td>-0.2843*</td>
<td>29590.45**</td>
<td>3127.89+</td>
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<tr>
<td>Male</td>
<td>0.2193</td>
<td>-0.8197+</td>
<td>-0.3399*</td>
<td>30131.18*</td>
<td>3408.62</td>
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<tr>
<td>Beijing Hukou</td>
<td>-0.0848</td>
<td>0.4036</td>
<td>0.0972</td>
<td>-20943.07+</td>
<td>-3203.31</td>
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<td>----------</td>
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<td>----------</td>
</tr>
<tr>
<td>Age 21-25</td>
<td>1.353</td>
<td>1.0227</td>
<td>0.0758</td>
<td>16854.57</td>
<td>-1222.12</td>
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<tr>
<td>Age 26-30</td>
<td>1.373</td>
<td>1.0984</td>
<td>0.0694</td>
<td>-4199.51</td>
<td>-3684.94</td>
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<tr>
<td>Age 31-35</td>
<td>1.4306</td>
<td>1.1057</td>
<td>0.069</td>
<td>-74.84</td>
<td>-2096.81</td>
</tr>
<tr>
<td>Age 36-40</td>
<td>0.8246</td>
<td>0.7992</td>
<td>-0.0411</td>
<td>15135.97</td>
<td>29.58</td>
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<tr>
<td>Age 41-45</td>
<td>0.2644</td>
<td>0.6915</td>
<td>-0.1345</td>
<td>-41719.16</td>
<td>-2068.14</td>
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<tr>
<td>Car = 1</td>
<td>0.2856</td>
<td>-0.2918</td>
<td>-0.1212</td>
<td>16690.45</td>
<td>1573.22</td>
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<tr>
<td>Car = 2</td>
<td>0.8017</td>
<td>-0.7305</td>
<td>-0.3426</td>
<td>28262.53</td>
<td>1709.65</td>
</tr>
<tr>
<td>Car = 3 or more</td>
<td>0.3576</td>
<td>-1.2203</td>
<td>-0.3657</td>
<td>-2188.65</td>
<td>-2677.89</td>
</tr>
<tr>
<td>Bike = 1</td>
<td>-0.9032</td>
<td>-0.6363</td>
<td>-0.0067</td>
<td>1741.8</td>
<td>-1109.06</td>
</tr>
<tr>
<td>Bike = 2</td>
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<td>0.486</td>
<td>0.1326</td>
<td>-10001.14</td>
<td>-1862.2</td>
</tr>
<tr>
<td>Bike = 3 or more</td>
<td>-2.4564*</td>
<td>0.5784</td>
<td>0.3989</td>
<td>-18255.28</td>
<td>-4690.07</td>
</tr>
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<td>0.0243</td>
<td>0.0515</td>
<td>0.0188</td>
<td>1801.16</td>
<td>413.82</td>
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<tr>
<td>PAQ:flexible</td>
<td>-0.0309</td>
<td>0.0282</td>
<td>0.011</td>
<td>1180.63</td>
<td>15.32</td>
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<tr>
<td>PAQ:attentive</td>
<td>-0.0602</td>
<td>-0.0614</td>
<td>-0.0123</td>
<td>417.</td>
<td>41.33</td>
</tr>
<tr>
<td>PAQ:isweekend</td>
<td>0.0401</td>
<td>0.0501</td>
<td>0.0181</td>
<td>-3190.23*</td>
<td>-366.03</td>
</tr>
<tr>
<td>PAQ:male</td>
<td>0.0302</td>
<td>0.1208+</td>
<td>0.044+</td>
<td>-3277.11+</td>
<td>-382.89</td>
</tr>
<tr>
<td>PAQ:Beijing Hukou</td>
<td>0.0712</td>
<td>-0.0469</td>
<td>-0.0195</td>
<td>4166.59*</td>
<td>658.13*</td>
</tr>
<tr>
<td>PAQ:Age21-25</td>
<td>-0.0424</td>
<td>-0.0917</td>
<td>-0.016</td>
<td>-453.56</td>
<td>221.74</td>
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<tr>
<td>PAQ:Age26-30</td>
<td>-0.0049</td>
<td>-0.0566</td>
<td>-0.0045</td>
<td>2335.3</td>
<td>673.31</td>
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<td>0.0723</td>
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<td>-0.0843</td>
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<td>-356.01</td>
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<td>PAQ:Bike = 3+</td>
<td>0.1698</td>
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<td>50.55</td>
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<td>PAQ:Bike = 1</td>
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<td>0.1121</td>
<td>0.0086</td>
<td>197.52</td>
<td>260.49</td>
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<td>PAQ:Bike = 2</td>
<td>0.0507</td>
<td>-0.0378</td>
<td>-0.0037</td>
<td>548.52</td>
<td>209.05</td>
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<td>PAQ:Bike = 3+</td>
<td>0.2389</td>
<td>-0.1381</td>
<td>-0.0586</td>
<td>-517.34</td>
<td>354.23</td>
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<td>hazziness:sensitive</td>
<td>-0.0974</td>
<td>0.0817</td>
<td>0.0325</td>
<td>4919.46</td>
<td>933.55</td>
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<tr>
<td>hazziness:flexible</td>
<td>0.0842</td>
<td>0.1341</td>
<td>0.0272</td>
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<td>0.0584</td>
<td>0.0313</td>
<td>0.0323</td>
<td>-2469.58</td>
<td>-457.78</td>
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<td>0.1434</td>
<td>0.1246</td>
<td>-0.0178</td>
<td>1806.77</td>
<td>572.38</td>
</tr>
<tr>
<td>hazziness:male</td>
<td>0.0155</td>
<td>0.2091</td>
<td>0.0477</td>
<td>-7101.95</td>
<td>-732.82</td>
</tr>
<tr>
<td>hazziness:Beijing</td>
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<td>-0.186</td>
<td>-0.0307</td>
<td>3530.13</td>
<td>984.31</td>
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<tr>
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<td>-670.81</td>
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<td>-0.0921</td>
<td>0.433</td>
<td>0.1636</td>
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<td>-793.36</td>
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<td>-0.1842</td>
<td>0.3809</td>
<td>0.0821</td>
<td>-5008.81</td>
<td>-1298.54</td>
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<td>-0.3804</td>
<td>0.4029</td>
<td>0.1942</td>
<td>-10078.93</td>
<td>-2539.39</td>
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<tr>
<td>hazziness:Age41-45</td>
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<td>0.8675+</td>
<td>0.2815+</td>
<td>-4278.</td>
<td>-1384.02</td>
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</tr>
<tr>
<td></td>
<td>-0.2178</td>
<td>-0.0133</td>
<td>0.0079</td>
<td>-4733.86</td>
<td>-86.71</td>
</tr>
<tr>
<td>odor: Bike = 3+</td>
<td>-0.309</td>
<td>-0.682</td>
<td>-0.4815+</td>
<td>30548.09</td>
<td>6418.93</td>
</tr>
<tr>
<td>headache/dizziness:sensitive</td>
<td>-0.1289</td>
<td>-0.1264</td>
<td>0.1369</td>
<td>2181.86</td>
<td>-435.4</td>
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<tr>
<td>headache/dizziness:flexible</td>
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<td>0.2726</td>
<td>-0.0292</td>
<td>-4729.32</td>
<td>-341.84</td>
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<tr>
<td>headache/dizziness:attentive</td>
<td>-0.3318</td>
<td>0.3919</td>
<td>0.1114</td>
<td>-2810.13</td>
<td>-492.24</td>
</tr>
<tr>
<td>headache/dizziness:isweekend</td>
<td>0.2263</td>
<td>0.174</td>
<td>-0.0079</td>
<td>-6196.81</td>
<td>-754.27</td>
</tr>
<tr>
<td>headache/dizziness:Beijing</td>
<td>0.1371</td>
<td>0.2525</td>
<td>0.2079</td>
<td>1537.06</td>
<td>-138.58</td>
</tr>
<tr>
<td>headache/dizziness:Male</td>
<td>0.188</td>
<td>0.3695</td>
<td>0.1505</td>
<td>-5375.81</td>
<td>167.06</td>
</tr>
<tr>
<td>headache/dizziness:Age21-25</td>
<td>-2.0422+</td>
<td>-0.1076</td>
<td>0.4625</td>
<td>-37710.55</td>
<td>-5582.18</td>
</tr>
<tr>
<td>headache/dizziness:Age26-30</td>
<td>-1.4715</td>
<td>-0.3439</td>
<td>0.2901</td>
<td>-25332.73</td>
<td>-3430.77</td>
</tr>
<tr>
<td>headache/dizziness:Age31-35</td>
<td>-0.9271</td>
<td>0.1379</td>
<td>0.3765</td>
<td>-37980.48</td>
<td>-5586.92</td>
</tr>
<tr>
<td>headache/dizziness:Age36-40</td>
<td>-1.4006</td>
<td>0.6614</td>
<td>0.8916**</td>
<td>-42693.25</td>
<td>-8524.62+</td>
</tr>
<tr>
<td>headache/dizziness:Age41-45</td>
<td>0.0568</td>
<td>-0.1764</td>
<td>0.2195</td>
<td>23883.16</td>
<td>1394.41</td>
</tr>
<tr>
<td>headache/dizziness:Car = 1</td>
<td>-0.172</td>
<td>-0.1897</td>
<td>-0.17</td>
<td>5846.75</td>
<td>406.5</td>
</tr>
<tr>
<td>headache/dizziness:Car = 2</td>
<td>0.0311</td>
<td>-0.1355</td>
<td>-0.0696</td>
<td>8267.04</td>
<td>2261.21</td>
</tr>
<tr>
<td>headache/dizziness:Car = 3+</td>
<td>-1.5128</td>
<td>0.2444</td>
<td>0.3754</td>
<td>25244.42</td>
<td>7928.09</td>
</tr>
<tr>
<td>headache/dizziness:Bike = 1</td>
<td>-0.4559</td>
<td>-0.0191</td>
<td>0.1371</td>
<td>4946.32</td>
<td>-377.36</td>
</tr>
<tr>
<td>headache/dizziness:Bike = 2</td>
<td>-0.8161</td>
<td>-0.1931</td>
<td>-0.0052</td>
<td>14998.08</td>
<td>1257.07</td>
</tr>
<tr>
<td>headache/dizziness:Bike = 3+</td>
<td>0.6681</td>
<td>1.4421+</td>
<td>0.6211*</td>
<td>-5761.68</td>
<td>-4526.96</td>
</tr>
</tbody>
</table>

Adjusted R-Squared | 0.0681 | 0.0384 | 0.0618 | 0.0687 | 0.0589

Significance codes:  ‘***’ under 0.001;  ‘**’ under 0.01;  ‘*’ under 0.05;  ‘.’ under 0.1

Unbalanced Panel: n=218, T=1-42, N=3284

6.4 Discussion

6.4.1 Model Evaluation and Limitations

Based on the regression results in this chapter, the association between air quality and travel behavior in Beijing is very weak. On one hand, the small adjusted R-squares indicate that the air-quality-related factors are not people’s primary concerns when making travel decisions. On the other hand, the few significant variables indicate that people do not make significant travel adjustments when the air quality changes.

We need to acknowledge that the regression models developed in this chapter are far from perfect. First, the relationship between travel behavior and air quality may not be linear, so the linear model may not be appropriate. When using AQI, the
measure is continuous, but it is possible that people do not take air quality into consideration unless AQI is really high. Thus the relationship is non-linear. When using PAQ, the measure is ordinal. The sensory ratings enter the model as dummy variables to partially address this problem, but it is not the best solution. Other models, such as a step function may suite the situation better. Second, when using PAQ to represent air quality, there is the two-way causality problem. How to address the problem by model specification and estimation should be further discussed. Third, there are other important variables that could affect travel behavior, like weather, the odd-and-even car plate polity, and so forth. Due to lack of information and time constraints, they are not considered in this chapter, which weakens the models. They should absolutely be addressed in future works.

6.4.2 Beijing Residents’ Response to Air Pollution

People could respond to air pollution in different levels.

• It is possible that people cannot sense the air pollution at all, not to mention making behavioral responses. The analysis from Chapter 5 denies this possibility by presenting a strong correlation between PAQ and AQI. On average, people can make reasonable judgments about the air quality based on their subjective feeling.

• Even if people can feel the air pollution, some may ignore its influence on health and thus do not make behavioral adjustments. People may believe that the health impact of the pollutants is minimal, or wearing a mask can reduce the negative health impact to minimal. In other words, people may deal with the air pollution in other ways rather than travel behavior change. Our data cannot address this hypothesis directly.

• There may be people who recognize the negative health impact of the air pollution and wish to reduce exposure to the pollutants by making travel behavior adjustments. However, other more important objectives prevent them from doing so. For instance, one needs to go to work no matter how the air quality is. When the fridge is empty, a shopping trip cannot be avoided. Such
situations are when people feel most frustrated about air pollution. They believe they should avoid going out, while they cannot.

- Finally, there are those who wish to reduce exposure to pollutants and actually have the capacity to adjust the travel behavior accordingly. Only this group of people can make the regression models presented in this chapter significant. This may not be the case for most people in most time, but it is possible to identify a subgroup of people acting like this in certain situations. According to the analysis in this chapter, odor seems to be a significant indicator for people to change travel behavior. More particular niches are to be found in future works.
Chapter 7

Conclusion

This chapter reviews the work presented thus far. Section 7.1 summarizes the major work done, analysis results and conclusions. Section 7.2 discusses the limitations and future research possibilities. Both sections are structured around the three major topics of this thesis: smartphone-based travel survey method, perceived air quality measure, as well as the association between air quality and travel behavior.

7.1 Summary

This thesis explores the travel behavior, air quality, and the association in between, based on a smartphone-based survey performed in Beijing, China since January 2016. Until March 13th 2016, 258 subjects have been recruited and became the sample for this thesis. The travel behavior data is collected through a smartphone-based travel survey. Considering that the smartphone-based travel survey is a promising but not completely mature method, the whole process from survey design to implementation is recorded and discussed in Chapter 3. Chapter 4 discusses methods to analyze the travel behavior data to identify major trips. The travel data recorded by smartphone is compared to that reported by the subjects based on memory, to understand the features of different travel data sources as well as explore possibilities for data fusion. On the air quality side, this thesis develops the Perceived Air Quality (PAQ) measure to capture residents’ subjective feelings about the air quality. The subjects report the PAQ ratings around the home, workplace and worst spot during commuting each day in the survey period. The PAQ results are analyzed and compared against the objective air quality measurements (Air Quality Index and concentrations of pollutants) published by
Beijing municipal government in Chapter 5. Based on the travel behavior data from Chapter 4 and the air quality data from Chapter 5, the association between them is evaluated in Chapter 6.

7.1.1 Smartphone-based Travel Survey Method

A smartphone-based travel survey is performed in Beijing since January 2016. The key aspects of performing a high quality survey that we conclude from designing and implementing the survey are listed as follows.

- **Choose/Design the smartphone app that best serves the research goal.** For the purpose of collecting daily trajectory data, the app should have automatic trajectory tracking function, reasonable battery drain, stability in the survey city, as well as a friendly data export platform. Capacity to differentiate travel modes would be a plus. If the researcher decides to design an app, then prompt questions can be added according to the research objectives.

- **Set up data quality standard and data quality monitoring system.** Compared with the traditional travel survey, the smartphone-based travel survey collects more detailed data for a longer period. To make sure the data is of high quality, it is helpful to set up a data quality standard. Accordingly, monitoring the data quality every day is necessary to identify and solve data problems in time.

- **Test all the details in the pilot phase.** Compared with the traditional travel survey, there are more technique issues involved with the smartphone-based travel survey. Whether the app works in the target city is a complicated and practical problem. It is extremely important to test every detail in the pilot phase.

- **Know the subjects.** It is important to know who are the potential subjects under a certain survey design framework and compensation level. Our survey indicates that currently in Beijing, the compensation of 120 Yuan (around 18 dollars) per two weeks is not particularly attractive. Plus that the Moves
authorization process takes some time, more female and young people are attracted to the survey. If a study has a strict sample distribution requirement, then the knowledge of the potential subjects would be helpful to adjust the design or compensation.

The data collected by Moves requires further processing to identify the important trips and stops. A DBSCAN clustering is performed on the locations to identify major places. Then the home and workplace locations are identified based on empirical rules and transport analysis objectives. Based on empirical thresholds, the trips are consolidated to form major trips. Then commuting trips are identified based on the origin and destination types.

After the major daily trips are constructed, they are compared with the memory-based self-reported travel surveys. On average, Moves reports 1.8 times more trips than the self-reported survey does. Then the Moves trips and survey trips are matched to each other one by one based on starting time. The match rate varies according to the match threshold. When the threshold is 30 minutes, 68.6% of the self-reported trips can be matched to a Moves trip, while 39.65% of the Moves trips can be matched to a self-reported trip. After two trips are matched, the travel mode is compared. It turns out that the travel mode match rate is around 85% in both directions.

The overlap between the Moves data and self-reported travel survey indicates the possibility of data fusion. Since the travel survey can obtain more accurate travel mode and trip purpose information, by matching them to the Moves trips more information about the trip will be revealed. Also, even if some Moves trips are not accompanied by a matching self-reported trip, with the matched pairs we can develop algorithms to infer the information of the unmatched trips.

### 7.1.2 Perceived Air Quality Measure

A PAQ measure is developed in this thesis based on past indoor PAQ measure and the characteristics of the outdoor environment. The subject is asked to evaluate the air quality of three spots each day: around the home location, around the workplace
location, and the worst spot during the commuting trip. For each place, first an overall rating is asked. The rating is from 1 to 6, representing very bad, bad, just unacceptable, just acceptable, good, and very good. If the overall rating is below 4, meaning that the feeling towards the air quality is negative, specific sensory ratings are asked, including level of air haziness, irritation, bad order, and headache or dizziness. The rating for these questions is from 1 to 4, representing very bad, bad, just noticeable, and not at all.

To understand the air quality in Beijing, as well as evaluate the effectiveness of the PAQ measure, the PAQ survey results are analyzed and compared with the objective measurements.

- **The day-to-day variation is larger than the spatial variation.** The PAQ survey results show that most people do not feel a spatial difference of the air quality in the same day. 83% of the time people believe that the perceived air quality in the three evaluated spots are the same. The temporal air quality difference is much more obvious. The standard deviation of the daily PAQ ratings for different subjects ranges from almost zero to more than 2, with the mean around 1.2. The objective measurements in the same period show a similar pattern: the day-to-day variation is larger than the spatial variation.

- **The PAQ rating is strongly correlated with the objective measurements in the aggregated level, but less predictive in the individual level.** The averaged result of the PAQ ratings made by all the subjects in the same day is strongly related to the pollutant concentrations and AQI of the day. The correlation between average PAQ and average AQI is -0.8397. The strong correlation indicates that the PAQ could become a meaningful indicator for air quality. However, the strong correlation only exists in the aggregated level. In the individual level, different people have different senses about the same environment. Those who believe themselves to be more sensitive to the air pollution do show a more acute differentiation between good days and bad days. One same person could have different senses about the similar environment in different days. Therefore, the PAQ ratings from a small number of individuals can hardly provide meaningful information about the true air quality.
• **The sensory ratings are not as accurate as the overall rating.** The sensory ratings are not so strongly correlated with the specific pollutant concentrations. The strongest correlation is between air haziness and PM10, which is -0.5034. The correlation between bad odor and the pollutant concentrations is the weakest. None of the pollutants has a correlation stronger than -0.06 with the feeling of bad odor. This is probably because the human sensory system is not accurate enough to differentiate the small variations of the pollutant concentrations, especially for the low-concentration pollutants. Therefore, the PAQ measure can only give an overall rating of the air quality, but not the specific pollutant levels.

### 7.1.3 Association between Air Quality and Travel Behavior

The travel data and behavior data are linked together to evaluate the association in between. Several panel data regression models are built to evaluate how the travel behavior changes according to air quality and variables that affect air quality perception and travel behavior decisions.

The regression results show that the association of travel behavior and air quality is very weak. On one hand, the small adjusted R-squares indicate that the air-quality-related factors are not people's primary concerns when making travel decisions. On the other hand, the few significant variables indicate that people do not make significant travel adjustments when the air quality changes. The weak association between air quality and travel behavior indicates that the general Beijing residents are not taking air quality as an important factor when making travel decisions.

### 7.2 Limitations and Future Work

The methods and analysis used to in this thesis can be improved and expanded in several ways. They are described in the following sections.
7.2.1 Smartphone-based Travel Survey Method

The travel survey takes months to reach the goal of 1,000 subjects, which has the advantage of capturing more transportation events like the Spring Festival, but also has the disadvantage of not having enough subjects during the same period. If all the 1,000 subjects took the survey in the same 2 weeks, then it would be a very strong panel data. The reason that the survey is taking so long is that by selecting Moves as the survey app the potential sample pool is severely limited. It is hard to recruit enough subjects in a few weeks given our survey design and compensation level.

Nevertheless, the dataset collected by this smartphone-based travel survey is very rich and by no means completely exploited by this thesis. There are many interesting and meaningful topics that can be explored with the dataset. For example, Moves cannot differentiate among the motorized travel modes, which could be done by the researcher by applying certain algorithms with some additional data. Once the public transit trips are differentiated from the private motorized trips, a lot more topics can be discussed. For the public transit trips, with our dataset a complete door-to-door OD matrix can be constructed. It is possible to learn how the last mile is dealt with by different people, how many transits are needed from one station to another, what is the waiting time and denied boarding rate, and so forth. Such information would greatly assist the evaluation and development of the public transit system.

Another interesting topic enabled by this dataset but not explored in this thesis is the Spring Festival transport behavior. The transportation behavior before and after the Spring Festival is the strongest inter-city transportation event in China. The traditional travel survey hardly captures such a special event. Out dataset links the small-scale intra-city daily movements with the large-scale inter-city event-level movements. With the dataset we can explore questions like what are the feeder transports for long-distance transports like train and airplane? When are people leaving and coming back to Beijing during the Spring Festival period? What are the daily mobility pattern differences between regular working days and long holidays like the Spring Festival? What are people's mobility patterns like when they are travelling to a different city?
7.2.2 Perceived Air Quality Measure

A major limitation of the PAQ ratings is that they cannot be linked to exact locations. The subjects are asked to rate the air quality around their home, around the workplace, and the worst spot during commuting. Although the home and workplace locations may not be exactly accurate, they can at least be inferred from the daily trajectories. We have completely no idea where is that worst spot during commuting. Additionally, if the subject takes the subway to commute, then he is basically isolated from the outdoor environment during the commuting. When he is rating the worst spot during commuting, he probably only has some sense around the home and workplace. Also, there is a non-trivial hour-to-hour air quality variation in Beijing. Therefore, at what time does the subject make the PAQ rating could make a difference. However, this information is not available either.

This problem can be easily solved if the app is developed by the researchers themselves. The PAQ rating could be asked through a prompt from the app. Then the app will collect the PAQ rating, the geo-location as well as the timestamp at the same time.

Although the PAQ ratings are not perfect, we still found that the average PAQ ratings could be a pretty good indicator for the air quality. Given that there are only 35 air quality monitor stations in Beijing, and that the cost of building and maintain such stations is very expensive, regular citizens can become a crowdsourcing air quality monitoring system. Residents in the city can all report the PAQ for their own location and check the average PAQ at another location reported by other people. If enough people are in the project, the spatial and temporal resolution of the PAQ ratings will both be very high. It could even become a real-time report. In addition, even though the PAQ rating itself can hardly provide detailed data on the specific pollutant concentrations, with certain inference algorithm and other data input, it can help infer those concentrations. Again it will help increase the spatial resolution of the air quality measurements greatly.
7.2.3 Association between Air Quality and Travel Behavior

There are several aspects that the regression models can improve. First, the relationship between travel behavior and air quality may not be linear, so the linear model may not be appropriate. When using AQI, the measure is continuous, but it is possible that people do not take air quality into consideration unless AQI is really high. Thus the relationship is non-linear. When using PAQ, the measure is ordinal. The sensory ratings enter the model as dummy variables to partially address this problem, but it is not the best solution. Other models, such as a step function may suite the situation better. Second, when using PAQ to represent air quality, there is the two-way causality problem. How to address the problem by model specification and estimation should be further discussed. Third, there are other important variables that could affect travel behavior, like weather, the odd-and-even car plate polity, and so forth. Due to lack of information and time constraints, they are not considered in this chapter, which weakens the models. They should absolutely be addressed in future works.
Bibliography


Jiang, S., Ferreira Jr, J., & González, M. C. Activity-Based Human Mobility Patterns Inferred from Mobile Phone Data: A Case Study of Singapore. In Int. Workshop on Urban Computing.


Zhongwei Hu, Xiaoyong Deng, Jifu Guo, and Huimin Wen (2013). Residents’ Travel Demand Analysis Based on Mobile Phone Location Data. Annual Conference on Intelligence Transportation Systems in China.
# Appendix I: Entry Questionnaire

## Introduction

Thank you for participating in the MIT ESI Clearer Skies in Beijing project survey. It takes 15 minutes to complete the survey. There is no right or wrong answers and please complete the survey according to your own attitude.

Participation in this survey is voluntary. If you choose to participate in the survey, you understand that your responses to the survey questions will be stored and accessed by our researchers. They will be used for research purposes only. The consent form regarding the security and privacy policy of the full study can be found at the following link: https://jlt.mit.edu/BeijingESI.

If you have any questions regarding this study, please contact zelinli@mit.edu.

**1. Do you agree to the above terms?** By clicking Yes, you consent that you are willing to participate in the MIT ESI Clearer Skies in Beijing study.

- [ ] Yes, I agree.
- [ ] No, I do not agree.

## Basic Information

2. What is your gender?

- [ ] Female
- [ ] Male

3. What is your age?

- [ ] Below 21
- [ ] 21-25
- [ ] 26-30
- [ ] 31-35
- [ ] 36-40
- [ ] 41-45
- [ ] 46-50
- [ ] 51-55
- [ ] 56-60
- [ ] 61-65
- [ ] above 65
4. How would you describe your employment status?

- [ ] fully employed with fixed working time
- [ ] fully employed with free working time
- [ ] fully employed with regular shifts
- [ ] have multiple jobs or working locations
- [ ] not employed/ work from home/ freelance
- [ ] student
- [ ] retired
- [ ] other
5. What is your hukou status?
- Beijing hukou
- non-Beijing hukou

6. How would you describe your health status
- Atopic (asthma, hay fever, or allergy)
- More sensitive to poor air quality than others
- None of the above

7. How would you describe your family structure? Choose all that apply.
- Single, live alone or with roommates
- Live with parents
- Live with spouse
- Live with children

8. Please select your current phone brand
- iPhone
- Samsung
- Xiaomi/Smartisan
- Huawei/Meizu/Lenovo/Honor/Oppo/Qiku/ZTE/Coop/Pad/Vivo
- Nokia/Motorola/HTC/LG/Microsoft/Sony
- Other

9. For how long time have you been using your current phone?
- Below 6 months
- 6 months - 1 year
- 1 - 2 years
- 2 - 3 years
- 3 - 4 years
- above 4 years
10. On average, for how many years would you keep using the same phone?

- [ ] Below 6 months
- [ ] 6 month - 1 year
- [ ] 1 - 2 years
- [ ] 2 - 3 years
- [ ] 3 - 4 years
- [ ] above 4 years
### Daily Trip Related Information

11. Do you have a driver's license?
   - [ ] Yes
   - [ ] No

12. How many cars do you or your family own?
   - [ ] 0
   - [ ] 1
   - [ ] 2
   - [ ] 3 or more

13. What is the last digit of your car plate number? List all if you or your family own more than one car. We are only using it for Beijing car use restriction analysis.
   - Last digit of first car's plate number: 
   - Last digit of second car's plate number: 
   - Last digit of third car's plate number: 

14. How many bicycles do you or your family own?
   - [ ] 0
   - [ ] 1
   - [ ] 2
   - [ ] 3 or more

15. Do you use e-hailing apps (e.g. Didi Dache)?
   - [ ] Frequently
   - [ ] Sometimes
   - [ ] Never

16. By now you should have downloaded Moves to your phone and created an account. Please put your username and password in below.
   - Username: 
   - Password: 

### Air Quality Questions
17. Please rate the current air quality in Beijing.

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bad</th>
<th>Just unacceptable</th>
<th>Just acceptable</th>
<th>Good</th>
<th>Very good</th>
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Air Quality Questions

18. Please further describe the air quality in Beijing.

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bad</th>
<th>Just noticeable</th>
<th>Not at all</th>
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</thead>
<tbody>
<tr>
<td>Air haziness</td>
<td></td>
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<tr>
<td>Irritation</td>
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<tr>
<td>Bad Odour</td>
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<tr>
<td>Headache/ dizziness</td>
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Air Quality Questions

19. Please rate the current air quality around your home.

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bad</th>
<th>Just unacceptable</th>
<th>Just acceptable</th>
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Air Quality Questions

20. Please further describe the air quality around your home.

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<tr>
<th></th>
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<th>Bad</th>
<th>Just noticeable</th>
<th>Not at all</th>
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<tbody>
<tr>
<td>Air haziness</td>
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<tr>
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<tr>
<td>Bad Odour</td>
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<tr>
<td>Headache/ dizziness</td>
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</tbody>
</table>

Air Quality Questions

21. Please rate the current air quality around your major working place.

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bad</th>
<th>Just unacceptable</th>
<th>Just acceptable</th>
<th>Good</th>
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Air Quality Questions

22. Please further describe the air quality around your major working place.

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bad</th>
<th>Just noticeable</th>
<th>Not at all</th>
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<tbody>
<tr>
<td>Air haziness</td>
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<tr>
<td>Irritation</td>
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<tr>
<td>Bad Odour</td>
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<tr>
<td>Headache/ dizziness</td>
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</table>
### Air Quality Questions

**23. Please rate the current air quality of the worst spot along your commuting trip.**

<table>
<thead>
<tr>
<th>Very bad</th>
<th>Bad</th>
<th>Just unacceptable</th>
<th>Just acceptable</th>
<th>Good</th>
<th>Very good</th>
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</table>

### Air Quality Questions

**24. Please further describe the air quality of the worst spot along your commuting trip.**

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bad</th>
<th>Just noticeable</th>
<th>Not at all</th>
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<tbody>
<tr>
<td>Air haziness</td>
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<tr>
<td>Irritation</td>
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<tr>
<td>Bad Odour</td>
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<tr>
<td>Headache/ dizziness</td>
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</table>

### End of Survey

Thank you for your participation!
Appendix II: Travel Diary

**Daily Travel Diary**

Please recall all the trips you made today, and fill in the starting and ending time, travel mode, and trip purpose for each trip. Fill in as many trips as you made today. Leave the extra questions blank.

1. **What's the date today?**
   
   Date (MM/DD/YYYY)  
   
   MM | DD | YYYY

2. **First trip: Duration**

   From  
   
   To  

3. **Travel mode**

4. **What's the purpose of this trip?**

5. **Second trip: Duration**

   From  
   
   To  

6. **Travel mode**

7. **What's the purpose of this trip?**

8. **Third trip: Duration**

   From  
   
   To  

9. **Travel mode**

10. **What's the purpose of this trip?**

11. **Fourth trip: Duration**

   From  
   
   To  

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</table>
25. What's the purpose of this trip?

26. Ninth trip: Duration

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<th>MM</th>
<th>AM/PM</th>
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27. Tavel mode

28. What's the purpose of this trip?

29. Tenth trip: Duration

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<th>AM/PM</th>
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</table>

30. Tavel mode

31. What's the purpose of this trip?
# Appendix III: PAQ Questionnaire

## Air Quality Questions

1. Today's date
   - **Date:**
   - **MM** / **DD** / **YYYY**

2. Please rate the current air quality around your home.
   - **Very bad**
   - **Bad**
   - **Just unacceptable**
   - **Just acceptable**
   - **Good**
   - **Very good**

## Air Quality Questions

3. Please further describe the air quality around your home.
   - **Air haziness**
   - **Imitation**
   - **Bed Odour**
   - **Headache/ dizziness**

## Air Quality Questions

4. Please rate the current air quality around your major working place.
   - **Very bad**
   - **Bad**
   - **Just unacceptable**
   - **Just acceptable**
   - **Good**
   - **Very good**

## Air Quality Questions
5. Please further describe the air quality around your major working place.

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bed</th>
<th>Just noticeable</th>
<th>Not at all</th>
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<tbody>
<tr>
<td>Air haziness</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Irritation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bed Odour</td>
<td></td>
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</tr>
<tr>
<td>Headache/dizziness</td>
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</tbody>
</table>

**Air Quality Questions**

6. Please rate the current air quality of the worst spot along your commuting trip.

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bad</th>
<th>Just unacceptable</th>
<th>Just acceptable</th>
<th>Good</th>
<th>Very good</th>
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</table>

**Air Quality Questions**

7. Please further describe the air quality of the worst spot along your commuting trip.

<table>
<thead>
<tr>
<th></th>
<th>Very bad</th>
<th>Bed</th>
<th>Just noticeable</th>
<th>Not at all</th>
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<tbody>
<tr>
<td>Air haziness</td>
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<td>Irritation</td>
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<td>Headache/dizziness</td>
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**End of Survey**

Thank you for your participation!
# Appendix IV: Exit Questionnaire

## Introduction

Thank you for participating in the MIT ES! Clearer Skies in Beijing project survey. It takes 5 minutes to complete the survey. There is no right or wrong answers and please complete the survey according to your own attitude. Your information provided in this survey will be used only for research purposes.

If you have any questions regarding this survey, please contact zelinli@mit.edu.

## 1. Sample number

## 2. Rate the performance of Moves from 1 (not accurate at all) to 7 (very accurate).

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<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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</table>

## 3. Rate the performance of Moves in the following aspects from 1 (not accurate at all) to 7 (very accurate).

<table>
<thead>
<tr>
<th>Aspect</th>
<th>1 Not accurate at all/ Serious problem</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7 Very accurate/ Free of the problem</th>
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<tbody>
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<td>travel mode</td>
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## 4. Are you willing to continue using Moves, and we will get the data, with a compensation of 10 Yuan per month?

- Yes
- No

## 5. Are you willing to be re-contacted by our researchers? If yes, please leave your phone number and e-mail address.

<table>
<thead>
<tr>
<th>Phone number</th>
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<tbody>
<tr>
<td>E-mail address</td>
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</table>

## 6. What is your Beijing public transit card number? We may match your public transit data to the Moves records to validate the trips.


7. Do you have any suggestions for our project?

[Blank box]

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