THREE ESSAYS IN RESIDENTIAL LOCATIONS, HOUSEHOLD COMMUTING PATTERNS, AND SPATIAL N-PERSON PRISONER'S DILEMMA: THE CASE STUDY OF BANGKOK, THAILAND

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Nij Tontisirin

August 2013

THREE ESSAYS IN RESIDENTIAL LOCATIONS, HOUSEHOLD COMMUTING PATTERNS, AND SPATIAL N-PERSON PRISONER'S DILEMMA: THE CASE STUDY OF BANGKOK, THAILAND

Nij Tontisirin, Ph. D.

Cornell University 2013

This dissertation consists of three chapters, each of which explores urban-related issues—built environment, residential locations, and transportation behaviors—in Bangkok, Thailand. The research highlights different analytical methods in regional science and aims to advance the knowledge empirically, methodologically, and theoretically.

The first chapter provides an empirical contribution by analyzing the residential locations of the creative class in Bangkok. The creative class literature is premised on the location calculus of innovative individuals that contrast sharply with the rest of the population. Yet few empirical studies have tested the creative class hypothesis—the proclivity of creative people to gravitate toward locations that offer certain built amenities. In the case of Bangkok, the pattern of residential locations of creative households is found to be significantly different from that of common ones, and the built environments that attract creative households are mass transit stations, shopping malls, and public parks.

The second chapter develops a method to forecast household travel mode choice and trip sharing behavior using household socio-economic survey, Geographic Information Systems (GIS), and trip table data. It demonstrate how standard household survey data that are not specifically designed for use in a modal split model

can be used to forecast household travel mode choice and estimate ridership for a mass transit mode. The forecast also reveals that households are more likely to share their trips when the first traveler is male or when there are school children.

The third chapter develops a theoretical framework to analyze traffic congestion from micro-behavioral foundation. This paper extends the evolution of an n-person prisoner's dilemma within actual geographical space, integrating an agent-based model with GIS, in conflicting spatial interactions that ultimately lead to the emergence of cooperation. The spatial agent-based model captures the response strategies of autonomous individuals in a landscape that contextualizes both the natural and the built environment. This theoretical framework thus serves as a basis for the analysis of collective strategic decisions on the use of a common resource from a game theoretical perspective

BIOGRAPHICAL SKETCH

Born and raised in Bangkok, Thailand, Nij Tontisirin has received her Bachelor of Architecture (first class honors) from Chulalongkorn University in 2003 and Master in Urban Planning from Harvard University Graduate School of Design in 2006. Her research interests focus on urban economics, in particular on the impacts of public transit on household residential locations and commuting patterns, as well as spatial data visualization and analysis.

Tontisirin received a merit-based scholarship from the Royal Thai Government to pursue her graduate studies from 2004 to 2010. While studying at Cornell, she has worked both as a researcher and a teaching assistant. In 2008, she worked with Professor Kieran Donaghy to analyze the economic impact of Cornell on local and New York State economies. Since 2009, she has worked as a research assistant in the Cornell Program on Applied Demographics, under the supervision of Professor Joe Francis. She has also been a teaching assistant of several graduate-level courses in microeconomics, macroeconomics, planning methods, and introduction to Geographic Information Systems. After the completion of her Ph.D., she returns to Thailand and works as a lecturer in the Faculty of Architecture and Planning at Thammasat University.

Besides her academic and research duties at Cornell, Tontisirin also has worked as a librarian assistant in the Maps & Geospatial Information Collection at John M. Olin Library. She has created many historical and contemporary maps illustrated in several dissertations and books, including *The Edge of The Woods: Iroquoia, 1534–1701* by Professor Jon Parmenter, *Islam: A Short Guide to the Faith* edited by Professor Shawkat Toorawa, and *Chinese Medicine and Healing: An Illustrated History* by Professor TJ Hinrichs.

Nij Tontisirin is married to Sutee Anantsuksomsri.

For My Beloved Husband, Sutee Anantsuksomsri

ACKNOWLEDGMENTS

Throughout my life, I have always been so grateful that I have been surrounded by so many wonderful people—who generously and kindly help me overcome any difficulties that I have encountered and make my life so delightful. Upon the completion of my doctoral studies, I would like to express my great appreciation to these people.

First and foremost, I would like to express my deepest gratitude to all of my committee members: Professor Kieran P. Donaghy, Professor Joe D. Francis, Professor Mark A. Turnquist, and Professor Yuri S. Mansury. As my committee chair, Professor Donaghy has always been able to find some time—from his already tight schedule—to kindly give me his insightful and invaluable guidance on my dissertation. I am also very thankful for the research and teaching opportunities he has given me for many years. I am greatly indebted to Professor Francis for constantly giving me his heartfelt care, generous supports, and constructive advice, as well as for the research opportunity at Cornell Program on Applied Demographics (PAD). He always greets me with a bright smile and a warm big hug every "mid-morning" of days we meet and once again at the end of the day before we depart at the bus stop —I will always cherish these memories for the rest of my life. I would like to express my sincere appreciation to Professor Turnquist for his creative and rigorous guidance on my research. He has always given me motivation and encouragement to overcome any obstacles during the research process. I am immensely grateful for the advice, mentorship, and friendship given by Professor Mansury, who has spent untold hours attentively discussing—and sometimes reshaping—every single detail of my research. In addition to my committee members, I would like to express my gratitude to Professor Iwan J. Azis, who first opened the door to Regional Science to me and has taught me many valuable lessons academically, professionally, and personally.

Financial supports from various sources make it possible for me to complete my doctoral studies. I would not be able to begin my graduate studies in the US without the 6-year funding from the Office of the Higher Education Commission, Thailand Ministry of Education. I very much appreciate several teaching and research assistantships that I have received from the Department of City and Regional Planning (CRP) and PAD. I am also very grateful to the Graduate School and CRP for their generous conference and travel funding, enabling me to travel around the world to present my research at conferences as well as to Thailand to collect data. I also would like to thank Cornell's Southeast Asia Program for giving me International Research Travel Grant, allowing me to make another trip to Thailand to collect additional data.

My life at Cornell has been so pleasant because I have shared many great memories with my good friends and colleagues. I would like to express my gratitude to Robert Kibbee, Boris Michev, Howard Brentlinger, Susann Argetsinger, and Suzanne Schwartz who make my five and a half years of working at the Olin Library Map & Geospatial Information Collection so special and enjoyable. I particularly thank Bob Kibbee for giving me my very first job on campus—even before my first semester started—and Boris Michev for being so flexible with my tight schedule in the last few years of my graduate studies. I really appreciate the opportunity to work with Professor Francis, Jan Vink, and Suzy Smith at PAD, and I did enjoy every moment working there. The research skills, knowledge, and professional experiences that I have gained from the map room and PAD are extremely valuable to me personally.

I am very fortunate to have many good friends who make my life in Ithaca so enjoyable. By no particular order, I wish to thank Dr. Sivalai Vararuth, Dr. Paitoon Wongsasutthikul, Pannarai Chingchitr, Anuk Serechetapongse and her lovely mother Chularat Niratisayakul, Dr. Pimnara Hirankasi, Dr. Benjarong Suwankiri, Dapong Boon-Long, Navara Boon-Long, Dr. Wannasarn Noonsuk and Nareerat Leelachat, Chayanee Chawanote, Anutchanat Jaroenjitrkam, Pimbucha Rusmevichientong, Tipaluck Krityakierne, Dr. Thanasin Tanompongphandh, Dr. Rujira Deewatthanawong, Apikanya McCarty, Dr. Tee and Sutani Havananda, and Chanita Somton Larsson for their invaluable friendships and great memories that we share. Special thanks to Supree Srisamran for his friendship and help throughout many years. I truly appreciate the kindness of Prasit Deewatthanawong, who helped us move until the very last minute. I am immensely grateful to Dr. Nattapong Pattanapong—who first introduced me to Regional Science—for his genuine supports and advice. I am particularly thankful to Ji-Won Park; we endured taking countless challenging classes together and shared many great memories during our first several years. I also would like to extend my appreciation to my friends in Regional Science and CRP: Dr. Nur Ain Shahrier, Thomas Hirtzig, Dr. Inka Yusgiantoro, Alvin Pratama, Danny Hermawan Adiwibowo, Ozlem Asik, Gunawan Wicaksono, Viktor Zhong, Xiaoling Li, Scarlett Zuo, and Hee-Hwa Min.

Beyond Cornell, I have received generous support, assistance, and guidance from numerous people. I am forever indebted to Professor Vimolsiddhi Horayankura for his kind help and support throughout my career and graduate studies. I truly appreciate the advice—on both academic and personal matters—given by Dr. Peeradorn Kaewlai. I would like to express my appreciation to Dr. Yinyon Seniwong Na Ayudhya and Pannarai Chingchitr who provide assistance on acquiring data of Bangkok. I would like to thank National Statistical Office of Thailand for providing me with household socio-economic survey of Thailand. I also wish to thank Dr. Parinya Tanadtang and Katanchalee Jina of the Office of Transport and Public Policy for providing me with the trip distribution table of Bangkok. I am extremely grateful to Dr. Susan Kesner Bland who made me feel more confident about my academic writing. I wish to thank Dr. Dilum Dissanayake for answering my inquiries about her research. I would also like to extend my deep appreciation to Richard O. Legendi, who always kindly answers my “bugging” questions on java and agent-based modeling.

Before coming to Cornell, I am very fortunate to meet wonderful friends who are very supportive and caring. I am immensely thankful to two wonderful couples: Dalin and Shusak Janpathompong, and Pranisa Boonkham and Dr. Pradya Prempraneerach, who are like my second parents. Dalin and Shusak also helped me tremendously during difficult times before I moved from Boston to Ithaca. They even came to Cornell with their twin to visit us twice. While I was in Boston, Pranisa and Dr. Pradya kindly helped me get settled in my life abroad. They brought us for grocery trips every week and never denied our request for help. I also would like to thank Pabhimol Sontitim for her kindness in helping us move to Cornell.

From the bottom of my heart, I would like to express my greatest appreciation to my beloved parents, Dr. Kraisid and Orathai Tontisirin, for their infinite and unconditional love, heartfelt care, inspirational encouragement, and wholehearted support throughout my life. They are indeed my role model in every aspect of my life. Special thanks to my siblings: Ora Srivannaboon, Dr. Sitt Tontisirin, Nuj Tontisirin, and Sutt Tontisirin, who have also been my friends, my mentors, and my companions ever since I was young. I also would like to thank my parents-in-law, Sutthi Anantsuksomsri and Sangklay Sirchai, who kindly welcome me with open arms as if I were their own daughter.

Last but not least, I am tremendously grateful to my dearest husband, Sutee Anantsuksomsri, for his love, companionship, care, and support in any possible way. Since we met, he has always been a truly indispensable part of my life. We grow, we live, and we learn—through all good times and bad—together. His love is always the nearest to my heart, and I certainly would not be what I am now without him.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLE

CHAPTER 1

THE IMPACT OF THE BUILT ENVIRONMENT ON THE LOCATION CHOICES OF THE CREATIVE CLASS: EVIDENCE FROM THAILAND

1.1 Introduction

Globalization has forced cities and regions to rely on creative innovations as a source of competitiveness and prosperity. As creative innovations have increasingly become an economic development strategy, several recent regional studies have suggested that it is the retention of a critical mass of creative workers that is the key to success of such a development strategy. Recent studies pioneered by Richard Florida (2002) on these creative workers—called the creative class by Florida—have emphasized the role of creative individuals as a key driver in urban and region growth. As Florida puts it, “our future of economic success is increasingly depending on our ability to harness the creative talents of each and every member of the workforce” (Florida, 2008, p.110). Considered a driving force of innovations, these creative individuals are highly mobile across geographical boundaries in search for ideal places to work and live. The creative class, according to Florida, clusters not only where the center of creativity is but also where they like to live. As such, regions with diversified, tolerant, and open-minded urban environments tend to attract the creative class, and thus have high productivity and growth.

The built environment is central in Richard Florida’s (2002, 2005) narrative of the creative class. The *Flight of the Creative Class* (2005) for example, begins with a historical account of the Lord of the Rings franchise, which started in an abandoned paint factory that later emerged as the studio that attracted movie talents from around the world. In the *Rise of the Creative Class*, Florida (2002) refers to the cutting edge office architecture in Silicon Valley and in North Carolina’s research triangle that features unconventional design style. For Asia, Florida (2005) cites the case of Lucasfilm Singapore, the animation studio's first-ever overseas production facility, which has drawn creative talents worldwide. He also recounts the Singaporean government's heavy investments in artistic activities by supporting street-level culture. Global creative centers appear to share a common feature, namely efficient and heavily trafficked subway and light-rail systems. These transportation links, Florida (2002) asserts, are the key built environment for innovative creators. To our knowledge, however, no study has formally established the causal effect of the built environment on the location decisions of creative individuals.

The creative class literature is premised on the location calculus of innovative individuals that contrasts sharply to the rest of the population. Yet few empirical studies have tested the creative class hypothesis – the proclivity of creative people to gravitate toward locations that offer certain built amenities. Certainly, we are not aware of any evidence supporting such a hypothesis in Asia. This is surprising in light of the growing number of Asian cities and regions that have spent an inordinate amount of resources to project the image of a creative-class-friendly place. Bangkok, for example, is promoted as a "creative city" for the government efforts toward knowledge-based economy, shifting from export-based economy, according to the Thailand development plan. It appears that the lack of micro-geographic information has been responsible for the paucity of empirical evidence. We address this gap in the literature drawing on the data that we pieced together from the survey of Bangkok Metropolitan Region (BMR) households.

The 2008 survey produces the first Thai dataset that contains location attributes, which give us a glimpse of the creative class' residential choices. The built environments that the present study focuses on are rail stations, schools, shopping malls, and parks. We use the terms "built environment," "public spaces," and “constructed amenities” interchangeably when we refer to the general class of publicly-accessible urban forms. It is important to note that, though a significant share of these constructed environments may be privately owned, they are all accessible to the general public, though quite possibly at different levels.

An example of heavily-trafficked and publicly-accessible spaces in the BMR is the skywalk, which connects Skytrain (Bangkok mass transit lines) to the nearest shopping centers, thus creating more options for those looking for a venue for after-hour business meetings. The skywalk (see the map in Figure 1.1) makes it easier for people to access dining places and coffee shops, all of which are extensively used for informal business meetings. Siam Square Station became the most popular destination primarily because of the skywalk that connects three transit stations to dining places across nine shopping centers in the Square.

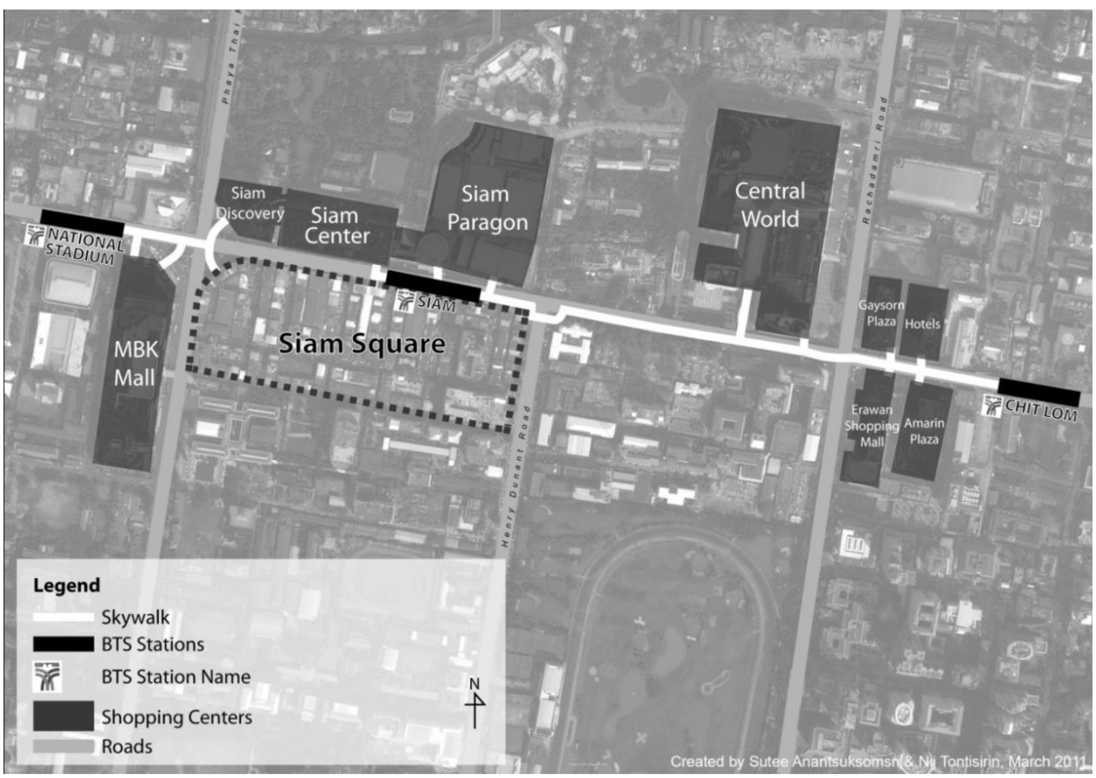


Figure 1.1: Skywalks at the Siam Square station, Bangkok, 2011

Following Florida's contributions, the creative class has been viewed by many as a silver bullet for regional development problems. This raises questions about the forces that attract talents and their social impact. Taking Florida's operationalization of the creative class for granted, the present study examines the implications for location choices. We are aware of the continuing debate on whether the creative class is a coherent group with distinct preferences and if so, how to identify members of the group so that its size can be measured (see, e.g., Reese *et al.*, 2010). In this paper we do not wish to engage in the debate. Our approach is to take Florida's broad definition as the starting point and examine whether—controlling for demographic characteristics—creativity has any ability left to explain differences in location choices.

Two main conclusions emerge from our identification procedures. First, household-level analyses reveal that the explanatory power of occupational status prevails even after accounting for the effects of age, education, gender, purchasing power and the like. Second, district-level analyses provide evidence of the importance of public spaces for the creative class. The findings have policy implications for regions struggling to keep their home-grown talent. In 1986 the creative class – as Florida defines it – constituted less than one-seventh of the Thai workforce. By 2002, the creative class share had grown to about 30 percent, which was comparable to the share in Spain and Italy, and higher than that in South Korea and Singapore. In that span it appears that Bangkok had been successful in nurturing its creative core, which grew by an average rate of 5.5 percent annually. In recent years, however, the trend has been reversed. Between 2004 and 2008 the creative class is share in the labor force fell from about 30 percent to the lower 20's. As the nation's ability to retain talents is stricken due to concerns over political stability and security, the role of constructed amenities is of growing interests to regional planners and policymakers.

In this chapter, what follows is a brief survey of relevant literature on creative class and residential location choices. The study area, the Bangkok Metropolitan Region (BMR), and the data used in this analysis are then introduced, followed by the discussion of methodology and analysis results. The chapter concludes with the discussion of policy implications and further research.

1.2 Relevant Literature Review

The theoretical underpinning for our empirical analysis is Alonso's (1964) bid-rent model of spatial equilibrium. According to this model, if everything else is constant across locations—including the level of amenities—then the bid-rent model predicts that lower housing prices should be fully offset by longer commutes. If amenities are allowed to vary, however, then locations that offer more comfort should command higher rents, ceteris paribus. Roback (1982) tests this hypothesis and finds convincing evidence that people indeed are willing to pay higher rents in exchange for better amenities.

The bid-rent framework can be extended to model the divergent location decisions of groups with heterogeneous preferences. Suppose creative individuals value certain amenities, for example access to a transit terminal, more than the common residents. Then the model predicts the former will pay higher rents for the right to live in places that are in the proximity of a rail station. Along with Florida (2002, 2005), other studies have noted the positive effect of constructed amenities on the location choices of creative individuals. Clark (2004) presents evidence of how urban forms drive relocations across cities and regions. Highly-educated individuals, in particular, appear less motivated by natural amenities than by elements of the built environment.

Why are talents attracted to certain built environments? Drawing on the endogenous growth literature (see the outline in Romer, 1994), a number of propositions have been advanced to back the existence of the clustering-productivity nexus. The source of sustained growth, according to this literature, is technological progress whose returns do not diminish over multiple uses (Lucas, 1988). Each innovation contributes not only to knowledge accumulation but also to the productivity of all involved who happen to be in the proximity. In R&D teams for example, talents constantly interact through intense face-to-face (F2F) contacts, which are prerequisites for a successful transmission of complex, uncodifiable information (Leamer and Storper, 2001). The spread of information then enhances the ability to produce new recipes. Simultaneously, innovations are often unintentionally produced as knowledge spills over when people interact within a compact arrangement (Henderson, 2007). Proximity is thus the thread that promotes both internal production of new technologies and external spillovers. Distances, in fact, are found to play an important role in industrial restructuring and technological development in Korea (Park and Koo, 2010). From here it seems reasonable to argue that information flows more fluidly within a crowded built environment than outside in the sparse open air.

Currid (2007) identifies the ways in which the built environment may facilitate F2F contacts. Creative workers according to Currid need to share the same dense space in order to draw inspirations from each other while simultaneously tapping into social networks in order to extract new information. Thus a packed nightclub is the kind of setting where innovations are seeded and employment opportunities are found. Currid concludes that the informal built environments in which creative people mingle are “instrumental in generating real economic value for those participating in it.” Though both Clark (2004) and Currid (2007) stress the role of constructed amenities, they do not quantify the differential impact of different urban forms. Which amenities and which ones matter more for talents are empirical questions that can only be addressed through a formal identification analysis.

Residential location choices in the presence of uneven amenities have caught the imagination of numerous researchers since the late 1970’s. Pioneering studies focus on the relationship between residential location and travel mode choices. This body of the literature includes the works of Lerman (1976), Quigley (1976), McFadden (1978), Anas and Chu (1984), Anas (1985), and Srinivasan and Ferreira. (2002). More recently, the built environment has become the focus of research on residential location choices. The seminal paper in this area is Guo and Bhat (2004), which identifies elements of the built environment that influence households’ residential decisions. More complete analyses are conducted in Bhat and Guo (2004; 2007), which examine the role of local neighborhood and accessibility, including public space availability and the proximity to the Central Business District.

The literature is still growing on the relationship between residential location choices and the built environment in developed countries. However, only a handful of studies have been done for developing countries in general and for Thailand in particular. Wisaweisuan (2001) focuses on households’ socio-economic factors and shows that these factors significantly explain location and tenure choices of Bangkok residents. To our knowledge, no study has analyzed the interrelation of the built environment and the residential locations of the creative class in the context of an emerging Asian economy. Building on previous research, the present study attempts to understand the location choices of creative workers through their relationship with the built environment.

1.3 Study Area: the Bangkok Metropolitan Region (BMR)

The study area covers the Bangkok Metropolitan Region (BMR), which consists of six provinces, that is, Bangkok and its five adjacent provinces. The BMR covers approximately 4,700 square kilometers (around 1,800 square miles) and houses over 11 million populations in 2010. Most urbanized areas are concentrated in four provinces, namely, Bangkok, Nonthaburi, Samut Prakan, and Pathum Thani, of which most data on physical attributes are available. Thus, these four provinces are the focus of this study (see Figure 1.2). Within these four BMR provinces, there are 69 districts, which can be divided further into 316 sub-districts. Figure 1.2 shows spatial distribution of the population density per square kilometer at the sub-district level in the BMR provinces, overlaying with its major highway network, the inner and outer ring roads, and major roads.

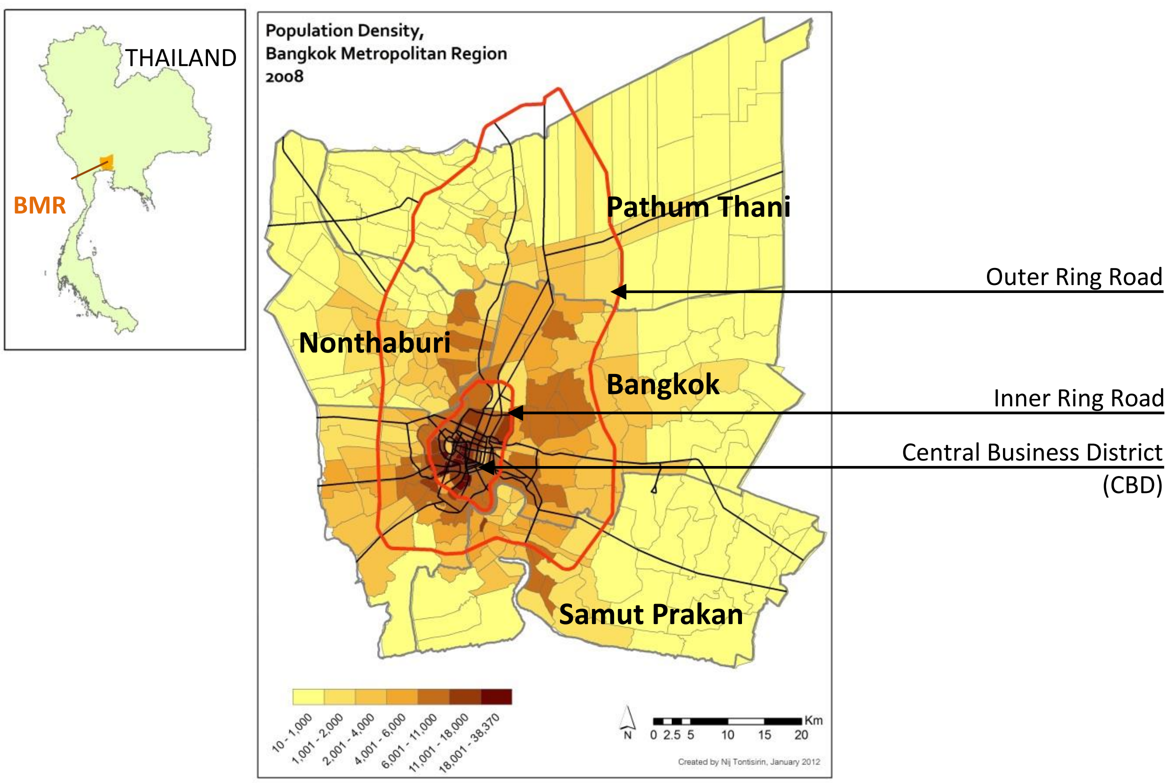
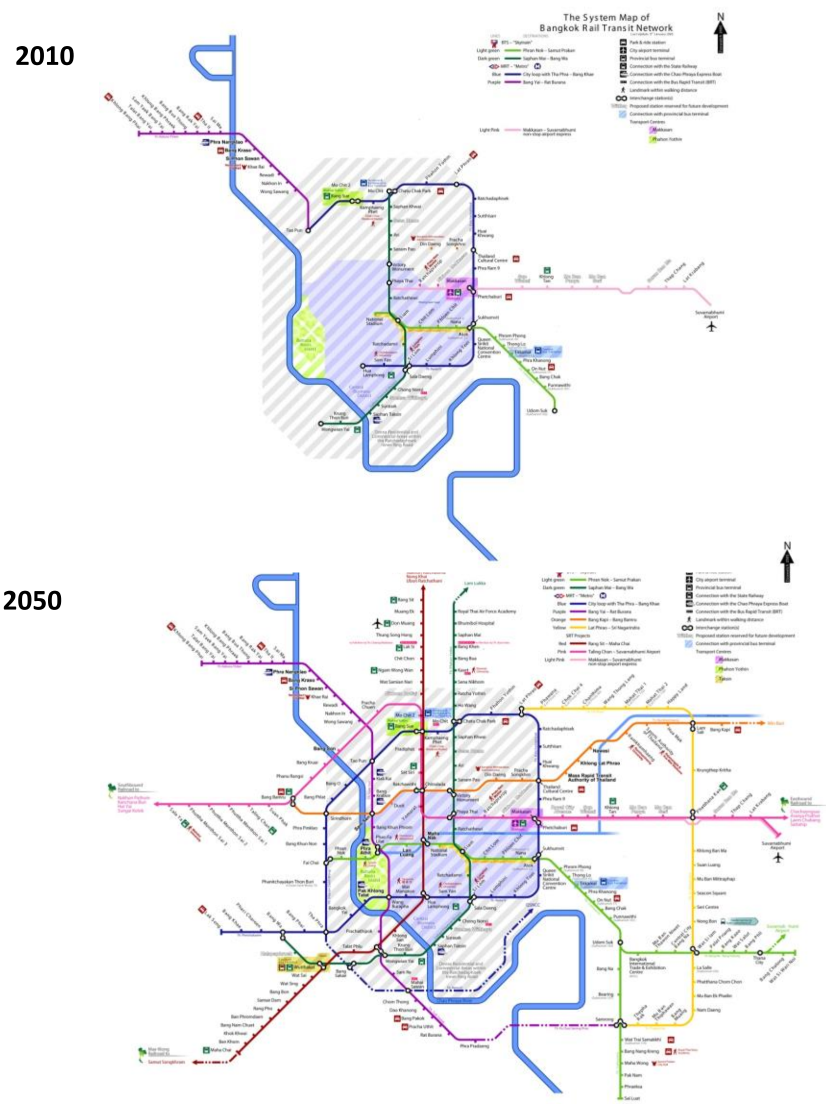


Figure 1.2: Population density per square kilometer, BMR sub-district, 2008

The highly dense areas are mainly within the inner ring road in Bangkok. In some sub-districts within the inner ring road, the population density is as high as 38,000 persons per square kilometer. According to the 2010 Population and Housing Census by Thailand National Statistical Office, the population density in Bangkok ranks as the highest in the country at 5,259 persons per square kilometer, followed by Nonthaburi (2,143 persons/sq.km.) and Samut Prakan (1,821 persons/sq.km.).



Source: Anantsuksomsri (2013)

Figure 1.3: Public transportation system in the BMR in 2010 and 2050

Facing the 1997 economic downturn and political opposition, the plan for new mass transit slowly began to materialize in the late 1990s. In December 1999, for the first time the elevated light-rail train, known as BTS Skytrain, was introduced to Bangkok residents, serving the inner city areas where major cultural, social, and economic activities take place. Running through the city above its congested major highways, the BTS Skytrain has provided its riders a new travel experience across the city with fast, comfortable, and reliable services (Jenks, 2005; Townsend and Zacharias, 2010). Because of the success of BTS Skytrain, the government has increasingly put more emphasis on public transportation projects in Bangkok. Since then, two additional transit systems have operated: Mass Rapid Transit (MRT Subway) in 2004 and Airport Link in 2010. These current transit systems are quite limited within the city center, covering about 71.5 kilometers, or 44.4 miles in length, which makes only one sixth of the entire plan. The map of current transportation systems are compared to the complete network in Figure 1.3. Undoubtedly, if the complete transportation network is fully in operation, it will transform the way Bangkok residents live and travel around the city.

As a new public transportation has brought a new travel experience to Bangkok residents, transit stations often serve not only as an entry point to rapid transit but also as a hub for social interactions. For example, many BTS stations in the city center are often well-connected to nearby shopping centers, hotels, and office buildings via elevated walkways. These walkways facilitate pedestrians to and from stations over the busy street level down below. The walking experience is enhanced by the presence of many small shops, like coffee shops, bakeries, or convenient stores. In turn, this Skywalk and transit stations facilitate face-to-face contact as it provides a space for socialization.

1.4 Data and Methodology

The data used in this analysis are drawn from two main sources: first, the 2008 household socio-economic survey (SES) from the National Statistical Office of Thailand, and second the physical environment data in Geographical Information Systems (GIS). The GIS data comes from the Department of Planning of the Bangkok Metropolitan Administration.

Creative class is defined on the basis of occupational status. In this study we stick to Florida's categorization of the creative class in order to be able to compare Florida's (2002) findings with ours. Our study, however, differs from Florida's original work in two important respects. First, we employ Thai data to demonstrate how lessons can be drawn from emerging Asian cities. Second, we employ formal econometric analyses in order to avoid the particularism of the case study approach that Florida adopted.

In Florida's (2002) terminology, the creative class can be subdivided into the "super creative class" and the "creative professionals." Super creative workers get paid to produce "readily-transferrable new forms or designs," and such workers include those in science and engineering, architecture and design, arts, entertainment, and music. Creative professionals are also engaged in creative problem solving, but for them innovations are a by-product. They include managers, business operators and financial workers, lawyers, and health practitioners.[1]

1.4.1 2008 Household Socio-economic Survey (SES)

The present study's inferential investigation draws on the most recent Household Socio-Economic Survey (SES) conducted in 2008 by the Thailand National Statistical

[1] We also include technicians (49 householders) to conform to Florida's broader definition of the creative class

Office.[2] The SES is a rich dataset suitable for a creative class study because it contains the mapping from households to their heads' occupational status. The dataset details information about 4,759 households in the BMR area. Of the total, we identify 1,455 households as those headed by members of the creative class.[3] The full list of job categories that are considered creative and the number of BMR households led by such workers is shown in Table 1.1. Majority of creative household heads works as general managers (31%), shop sale personnel (21%), and stall and market sale personnel (10%).

Householder' industry of employment is originally broken up into 18 non-overlapping categories, which we aggregate into ten broad sectors. The 2008 survey also divides employment status into 14 categories.[4] In our regression analysis we exclude seven categories, which refer to economically-inactive or unemployed householders, since these households' residential choices are likely based on a very different locational calculus.[5] Moreover Florida's categorization of the creative class is occupation based; it automatically excludes the inactive and the unemployed. To reduce potential heterogeneity, we exclude the inactive and the unemployed from the pool of common (non-creative) households.

---

[2] The SES is available upon request from the Thailand National Statistical Office. (for more information, see http://web.nso.go.th/en/survey/house_seco/socio.htm)

[3] It turns out that only 206 householders can be identified as super creative workers, or 4.3 percent of the entire sample. Because creative professionals overwhelmingly make up the BMR creative class, we do not attempt to run separate analysis for the super creative group.

[4] The categories are 1 = employers, 2 = self-employed, 3 = unpaid family workers, 4 = civil servants, 5 = state-owned enterprise employees, 6 = private company employees, 7 = co-operative group members, 8 = housewives, 9 = students, 10 = dependent children and retirees, 11 = disabled persons, 12 = actively looking for a job, 13 = unemployed, 14 = others.

[5] Unemployed householders are likely confronted with a severe budget constraint, which causes their location choices to be systematically different from employed householders.

Table 1.1: Job description of creative workers and household sample of creative households in the BMR, ranked by percent share

Job Description of the Head of Household	Number of Household Sample	Percent Share
General managers	453	31.1%
Shop sales persons and demonstrators	311	21.4%
Stall and market sales persons	139	9.6%
Other department managers	71	4.9%
Finance and sales associate professionals	67	4.6%
Architects, engineers and related professionals	49	3.4%
Physical and engineering science technicians	48	3.3%
Business professionals	44	3.0%
Administrative associate professionals	41	2.8%
Production and operations department managers	39	2.7%
Legal professionals	32	2.2%
Directors and chief executives	28	1.9%
College, university and higher education teaching professionals	19	1.3%
Health professionals (except nursing)	17	1.2%
Artistic, entertainment and sports associate professionals	14	1.0%
Optical and electronic equipment operators	12	0.8%
Business services agents and trade brokers	11	0.8%
Nursing and midwifery professionals	9	0.6%
Writers and creative or performing artists	9	0.6%
Computer associate professionals	8	0.5%
Computing Professionals	7	0.5%
Life science technicians and related associate professionals	6	0.4%
Life science Professionals	5	0.3%
Social science and related professionals	5	0.3%
Modern health associate professionals (except nursing)	5	0.3%
Mathematicians, statisticians and related professionals	3	0.2%
Physicists, chemists and related professionals	1	0.1%
Archivists, librarians and related information professionals	1	0.1%
Fashion and other models	1	0.1%
TOTAL	**1,455**	100%

Education is an ordinal variable broken up into six categories of householders' last enrollment,[6] regardless of degree conferral. Thus a householder classified as college educated may be one who had enrolled in a university without completing a degree. The detailed education breakdown allows us to test for a possible rival hypothesis, namely it is human capital rather than creative occupation that explains location choices.

In terms of demographic characteristics, in general the BMR creative households seem to bear some similarity to the non-creative ones; both have no difference in terms of number of earner, number of children, average age of household head, percent male household head and percent married. Although the creative households tend to have the same number of earners than those who are non-creative class, they tend to have higher percent of vehicle and home ownership. Around three-fourth of creative households own at least a car or motorcycle.

Since the 2008 SES is expenditure-based survey, household income is not directly observed. Thus, household monthly expenditure is used as a proxy to represent household spending power. Average expenditure per adult equivalent[7] is calculated to represent household purchasing power. The creative households on average have much higher household expenditure than the non-creative counterpart. These characteristics suggest that BMR creative households seem to have stronger purchasing power than the non-creative ones.

For every household, the SES dataset discloses the sub-district of residence during the sampling period. Officially, Bangkok Metropolitan Region consists of six provinces, including Bangkok and its five adjacent provinces. This study however

[6] The categories are 0 = no schooling, 1 = 1-6 years (grade 6 or lower), 2 = 7-9 years (at least grade 7 and at most completed middle-school), 3 = 10-12 years (at least grade 10 and at most completed high-school), 4 = at least 1 year of college education, 5 = college degree or higher.

[7] We use OECD Equivalence Scale, which weight household head = 1, other adult = 0.7, and children age 15 and below = 0.5. (see http://www.oecd.org/social/familiesandchildren/35411111.pdf)

includes only four provinces, specifically Bangkok, Samut Prakan, Nonthaburi, and Pathum Thani, because urbanized areas are mainly concentrated in these four provinces. The four BMR provinces together are composed of 69 districts, which can be divided further into a total of 316 sub-districts. Our analysis however covers only 202 sub-districts because, as it turns out, the rest of the sub-districts are not represented in the sample. The residential information is particularly useful because it allows Geographic Information Systems (GIS) to pin down the Cartesian coordinates of every household's sub-district.

1.4.2 GIS Data

The publicly-accessible spaces that we consider are MRT Subway stations, MRT Purple terminals, top secondary schools,[8] shopping malls, and parks. Their point locations across BMR sub-districts are gleaned from the Thailand Department of Public Works and Town & Country Planning 2008 database.[9] Data for other potentially relevant built amenities, such as hotels and government offices, are only available for select districts. Other built amenities, such as plazas, coffee shops and restaurant establishments, that we think are promising for creative class research are currently not covered by the Department of Public Works and Town & Country Planning surveys.[10]

Figure 1.4 illustrates locations of these urban amenities as well as mass transit stations. As can be seen, most of these amenities, particularly schools, hospitals, and transit stations, are concentrated mainly in the city center. Locations of mass transit

---

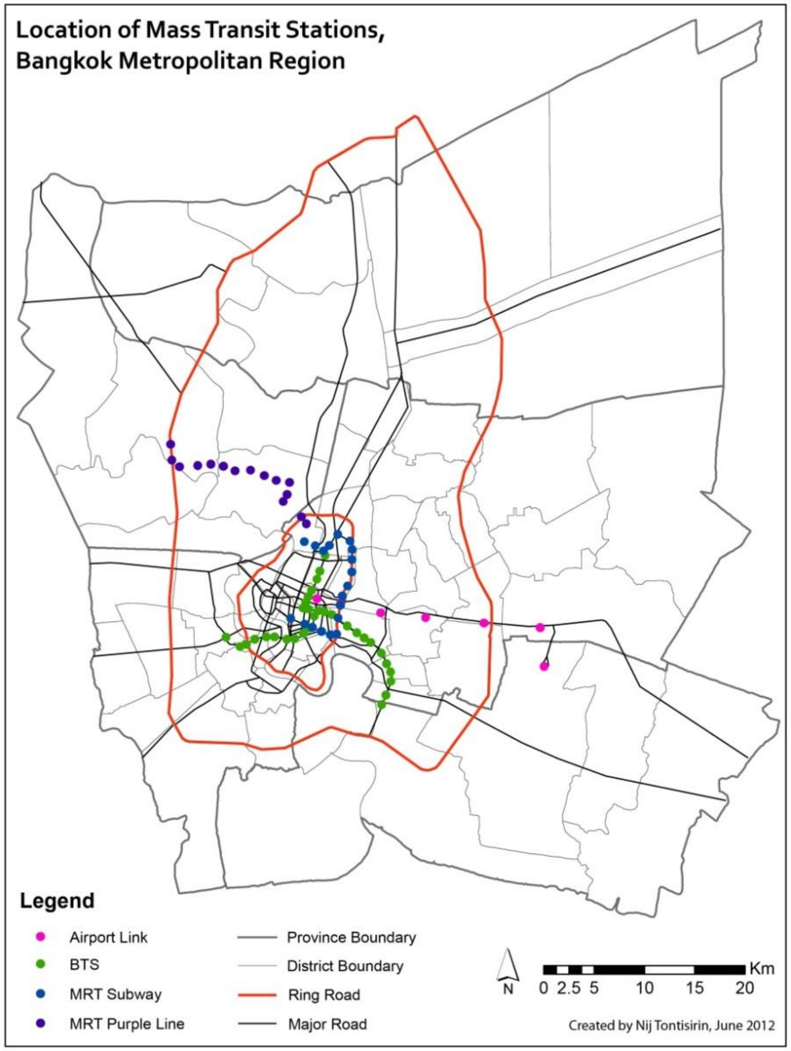
[8] A secondary school is considered "top" ranked if a significant percentage of its graduates either received government-funded college scholarships or were admitted to the elite national universities (see the website of the Thai Ministry of Education, http://www.moe.go.th).

[9] See the website of Thailand Department of Public Works and Town & Country Planning, http://eservices.dpt.go.th/eservice_8/webgis/datagis.html (in Thai)

[10] The few BMR museums are concentrated in one area, while galleries and libraries at the moment do not have a significant influence on the everyday life of Bangkokians.

stations include both current systems (BTS Skytrain, MRT Subway, and Airport Links— shown in green, blue, and pink, respectively) as well as the most current additions to the mass transit system, the MRT Purple line (shown in purple). MRT Subway is a 21-kilometer underground system that has been in operation since 2004. Carrying over 400,000 riders a day, the subway lines have primarily served the inner city areas. The MRT Purple line, on the other hand, started construction in 2010 and is scheduled for completion in 2014. This 23-kilometer new line is to serve residential areas in the outskirts of Bangkok inner ring where transit links were previously unavailable.

For every administrative level, each boundary may be represented as a point location using its centroid (or geometric center of a polygon). The point locations of built environment, on the other hand, are recorded in geographic coordinates (e.g. latitude and longitude). The GIS data of both administrative boundaries and built environments enable us to acquire spatial relationships between residential locations and the built environments. For example, proximity is computed as the Euclidian distance between a household's sub-district center and the nearest facility. These distances are calculated using the '*pointdistances*' tool available in Geospatial Modelling Environment (GME). We note in passing that the distance variables give a different perspective from the quantities on how public spaces affect location decisions. Distance measures accessibility, while the number of facilities represents a sub-district's total capacity to provide services.



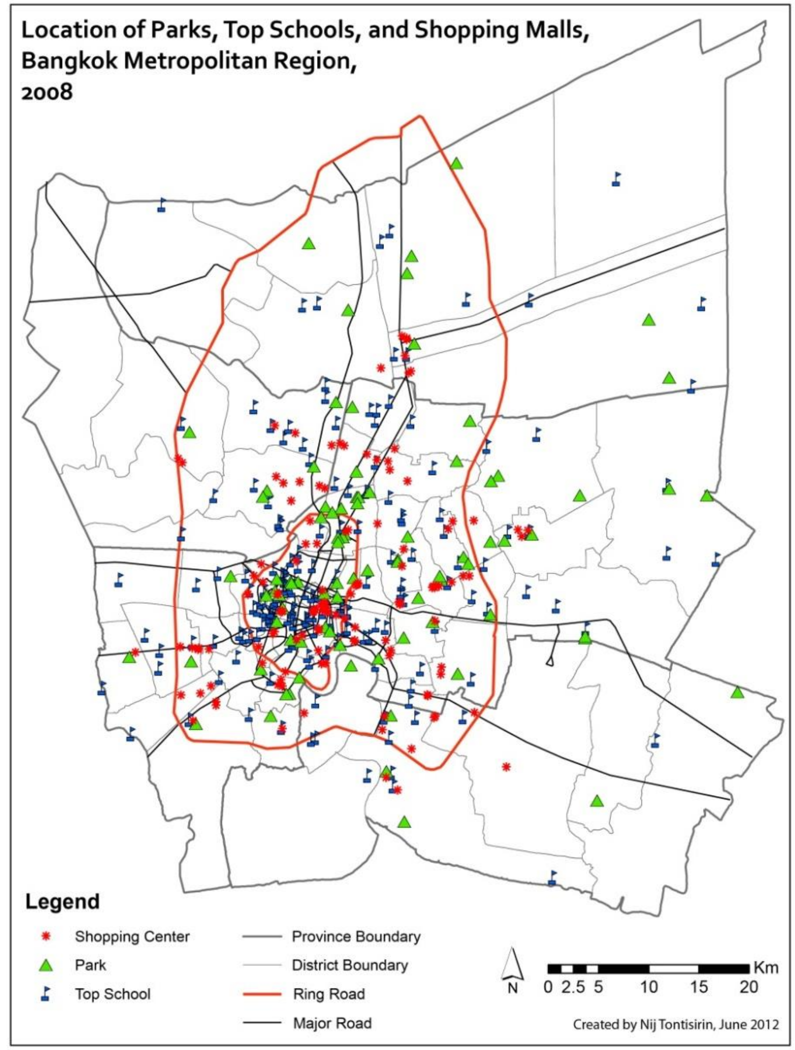


Figure 1.4: Spatial distribution of publicly accessible space, BMR

The SES dataset also provides information about every household's location in relation to the city center, where the central business district is part of. A household is identified to be an inner-ring resident if the household's district falls within the area demarcated by the inner-ring road. In total there are 22 districts situated inside the inner-ring borders. Both the 2008 SES and GIS data enable us to analyze residential location patterns of the creative households and factors determining these patterns in the BMR. We first identify the spatial distribution of the BMR creative households and examine whether distinguishing geographic clusters can be observed. The analysis is discussed in the following section.

1.5 Creative Class in the BMR

We highlight first the demographic characteristics of a typical BMR creative household. The median age of creative householders is 45, and 68 percent are male. About 70 percent are married, and 38 percent have at least one child. Creative householders are top-heavy with four-year college graduates, which represent 38 percent of the total. The modal employment status is self-employed (37%). The modal industry for creative households is Retail Trade (39%), followed by Services (27%). The rest of the sample differs in important respects. Only about half of common householders have more than primary school education, of which a quarter have at least one year of college education. The modal occupation is private-company employee (46%). Among employed common householders, the main industry of employment is Manufacturing (35%). By contrast, only 12 percent of creative householders were manufacturing workers. The data thus indicate that while the traditional economic base (i.e., manufacturing) continues to be important for the common BMR households, it is no longer the case for the creative ones. The summary statistics of these characteristics are shown in Appendix A.

Creative households clearly enjoy significant advantages in terms of purchasing power as well as overall material well being. Median monthly expenditure for creative households is 30,971 Baht (US$ 928).[11] Over 4/5 have at least one car. By contrast, median monthly expenditure for non-creative households is 18,326 Baht (US$ 549). Only a fifth own a car. In terms of information access, about half of creative households have at least one computer, but less than a third of their common peers have computers at home.

We perform a series of non-parametric tests—without controlling for confounding factors—to get a sense of whether a relationship exists between occupations (i.e., whether householder is member of the creative class) and the other variables. Specifically, the chi-square test soundly rejects the null hypothesis of no relationship between class on one hand and education, industry on the other hand, all by a wide margin at the 0.1-percent level of significance. Simply put, there are statistically significant differences in terms of educational attainment as well as industry of employment between creative and common householders.

Housing rent is an important control variable in any formal model of residential location choices. The median monthly rent payment for creative households is 5,000 baht (US$ 150), but for the common ones only half of that. On average, a typical creative household pays 62-percent higher rent (per bedroom) than the typical common one. In districts where the density of creative workers is highest (top five), households pay over 60-percent higher rents than in districts where the density of creative workers is lowest (bottom five).

We compare next the location decisions of creative households with those of the non-creative ones. We use the Hoover concentration index to measure the degree

[11] Based on 2008 exchange rate = 33.36 THB/US$. Source: Bank of Thailand <http://www.bot.or.th/English >

to which BMR households are dispersed across territorial units (see Long and Nucci, 1997).[12] The index is computed as:

$$H_t = 0.5 \sum_{i=1}^{n} |p_{it} - a_i| 100.$$

We found that Hoover index for creative households is 53, while for the common ones is 42. This implies that more than half of BMR creative households would have to be redistributed in order to attain a uniform spatial distribution. The corresponding number for common households is only a little over 40 percent. Thus, consistent with the knowledge-spillovers hypothesis, creative households in BMR consolidate more spatially than common ones.

Table 1.2: Average distances to public spaces of creative & common households and *t*-test, 2008

Distances to	Creative class	Non-Creative class	*t*-test
CBD	16,741.64	18,361.16	4.69
	(10,798.23)	(11,388.25)	
BTS or MRT Subway	9,805.46	11,283.08	4.97
	(9,262.84)	(9,864.59)	
MRT Purple	12,784.68	15,327.30	8.62
	(9,058.80)	(10,047.21)	
Top schools	2,069.75	2,308.27	3.98
	(1,842.47)	(2,032.86)	
Shopping malls	3,357.67	4,126.82	5.09
	(4,587.40)	(5,271.04)	
Public parks	2,768.21	3,195.34	5.20
	(2,457.59)	(2,921.99)	
Number of Household	1,455	3,304	

[12] The index would be zero if every district has the same share of BMR's households, and approaches 100 if all households cluster in a single district.

It appears that creative households pay premium rents for locations that give superior access to certain public spaces. The descriptive statistics in Table 1.2 bear witness to the creative household's tendency to gravitate to rail lines, malls, schools, and parks. For example, the average distance between a creative household's resident and the nearest mass rapid transit (MRT) terminal is 9.8 kilometers, or 4/5 that for a common one.

We next investigate the difference in geographic distribution of creative households and those of the non-creative ones across the BMR. To measure spatial clustering or dispersion, we perform two tests for spatial autocorrelation: Moran's I and Local Indicator of Spatial Association or LISA (Anselin, 1995). Moran's I is a measure of global spatial autocorrelation, that is, it indicates whether a spatial pattern can be observed when considering the entire BMR. On the other hand, LISA measures local spatial association and clustering pattern. It indicates which district is significantly spatially autocorrelated with neighboring districts, thus identifying "clusters." LISA is also known as the localized Moran statistic. The specification of LISA is as follows:

$$I_i = \frac{Z_i}{m_2} \sum_j W_{ij} Z_j \ ,$$

where Z_i= deviation from the mean, $m_2 = \frac{\sum_i Z_i^2}{N}$,

W_{ij}= weight matrix, N = number of observation,

$I = \sum_i \frac{I_i}{N}$

Moran's I statistic can be computed as follows:

$$I = \frac{\frac{N}{S_0} \sum_i \sum_j W_{ij} Z_i Z_j}{\sum_i Z_i^2},$$

where Z_i= deviation from the mean,

W_{ij}= weight matrix, and

$S_0 = \sum_i \sum_j W_{ij}$.

The variable of interest in this pattern analysis is the number of creative households in each district. The spatial weight matrix is based on the inverse distance (nearby neighboring districts have higher influence than the farther away ones) of 8.6 kilometers. Moran's I statistic of creative households is 0.073 and significant at 0.1 level, while for the common ones is 0.044 and not significant (see Figure 1.5and Figure 1.6, respectively). This observed geographic cluster of the creative household confirms our earlier findings with the Hoover Index that BMR creative households tend to cluster more than the common households.

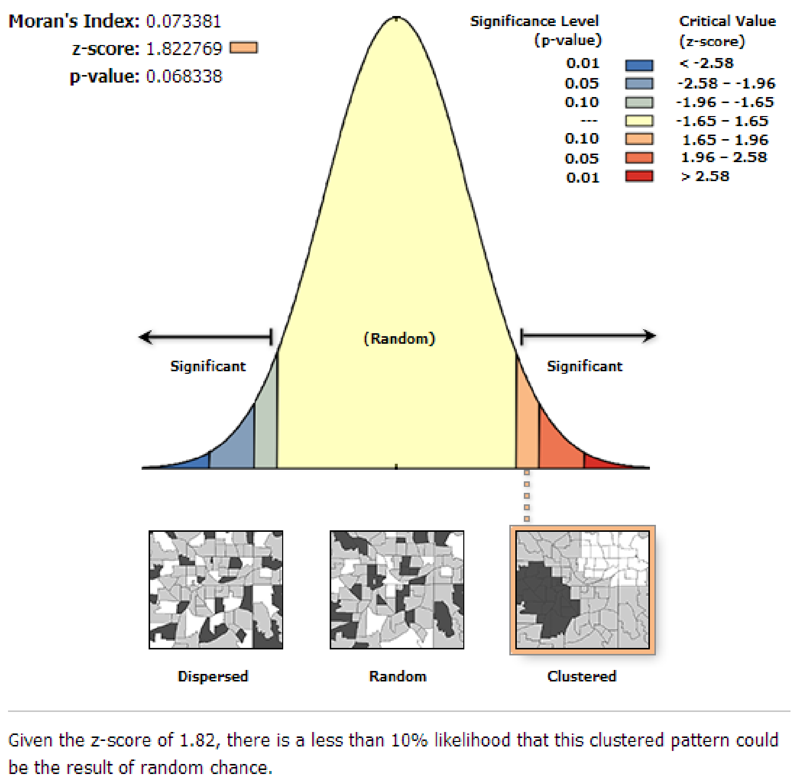


Figure 1.5: District-level Moran's I of creative households, BMR, 2008

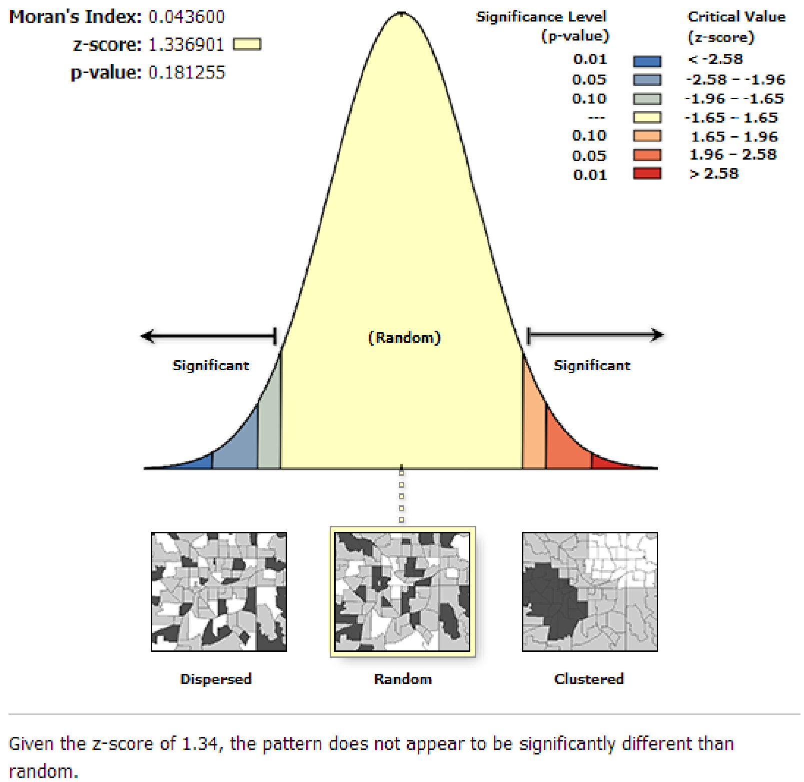


Figure 1.6: District-level Moran's I of common households, BMR, 2008

The distinct locational patterns are also apparent from Figure 1.7, which shows that BMR creative households tend to cluster in the north of the inner ring road, while common households cluster in the district in the southeast of the city center. Both the visual inspection and the formal test thus detect systematic differences between the settlement patterns of creative and common households.

The informal exploration suggests that creative workers actively seek out housing in the proximity of public spaces, which bring forth the spatially segmented pattern of residential locations. We turn next to formal identification analyses.

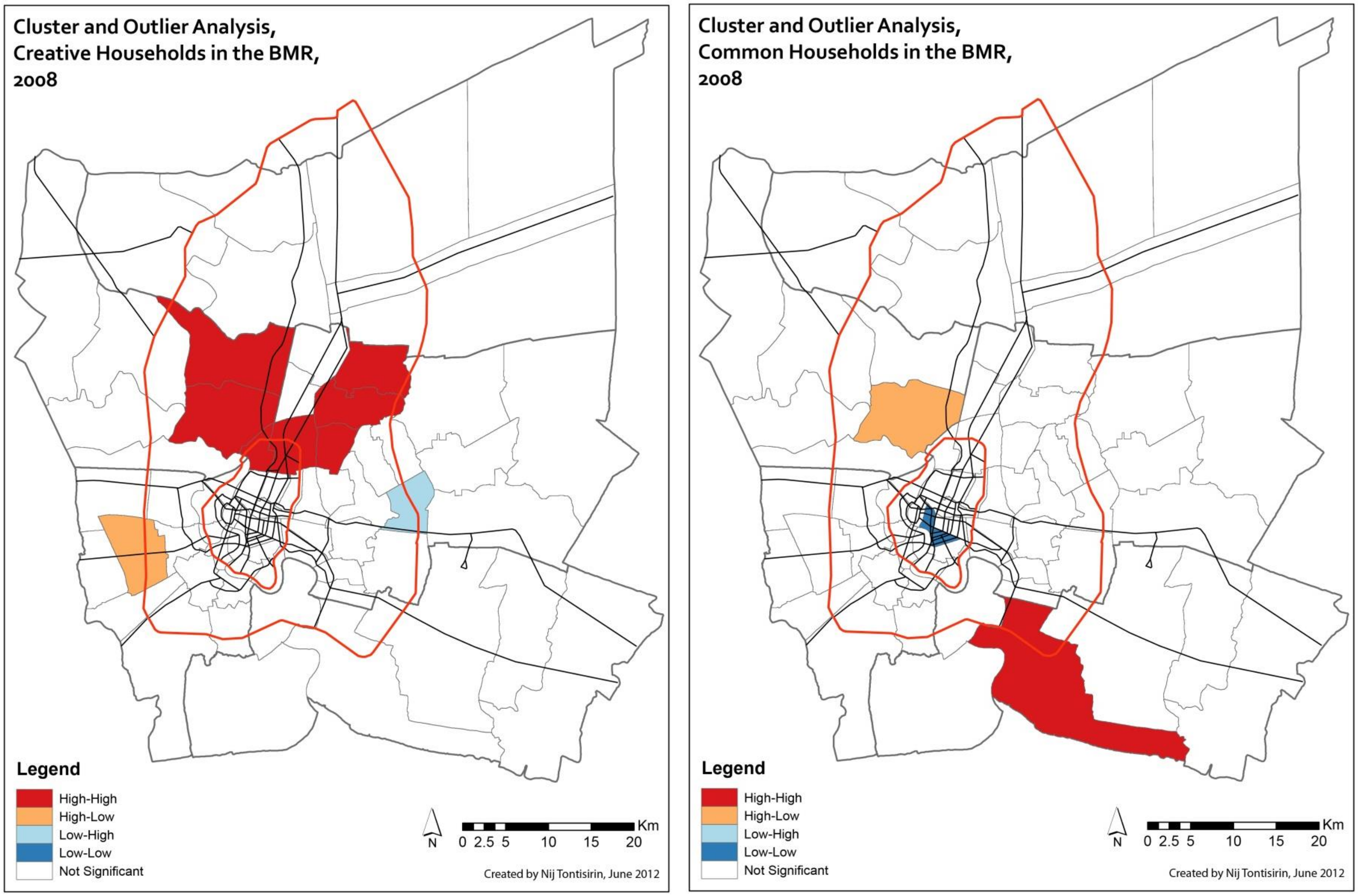


Figure 1.7: Cluster and outlier analysis of creative and common households, BMR, 2008

1.6 Factors Determining Creative Households' Residential Locations

Our formal identification begins with an analysis of the propensity of creative households to reside in the proximity of constructed amenities. We start by addressing six questions to demonstrate that being a creative class member has a discernible impact on location choices. We will show the predictive power of the creative class prevails even after controlling for standard demographic characteristics.

To facilitate comparability, across all regressions we maintain a fixed vector of controls, which includes the number of earners in the household, gender dummy, householder's age, marital status, employment dummy (1 = employed), educational attainment, number of children, retail dummy (1 = in retail sector), vehicle dummy (1 = own a vehicle), ownership dummy (1 = own the property), and average monthly expenditures. To control for household expenditure variation due to family size, we divide expenditures by the number of adult-equivalent family members.[13] To guard against the possibility of arbitrary heteroskedasticity (Wooldridge, 2002), we employ robust standard-error estimations.[14] The complete output is reported in Appendix B.

It is important to note why the retail sector is singled out. As we have noted above, Retail Trade is the modal industry of employment for Florida's creative householders in the BMR. Additionally, numerous anecdotes suggest that many creative householders are small-to-medium entrepreneurs (typically with less-than 50 employees) peddling their own creative output. These include not only young, aspiring designers who started their own boutiques, but also budding entrepreneurs in non-arts businesses. For instance, self-proclaimed ice-cream designer Prima Chakrabandhu Na

[13] We employ the OECD equivalence scale, which assigns one to household head, 0.5 to other adults, and 0.3 to children younger than 15-years old (see http://www.oecd.org).

[14] The use of a full sample, where the inactive and the unemployed are included, does not have a material effect on the estimates.

Ayudhya became a celebrity among Bangkokians because of her exotic ice-cream flavors and unusual presentation.

Question 1: Are creative households more likely to live within the inner-ring borders?

We first ask whether there are systematic differences in the general pattern of residential locations between creative and common households. The inference is drawn from estimation of a binary response model:

$$InnerRing_i = \beta_0 + \beta_1 Creative_i + \beta_2 (Creative \times retail) + \Gamma \cdot X_{\mathrm{i}} + \varepsilon_i,$$

where i denotes a household. The dependent variable is categorical defined = 1 for households residing within the inner ring road, and = 0 otherwise. X is the vector of controls. We also include interaction effects between creative class and retail employment.

Both the Akaike and Bayesian Information Criteria indicate that the probit model is favored over the logit. The estimates imply the probability of a non-creative non-retail household to be located in the inner ring while fixing the control variables at the mean values is = 0.17. The corresponding probability for a creative non-retail one = 0.25, while for a creative retail one = 0.30. That is, a creative non-retail household is almost 50 percent more likely to live inside the inner ring road than a non-creative one. Further, a creative retail household is 22 percent more likely to live inside the inner ring road than a creative non-retail one. The chi-square test rejects the null hypothesis of equal coefficients for the creative retail and creative non-retail dummies. In general therefore creative households are more likely to live within the borders of the inner ring than non-creative ones. The probability is significantly enhanced, however, when the householder is in retail. Casual observation suggests that many entrepreneurs in the retail industry live in mixed-use developments where the retail space is located in the first floor, while the upper floors are reserved for residential use. This explains the higher probability to locate in the inner ring associated with creative householders employed in the retail industry.

For each of the next five questions, the dependent variable is the Euclidian distance from household's sub-district center to the nearest publicly-accessible space.

Question2: Do creative households live more closely to MRT stations?

We estimate the following model using OLS:

$$Dist\_MRT_i = \beta_0 + \beta_1 Creative_i + \Gamma \cdot X_{\mathrm{i}} + \varepsilon_i \qquad .$$

The estimated coefficients indicate that a creative household whose head is not in retail on average is located 1.8 kilometers closer to an MRT line than a common, non-retail one (the benchmark household). Creative retail householders on average appear to locate even closer to a rail line than the creative but non-retail peers. The F-test however, fails to reject the null hypothesis of equal coefficients for the creative retail and creative non-retail dummies. The evidence thus suggests that creative households in general are more likely to live closer to a rail station.

Question3: Do creative households live more closely to future MRT Purple lines?

We estimate the following model using OLS:

$$Dist\_MPURPLE_i = \beta_0 + \beta_1 Creative_i + \Gamma \cdot X_{\mathrm{i}} + \varepsilon_i \qquad .$$

The coefficient for the creative class non retail dummy is -2229, while the coefficient for the creative class retail is -2849, both significant at the one-percent levels. The F-test, however, fails to reject the null hypothesis of equal coefficients for the creative retail and creative non-retail households. The estimate implies that a creative household on average is located at least two kilometers closer to a future MRT Purple line than a common, non-retail one.

Question4: Do creative households live more closely to top schools?

We estimate the following model using OLS:

$$Dist\_School_i = \beta_0 + \beta_1 Creative_i + \Gamma \cdot X_{\mathrm{i}} + \varepsilon_i \qquad .$$

The estimates imply that a creative non-retail household on average resides 0.2 kilometer from the nearest top school. A creative retail household on average appears to reside even closer to the nearest top school than a creative but non-retail one. There is no good causal explanation, however, why creative retail households value proximity to top schools more than creative non-retail ones. Casual observation reveals that most top schools are located within the inner ring, which is also where most of the high-end creative retail activities are. This suggests that the greater estimated propensity for creative retail households is likely to be spurious.

Question5: Do creative households live more closely to shopping malls?

We estimate the following model using OLS:

$$Dist\_Mall_i = \beta_0 + \beta_1 Creative_i + \Gamma \cdot X_{\mathrm{i}} + \varepsilon_i \qquad .$$

The estimates suggest that, in general, a creative household on average live one-km closer to a shopping mall than a common, non-retail one.

Question6: Do creative households live more closely to public parks?

We estimate the following model using OLS:

$$Dist\_Park_i = \beta_0 + \beta_1 Creative_i + \Gamma \cdot X_{\mathrm{i}} + \varepsilon_i.$$

In the model with two interaction terms (i) between creative class and retail, and (ii) between creative class and rent/bedroom, we found interaction effects that are significant at the one-percent levels. Specifically, the creative class non-retail dummy coefficient = -637, while the creative class retail coefficient = -755. The F-test however, fails to reject the null hypothesis of equal coefficients for the creative retail and creative non-retail dummies. The estimates suggest that, in general, creative households value proximity to public parks more than their common peers.

1.6.1 District-level regression

We have presented the empirical evidence showing that the creative workers' location choices are different from those of the common ones. The typical BMR creative worker exhibits greater tendency to live within the inner ring in the proximity of MRT stations, top schools, malls, and parks. We turn now to the question of which types of public spaces matter the most at the district level in terms of attracting creative workers. The underlying hypothesis is that distinct types of built environments have differential impact on the creative class size. We seek to identify which type of publicly accessible spaces is the best predictor of success in attracting talents.

We estimate the following equation:

$$CC_i = \beta_0 + \Psi \cdot \mathrm{Build} + \Gamma \cdot \mathrm{X} + \varepsilon_i, \tag{1}$$

where the dependent variable is the number of creative households. Build is a vector of built environment variables, including combinations of the number of MRT Purple line stations, MRT Subway stations, shopping malls, top schools, and public parks in each district. We also use distance variables to capture the extent to which these facilities are accessible. For example, in a separate regression we include distance to the nearest MRT station from the district's center. X is a vector of other location factors, which include average monthly rent per bedroom (Rent), district population (Population), the district's geographic area (Area), percent of male-headed households (Pct Male), average age of householders (Age), percent of married householders (Pct Married), average number of children in households (Kids). A preliminary analysis with OLS shows that all the distance variables have the negative sign as expected: longer distance between the facility and the district center is associated with fewer creative workers. However, only distances to shopping malls and parks are significant statistically. OLS estimates suggest there is gravity pull of publicly-accessible spaces, but this pull is weak. Non-linear specifications, including semi-elasticity as well as quadratic distance forms, yield very similar results. We also apply spatial econometrics to estimate both the spatial lag and spatial error models (Anselin, 1988). We use the spatial matrix where the weights are computed as the inverse of the center-to-center distance. The results not only are very similar, but also fail to reject the null hypothesis of spatial independence.

A potential problem is that we have a discrete dependent variable. Obviously, the number of creative households can only take non-negative integer values. But that does not necessarily mean OLS is inappropriate as long as the distribution of the dependent variable is approximately normal. Visual inspection, however, reveals that the unconditional distribution has a long upper tail. Because of the highly-skewed distribution of the number of creative households, we resort to maximum likelihood methods.

We estimate first the Poisson regression model. The chi-square test, however, rejects the null hypothesis of Poisson distribution at the 0.1 percent level. We turn next to the negative binomial (NB) regression model, which relaxes the Poisson assumption that the variance is exactly equal to the mean (see Long and Freese, 2006). In all the NB estimation results that we report below, the likelihood ratio statistic confirms the rejection of the Poisson distributional assumption in favor of an NB one.

1.6.2 Negative Binomial Regression Results

Table 1.3 shows the results. We found that it is not the number of public transportation links that matters. Instead, it is either the presence or the distance to these facilities that has a discernible impact on the creative workers' location choice. What attracts is the spatial distribution of MRT links but not the local capacity to provide service. MRT terminal shows up with a positive and significant impact at the five-percent level. Roughly, the presence of an MRT line doubles a district's creative class size. Put differently, a district with at least an MRT line is expected to attract 19 additional creative workers over the baseline district when all other explanatory variables are evaluated at the sample mean. Since, on average, a district hosts 21 creative workers, the impact represents over 90 percent increase of creative workers from the mean.

Creative households are clearly attracted to locations in the proximity of (a future) MRT Purple line, shopping malls, and parks. In Table 3 we calculate the percentage changes in the number of creative households due to a one-km increase in mean distance. The odd-numbered rows in particular correspond to the models where distances enter in levels. Table 1.4 also displays the marginal impact of a one-kilometer increase in distance on creative class size at three hypothetical districts; namely where the initial distance is exactly equal the sample mean, as well as in districts where the distance is half and a full standard deviation larger than the mean. We find that shorter distance to publicly-accessible spaces invariably attracts a greater concentration of talent. For example, a one-kilometer decrease in the distance to the nearest Purple line is associated with over three-percent increase in the creative class size. Evaluated at the sample mean, an increase in the distance to the nearest Purple line by 10 kilometers is predicted to reduce the district's talent pool by five creative households.

The impact of proximity to shopping malls seems to stand out. A one-kilometer reduction in the distance to the closest mall boosts the talent pool by almost nine creative households. Proximity to public parks is second in terms of impact magnitude. Specifically, in a typical district, a 10- kilometer increase in the distance to the nearest park is estimated to bring about a loss of over eight creative households. Rounding up, a 10- kilometer increase in the distance to top schools is associated with a loss of almost six creative households, but the coefficient is not statistically significant.

There are also indications of non-linearity. Table 1.3 shows that all the squared distance variables are significant at least at the five-percent levels. The even-numbered rows in Table 1.4 refer to the models where distances enter in quadratic form. Consider the non-linear impact of proximity to shopping malls. In districts where the distance is roughly equal to the sample mean, a one-kilometer increase in distance leads to a loss of four creative households. However, in districts where the distance is a full standard deviation larger than the mean, the same one-kilometer increase in distance is expected to be accompanied by a loss of seven creative households. In general, distance and creative class size exhibit a concave relationship.

This means a movement even farther out from locations that are initially farther away from public spaces leads to a steeper fall in creative class size.

We note that results are robust to alternative specifications and different sets of controls. In particular, controlling for average expenditures per adult equivalent – a proxy of purchasing power – does not materially affect the NB regression results. We also checked for potential linear dependencies among the explanatory variables. The average variance inflation factors (VIF) is about 1.3, and none of the VIF's exceeds five (the rule of thumb). The VIF for the rent coefficient, in particular, is smaller than 1.5 across all models. Thus we did not find evidence of multicollinearity in the district-level analysis.[15]

[15] Nor did we find evidence of multicollinearity in the household-level analyses.

Table 1.3: Impact of public spaces on creative class size, Negative Binomial regression estimates: Dependent variable is the number of creative households in the district

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Area	0.001	0.002*	0.003**	0.003*	0.002*	0.001	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.028	-0.034*	-0.028	-0.018	-0.010	-0.027	-0.025	-0.023	-0.021
	(0.021)	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	(0.021)	(0.021)	(0.020)
Pct Married	-0.011	-0.009	-0.010	-0.012	-0.009	-0.011	-0.011	-0.008	-0.008
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Kids	0.747	0.965*	0.949	1.005	0.949	0.781	0.820	0.739	0.704
	(0.606)	(0.559)	(0.582)	(0.626)	(0.624)	(0.588)	(0.607)	(0.604)	(0.602)
Population	0.007***	0.006***	0.006***	0.006***	0.006***	0.007***	0.007***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Rent	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MRT Subway	0.251**								
	(0.125)								
Dist MRT Purple		-0.032***							
		(0.012)							
sqDist MRT Purple			-0.001***						
			(0.000)						
Dist Shop				-0.052**					
				(0.023)					
sqDist Shop					-0.002***				
					(0.001)				
Dist School						-0.036			
						(0.058)			
sqDist School							-0.009**		
							(0.004)		
Dist Park								-0.052***	
								(0.020)	
sqDist Park									-0.003***
									(0.001)
Constant	3.284**	3.826***	3.374**	3.020**	2.406*	3.375**	3.279**	3.110**	2.904**
	(1.432)	(1.382)	(1.413)	(1.398)	(1.434)	(1.467)	(1.441)	(1.398)	(1.399)
Ln alpha constant	-1.218***	-1.363***	-1.348***	-1.269***	-1.305***	-1.208***	-1.233***	-1.241***	-1.256***
	(0.222)	(0.255)	(0.241)	(0.240)	(0.224)	(0.219)	(0.219)	(0.227)	(0.220)
R-squared	0.062	0.076	0.075	0.068	0.072	0.060	0.063	0.064	0.066
Log-Likelihood	-256.9188	-252.9957	-253.2975	-255.2293	-254.2298	-257.2792	-256.5267	-256.2797	-255.8569
N	69	69	69	69	69	69	69	69	69

Note: Estimation is by negative binomial regression. Robust standard errors are in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Rent = district average rent per bedroom. Area = district area in sq.km., Age = district average age of household head, Pct Married = share of married household head, Kids = district average number of children, MRT Subway = 1 if there is at least one MRT station in the district, = 0 otherwise, Dist MRT Purple = distance to the nearest MRT Purple line (km.), Dist Shop = distance to the nearest shopping malls (km.), Dist School = distance to the nearest top school (km.), Dist Park = distance to the nearest public parks (km.)

Table 1.4: Impact of distance increase on creative class size

Model	Explanatory Variable	% Change	Marginal Impact of 1 km Increase		
			Evaluated at mean	Evaluated at mean plus 0.5 std dev	Evaluated at mean plus 1 std dev
1	Distance to nearest MRT Purple station	-3.1	-0.577	-0.495	-0.424
2	Squared distance to MRT Purple station	-0.1	-0.432	-0.502	-0.529
3	Distance to nearest mall	-4.7	-0.879	-0.663	-0.662
4	Squared distance to mall	-0.2	-0.369	-0.554	-0.687
5	Distance to nearest top school	-3.1	-0.582	-0.564	-0.548
6	Squared distance to top school	-0.8	-0.795	-1.025	-1.214
7	Distance to nearest public park	-4.4	-0.831	-0.769	-0.711
8	Squared distance to public park	-0.3	-0.388	-0.538	-0.663

Note: based on negative binomial regression results detailed in Table 1.3.

1.7 Social Impacts

In the Rise of the Creative Class, Florida (2002) warns against an unequivocal support for creativity. He points out that American cities that have a significant presence of creative workers are also those that are most unequal in terms of the distribution of income. The growing concern for Thailand is that it is increasingly becoming a divided nation of the sort that Florida refers to. The frequent confrontations between the "yellow shirts" and the "red shirts" suggest that Thailand is splitting into two separate factions with very different ideologies. The red shirts are ardent supporters of the exiled former Prime Minister, Thaksin Shinawatra, while the yellow shirts seek to maintain the primacy of Thai's monarchy. Many red shirts identify themselves with the traditional rural poor, while the yellow shirts are more urban, middle class, and educated. The main source of animosity appears to be the widening gap between the poor and the rich. A recent report of the Thai National Economic and Social Development Board (NESDB, 2011) reveals that aggregate inequality for the entire nation – measured by the Gini coefficient – had been more or less stable between 1988 and 2009, and actually declined slightly. In the same period, the Gini for Bangkok had increased by over 20 percent from 0.388 to 0.468. Clearly the Metropolitan Region had experienced a dramatic and secular rise in income inequality.

We test next the inequality-enhancing hypothesis using the BMR data. We use two conventional inequality indices—the Gini index and the coefficient of variations—corresponding to disparities in household expenditures per adult equivalent. To motivate the formal analysis, we check first the simple association between inequality and creative class size. The left scatter diagram in Figure 1.8 plots creative class size against district Gini coefficients, while that in the right plots size against the coefficient of variations. A positive correlation is evident from the scatterplots: a larger population of creative households is associated with higher inequality. Correlation of course does not imply causality. We perform multiple regressions next to control for confounding factors.

We regress measures of inequality against creative class size. The control variables are 2002 population density (Pop Density), the district's geographic area (Area), average age of householders (Age), percent of male-headed HHs (Pct Male), percent of married householders (Pct Married), and percent of college-educated HHs (college). Across the board the coefficient on creative class remains positive and significant statistically.

Table 1.5 shows that even after controlling, a larger population of creative households is still associated with widening disparities. Specifically, a one-percent increase in the number of creative households is associated with a 0.00026 increase in the Gini index, and with a 0.00125 increase in the coefficient of variations. Evaluated at the mean, they correspond to 0.06-percent increase in the Gini coefficient or 0.12-percent increase in the coefficient of variations.

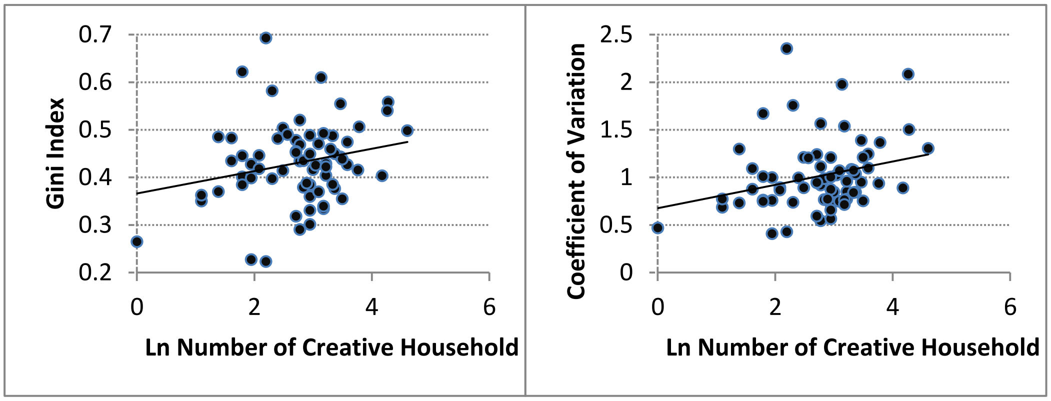


Figure 1.8: Inequality and creative class presence, BMR, 2008.

Table 1.5: District inequality and the creative class presence

	Dependent var: Gini Coefficient		Dependent var: Coefficient of	
	(1)	(2)	(1)	(2)
Pop Density	-4.562***	-4.633***	-15.290***	-15.644***
	(1.677)	(1.705)	(5.739)	(5.850)
Area	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Pct Male	-0.002	-0.002	-0.009	-0.011
	(0.002)	(0.002)	(0.010)	(0.009)
Age	0.004	0.004	0.010	0.009
	(0.003)	(0.003)	(0.013)	(0.012)
Pct Married	0.001	0.001	0.004	0.005
	(0.001)	(0.001)	(0.005)	(0.005)
College	-0.023	-0.067	0.109	0.015
	(0.157)	(0.158)	(0.626)	(0.642)
Creative	0.001*		0.006**	
	(0.000)		(0.003)	
Ln Creative		0.026**		0.125**
		(0.011)		(0.051)
Constant	0.373*	0.344	0.902	0.783
	(0.219)	(0.212)	(0.898)	(0.881)
R-squared	0.096	0.108	0.088	0.080
N	69	69	69	69

Note: Estimation is by OLS. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Pop Density = 2008 district population density, Area = district area in sq.km., Male = share of male headed households, Age = district average age of household head, Married = share of married household head, College = District percent share of college educated population, Creative = Number of creative households in the district, Ln Creative = number of creative households in the district (in natural log).

1.8 Conclusion

The global competition for talent has forced local authorities to rethink constructed amenities and their role in attracting and retaining the creative class. People gravitate to places that offer certain types of amenities; the result is a highly clustered pattern of settlements. The growing recognition of the New Economic Geography is due to its success in explaining spatial clustering within a general equilibrium framework where production and consumption are inextricably linked (see Krugman, 1991; Baldwin *et al.*, 2003). But empirical studies tend to look at agglomeration through the lens focusing on either formal production or informal consumption. The literature strand that deals with the demand side, on one hand, overemphasizes the consumption motive (Roback, 1982; Glaeser *et al.*, 2001; Terry, 2004). According to this view, people choose an urban life because of the irresistible lure of city goods, services, and amenities. On the other hand, the link to the demand side is at best of secondary importance in conventional accounts of agglomeration economies (Rosenthal and Strange, 2001; Duranton and Overman, 2005). Yet in Asia, as in elsewhere, the line between work and leisure is evaporating as production and consumption are increasingly carried out in the same space. Publicly-accessible spaces in particular create a locus of not just consumption and transit but also of idea exchanges and knowledge spillovers.

What the Thai data seem to say is that certain spaces attract more than others because of the opportunity they afford for direct interpersonal contact and information exchanges. Bangkokians for sure are attracted to public spaces because of the possibility of consuming relational goods; of deriving satisfaction from a meaningful conversation. To paraphrase Lucas (1988, p. 39), what can creative workers be paying the high rents in the Samphanthawang, Din Daeng, and Sathon districts for, if not because of the desire to be around each other? The higher rents in talent-dense environment must reflect some advantage.

Lucas' reasoning is provocative but incomplete because it does not explain the precise channels through which creative workers gain from being around each other. The estimation results that we present in this study can be provisionally interpreted as evidence of spatial constraint in the diffusion of new ideas. Space is a constraint when communication expenses increase with distance. Public spaces draw creative people because they provide the venue to pass on idiosyncratic information through F2F contact, and in doing so minimize communication expenses.

Our data do not allow us to *directly* test whether public spaces drew knowledge workers because they facilitate creative interactions. However, a pilot survey that we have conducted suggests that a significant proportion went to malls for social reasons. In particular, only a fourth spent their time alone while in a shopping centre. Further, among those who spent time in malls with friends or colleagues, the majority discuss work-related topics at least occasionally. We also explored the nature of information being exchanged. Thus we asked whether respondents share work-related knowledge when shopping with friends or colleagues. An example of work-related knowledge is how to use a computer program or the solution to a technical problem. We found that the majority (75%) did so on a regular basis. Similarly, we found that a significant proportion of respondents discuss work and share knowledge in transit stations. Though it is not yet clear whether exchanges in these public spaces actually led to innovations, the overwhelming majority of respondents (85%) indicated that exchanges were at least "somewhat useful" for work. Our qualitative research remains in progress and is the subject of a follow-up work. For now, we think it is reasonable to infer that creativity was exercised during social interactions, which in turn led to productivity gains in the workplace.

What regional policies will attract creative households? Our empirical analysis suggests that a typical BMR creative household seeks out housing close to transport hubs and shopping malls. Some of these decisions undoubtedly are driven by leisure and consumption motives. Our overarching hypothesis, however, is that publicly accessible spaces are conducive for F2F communication, which in turn allows eye contact and emotional rapport to be established. Informal exchanges of new, creative ideas often ensue once the relationship bond is in place. Regression results reveal it is the geography, rather than the quantity, of constructed amenities that matters. Access has a discernible effect but not the total capacity to render services.

Beyond the need for proximate interactions, BMR creative households are also drawn to constructed "natural" environments. It appears that access to public parks fulfills the creative class's desire for ecological connection, which is distinct from but no less important than the preference for geographic proximity. Our results suggest that providing more publicly-accessible parks not only benefits the overall population but also potentially attracts creative households.

If the models for transit terminals, shopping malls, and parks are identified, the results point to increasing access as the appropriate policy instrument to build a creative community. Before pouring scarce resources into urban amenities, however, it is important to recognize that a burgeoning creative cluster could have potentially adverse repercussions on the local social fabric. In the United States for example creative centers are among the most unequal regions. A separate regression analysis using the 2008 BMR data also strongly suggests that a sizable creative community is associated with a large discrepancy in living standards. Widening disparities likely seed the kind of confrontations that could threaten the region's prospects going forward.

APPENDIX A

Table A1.1: Education attainment of household head, Bangkok Metropolitan Region, 2008

Education of Household Head	Creative Class		Non-creative Class	
	Households	Percent	Households	Percent
No formal education	2	0%	1	0%
Less than 6 years	415	29%	1,581	48%
7-9 years	159	11%	522	16%
10-12 years	307	21%	707	21%
At least 1 year in college	6	0%	23	1%
College degree or higher	549	38%	380	12%
Unknown	17	1%	90	3%
Number of Household	1,455	100%	3,304	100%

Table A1.2: Job industry of the head of households, Bangkok Metropolitan Region, 2008

Industry	Creative class		Non-creative class	
	Households	Percent	Households	Percent
Inactive	0	0%	972	29%
Agriculture and mining	14	1%	65	2%
Manufacturing	176	12%	818	25%
Utility	17	1%	19	1%
Construction	92	6%	151	5%
Retail	570	39%	262	8%
Services	391	27%	602	18%
Public administration	72	5%	153	5%
Education and Health	123	8%	228	7%
Other activities	0	0%	34	1%
Total	1,455	100%	3,304	100%

Table A1.3: Descriptive statistics of household characteristics, non-creative and creative BMR households, 2008

Variable	Creative Class	Non-creative Class	*t-test*
Average number of earner	2.04	1.73	9.4267
	(0.027)	(0.018)	
Average number of children	0.56	0.47	3.569
	(0.022)	(0.013)	
Average age of household head	45.5	46.9	-3.5388
	(0.279)	(0.281)	
Percent male household head (%)	67.6	66	1.0742
	(0.012)	(0.008)	
Percent married (%)	69.6	65.3	2.944
	(0.012)	(0.008)	
Percent owned vehicle (%)	78.1	57.8	14.6641
	(0.011)	(0.009)	
Percent home owner (%)	53.4	43.9	6.0319
	(0.013)	(0.009)	
Average expenditure per adult equivalent (THB)	4,038.23	2,815.06	8.0095
	(169.746)	(68.448)	

Note: standard errors are shown in parenthesis

APPENDIX B

Regression results reported in the following tables are based on estimates that share a common set of controls, namely:

Earners	= Number of earner in a household
Male	= Male household head dummy
Age	= Age of household head
Married	= Married household head dummy
Edu	= Educational attainment of household head
Work	= Work status dummy
Vehicle	= Vehicle ownership dummy
Tenure	= Housing ownership dummy
Kids	= Number of children
ExpPerAdult	= Household expenditure per adult equivalence

Table B1.1: Probit model: Dependent variable is InnerRing, defined = 1 for households residing within the inner ring road, = 0 otherwise

	(1)	(2)	(3)
Earners	0.115***	0.116***	0.116***
	(0.027)	(0.027)	(0.027)
Male	-0.092	-0.100*	-0.099*
	(0.056)	(0.057)	(0.057)
Age	0.012***	0.012***	0.012***
	(0.002)	(0.002)	(0.002)
Married	-0.008	-0.010	-0.010
	(0.059)	(0.060)	(0.060)
Edu	-0.003	-0.008	-0.008
	(0.018)	(0.018)	(0.018)
Vehicle	-0.169***	-0.171***	-0.170***
	(0.056)	(0.056)	(0.056)
Tenure	-0.347***	-0.345***	-0.344***
	(0.056)	(0.056)	(0.056)
Kids	0.038	0.037	0.037
	(0.032)	(0.032)	(0.032)
ExpPerAdult	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Creative	0.203***		
	(0.056)		
Retail	0.297***		
	(0.058)		
CCretail		0.453***	0.469***
		(0.067)	(0.075)
CCnonretail		0.287***	0.305***
		(0.064)	(0.074)
nCCretail		0.491***	0.491***
		(0.089)	(0.090)
CCExpPerAdult			-0.000
			(0.000)
Constant	-1.449***	-1.466***	-1.474***
	(0.125)	(0.126)	(0.127)
R-squared	0.041	0.043	0.043
Log Likelihood	-1,889.095	-1,885.213	-1,885.089
AIC	3,802.19	3,796.426	3,798.177
BIC	3,876.922	3,877.386	3,885.364
N	3,743	3,743	3,743

Note: Robust standard errors are in parentheses; *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Creative = creative class dummy, Retail = retail sector dummy, CCretail = Interaction term between creative class dummy and retail, CCnonretail = Interaction term between creative class dummy and non-retail, nCCretail = Interaction term between non-creative class dummy and retail, CCExpPerAdult = Interaction term between creative class and household expenditures.

Table B1.2: OLS model: Dependent variable is distance to the nearest BTS or MRT subway station

	(1)	(2)	(3)
Earners	-582.617***	-586.402***	-597.627***
	(183.436)	(183.239)	(181.707)
Male	52.077	117.651	96.851
	(391.614)	(392.108)	(392.533)
Age	-79.472***	-80.190***	-79.391***
	(16.635)	(16.605)	(16.592)
Married	36.055	39.625	39.216
	(409.158)	(408.996)	(410.074)
Edu	-371.246***	-327.840***	-319.923***
	(121.711)	(122.242)	(120.919)
Vehicle	2,523.981***	2,531.101***	2,534.502***
	(363.031)	(362.751)	(363.072)
Tenure	1,860.263***	1,834.455***	1,809.455***
	(388.016)	(387.731)	(388.269)
Kids	150.238	159.932	132.295
	(231.160)	(230.826)	(228.985)
ExpPerAdult	-0.230***	-0.227***	-0.314***
	(0.063)	(0.063)	(0.083)
Creative	-1,035.208***		
	(381.613)		
Retail	-2,088.072***		
	(381.290)		
CCretail		-2,596.990***	-2,978.855***
		(475.539)	(575.041)
CCnonretail		-1,754.606***	-2,192.309***
		(431.322)	(560.536)
nCCretail		-3,916.112***	-3,921.728***
		(549.148)	(547.752)
CCExpPerAdult			0.129
			(0.101)
Constant	15,452.346***	15,539.059***	15,787.050***
	(846.267)	(844.648)	(858.721)
R-squared	0.051	0.054	0.055
N	3,743	3,743	3,743

Note: Estimation is by OLS. Robust standard errors are in parentheses; *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Creative = creative class dummy, Retail = retail sector dummy, CCretail = Interaction term between creative class dummy and retail, CCnonretail = Interaction term between creative class dummy and non-retail, nCCretail = Interaction term between non-creative class dummy and retail, CCExpPerAdult = Interaction term between creative class and household expenditures.

Table B1.3: OLS model: Dependent variable is distance to the nearest MRT Purple Line station

	(1)	(2)	(3)
Earners	213.530	209.626	211.992
	(177.906)	(177.515)	(177.730)
Male	594.391	662.025*	666.408*
	(397.347)	(398.552)	(398.994)
Age	-118.293***	-119.033***	-119.202***
	(16.899)	(16.875)	(16.884)
Married	125.592	129.275	129.361
	(415.365)	(415.362)	(415.313)
Edu	-1,068.453***	-1,023.684***	-1,025.353***
	(117.007)	(117.811)	(118.016)
Vehicle	172.994	180.338	179.622
	(370.785)	(370.448)	(370.451)
Tenure	2,203.930***	2,177.311***	2,182.580***
	(382.914)	(382.433)	(382.161)
Kids	95.787	105.785	111.609
	(225.080)	(224.682)	(224.995)
ExpPerAdult	-0.080**	-0.078**	-0.059
	(0.033)	(0.033)	(0.046)
Creative	-1,486.651***		
	(380.435)		
Retail	-1,904.830***		
	(373.187)		
CCretail		-2,848.659***	-2,768.189***
		(446.356)	(505.394)
CCnonretail		-2,228.644***	-2,136.408***
		(433.685)	(513.152)
nCCretail		-3,790.288***	-3,789.105***
		(558.077)	(558.233)
CCExpPerAdult			-0.027
			(0.062)
Constant	21,728.286***	21,817.723***	21,765.464***
	(849.702)	(848.492)	(855.442)
R-squared	0.064	0.067	0.067
N	3,743	3,743	3,743

Note: Estimation is by OLS. Robust standard errors are in parentheses; *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Creative = creative class dummy, Retail = retail sector dummy, CCretail = Interaction term between creative class dummy and retail, CCnonretail = Interaction term between creative class dummy and non-retail, nCCretail = Interaction term between non-creative class dummy and retail, CCExpPerAdult = Interaction term between creative class and household expenditures.

Table B1.4: OLS model: Dependent variable is distance to the nearest top school

	(1)	(2)	(3)
Earners	-154.226***	-154.575***	-156.662***
	(38.526)	(38.492)	(38.290)
Male	10.798	16.857	12.990
	(79.513)	(79.652)	(79.720)
Age	-17.357***	-17.423***	-17.275***
	(3.446)	(3.446)	(3.445)
Married	83.354	83.684	83.607
	(81.212)	(81.216)	(81.360)
Edu	-136.315***	-132.304***	-130.832***
	(23.355)	(23.204)	(22.976)
Vehicle	299.584***	300.242***	300.875***
	(77.795)	(77.810)	(77.878)
Tenure	574.172***	571.787***	567.140***
	(80.866)	(80.652)	(80.619)
Kids	-31.436	-30.540	-35.678
	(44.551)	(44.538)	(44.381)
ExpPerAdult	-0.035***	-0.035***	-0.051***
	(0.010)	(0.010)	(0.015)
Creative	-108.038		
	(78.179)		
Retail	-344.687***		
	(76.044)		
CCretail		-404.096***	-475.083***
		(93.183)	(111.120)
CCnonretail		-174.510**	-255.878**
		(88.124)	(110.667)
nCCretail		-513.597***	-514.641***
		(109.952)	(109.810)
CCExpPerAdult			0.024
			(0.017)
Constant	3,394.027***	3,402.040***	3,448.140***
	(176.780)	(177.112)	(180.554)
R-squared	0.042	0.042	0.043
N	3,743	3,743	3,743

Note: Estimation is by OLS. Robust standard errors are in parentheses; *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Creative = creative class dummy, Retail = retail sector dummy, CCretail = Interaction term between creative class dummy and retail, CCnonretail = Interaction term between creative class dummy and non-retail, nCCretail = Interaction term between non-creative class dummy and retail, CCExpPerAdult = Interaction term between creative class and household expenditures.

Table B1.5: OLS model: Dependent variable is distance to the nearest shopping mall

	(1)	(2)	(3)
Earners	-218.672**	-220.585**	-224.596**
	(91.723)	(91.611)	(91.344)
Male	-84.930	-51.782	-59.214
	(205.307)	(205.904)	(206.320)
Age	-43.612***	-43.975***	-43.689***
	(8.906)	(8.890)	(8.892)
Married	-166.947	-165.143	-165.289
	(214.037)	(213.921)	(214.227)
Edu	-379.857***	-357.915***	-355.086***
	(62.167)	(62.480)	(62.198)
Vehicle	967.721***	971.320***	972.536***
	(183.392)	(183.182)	(183.337)
Tenure	1,369.979***	1,356.933***	1,347.999***
	(214.530)	(214.028)	(213.716)
Kids	129.811	134.712	124.836
	(127.235)	(126.904)	(126.467)
ExpPerAdult	-0.083***	-0.081***	-0.113***
	(0.025)	(0.025)	(0.036)
Creative	-481.233**		
	(194.582)		
Retail	-731.154***		
	(185.652)		
CCretail		-946.342***	-1,082.799***
		(243.848)	(289.153)
CCnonretail		-844.894***	-1,001.304***
		(223.438)	(282.461)
nCCretail		-1,655.244***	-1,657.250***
		(250.096)	(249.797)
CCExpPerAdult			0.046
			(0.043)
Constant	6,684.201***	6,728.035***	6,816.653***
	(438.740)	(438.293)	(445.061)
R-squared	0.045	0.048	0.048
N	3,743	3,743	3,743

Note: Estimation is by OLS. Robust standard errors are in parentheses; *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Creative = creative class dummy, Retail = retail sector dummy, CCretail = Interaction term between creative class dummy and retail, CCnonretail = Interaction term between creative class dummy and non-retail, nCCretail = Interaction term between non-creative class dummy and retail, CCExpPerAdult = Interaction term between creative class and household expenditures.

Table B1.6: OLS model: Dependent variable is distance to the nearest public park

	(1)	(2)	(3)
Earners	-221.224***	-222.038***	-226.871***
	(49.742)	(49.683)	(49.188)
Male	-203.056*	-188.956	-197.913*
	(115.828)	(115.740)	(116.055)
Age	-19.912***	-20.066***	-19.722***
	(5.073)	(5.072)	(5.065)
Married	150.323	151.091	150.914
	(110.846)	(110.671)	(110.968)
Edu	-151.572***	-142.239***	-138.830***
	(34.071)	(34.048)	(33.335)
Vehicle	395.772***	397.303***	398.768***
	(103.354)	(103.312)	(103.337)
Tenure	883.763***	878.214***	867.449***
	(123.093)	(122.756)	(122.354)
Kids	-12.255	-10.170	-22.071
	(68.057)	(67.893)	(67.140)
ExpPerAdult	-0.058***	-0.057***	-0.095***
	(0.017)	(0.017)	(0.020)
Creative	-294.157***		
	(104.623)		
Retail	-410.002***		
	(102.519)		
CCretail		-590.995***	-755.423***
		(138.845)	(164.538)
CCnonretail		-448.842***	-637.312***
		(117.978)	(151.833)
nCCretail		-803.068***	-805.486***
		(139.207)	(138.635)
CCExpPerAdult			0.056**
			(0.024)
Constant	4,549.244***	4,567.889***	4,674.671***
	(249.678)	(249.974)	(254.514)
R-squared	0.045	0.047	0.049
N	3,743	3,743	3,743

Note: Estimation is by OLS. Robust standard errors are in parentheses; *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Creative = creative class dummy, Retail = retail sector dummy, CCretail = Interaction term between creative class dummy and retail, CCnonretail = Interaction term between creative class dummy and non-retail, nCCretail = Interaction term between non-creative class dummy and retail, CCExpPerAdult = Interaction term between creative class and household expenditures.

REFERENCES

Alonso, W. (1964). *Location and Land Use*. Harvard University Press, Cambridge, MA.

Anantsuksomsri, S. (2013). *Three Essays in Real Estate and Urban Economy*. PhD thesis, Cornell University.

Anas, A., & Chu C. (1984). Discrete choice models and the housing price and travel to work elasticities of location demand. *Journal of Urban Economics*, 15(1), 107-123.

Anas, A. (1985). The combined equilibrium of travel networks and residential location markets. *Regional Science and Urban Economics*, 15(1), 1-21.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer, Dordrecht, the Netherlands.

Anselin, Luc. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis*. 27, 93-115.

Baldwin, R., Forslid, R., Martin, P., & Ottaviano, G. (2003). *Economic Geography and Public Policy*. Princeton University Press, Princeton, NJ.

Beyer, H. L. (2011). *Geospatial Modeling Environment*. Spatial Ecology LLC. Retrieved January 2011, from http://www.spatialecology.com/gme/index.htm

Bhat, C. R., & Guo, J. (2004). A mixed spatially correlated logit model: formulation and application to residential choice modeling. *Transportation Research Part B: Methodological*, 38(2), 147-168.

Bhat, C. R., & Guo, J. Y. (2007). A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. *Transportation Research Part B: Methodological*, 41(5), 506-526.

Clark, T. N. (2004). *The City as an Entertainment Machine*. Elsevier/JAI Press, Netherlands.

Currid, E. (2007). *The Warhol Economy: How Fashion, Art, and Music Drive New York City*. Princeton University Press, Princeton, NJ.

Duranton, G., & Overman, H. G. (2005). Testing for localization using micro-geographic data. *Review of Economic Studies*, 72(4), 1077-1106.

Florida, R. (2002). *The Rise of the Creative Class*. Basic Books, Cambridge, MA.

Florida, R. (2005). *The Flight of the Creative Class: The New Global Competition for Talent*. HarperCollins, New York.

Florida, R. (2008). *Who's your city?: How the creative economy is making where to live the most important decision of your life*. New York: Basic Books.

Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. Journal of Economic Geography, 1, 27-50.

Guo, J., & Bhat, C. (2004). Modifiable areal units: problem or perception in modeling of residential location choice? *Transportation Research Record: Journal of the Transportation Research Board*, 1898(-1), 138-147.

Guo, J. Y., & Bhat, C. R. (2007). Operationalizing the concept of neighborhood: Application to residential location choice analysis. *Journal of Transport Geography*, 15(1), 31-45.

Henderson, J. V. (2007). Understanding knowledge spillovers. *Regional Science and Urban Economics*, 37, 497-508.

Jenks, M. (2005). Above and below the line: Globalization and urban form in Bangkok *Globalization and urban development* (pp. 311-321): Springer.

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, 99 (3), 483-499.

Leamer, E. E. & Storper M (2001). The economic geography of the internet age. *Journal of International Business Studies*, 32 (4), 641-665.

Lerman, S. R. (1976). Location, housing, automobile ownership, and mode to work: A joint choice model. *Transportation Research Record*, 610, 6-11.

Long, J. S., & Freese, J. (2006). *Regression Models for Categorical Dependent Variables Using Stata*. StataCorp, College Station, TX.

Long, L., & Nucci, A. (1997). The Hoover Index of population concentration: a correction and update. *Professional Geographer*, 49 (4), 431 - 440.

Lucas, R. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22 (1), 3–42.

McFadden, D. (1978). Modelling the choice of residential location. in A. Karlqvist, L. Lundqvist, F. Snickars, and J. Weibull (eds.), *Spatial Interaction Theory and Planning Models*, 75-96, North Holland, Amsterdam.

Park, S. O., & Koo, Y. (2010). Evolution of new spatial division of labour and spatial dynamics in Korea. *Regional Science Policy & Practice*, 2, 21–38.

Quigley, J. M. (1976). Housing demand in the short run: An analysis of polytomous choice. *National Bureau of Economic Research: Explorations in Economic Research*, 3(1), 76-102.

Reese, L., Faist, J. M., & Sands, G. (2010). Measuring the creative class: Do we know it when we see it? *Journal of Urban Affairs*, 32 (3), 345-366.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy*, 90 (4), 1257-78.

Romer, P. M. (1994). The origins of endogenous growth. *Journal of Economic Perspectives*, 8 (1), 3-22.

Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, 50, 191-229

Srinivasan, S., & Ferreira, J. (2002). Travel behavior at the household level: understanding linkages with residential choice. *Transportation Research Part D: Transport and Environment*, 7(3), 225-242.

Townsend, C., & Zacharias, J. (2010). built environment and pedestrian behavior at rail rapid transit stations in Bangkok. *Transportation*, 37(2), 317-330.

Thailand National Statistical Office. (2012a). *Executive Summary: The 2010 Population and Housing Census*. Retrieved from http://popcensus.nso.go.th/upload/census-report-6-4-54-en.pdf

Thailand National Statistical Office. (2012b). *Preliminary Report: The 2010 Population and Housing Census*. Retrieved from http://popcensus.nso.go.th/upload/popcensus-08-08-55-E.pdf

Wisaweisuan, N. (2001). *An Economic Analysis of Residential Location Patterns: A Case Study of Bangkok, Thailand*. PhD thesis, University of Cambridge.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

Reference in Thai:

National Economic and Social Development Board (2011). *2011 Annual Statistical Report: Key Social Indicators*. Retrieved from http://social.nesdb.go.th/SocialStat/StatReport_Final.aspx?reportid=322&template=1R1C&yeartype=M&subcatid=51.

CHAPTER 2

USING HOUSEHOLD SURVEY TO FORECAST HOUSEHOLD MODE CHOICE AND TRIP SHARING: A CASE STUDY OF THE BANGKOK METROPOLITAN REGION

2.1 Introduction

Urban travel patterns have become increasingly complex due to the interdependence of travel activities and complicated available mode choices. As such, traditional individual trip-based transportation models may be overly simplified and thus may not be appropriate to forecast urban travel demand. A simple individual trip-based analysis cannot incorporate complexity in travel patterns, including shared household mode choices and trip chaining behaviors. Many researchers have emphasized that the analysis of urban travel demand should be conducted at the household level—rather than at the individual level—since it can better incorporate complex travel patterns and interdependence of travel activities (Adler and Ben-Akiva, 1979; Dissanayake and Morikawa, 2002, 2010).

Household travel demand forecasting is complex because it is affected by several socio-economic factors such as household income, vehicle ownership, and household demographics. In addition to these household characteristics, physical attributes of urban structure and the quality of public transportation also play an important role in household travel behavior. The complexity of factors is a challenge in household travel analysis. Particularly in developing countries, household travel demand forecasting is important because daily trips of household members are highly interdependent (Dissanayake and Morikawa, 2002).

Although much previous research on household travel behavior has been done in the context of cities in developed countries, little is known about household traveling patterns in developing countries. As public transportation in these developing countries tends to be insufficient for covering all metropolitan areas and meeting the needs of commuters, households in developing countries are often faced with complicated mode choices (Dissanayake and Morikawa, 2002). In Bangkok, for example, most commuters need to rely on feeder transportation services, such as hired motorcycles (or motorcycle-taxis), tricycle-taxis (or tuk-tuk), and jitneys, as illustrated in Figure 2.1, in order to have access to formal transportation, such as buses, taxis, or public transit, on the main road. Hence, a simple trip-based analysis may not be suitable for examining travel behavior in the context of developing countries. Further, transportation analyses in developing countries are quite limited due to a lack of data availability.

Generally, to analyze the household travel demand, researchers may choose to conduct their own travel survey, which can be very costly and time consuming. In a developing country like Thailand, where most data are not readily available to the public, ability to effectively use data sets that are regularly produced, yet underutilized, is highly beneficial.

Source: Wikimedia.com

Figure 2.1: Feeder transportation in Bangkok, from left to right, hired motorcycle, tricycle-taxi, and jitney

This paper examines commuting behaviors of an urban subpopulation—two-traveler households—in the Bangkok Metropolitan Region (BMR) when trip sharing is one of the available mode choices, taking into account vehicle ownership. In this paper, a procedure that combines a regularly produced household socio-economic survey, Geographic Information Systems (GIS), and trip distribution tables to forecast household travel demand is proposed. The results of this study shed light on household commuting patterns in Bangkok. To the best of our knowledge, this paper is one of the first empirical works that focuses on forecasting household travel mode choices when trip sharing is one of the alternative modes.

This paper is also the first attempt that utilizes a household socio-economic survey to forecast household travel mode choices. Like many other developing countries, data on household transportation in Thailand is not readily available or not even produced on a regular basis, and it is very costly to conduct a transportation survey of the entire metropolitan area. The contribution of this study, therefore, is to demonstrate how standard household survey data that are not specifically designed for use in a modal split model can be used to forecast household travel mode choice and estimate ridership for a mass transit mode.

The proposed procedure is constructed and developed from various components, both in terms of databases and previous empirical studies. First, the trip table provides the distribution of daily trips within the BMR in an aggregated way for each origin-destination pair of traffic analysis zones (TAZs). In addition, travel-related attributes such as travel distances and level-of-service are calculated based on Euclidean distances between TAZs. The trip table, however, does not give the socio-economic or demographic characteristics of travelers who initiate such trips. These missing pieces of information can be drawn from the second component of the procedure—the household socio-economic survey. By associating the locations of the survey geographies to the TAZs, we are able to gather traveler's characteristics from small household samples in a survey geography that coincides with a particular TAZ. In addition to traveler's individual characteristics, the household survey provides the information at the household level, particularly the household vehicle ownership. This vehicle ownership is an important basis for the implementation of the estimation model by Dissanayake and Morikawa (2011), which is the third component of the procedure. The methodology presented here shows how to integrate these components in a constructive way, enabling us to forecast household mode choice when trip sharing is one of the available mode choices.

What follows in this chapter is a review of relevant literature on travel demand forecasting, particularly in the context of the Bangkok Metropolitan Region. A unique traveling characteristic of households in the BMR—trip sharing—is then introduced. Next, the study area, data, and methodology employed in this study are introduced and discussed, followed by a brief description of the nested logit model by Dissanayake and Morikawa (2010). After the results are presented, the chapter concludes with the discussion of results, implications on urban transportation policies, and further studies.

2.2 Literature Review

Trip sharing is generally defined as a linkage between two travelers in such a way that the first traveler accompanies the second traveler to the second traveler's destination and then continues to his/her final destination as illustrated in the second diagram in Figure 2.2. This trip chain can be a linkage of different types of purposes, for example, work, shopping, school, personal business, or recreation.

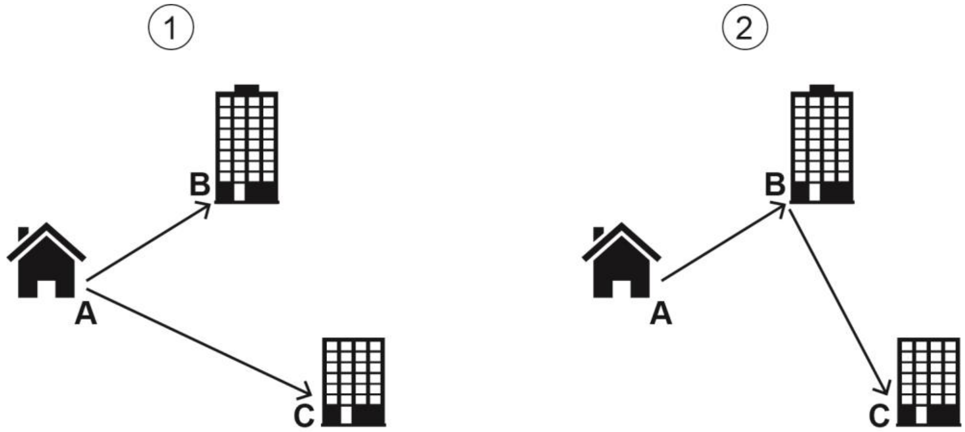


Figure 2.2: Household-based trip: (1) non trip sharing and (2) trip sharing

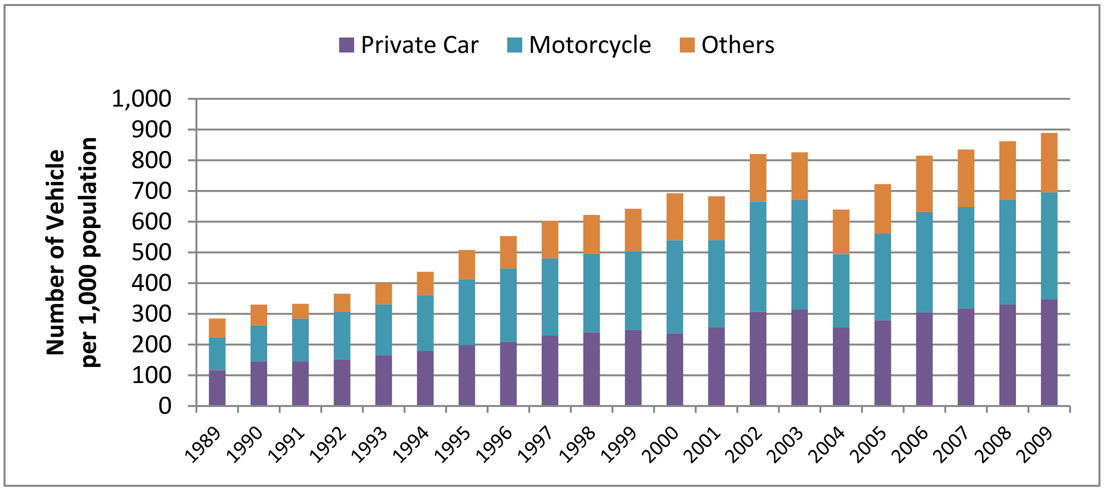
In urban travel, trip sharing has increasingly become important in travel demand forecasting as it represents more realistically travel behaviors, and thus gives researchers a better understanding of the urban travel demand. In their seminal work, Adler and Ben-Akiva (1979) addressed theoretical and empirical issues in modeling complex travel patterns. Based on utility maximization theory, their model was calibrated empirically using a multinomial logit (MNL) model. Kitamura (1984) formulated an analytical framework to study the effect of trip chaining on destination choices, employing prospective utility of a destination zone as a measure of its attractiveness. He emphasizes that if interdependencies of trips across choices are neglected, the evaluations of effects of zonal attributes and travel time may be biased.

Wegmann and Jang (1998) found that individuals who work in urban areas tend to develop trip sharing patterns. Commuters' socio-economic characteristics, workplace conditions, and traffic system characteristics also play an important role in trip sharing patterns (Jou and Mahmassani, 1997; Goulias and Kitamura, 1989). De Palma *et al.* (2001) found that compatible trip times contribute to trip chaining decisions of household members.

The MNL model has long been used to analyze trip-chaining behaviors (Ben-Akiva and Lerman, 1985). However, due to its very strict assumption on independence of irrelevant alternatives (IIA), MNL models may impose too strong restrictions on the relative preferences between the different alternatives, which are crucial if the purpose of the analysis is to forecast how choices would change when new alternative is introduced or existing one disappears. Other models like the nested logit model and multinomial probit model may be used instead because the IIA assumptions are relaxed to some extent. The nested logit model, in particular, is considered an attractive alternative when there are some similarities in subgroups (Knapp *et al.*, 2001).

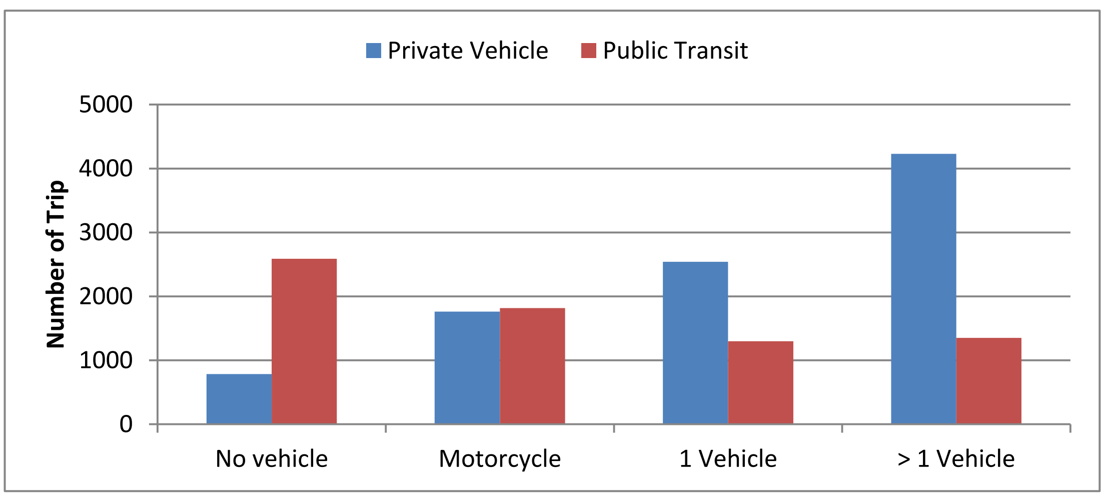
Although most studies have focused on trip chains created by individuals, little attention is paid to household-based trip chaining behaviors, especially in the context of developing countries like Thailand. Travel decisions of households in developing countries often reflect joint decisions for individuals in the household (Zegars and Srinivasarn, 2007; Dissanayake and Morikawa, 2010). As households in developing countries are less likely to own multiple vehicles, travel decisions of household members are highly dependent, and trip sharing is an important component in the analysis of household urban travel demand.

Additionally, since public transportation services in developing cities tend to be insufficient and of inferior quality, travelers in these cities are likely to own and use private vehicles. Particularly in Bangkok where public transit currently serves only the inner city areas, private vehicles such as cars and motorcycles are considered a predominant mode of transportation as they can provide greater comfort, flexibility, and reliability than other forms of public transit such as buses or taxis. As a symbol of social and economic status, private car and motorcycle ownership has grown steadily since 1989 (see Figure 2.3). Both private car and motorcycle ownership per 1,000 people has tripled over these two decades. Vehicle ownership, among other things, is an important factor determining travel mode choice in Bangkok. Households with more cars tend to use private automobile as a commuting mode (Fukuda *et al.*, 2005). As statistics also shown, people who own more vehicles are less likely to use public transit (see Figure 2.4).



Source: Office of Transport and Traffic Policy and Planning

Figure 2.3: Registered vehicle per 1,000 population, Bangkok, 1989-2009



Source: Office of Transport and Traffic Policy and Planning 2009 Annual Report

Figure 2.4: Number of daily trips by private vehicle and public transit, by vehicle ownership, Bangkok, 2009

Although this stylized fact has shown that vehicle ownership in Bangkok has grown steadily since the 1980s, the level of vehicle ownership by household income is much less than those in developed countries. By comparing vehicle ownership of households in Bangkok and the United Kingdom by the level of household income, Dissanayake and Morikawa (2010) found that high-income households in the UK tend to own multiple vehicles as their income increases, while households in Bangkok are more likely to own only one car even though their incomes grow. In fact, this single-vehicle ownership is quite common in many developing countries where prices of car are relatively much higher than the income level. Zegras and Srinivasan (2007) also show that households in developing countries have higher propensity for trip sharing even though their incomes increase.

As households in Bangkok are likely to own a single vehicle, either one car or motorcycle, they tend to share their trips with other household members. As a result, traveling decisions of household members are closely interrelated (Dissanayake and Morikawa, 2010). Trip sharing, in fact, is very evident in Bangkok. One can easily observe a husband dropping off his wife at her workplace or delivering his children to school before going to work. During morning rush hours, many streets leading to schools are gridlocked, and long lines of private vehicles like cars and motorcycles are commonly seen as parents drop off their children to school before going to work (see Figure 2.5). Travel demand forecasting in Bangkok, therefore, should be conducted at a household level, rather than at an individual level, and should take into consideration explicitly this unique household trip sharing characteristic and household vehicle ownership.

Source: http://061635522.multiply.com/journal/item/93/93 (left) and Supak Tontisirin (right)

Figure 2.5: A common scene of morning commute trips of household with school children in Bangkok

Fukuda *et al.* (2005) examine the possibility of car sharing as both feeder and main mode of transportation for Bangkok commuters. The study found that the level of services and socio-economic attributes such as vehicle ownership, occupation, age, and income, play an important role in determining the usage of car sharing. More recently, Dissanayake and Morikawa (2010) examine household trip sharing in Bangkok, taking into consideration household vehicle ownership and traveler characteristics such as job industry, age, and income. The model jointly estimates parameters from both Stated Preference (SP) and Revealed Preference (RP), and thus can be used to forecast household travel demand of new public transit services in Bangkok.

2.3 Study Area

The capital of Thailand, Bangkok is home to over 10 million registered residents in 2010 (Thailand National Statistical Office, 2010). A city once known as "the Venice of the East" for its canal and river networks, Bangkok today is notorious for its highly automobile dependence, severely congested traffic, and air pollution (Kenworthy, 1995). Unplanned growth, uncontrolled car ownership, inadequate road systems, and a lack of effective public transportation have resulted in extremely congested traffic in the city (Poboon, 1997; Jenks, 2005). Severe traffic congestion takes a large toll on the economy, environment, and society. During rush hours in the city, for example, cars can move at merely 15 kilometers per hour on average. Further, travelers are often facing long and wasteful commuting, and consequently countless hours and gallons of fuel are wasted every day in Bangkok's idle traffic. To illustrate this, Figure 2.6 shows typical traffic conditions that can be seen everywhere in Bangkok city center. One can clearly see infinite lines of traffic on all major roads in Bangkok.

Bangkok and its vicinity are officially called the Bangkok Metropolitan Region (BMR). The BMR consists of Bangkok and its five adjacent provinces, including Nakhon Pathom, Pathum Thani, Nonthaburi, Samut Prakan, and Samut Sakhon. As an automobile-dominant city, roads and highways are major components of Bangkok urban forms. Figure 2.7 illustrates a major road network as well as inner and outer ring roads, overlaying with BMR provinces and districts within each province. Most densely-populated urbanized areas are within the inner ring roads. Following Dissanayake and Morikawa (2010), the study areas are separated by inner and outer ring roads into three major analysis zones: inner city, inner suburbs, and outer suburbs (see Figure 2.7).

Source: Wikimedia.com

Figure 2.6: Typical traffic congestions in Bangkok

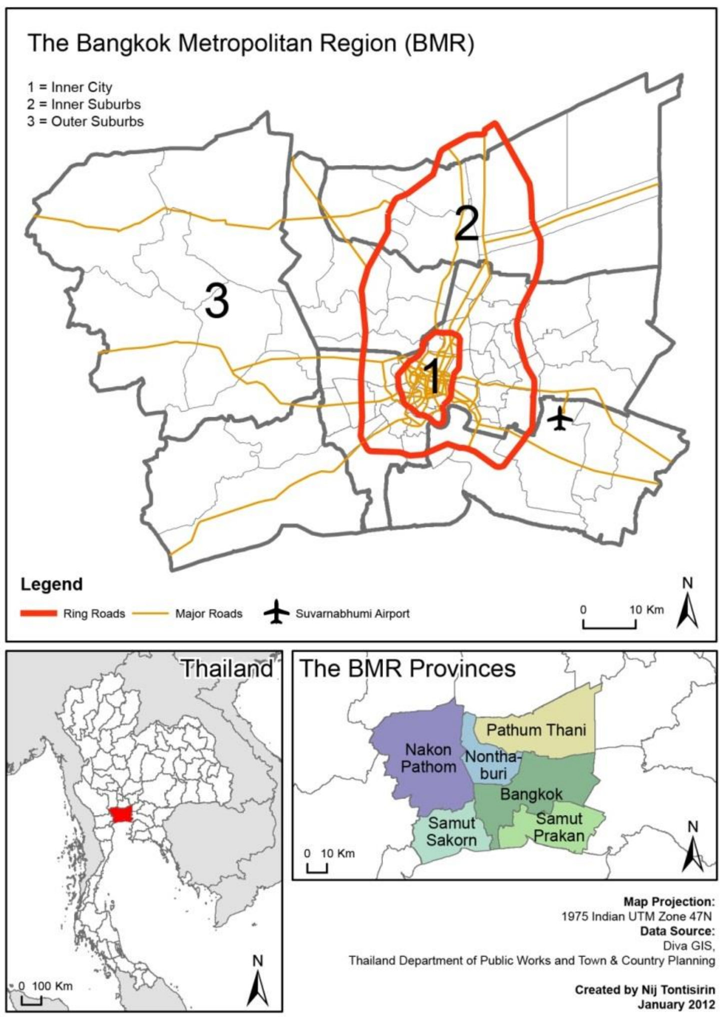


Figure 2.7: The Bangkok Metropolitan Region and major zoning configuration

2.4 Data

The data used in this research are drawn from two main datasets: first, the 2008 Household-Socio Economic Survey (SES) from the National Statistical Office of Thailand, and second, the Origin-Destination (O-D) table showing trip flows from all 737 internal traffic zones in the BMR from the Office of Transport and Traffic Policy and Planning (OTP). These two datasets, in fact, are complementary to each other for the purpose of the analysis. The other important component of the analysis is the nested logit estimation model calibrated by Dissanayake and Morikawa (2010), which will be discussed in detail later. These two datasets, together with the estimation model, enable us to forecast household travel mode choices. Table 2.1 summarizes the data and model used in this study.

Table 2.1: Data description

Data/Model	**Description**	**Source**
2008 Household-Socio Economic Survey (SES)	- Nationwide survey of household demographics, economic status, income and expenditure, housing, and property ownership - Produced biennially - Selected summary statistics available publicly through the website	Thailand National Statistical Office (NSO)
Origin-Destination Table (O-D table) and Traffic Analysis Zone (TAZ) geography	- Trip flows between 737 internal traffic zones within the BMR as well as 24 external zones - Internal traffic zones available in a GIS shapefile (upon request) - Number of school enrollment and jobs (by primary, secondary, and tertiary sector) also available in the attribute of each internal traffic zone	Office of Transport and Traffic Policy and Planning (OTP)
Nested Logit Model	- Mode choice model of two travelers in the BMR, with vehicle ownership in the first level of a nested structure and trip sharing as one of alternatives - Using Stated Preference (SP) and Revealed Preference (RP) data	Dissanayake and Morikawa (2010)

2.4.1 Household Socio-economic Survey (SES)

The Household-Socio Economic Survey (SES) was first conducted by the National Statistical Office of Thailand (NSO) in 1957. At that time, it was known as the Household Expenditure Survey. With the rapid economic expansion, the SES has been produced biennially since 1986. The main purpose of the survey is to collect data on household income and expenditure, household consumption, changes in assets and liabilities, durable goods ownership, and housing characteristics. The survey covers all private, non-institutional households nationwide.

The 2008 SES is used in this study; it contains characteristics of both household members and household levels. Characteristics of each household member include gender, age, education, and occupation, while household characteristics consist of household expenditure, assets, housing, and vehicle ownership. These characteristics are later used as a basis for forecasting household commuting destination and mode choices. Further, for the first time the households in the 2008 survey can be associated with the district in which they reside, thus allowing for home-based trip analysis.

To examine household trip sharing behavior, only households that are likely to share their trips are included in this study. Certainly, these households must consist of at least two travelers, which can be two earners or one earner with one or more children. With such selection criteria, 2,350 BMR households in the 2008 SES, or 40% of the total household samples (5,824 households) in the BMR, are households with two travelers. Among these households, 22 percent own cars[1]; 38 percent own motorcycles; 40 percent do not own any vehicles. Almost three quarters of these households are headed by a male, and average monthly household income is 25,192

[1] For the purpose of this analysis, households that own both cars and motorcycles are categorized as car ownership group.

Thai Baht (approximately US $756 in 2008[2]). These descriptive statistics of household characteristics by BMR province are shown in Table 2.2.

Statistics also show that cars and motorcycles are predominant in two-traveler households in the BMR. Among the BMR provinces, Nonthaburi has the highest proportion of households owning cars, while Nakhon Pathom is the BMR province with the highest share of households that own motorcycles. Average monthly household income of two-traveler households in Bangkok is the highest at 30,093.90 Thai Baht (or around US$ 903.45), while Samut Sakhon has the lowest average monthly household income. On average, households in Bangkok and Nonthaburi seem to be well-off in comparison with ones in the other provinces as the proportions of car and motorcycle owners of these provinces are higher than the other BMR provinces. Average monthly household income of Bangkok and Nonthaburi residences is also higher than others.

Table 2.2: Sample size, vehicle ownership, and household characteristics of two-traveler households by BMR province

BMR Province	HH with 2 Travelers	Vehicle Ownership			% Male Headed HH	Average HH Income* (THB)
		% Car	% Motorcycle	% No Vehicle		
Bangkok	1,094	27.0%	28.5%	44.5%	70.5%	30,093.90
Samut Prakan	227	10.6%	36.6%	52.9%	78.9%	17,217.16
Nonthaburi	310	33.5%	31.0%	35.5%	69.4%	29,909.00
Pathum Thani	265	20.8%	47.9%	31.3%	72.1%	22,175.29
Nakhon Pathom	236	11.9%	67.8%	20.3%	66.1%	17,193.56
Samut Sakhon	218	7.3%	49.1%	43.6%	77.5%	14,517.56
Total	**2,350**	**22.2%**	**37.7%**	**40.1%**	**71.5%**	**25,192.24**

*Imputed by the author

[2] According to Bank of Thailand, annual exchange rate in 2008 was 33.31 THB/US$.

2.4.2 Trip Table or Origin-Destination Table (O-D Table)

The second main data source used in this analysis is the Origin-Destination table (O-D Table), also known as the trip table, which is produced from the survey by Transport Data and Model Center (TDMC), the Office of Transport and Traffic Policy and Planning (OTP). Unlike the SES data, which provides household demographics and vehicle ownership, the trip table gives the information of trip distribution among 761 traffic analysis zones (TAZs), of which 737 are internal BMR zones. Travel modes of these trips include cars, motorcycles, low- and high-comfort public transit, taxis, and trucks. Generally, the low-comfort mode is non-air-conditioned bus trips, while the high-comfort represents air-conditioned bus trips as well as mass transit trips. For TAZs near existing mass transit, MRT trips are categorized in the high-comfort public transit mode with other air-conditioned bus trips. Since this study examines household travel patterns of commuting trips, truck trips as well as external trips are excluded from the analysis. Altogether, trip distribution of cars, motorcycles, low- and high-comfort public transit, and taxis is used to generate travel destinations of each traveler.

2.4.3 Traffic Analysis Zone Geography

In addition to the trip table, the accompanying base map of the 737 internal traffic analysis zones in GIS not only shows spatial distribution of the internal BMR zones but also the number of school enrollments as well as employment by primary, secondary, and tertiary sectors in each corresponding traffic analysis zone. These school enrollments and employment representing school and job locations are considered to be zonal attractions of commuting trips, which are used as important factors determining travel destinations of each household member.

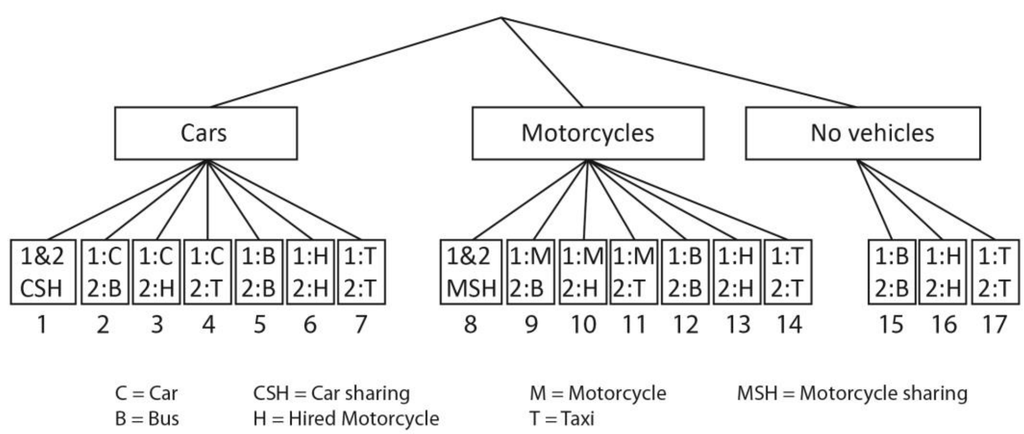
Figure 2.8: Employment by sector and school enrollment by traffic analysis zones in the BMR as a percent of total

Figure 2.8 depicts spatial distribution of school enrollment and sectorial employment as a percent of total in the BMR. As in many other metropolitan cities, the employment in the primary sector is predominantly in the periphery of the outer suburb, while employment in secondary and tertiary as well as school enrollment are concentrated in inner city and inner suburbs areas. As can be seen, traffic analysis zones in the outer suburb have higher percent shares of employment in the primary sector, suggesting that agriculture is predominant in areas further away from the city center. Areas with a high percent share of employment in secondary sector are concentrated along major roads in the north of inner suburb and in the east and west in the outer suburb due to the fact that many manufacturers are located in these areas. Industrial estates, for example, are located to the north of the BMR in Ayutthaya province. Similar patterns can be found in the employment in tertiary sector and school enrollment. Employment in the tertiary sector is predominantly within the inner city and inner suburb areas.

2.4.4 Forecasting Model

The modal choice forecasting model is adopted from the study of Dissanayake and Morikawa (2010), which combines Revealed Preference (RP) and Stated Preference (SP) and takes into account explicitly BMR household vehicle ownership in the first level of a nested logit model. Two models are presented in Dissanayake and Morikawa (2010); one is calibrated from RP data, and the other from the combined RP/SP data. In the RP model, the upper level of the nested structure represents three basic choices of vehicle ownership, that is, car, motorcycle, and no vehicle. The lower level consists of 17 mode choice combinations of two travelers, of which trip sharing is considered one of the options. Figure 2.9 illustrated the nested structure of the RP model. The parameters from the model include mode specific constants, vehicle ownership constants, coefficients for level-of-service variables, and coefficients for alternative specific dummies. The values of estimated parameters by mode choices are shown in Appendix B.

In the combined RP/SP model, the analysis of the mass transit use of commuter (first traveler) is introduced. The SP model was calibrated from a multinomial model with three choices: car, bus, and MRT, which are available only for the first traveler. Additional variables include those for mass transit use such as mode specific constants.   These calibrated parameters allow for predicting household travel mode choices when trip sharing is one of the alternatives. In addition to 17 mode choice combinations in the RP model, the nested structure of the combined RP/SP model includes nine other household mode choices—three choices for each vehicle ownership group—of which MRT is the first traveler's alternative in combination with bus, hired motorcycle, and taxi of the second traveler respectively (see Figure 2.10). The values of estimated parameters by mode choices are also shown in the Appendix B.



Source: Dissanayake and Morikawa (2010)

Figure 2.9: The nested structure of Revealed Preference (RP) model

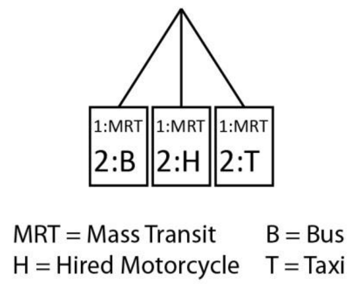


Figure 2.10: Additional mode choices in the combined Revealed and Stated Preference (RP/SP) model

To use this mode split model to forecast ridership for a new MRT services, we need information on household vehicle ownership for the first level of nested structure as well as other household- and individual-level characteristics, including household income, gender, age, and job industry or school enrollment, for the lower level of the model. In addition, other information needed for this mode split model is travel-related attributes such as commuting destinations, travel distances, and level-of-service measures such as travel time and cost. The demographic and economic characteristics can be extracted from the household survey, while the travel-related attributes can be derived primarily from the O-D table and TAZ geography. The following section discusses the forecasting procedure in more detail.

2.5 Methodology

The procedure of forecasting household travel mode choices involves three main steps: (1) selecting and sorting two-traveler households, (2) assigning travel destination to household members, and (3) forecasting household travel mode choices. As illustrated in Figure 2.11 below, the first step involves selecting two-traveler households in the BMR from the entire SES and sorting these households by vehicle ownership. The second step is then using trip distribution and zonal attraction in the trip table to assign travel destination of each travel member. The final step is to forecast household mode choices by computing household utilities, taking into account household attributes, level-of-service measures, and vehicle ownership. Each step is described in detail in the following sections.

2.5.1 Selecting Two-traveler Households from the SES

The first step is to select the two-traveler households in the district of interest from the full SES data, which contains information at both household and individual levels. Out of the entire 5,824 survey households in the BMR, 2,350 or 40.4% are selected as two-traveler households—those with two earners with no children, or one earner with one or more children. The table showing percent of two-traveler households by BMR province is shown in Appendix A.

Once only BMR households are selected, these households are then categorized into three groups by their vehicle ownership: car, motorcycle, and no vehicle owning. Households that own both cars and motorcycles are categorized as car owning group since cars are presumably a preferred mode of transportation for commuting trips. In addition to vehicle ownership, other household characteristics are also extracted from the SES data, which will be used in the later stage. The variables include the number of children in the household, household expenditure, and characteristics of the household head, including gender, education, and marital status. Almost three-fourths of selected households are headed by a male, and the average age of household heads is 43 years (see Appendix A).

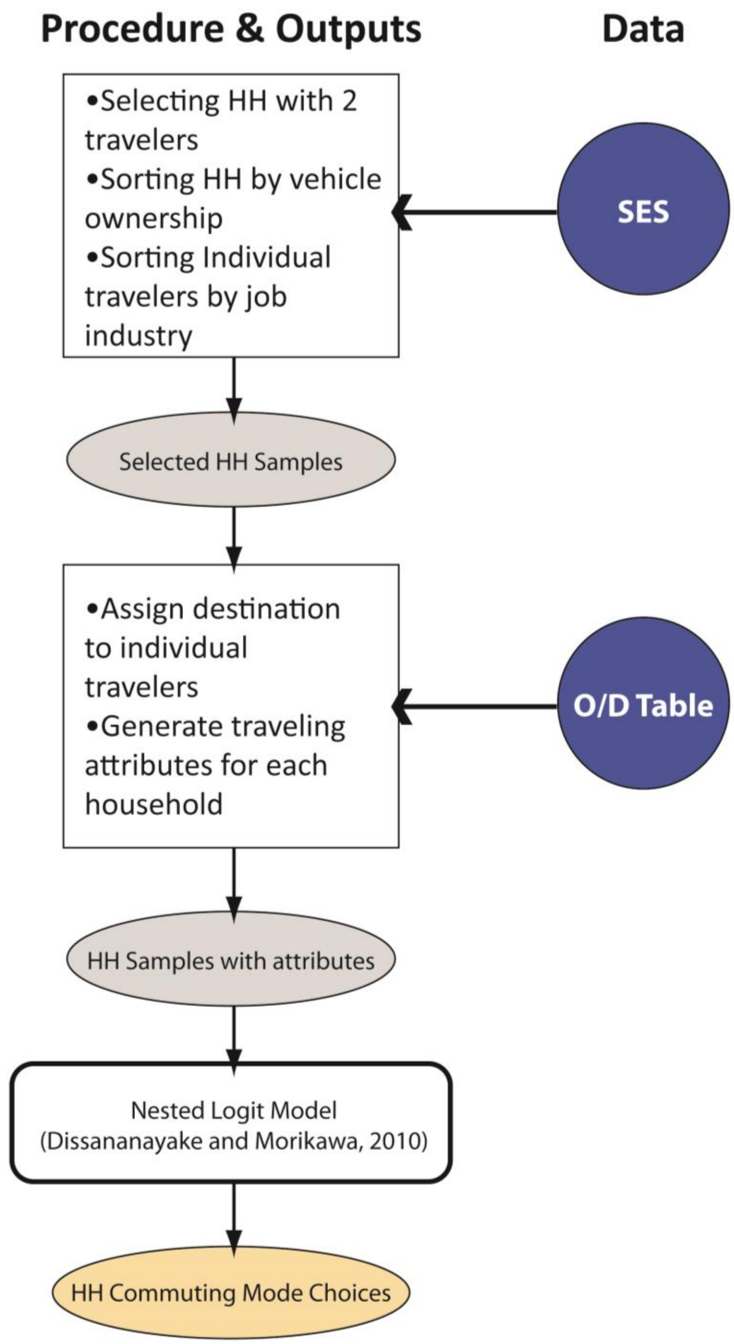


Figure 2.11: Overview of procedure to forecast two-traveler households in the BMR

As mentioned earlier, the 2008 SES survey is expenditure-based; it does not have information on household income; yet, household income is needed to compute households' utilities in the forecasting household mode choices. Therefore, household income is estimated using the household average propensity to consume (APC), which is by definition the ratio of household consumption to income. The APCs of Thai households are derived from 2007 Thailand Social Accounting Matrix of which the households are categorized into ten percentile groups based on their incomes. The APCs, ranging from 0.9076 for the lowest income group to 0.7688 for the richest, are reported in Appendix A. To compute household income ($HH\ Income$), the full, nationwide household samples are sorted into ten percentile groups based on their household expenditure ($HH\ Exp$). Household income is then computed by dividing household expenditure with the APC of its respective group as shown below.

$$HH\ Income = \frac{HH\ Exp}{APC} \tag{2.1}$$

In addition to household characteristics, individual characteristics are also extracted from the household survey, particularly work/study status and job industries, which are used in the next step to assign travel destinations of each traveler. The job industries of workers are categorized into three sectors: primary, secondary, and tertiary, while students are placed in a student category.   As can be seen in Table 2.3, the majority of travelers living in Bangkok, Nonthaburi, and Pathum Thani work in the tertiary sector. On the contrary, over 60 percent of travelers in Samut Prakan and Samut Sakhon—BMR provinces predominant in manufacturing—work in the secondary sector. From individual job categories, dummy variables for executive and business related jobs are also created.

Table 2.3: Distribution of individuals in two-traveler households by job industries and BMR provinces

	BMR Provinces						
	Bangkok	Samut Prakan	Nonthaburi	Pathum Thani	Nakhon Pathom	Samut Sakhon	BMR Total
Total	2,188	454	620	530	472	436	4,700
Primary	23	7	12	25	66	30	163
% Total	1.1%	1.5%	1.9%	4.7%	14.0%	6.9%	3.5%
Secondary	631	287	177	212	161	276	1,744
% Total	28.8%	63.2%	28.5%	40.0%	34.1%	63.3%	37.1%
Tertiary	1,384	142	395	267	229	121	2,538
% Total	63.3%	31.3%	63.7%	50.4%	48.5%	27.8%	54.0%
Student	150	18	36	26	16	9	255
% Total	6.9%	4.0%	5.8%	4.9%	3.4%	2.1%	5.4%

2.5.2 Assigning Travel Destinations Based on Trip Distribution

Given that job industries of individual travelers are known from the SES data in the first step, in the second step each traveler is then assigned a travel destination based on the trip distribution and zonal attractions of each TAZ. The distribution is defined as the joint probability of trip distribution from the O-D table and percent share of total employment in the BMR (or percent share of school enrollment) from the TAZs attributes. Formally, the trip distribution from traffic analysis zone *i* to destination *j* is defined as:

$$\mu_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}, \qquad (2.2)$$

where μ_{ij}= probability of trips originated in zone *i* to destination j, and

T_{ij}= number of trips originated in zone *i* to destination j.

Similarly, the percent share of total employment, or school enrollment, in the BMR represents zonal attractions and is defined as:

$$\theta_j^k = \frac{H_j^k}{\sum_j H_j^k}, \tag{2.3}$$

where θ_j^k= share of employment in a *k* sector in destination zone *j*, and

H_j^k= number of employment or enrollment in *k* sector in zone *j*, where

$k \in \{Prim, Scnd, Tert, Sch\}$.

Assuming that trip distribution is independent of zonal attractions, the joint probability of trip distribution by the percent share of sectorial employment or school enrollment is defined as:

$$p_{ij|k} = \frac{\mu_{ij} * \theta_j^k}{\sum_j \mu_{ij} * \theta_j^k}, \tag{2.4}$$

where $p_{ij|k}$ = probability of trips from zone *i* to *j* given a traveler engaged in a *k* sector activity, where $k \in \{Prim, Scnd, Tert, Sch\}$,

μ_{ij}= probability of trips originated in zone *i* to destination *j*, and

θ_j^k= share of employment in a k sector in destination zone *j*.

From these probabilities of trip distribution and zonal attraction, the cumulative frequency distribution can be derived and thus used to assign travel destinations. Let $P_{i|k}$ denotes cumulative frequency distribution of trips in *k* sector originated in zone *i*. The cumulative frequency distribution is defined as:

$$P_{i|k}(n) = \sum_{j \leq n} p_{ij|k}, \tag{2.5}$$

where n = the number of internal traffic analysis zones.

The destination assignment procedure begins with a uniformly-distributed random number, ranging between zero and up to one, being generated for each traveler. This random number is then looked up through the derived cumulative frequency distribution, and a traffic zone with the same range of cumulative distribution is assigned to a traveler. Figure 2.12 graphically illustrates the destination assignment procedure of a traveler working in the secondary sector. Let *x* denotes a generated random number, depicted on the y-axis. The generated random number *x* is matched against the cumulative frequency of the corresponding sector to find a traffic analysis zone. A traveler is destined in zone *n* when:

$$P_{i|k}(n-1) < x \leq P_{i|k}(n) \tag{2.6}$$

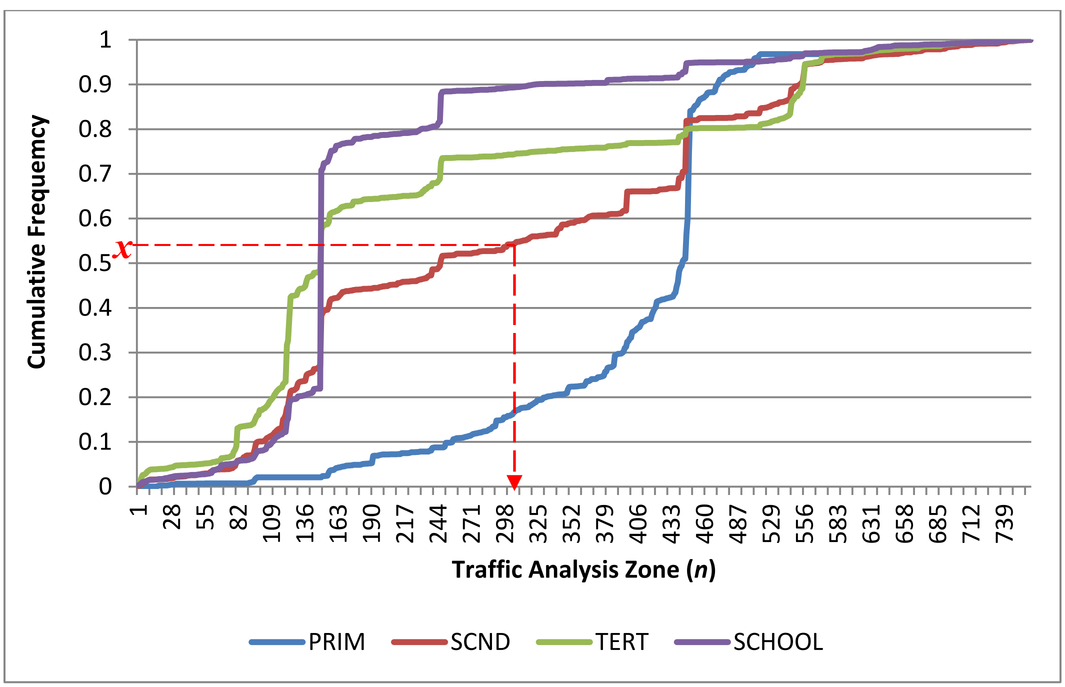


Figure 2.12: Cumulative frequency distribution of primary (PRIM), secondary (SCND), tertiary (TERT), and school sectors from a TAZ in the BMR

If assigned correctly, the resulting trip distribution must be similar to the original trip distribution from the trip table. To make sure that the distribution generated by the assignment algorithm mimics the original trip distribution, this algorithm was tested with 1,000 hypothetical travelers working in the tertiary sector. As can be seen in Appendix C, the results are consistent with the original trip distribution, for example, we can observe similar distributional pattern in the top most assigned destinations in the original distribution from the results.

One caveat worth mentioning here is that travel destinations of each traveler in a household are assumed to be independent. We acknowledge that our assumption may not be realistic as travel destinations of household members may be interrelated. However, due to the absence of empirical data, we are unable to test this correlation structure. Thus, for this study, we are assuming that destinations of each traveler are independent. Another assumption we make is that households living in the same district share similar characteristics. Since districts cover larger areas than traffic analysis zones, several traffic analysis zones are within the same district. As two-traveler household sample size in each districts are relatively small, we assume here that the traffic zones in the same district share similar household characteristics. In other words, the same set of households is used across traffic zones within the same district.

Once travel destinations are assigned, household travel distances, which have direct implication on travel time and costs, can be calculated. Due to insufficient quality of the road network data, Euclidean distances among traffic analysis zones are used instead of network distances. With geographical boundaries of traffic analysis zones, Euclidean distances between each TAZ are calculated from a centroid of each zone using Geospatial Modeling Environment (GME) by Beyer (2011) and ArcGIS.

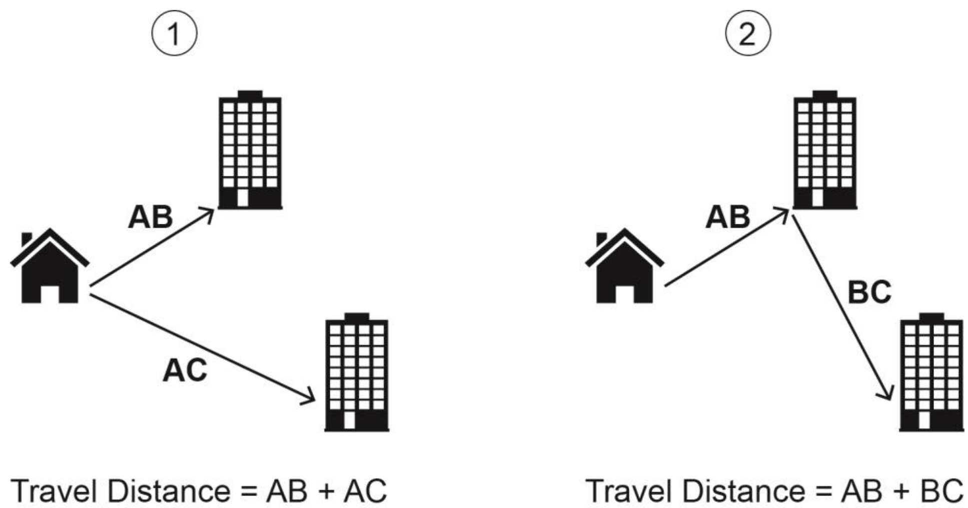


Figure 2.13: Two types of household travel distances: (1) without trip sharing and (2) with trip sharing

Since we do not know whether household members choose trip chain or not, two types of distances are calculated. As shown in Figure 2.13, point A depicts a household's residential location, while point B and C represent a workplace or school location of each traveler. The first type of household distance—the distance AB and AC—is calculated for non-trip sharing. On the other hand, the second type of distance—the distance AB and BC—is generated for trip sharing. Based on these calculated distances, travel time in hour is first calculated, assuming that average travel speed is 15 kilometer per hour (OTP Annual Report, 2009). Travel costs are then calculated by multiplying travel time by the value of time (VOT) parameter from Dissanayake and Morikawa (2010). The VOT parameter is 42 Thai Baht per hour (around US $1.5 per hour).

After both types of household travel distances, travel time, and travel costs are computed, the household samples are arranged in the same order as dummy variables in Dissanayake and Morikawa (2010). The full list of variables is shown in Appendix

B. The entire mechanism of this destination assignment and household attribute formatting is done using Visual Basic Application in Microsoft Excel.

2.5.3 Forecasting Household Commuting Mode Choices

The last step is to forecast household travel mode choices using a nested model purposed by Dissanayake and Morikawa (2010). Based on the RP model structure, vehicle ownership defines available travel mode choices for each household (see Figure 2.9). Households' travel mode choices are predicted based on estimated utility level of each available mode choice. A household is expected to select a mode choice that gives the highest utility level. Following Dissanayake and Morikawa (2010), the household utility for each alternative is calculated as follows:

Estimated utility of household *i* in car ownership group if choosing mode choice *m*:

$$\widehat{U}_{im,car} = \alpha_m + (\beta * \boldsymbol{LOS}_i) + (\gamma_{m,car} * \boldsymbol{DUMMY}_i). \tag{2.7}$$

Estimated utility of household *i* in motorcycle ownership group if choosing mode choice *m*:

$$\widehat{U}_{im,mc} = \alpha_m + \delta_{mc} + (\beta * \boldsymbol{LOS}_i) + (\gamma_{m,mc} * \boldsymbol{DUMMY}_i). \tag{2.8}$$

Estimated utility of household *i* in no-vehicle ownership group if choosing mode choice *m*:

$$\widehat{U}_{im,no\_veh} = \alpha_m + \delta_{no\_veh} + (\beta * \boldsymbol{LOS}_i) + (\gamma_{m,no\_veh} * \boldsymbol{DUMMY}_i), \tag{2.9}$$

where $\boldsymbol{LOS}_i$ = a matrix of level-of-service variables

= {travel time (h), travel cost/income},

$\boldsymbol{DUMMY}_i$= a matrix of alternative specific dummies,

α_m= mode specific constants for both travelers,

$\delta_{mc}, \delta_{no\_veh}$ = vehicle ownership constants for motorcycle and no-vehicle,

β = coefficients of level-of-service variables, and

$\gamma_{m,car}, \gamma_{m,mc}, \gamma_{m,no\_veh}$ = coefficients of alternative specific dummies

The table reporting parameters of both RP and RP/SP models is shown in Appendix B. Like in the destination assignment step, this household mode choice forecasting is done using Visual Basic Application in Microsoft Excel.

2.6 Simulation Results and Discussions

The procedure previously discussed can be applied to all TAZs in the BMR to gain a full estimation of two-traveler households' mode choices. In this analysis, however, we will demonstrate the forecasting procedure by selecting six TAZs—with varying degree of household sample sizes and vehicle ownership—and examining mode choices of two-traveler households in these TAZs. Within each major zone—inner city, inner suburb, and outer suburb—two TAZs are selected: one with the existence of mass transit (both in the present or future) and the other without mass transit. Figure 2.14 below shows the locations of selected traffic analysis zone, called by their identifier number for convenience, overlaying with major highways, ring roads, and locations of mass transit stations. As can be seen, the zones within the inner city includes zone 150 (in Chatuchak district) and 87 (Bang Kho Laem); within the inner suburbs are zone 677 (Muang Nonthaburi) and 240 (Lat Phrao); within the outer suburbs are zone 613 (Lat Krabang) and 461 (Nakonchaisri). Overall, out of the selected 236 households, 86 (36 percent) are categorized in car-owning group, while both motorcycle owning and no vehicle owning group each equally has 75 households or 32 percent. The number of household samples is shown by their vehicle ownership and TAZ in Table 2.4. As can be seen, vehicle ownership in these selected TAZs varies considerably. Household samples in outer suburb TAZs have less share of car ownership, while around 50% of household samples in the inner city and inner suburb are car owning group. The majority of household samples in the outer suburb are in the motorcycle owner group, while those in inner city and inner suburb own cars.

Table 2.4: Vehicle ownership of two-traveler households by selected Traffic Analysis Zones

	Location					
	Inner City		Inner Suburb		Outer Suburb	
Mass Transit	**With**	**Without**	**With**	**Without**	**With**	**Without**
Traffic Analysis Zone	**150**	**87**	**677**	**240**	**613**	**461**
Vehicle Ownership (HH)						
Car owning	17 (46%)	10 (56%)	39 (37%)	14 (67%)	2 (6%)	4 (18%)
Motorcycle owning	8 (22%)	3 (17%)	32 (30%)	4 (19%)	13 (41%)	15 (68%)
No Vehicle owning	12 (32%)	5 (28%)	35 (33%)	3 (14%)	17 (53%)	3 (14%)
Total Households	**37**	**18**	**106**	**21**	**32**	**22**

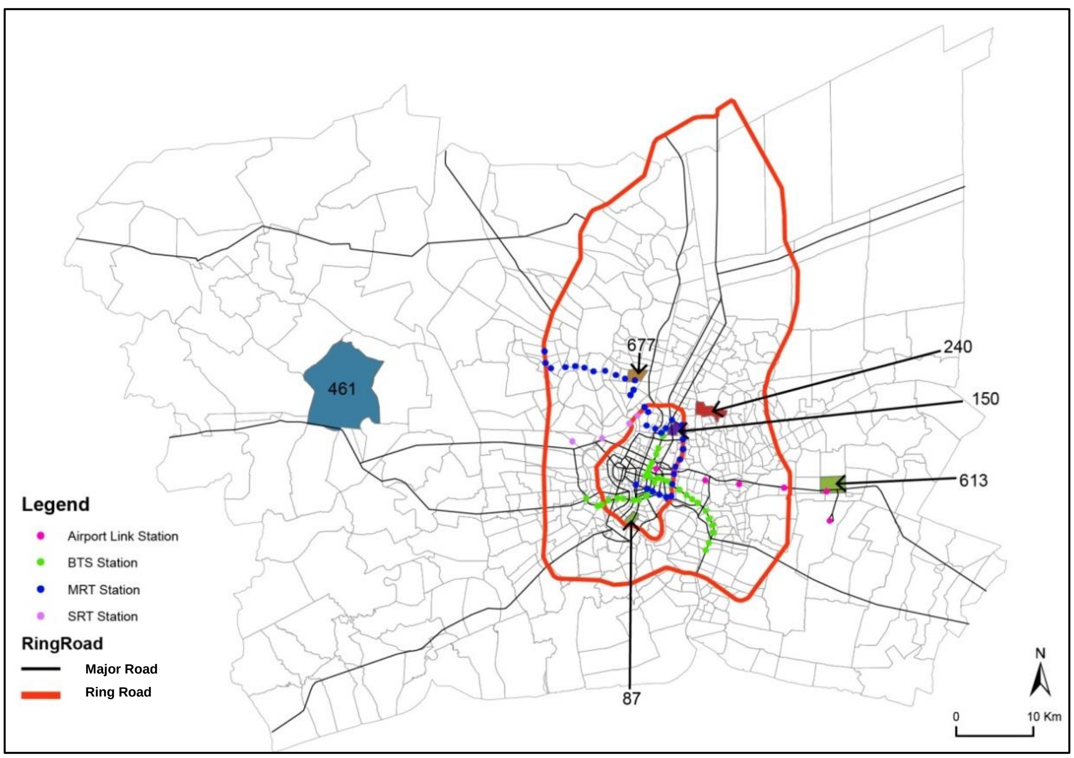


Figure 2.14: Six selected Traffic Analysis Zones in the BMR

The Table 2.5 and Table 2.6 respectively shows the forecasted household travel mode choices of these selected TAZs using RP and RP/SP models. Without the presence of mass transit, the RP model predicts some extent of trip sharing in both car owners and motorcycle owners; around one-third of car-owning households share their trips. Car-owning households are also slightly less likely to share their trips compared to motorcycle-owning ones. The RP model also predicts that both travelers in no-vehicle households tend to use buses; these results are quite reasonable since bus fares in Bangkok, ranging from $0.25 to $0.75 a ride in 2008 (Bangkok Mass Transit Authority), are considerably cheaper than any other modes of transportation. The results are also consistent with the fact that buses are major public transportation mode of transportation in Bangkok. The modal share of the results is also consistent with the modal share of the survey that Dissanayake and Morikawa used to calibrate the RP model (see Dissanayake & Morikawa (2010) for detail).

Table 2.5: Simulation results of RP model

	Traffic Analysis Zone						
Household mode	**150**	**87**	**677**	**240**	**613**	**461**	**Total**
Car owning	17 (100%)	10 (100%)	39 (100%)	14 (100%)	2 (100%)	4 (100%)	**86 (100%)**
car sharing	5 (29%)	1 (10%)	12 (31%)	6 (43%)	0 (0%)	1 (25%)	25 (29%)
1: car, 2: bus	12 (71%)	9 (90%)	27 (69%)	8 (57%)	2 (100%)	3 (75%)	61 (71%)
Motorcycle owning	8 (100%)	3 (100%)	32 (100%)	4 (100%)	13 (100%)	15 (100%)	**75 (100%)**
MC sharing	2 (25%)	3 (100%)	11 (34%)	2 (50%)	5 (38%)	7 (47%)	30 (40%)
1: mc, 2 :bus	6 (75%)	0 (0%)	21 (66%)	2 (50%)	8 (62%)	8 (53%)	45 (60%)
No Vehicle owning	12 (100%)	5 (100%)	35 (100%)	3 (100%)	17 (100%)	3 (100%)	**75 (100%)**
1: bus, 2:bus	12 (100%)	5 (100%)	35 (100%)	3 (100%)	17 (100%)	3 (100%)	75 (100%)
Total households	**37**	**18**	**106**	**21**	**32**	**22**	**236**

Table 2.6: Simulation results of RP/SP model

Household Mode	Traffic Analysis Zone 150	87	677	240	613	461	Total
Car owning	17 (100%)	10 (100%)	39 (100%)	14 (100%)	2 (100%)	4 (100%)	**86 (100%)**
1: car, 2: bus	1 (6%)	0 (0%)	3 (8%)	2 (14%)	2 (100%)	2 (50%)	10 (12%)
1: MRT, 2: bus	16 (94%)	10 (100%)	36 (92%)	12 (86%)	0 (0%)	2 (50%)	76 (88%)
Motorcycle owning	8 (100%)	3 (100%)	32 (100%)	4 (100%)	13 (100%)	15 (100%)	**75 (100%)**
MC sharing	2 (25%)	1 (33%)	5 (16%)	1 (25%)	5 (38%)	6 (40%)	20 (27%)
1: MRT, 2: bus	6 (75%)	2 (67%)	27 (84%)	3 (75%)	8 (62%)	9 (60%)	55 (73%)
No Vehicle owning	12 (100%)	5 (100%)	35 (100%)	3 (100%)	17 (100%)	3 (100%)	**75 (100%)**
1: MRT, 2: bus	12 (100%)	5 (100%)	35 (100%)	3 (100%)	17 (100%)	3 (100%)	75 (100%)
Total households	**37**	**18**	**106**	**21**	**32**	**22**	**236**

On the other hand, the simulation results from the combined RP/SP model suggest that most first travelers change their transportation mode to MRT (See Table 2.6). Clearly, the result is strongly biased toward MRT, and small sample sizes in this simulation may be contributing to these results. In particular, the model predicts that the first traveler in car-owning and no-vehicle households tend to use MRT. A closer inspection of the predicted household utilities reveals that the MRT mode gives much higher utility than other modes, suggesting that, when available, MRT is a very attractive mode of transportation for both car and bus users. The results are in fact consistent with the previous empirical study that most MRT users are previous bus riders (Hayashi, 1998). In addition, one caveat worth mentioned here is that structure of SP model only takes into account the use of MRT by the first traveler and does not capture the attractiveness of trip sharing. Hence, we can forecast the MRT uses only by the first traveler and the results may be highly biased toward MRT.

In addition to mode share by vehicle ownership, we could shed more light on the relation of household characteristics and trip sharing behavior. As shown in Table 2.7, male first travelers tend to share their trip with the second travelers. Among households with car ownership or motorcycle ownership, almost all households choosing to share their trips have male heads of household. The results are consistent with Dissanayake and Morikawa (2010) that male household heads are responsible in taking care of other family members. It reflects cultural behavior and norm, which is very common in developing countries.

Table 2.7: Household travel mode choice by vehicle ownership and gender of first traveler predicted by RP model

Household Mode by Vehicle Ownership	First Traveler's Gender				Total	
	Female		Male			
Car-owning	40	(100%)	46	(100%)	86	(100%)
car sharing	0	(0%)	25	(54%)	25	(29%)
1: car, 2: bus	40	(100%)	21	(46%)	61	(71%)
Motorcycle-owning	26	(100%)	49	(100%)	75	(100%)
MC sharing	3	(12%)	29	(59%)	32	(43%)
1: mc, 2 :bus	23	(88%)	20	(41%)	43	(57%)
No-vehicle	31	(100%)	44	(100%)	75	(100%)
1: bus, 2:bus	31	(100%)	44	(100%)	75	(100%)
TOTAL	**97**	**(41%)**	**139**	**(59%)**	**236**	

Table 2.8: Household travel mode choice by vehicle ownership and gender of first traveler predicted by RP/SP model

Household Mode by Vehicle Ownership	First Traveler's Gender				Total	
	Female		Male			
Car-owning	40	(100%)	46	(100%)	86	(100%)
1: car, 2: bus	4	(10%)	6	(13%)	10	(12%)
1: MRT, 2: bus	36	(90%)	40	(87%)	76	(88%)
Motorcycle-owning	26	(100%)	49	(100%)	75	(100%)
MC sharing	1	(4%)	19	(39%)	20	(27%)
1: MRT, 2 :bus	25	(96%)	30	(61%)	55	(73%)
No-vehicle	31	(100%)	44	(100%)	75	(100%)
1: MRT, 2:bus	31	(100%)	44	(100%)	75	(100%)
TOTAL	**97**	**(41%)**	**139**	**(59%)**	**236**	

Table 2.9: Household travel mode choice by vehicle ownership and second traveler predicted by RP model

Household Mode by Vehicle Ownership	Second Traveler				Total	
	Not Student		Student			
Car-owning	45	(100%)	41	(100%)	86	(100%)
car sharing	12	(27%)	13	(32%)	25	(29%)
1: car, 2: bus	33	(73%)	28	(68%)	61	(71%)
Motorcycle-owning	75	(100%)			75	(100%)
MC sharing	32	(43%)			32	(43%)
1: mc, 2 :bus	43	(57%)			43	(57%)
No-vehicle	75	(100%)			75	(100%)
1: bus, 2:bus	75	(100%)			75	(100%)
TOTAL	**195**	**(83%)**	**41**	**(17%)**	**236**	

Table 2.10: Household travel mode choice by vehicle ownership and presence of children predicted by RP/SP model

Household Mode by Vehicle Ownership	Second Traveler				Total	
	Not Student		Student			
Car-owning	45	(100%)	41	(100%)	86	(100%)
1: car, 2: bus	7	(16%)	3	(7%)	10	(12%)
1: MRT, 2: bus	38	(84%)	38	(93%)	76	(88%)
Motorcycle-owning	75	(100%)			75	(100%)
MC sharing	20	(27%)			20	(27%)
1: MRT, 2 :bus	55	(73%)			55	(73%)
No-vehicle	75	(100%)			75	(100%)
1: MRT, 2:bus	75	(100%)			75	(100%)
TOTAL	**195**	**(83%)**	**41**	**(17%)**	**236**	

The prediction from the RP/SP suggests that MRT can attract first travelers who share their trips in the RP model results, especially in the car-owning group. The results also suggest that car is still an attractive mode of transportation for car owners; about fifteen percent of drivers in RP model still use their cars in the RP/SP model.

On the other hand, over 50 percent motorcycle-owning still share their trips in the RP/SP model. All first travelers in no-vehicle owning group use MRT.

Further, households in car ownership group tend to share their trips if the second traveler is a school student. Out of Seventeen percent of sample households with second travelers that are students, around one-third share their trips, slightly higher than households with second travelers that are not school children (see Table 2.9). Like in the previous results, the RP/SP model predicts a proportionally large number of car-owning households shifting to MRT and bus use. As shown in Table 2.10, over 90 percent of households with student second traveler use MRT and bus, compared to 84 percent in the households without students group.

This household forecasting methodology has demonstrated how households commuting mode choices can be predicted from the regular socio-economic household survey. This method enables the researchers to examine household mode choices without necessarily conducting a time-consuming and costly household traveling survey.

2.7 Conclusion

This study demonstrates how one can fully utilize the household socio-economic survey—the data set not designed for analyzing household travel patterns—with the trip distribution table (O-D table) to examine traveling patterns. By combining household attributes and vehicle ownership, the BMR trip table, and the Revealed and Stated Preference forecasting model, this methodology allows for examining travel mode choices of urban subpopulation in the BMR. Specifically, this study examines mode choices of two-traveler households in the BMR when trip sharing is one of the mode alternatives.

Using the Revealed Preference (RP) forecasting model calibrated by Dissanayake and Morikawa (2010), the results suggest that households tend to share their trips when the first traveler is male and when there is a presence of school children. Male traveler, presence of children, travel distance of the second traveler, and destination of trips play an important role in the trip sharing choices of households.

In addition, the model allows for analysis of the use of new MRT system, and the result suggests that most MRT users are converted from bus users, which conforms to the results of previous study by Hayashi (1998). Nonetheless, due to small number of household sample sizes, the results are highly biased toward the use of MRT. Upon the data availability of network, the study can be expanded further to incorporate route choices with network travel distances, time and travel costs.

APPENDIX A

Table A2.1: Two-traveler household samples by BMR provinces, 2008

BMR Province	Number of Sampled HH	HH with 2 Travelers	% Sampled HH
Bangkok	2,832	1,094	38.6%
% Total	48.6%	46.6%	
Samut Prakan	509	227	44.6%
% Total	8.7%	9.7%	
Nonthaburi	804	265	33.0%
% Total	13.8%	11.3%	
Pathum thani	614	265	43.2%
% Total	10.5%	11.3%	
Nakhon pathom	584	236	40.4%
% Total	10.0%	10.0%	
Samut sakhon	481	218	45.3%
% Total	8.3%	9.3%	
Total	**5,824**	**2,350**	**40.4%**

Table A2.2: Demographic statistics of two-traveler households in the BMR, 2008

Household Level Variables	N	Mean	Std. Dev.	Min	Max
Number of earner	2,350	1.91	0.29	1	2
Number of household member	2,350	2.90	1.13	2	8
% male head of HH	2,350	0.72	0.45	1	2
Head of HH age	2,350	42.73	13.84	16	99
% HH with children	2,350	0.53	0.78	0	5
% HH with elderly	2,350	2.39	0.72	1	6
HH monthly total expenditure (THB)	2,350	25,192.24	21,161.36	2,782	331,373
Monthly rent (THB)	2,350	3,801.26	11,047.05	300	500,000

Table A2.3: Average propensity to consume (APC) coefficients used to estimate household income

Percentile	Household Expenditure (THB)	Average Propensity to Consume (APC)
10th	Less than 5,093	0.9076
20th	5,093 - 6,902	0.8857
30th	6,903 - 8,501	0.8729
40th	8,502 - 10,217	0.8643
50th	10,218 - 12,263	0.8635
60th	12,264 - 14,779	0.8127
70th	14,780 - 18,151	0.7854
80th	18,152 - 23,598	0.7742
90th	23,599 - 33,449	0.7626
100th	More than 33,449	0.7688

Source: Author's calculation based on 2007 Social Accounting Matrix (SAM) of Thailand

APPENDIX B

Table B2.1: Coefficients from Revealed Preference estimation model of Dissanayake and Morikawa (2011)

	Car-owning Mode Choice						
Parameters	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Mode Specific Constant	3.4	4.69	3.49	1.52	2.61	0.81	
Alternative Specific Constants							
Level-of-service parameter							
Travel Time (h)	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55
Travel Cost/Income/100	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15
Dummy variables							
Male commuter	1.63						
Travel distance for both travelers > 30km		1.61					
Distance between destinations ≥ 10km							
Distance between destinations ≤ 15km	0.83						
Second travelers travel distance > 5km			-2.2				
Distance share of both travelers > 75%							
Commuter’s job (executive)							
Commuter’s job (executive or business)	1.29	1.29	1.29	1.29	1.29	1.29	1.29
Travelers jobs are not executive							
Commuter’s age > 50yrs							
School children in the household ≥ 1	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Household income ≤ 25000 Baht							
Trips touching CBD		0.82					
Trips within CBD	-0.8	-0.8	-0.8	-0.8	-0.8	-2.62	-0.8

Table B2.1: Coefficients from Revealed Preference estimation model of Dissanayake and Morikawa (2011)

Parameters	Motorcycle-owning Mode Choice						
	8	**9**	**10**	**11**	**12**	**13**	**14**
Mode Specific Constant	3.8	4.71	3.51	1.54	2.61	0.81	
Alternative Specific Constants	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Level-of-service parameter							
Travel Time (h)	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55
Travel Cost/Income/100	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15
Dummy variables							
Male commuter	1.63						
Travel distance for both travelers > 30km							
Distance between destinations ≥ 10km		1.1					
Distance between destinations ≤ 15km	0.83						
Second travelers travel distance > 5km							
Distance share of both travelers > 75%	0.58						
Commuter's job (executive)	-1						
Commuter's job (executive or business)							
Travelers jobs are not executive							
Commuter's age > 50yrs							
School children in the household ≥ 1							
Household income ≤ 25000 Baht							
Trips touching CBD							
Trips within CBD	-1.1					-1.82	

Table B2.2: Coefficients from Revealed Preference estimation model of Dissanayake and Morikawa (2011)

	No Vehicle Mode Choice		
Parameters	**15**	**16**	**17**
Mode Specific Constant	2.61	0.81	
Alternative Specific Constants	2.23	2.23	2.23
Level-of-service parameter			
Travel Time (h)	-0.55	-0.55	-0.55
Travel Cost/Income/100	-2.15	-2.15	-2.15
Dummy variables			
Male commuter			
Travel distance for both travelers > 30km			
Distance between destinations ≥ 10km			
Distance between destinations ≤ 15km			
Second travelers travel distance > 5km			
Distance share of both travelers > 75%			
Commuter’s job (executive)			
Commuter’s job (executive or business)			
Travelers jobs are not executive	0.51	0.51	0.51
Commuter’s age > 50yrs	0.59	0.59	0.59
School children in the household ≥ 1			
Household income ≤ 25000 Baht	1.67	1.67	1.67
Trips touching CBD			
Trips within CBD		-1.82	

Table B2.3: Coefficients from Revealed/Stated Preference estimation model of Dissanayake and Morikawa (2011)

	Car-owning Mode Choice									
Parameters	**1**	**2**	**2.1**	**3**	**3.1**	**4**	**4.1**	**5**	**6**	**7**
Mode Specific Constant	2.86	4.53	6.53	3.31	5.31	1.43	3.43	2.55	0.71	
Alternative Specific Constants										
Level-of-service parameter										
Travel Time (h)	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57
Travel Cost/Income/100	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51
Dummy variables										
Male commuter	1.65									
Travel distance for both travelers > 30km		1.8								
Distance between destinations ≥ 10km										
Distance between destinations ≤ 15km	0.79									
Second travelers travel distance > 5km				-2.3						
Distance share of both travelers > 75%										
Commuter's job (executive)										
Commuter's job (executive or business)	1.37	1.37	1.37	1.37	1.37	1.37	1.37	1.37	1.37	1.37
Travelers jobs are not executive										
Commuter's age > 50yrs										
School children in the household ≥ 1	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
Household income ≤ 25000 Baht										
Trips touching CBD										
Trips within CBD	-0.85	-0.85	-0.85	-0.85	-0.85	-0.85	-0.85	-0.85	-2.67	-0.85
RP mode, Bus, Car:SP	2.48	2.48	2.48	2.48	2.48	2.48	2.48	2.48		
Car ownership or Car and Motorcycle ownership	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89

Table B2.2: Coefficients from Revealed/Stated Preference estimation model of Dissanayake and Morikawa (2011) (Continued)

Parameters	Car-owning Mode Choice									
	8	**9**	**9.1**	**10**	**10.1**	**11**	**11.1**	**12**	**13**	**14**
Mode Specific Constant	2.92	4.56	6.53	3.34	5.31	1.46	3.43	2.55	0.71	
Alternative Specific Constants	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71
Level-of-service parameter										
Travel Time (h)	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57
Travel Cost/Income/100	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51
Dummy variables										
Male commuter	1.65									
Travel distance for both travelers > 30km										
Distance between destinations ≥ 10km		1.6								
Distance between destinations ≤ 15km	0.79									
Second travelers travel distance > 5km										
Distance share of both travelers > 75%	0.56									
Commuter’s job (executive)	-1.4									
Commuter’s job (executive or business)										
Travelers jobs are not executive										
Commuter’s age > 50yrs										
School children in the household ≥ 1										
Household income ≤ 25000 Baht										
Trips touching CBD										
Trips within CBD	-1.4								-1.82	
RP mode, Bus, Car:SP			2.48		2.48		2.48	2.48		
Car ownership or Car and Motorcycle ownership	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89

Table B2.2: Coefficients from Revealed/Stated Preference estimation model of Dissanayake and Morikawa (2011) (Continued)

	No vehicle					
Parameters	**15**	**15.1**	**16**	**16.1**	**17**	**17.1**
Mode Specific Constant	2.55	6.53	0.71	5.31		3.43
Alternative Specific Constants	2.1	2.1	2.1	2.1	2.1	2.1
Level-of-service parameter						
Travel Time (h)	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57
Travel Cost/Income/100	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51
Dummy variables						
Male commuter						
Travel distance for both travelers > 30km						
Distance between destinations ≥ 10km						
Distance between destinations ≤ 15km						
Second travelers travel distance > 5km						
Distance share of both travellers > 75%						
Commuter's job (executive)						
Commuter's job (executive or business)						
Travelers jobs are not executive	0.54	0.54	0.54	0.54	0.54	0.54
Commuter's age > 50yrs	0.63	0.63	0.63	0.63	0.63	0.63
School children in the household ≥ 1						
Household income ≤ 25000 Baht	1.75	1.75	1.75	1.75	1.75	1.75
Trips touching CBD						
Trips within CBD			-1.82			
RP mode, Bus, Car: SP	2.48					
Car ownership or Car and Motorcycle ownership						

APPENDIX C

Table C2.1: Simulation results of destination assignment algorithm, using 1,000 travelers originated from TAZ# 150, Top 40 destination TAZs

Simulation #1			Simulation #2			Simulation #3				O-D Distribution	
Destination TAZ	Frequency	% share	Destination TAZ	Frequency	% share	Destination TAZ	Frequency	% share		Destination TAZ	% share
150	111	0.111	150	103	0.103	122	87	0.087		150	0.095
122	87	0.087	122	95	0.095	150	87	0.087		122	0.083
124	44	0.044	124	58	0.058	124	46	0.046		124	0.050
247	42	0.042	247	44	0.044	125	46	0.046		125	0.047
125	37	0.037	125	43	0.043	247	43	0.043		82	0.041
557	30	0.03	82	40	0.04	556	34	0.034		247	0.038
82	29	0.029	556	27	0.027	82	33	0.033		557	0.030
157	25	0.025	546	21	0.021	557	31	0.031		556	0.026
556	23	0.023	557	20	0.02	546	25	0.025		546	0.024
546	22	0.022	123	16	0.016	157	19	0.019		157	0.018
446	16	0.016	157	16	0.016	440	14	0.014		440	0.013
138	15	0.015	446	15	0.015	446	14	0.014		446	0.013
571	15	0.015	440	14	0.014	4	13	0.013		138	0.012
248	14	0.014	100	12	0.012	81	12	0.012		571	0.011
4	11	0.011	4	11	0.011	100	12	0.012		100	0.011
554	11	0.011	248	11	0.011	139	11	0.011		4	0.010
176	10	0.01	79	10	0.01	248	11	0.011		123	0.010
81	9	0.009	131	10	0.01	96	10	0.01		79	0.009
100	9	0.009	138	10	0.01	176	10	0.01		554	0.009
123	9	0.009	521	10	0.01	5	9	0.009		248	0.009
440	9	0.009	119	9	0.009	79	9	0.009		131	0.009
5	7	0.007	571	9	0.009	131	9	0.009		176	0.008
69	7	0.007	139	8	0.008	521	9	0.009		139	0.008
97	7	0.007	176	8	0.008	8	8	0.008		81	0.008
98	7	0.007	2	7	0.007	123	8	0.008		119	0.007
107	7	0.007	5	7	0.007	132	8	0.008		97	0.007
112	7	0.007	69	7	0.007	98	7	0.007		96	0.007
119	7	0.007	111	7	0.007	119	7	0.007		240	0.007
77	6	0.006	114	7	0.007	138	7	0.007		5	0.007
79	6	0.006	81	6	0.006	547	7	0.007		112	0.006
108	6	0.006	113	6	0.006	571	7	0.007		521	0.006
132	6	0.006	232	6	0.006	9	6	0.006		144	0.006
139	6	0.006	234	6	0.006	97	6	0.006		552	0.006
184	6	0.006	246	6	0.006	103	6	0.006		69	0.005
240	6	0.006	549	6	0.006	126	6	0.006		108	0.005
536	6	0.006	552	6	0.006	549	6	0.006		549	0.005
545	6	0.006	98	5	0.005	69	5	0.005		547	0.005
552	6	0.006	106	5	0.005	144	5	0.005		156	0.005
144	5	0.005	132	5	0.005	151	5	0.005		98	0.005
151	5	0.005	151	5	0.005	240	5	0.005		234	0.005

REFERENCES

Adler, T., & Ben-Akiva, M. (1979). A theoretical and empirical model of trip chaining behavior. *Transportation Research Part B: Methodological, 113*(3), 243-257.

Beyer, H. L. (2011) *Geospatial Modeling Environment (GME)*. Spatial Ecology LLC. Retrieved January 2011, from http://www.spatialecology.com/gme/index.htm

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand*. Cambridge, Mass: MIT Press.

De Palma, A., Fontan, C., & Liu, R. (2001). Trip Timing and Chaining *Travel Behaviour Research: the Leading Edge*. Amsterdam: Pergamon.

Dissanayake, D., & Morikawa, T. (2002). Household travel behavior in developing countries: nested logit model of vehicle ownership, mode choice, and trip chaining. *Transportation Research Record: Journal of the Transportation Research Board, 1805*(-1), 45-52.

Dissanayake, D., & Morikawa, T. (2002). A combined revealed preference/stated preference (rp/sp) nested logit model of vehicle ownership, mode choice and trip chaining in developing countries. *Proceedings of the ICTTS 2002: Traffic and Transportation Studies; Guilin; People's Republic of China*.

Dissanayake, D., & Morikawa, T. (2010). Investigating household vehicle ownership, mode choice and trip sharing decisions using a combined revealed preference/stated preference Nested Logit model: case study in Bangkok Metropolitan Region. *Journal of Transport Geography, 18*(3), 402-410.

Fukuda, T., Kashima, S., Fukuda, A., & Narupiti, S. (2005). Analysis of car sharing application on consumer orientation and their modal selection in Bangkok. *Journal of the Eastern Asia Society for Transportation Studies, 6,* 1971-1986.

Goulias, K. G., & Kitamura, R. (1989). Recursive Model System for Trip Generation and Trip Chaining. *Transportation Research Record, 1236,* 59-66.

Hayashi, Y., Anurakamonkul, K., Okuda, T., Osman, O., & Nakamura, H. (1998). Examining the effects of a mass rapid transit system on easing traffic congestion in auto-dependent Bangkok. *Regional Development Studies: UNCRD, 4*, 65–85.

Jenks, M. (2005). Above and below the line: Globalization and urban form in Bangkok *Globalization and urban development* (pp. 311-321): Springer.

Jou, R.-C., & Mahmassani, H. S. (1997). Comparative analysis of day-to-day trip-chaining behavior of urban commuters in two cities. *Transportation Research Record: Journal of the Transportation Research Board, 1607*, 163-170.

Kenworthy, J. (1995). Automobile dependence in Bangkok: an international comparison with implications for planning policies. *World transport policy and practice, 1*(3), 31-41.

Kitamura, R. (1984). Incorporating trip chaining into analysis of destination choice. *Transportation Research Part B: Methodological, 18*(1), 67-81.

Knapp, T. A., White, N. E., & Clark, D. E. (2001). A nested logit approach to household mobility. *Journal of Regional Science, 41*(1), 1-22.

Office of Transport and Traffic Policy and Planning. *2009 OTP Annual Report*. 2009

Poboon, C. (1997). Anatomy of a traffic disaster: towards a sustainable solution to Bangkok's transport problems.

Thailand National Statistical Office. 2008 Household Socio-economic Survey.

Thailand National Statistical Office (2010). *Population Data by Sub-District*. Retrieved March 2011, from http://service.nso.go.th/nso/nsopublish/districtList/page1.htm

Wegmann, F. J., & Tae Youn, J. (1998). Trip Linkage Patterns for Workers. [Article]. *Journal of Transportation Engineering, 124*(3), 264.

Zegras, P., & Srinivasan, S. (2007). household income, travel behavior, location, and accessibility: sketches from two different developing contexts. *Transportation Research Record: Journal of the Transportation Research Board, 2038/2007*, 128-138.

CHAPTER 3

EVOLUTIONARY GAME THEORY IN SPACE: A MICRO-FOUNDATION AGENT-BASED MODEL OF CONGESTION

3.1 Introduction

Game theory has long been applied to explain the competitive/cooperative behaviors of agents based on their strategic interactions. It is the study of how people behave when considering how others might respond to such behavior. In particular, the paradox of prisoner's dilemma has been extensively examined in the field of sociology and biology as a metaphor of a simple and interesting situation when actions of rational individuals pursuing their self-interest lead to a worse outcome as a whole than if they were to cooperate. This analytical framework of prisoner's dilemma is simple, yet powerful in explaining many real-life phenomena, for instance, the study of price wars among major airlines, or how a country and its trading partners initiate trade barriers.

Further, the prisoner's dilemma also provides a basis for the analysis of governing the use of common-pool resource, also known as collective action problems— a situation when no contributions are made by rational self-interested individuals toward the production of a common goods. The common-pool resource includes not only natural but also man-made ones such as forests, irrigation systems, infrastructure, and road networks, which often face a problem of congestion or overuse when not well managed (Ostrom, 1990). Ostrom (2000) discusses experimental and empirical evidence of various design regimes of self-organization and governance to achieve the benefits of collective action. In her view, contextual factors, such as communications, trusts, governance rules, and social norms, play a key role in promoting or discouraging cooperation, which in turn affects the rate of contribution to public goods. One important question arises, however, that how these contextual factors affect and maintain cooperation through time. Taking an evolutionary theory approach, Ostorm argued, is the essential first step to address how context matters.

Most of the literature, nonetheless, often focuses on the evolution of cooperation of either two- or multiple-player iterated games, without taking into consideration the contextual space on which agents locate, migrate, and interact. Little has been done on examining the role of the spatial context on how agents adapt and interact in the prisoner's dilemma. This paper aims to fill in these gaps. It develops an analytical framework and visual representation tool to examine traffic congestion from the micro-behavioral, game theoretical perspective. Traffic congestion in public road networks is one of many examples of common-pool resource problems. As more and more motorists entering the road, they not only have direct impacts on their own travel time but also on overall travel time of all motorists in the system. In addition, local interactions among motorists—such as overtaking or yielding—are a contributing factor to traffic congestion (Levinson, 2005). As this analysis shows, negligent motorists who are motivated by their own time saving interest, if there are many of them on the road, may cause even more congestion than when all motorists drive responsibly.

The basic concept of the congestion game (Levinson, 2005) serves as a basis for the analysis of strategic interactions among agents undertaken in this study. However, this study has taken a rather different approach from the congestion model of Levinson (2005). It follows agents' adaptive behavior in Cohen *et al.* (1999) and extends the study of the evolution of n-person prisoner's dilemma games within actual geographical space, integrating an agent-based model with Geographical Information Systems (GIS). The model explicitly allows for vehicle movement and spatial interactions among agents. This spatial agent-based model captures the response strategies of autonomous individuals, while GIS contextualizes both the natural and built environments. The analytical framework serves as a micro-foundation to analyze traffic congestion, using Bangkok as a case study. Bangkok city center is one of the areas with busiest road traffic, suitable for analyzing travel behaviors and congestion.

The rest of this chapter is organized into four main sections. The review of relevant literature, including agent-based model, prisoner's dilemma, and congestion game, is in the following section. The methodology and model structure is then described in section 3.3, and simulation results are presented in section 3.4. The chapter concludes in section 3.5 with discussions of policy implications and possible extensions of the analysis.

3.2 Literature Review

Physical space plays an important role in the emergence of urban phenomena from individual choices. For example, proximity to other neighboring agents in Schelling's segregation model is one of the contributing factors to urban segregation phenomena (Schelling, 1971). In Computer Prisoner's Dilemma Tournaments, Axelrod (1984) shows that spatial structure, in addition to evolutionary strategies, is an important factor in creating cooperation. The seminal work of Nowak and May (1992) examines two simple kinds of player, those who always cooperate and those who always defect, in iterated prisoner's dilemmas with the presence of two-dimensional spatial array. They found that spatial context has indeed played an important role in agents' interactions.

Cohen *et al.* (1999) emphasize how context-preservation can promote cooperation among adaptive agents in iterated prisoner's dilemma games. The relatively stable "neighborhood" of the agents over time, known as context-preservation, is enormously contributing to the emergence and maintenance of mutual cooperation. With agents arranged in a 2-dimentional array, context-preservation creates the "shadow of the adaptive future," a situation in which the descendants of agents' current strategies will be playing with the descendants of their neighbors' current strategies. More recently, Power (2009) presents a spatial agent-based model of an N-person prisoner's dilemma to examine the cooperation among socio-geographic community. The results show that agent mobility and context preservation can lead to different effects on the evolution of cooperative behavior.

The use of game theory is considerably extensive in social sciences. In the field of urban transportation, for example, game theory has also been applied in many transportation-related problems, for example, airport landing fees (Littlechild and Thompson, 1977), truck weight limits (Hilderbrand *et al.*, 1990), yielding and merging behavior (Liu *et al.*, 2007), vehicle safety (Tay, 2002), and traffic congestion (Levinson, 2005; Zou and Levinson, 2006). Unlike most well-established models in transportation, which are highly aggregated and macroscopic, game theoretic models provide a micro-behavioral insight into agents' behavior. Traffic congestion, in particular, is profoundly a micro-behavioral problem. As Zou and Levinson (2006) put it, "congestion is a phenomena caused by multiple interacting individuals seeking to use a temporarily scarce resource in a short period of time." As such, congestion *emerges* as a result of the interaction of multiple players—or multiple vehicles—on the road. Levinson (2005) describes a congestion game as a variant of prisoners' dilemma game. At its simplest form, the congestion game involves two interacting players (or vehicles) whose payoffs represent costs associated with early arrival, late arrival, and journey delay.

Urban transportation systems are naturally complex and dynamic—in such a way that traffic behaviors change over time. The states of the systems—the past, present, or future—also highly interrelate and directly affect travel behaviors, making it impossible and impractical to represent the systems in a closed analytical form. This complex nature of urban transportation systems suggests that simulation techniques such as agent-based modeling (ABM) are suitable for analyzing urban travel behaviors. The ABM can be categorized in the *microscopic* category of traffic flow model, the model that traces movement of individual vehicles and their interactions in the transportation network (Banks, 2002). It provides a micro-foundation analytical framework for behavioral responses to interactions with other motorists or to changes in transportation policies. As such, the model explicitly addresses the complexity in urban transportation as well as behavioral reasoning and adaptability of human beings. Planners and policy makers, therefore, can simulate this artificial transportation system under different policy scenarios and explore their consequences in a timely manner.

3.2.1 Agent-based Model

Agent-based modeling is a relatively new approach to examine complex systems that emerge through interactions among autonomous agents (Macal *et al.*, 2010). By modeling the system from the ground-up (i.e., agent-by-agent and interaction-by-interaction), patterns, structure, and behaviors can be observed. Agent-based models are used across a wide range of disciplines, including computer science, biology, sociology, and economics. The analysis of Complex Adaptive System (CAS), in particular, is one of the applications of the Agent-based modeling as it focuses not only on behavior emerged from agents' interactions but also the agents' capability to adapt in response to their previous interactions.

A typical agent-based model consists of three basic components: agents, agent's relationship, and agent's environment. An agent is an autonomous, selfcontained, and uniquely identifiable individual who may be adaptive, goal-directed, or heterogeneous (Macal *et al.*, 2010). The agent relationship specifies the neighborhood of an agent based on its localized environment and the interaction mechanisms among agents, meaning that an agent interacts with the subset of all agents as oppose to the entire agents. For example, an agent may only interact with its neighbors located nearby in geographic environment or with its most socially-connected. Lastly, the agent environment provides spatial context of agent's locations in relation to other agents. The environment can represent hypothetical 2-dimensional space or actual geographic information such as GIS.

Agent-based modeling has been applied to several game theoretical analyses (see, for example, Axelrod (1984), Axelrod (1997), Nowak and May (1992), Cohen *et al.* (1999), and Power (2009)). Agent-based modeling makes it possible to study agent's interaction at the individual level with certain sets of rules or mechanisms while observing emerging social phenomena as a whole—which is exactly the foundation of prisoner's dilemma games. Bazzan *et al.* (2002), for instance, examine agents with moral sentiment in their simulation of iterated prisoner's dilemma. The authors show that agents with moral sentiments have a positive impact on social group in which they belong.

3.2.2 Prisoner's Dilemma

One aspect of game theory that perhaps has been extensively studied in economics and decision theory is the prisoner's dilemma. The classic example of the prisoner's dilemma comes from a story of two prisoners who face two choices of action: to remain silent (cooperate, C) or to testify against the other (defect, D). Without knowing each other's strategies, a prisoner must decide whether to confess or not to confess. In a generic form, the value for their judgment is presented in payoff matrix shown in Table 3.1.

Table 3.1: Payoff matrix in a classical prisoner's dilemma

		Player 2	
		Cooperate	Defect
Player1	Cooperate	R, R	S, T
	Defect	T, S	P, P

R is the payoff value if both players cooperate, while P is the value if both players defect. T and S are payoff values when a player defects alone and cooperates alone, respectively[1]. According to Axelrod (1984), what characterize the prisoner's dilemma are not the absolute values in the payoff matrix, but rather the rank ordering of the payoffs. These payoff values are such that T > R > P > S to ensure that a player always has an incentive to defect since the payoff value is greater than when both cooperate. As a result, regardless of the other's action, both prisoners choose to defect, and both are worse off than if they both cooperate. This classic example of the prisoner's dilemma precisely demonstrates how individual rationality could lead to a worse outcome for both players (Axelrod, 1984).

This classical prisoner's dilemma, in fact, has been appealing broadly to researchers in sociology, biology, economics, and computing sciences because of its simplicity yet robustness in representing very common and interesting situations when actions of self-interest individuals collectively lead to a worse outcome. It also provides a basic theoretical framework for analyzing the incentive mechanisms that encourage agents to behave in a particular way without the enforcement of central authority. Nonetheless, the shortcomings of the classical prisoner's dilemma stem from its simplicity. As discussed in Power (2010), since the prisoner's dilemma is intended to study only two person interactions, it does not represent realistic

[1] As discussed in Axelrod (1984), R – rewards for mutual cooperation; P – punishment for mutual defection; T – temptation to defect; S – sucker's payoff.

interactions of individuals. In addition, it is assumed that there is no communication among players and no memory of the past interactions, which may lead to collaborative strategies. Furthermore, as players are assumed to be rational, both players will always choose to defect to maximize their utilities.

Several extensions to the classical prisoner's dilemma introduce multiple players as well as the time into the model. Agents are also allowed to play consecutive games—known generally as Iterated Prisoner's Dilemma (IPD) —and are able to learn from their past encounters, known as Evolutionary Prisoner's Dilemma (EPD). These extensions make it possible to observe many-agent interactions over a long period of time.

3.2.3 Evolutionary Prisoner's Dilemma

An extension of the classical prisoner's dilemma presented by Axelrod (1984) is known as Evolutionary Prisoner's Dilemma (EPD). Like the classical prisoner's dilemma, communications among players are not possible in the EPD. Unlike the classical prisoners' dilemma, the EPD allows players to repeatedly choose strategies, or decision rules, based on their memory of previous encounters. Players' current actions are drawn only from their previous interactions with others; in other words, players are myopic decision makers. Evolutionary prisoner's dilemma is also applicable to the interaction with more than two players as in classical game to examine collective behavior of social groups as strategies that work well with individuals may not be appropriate for group decisions.

Similar to the classical prisoner's dilemma, participants in the EPD play several consecutive games using the payoff matrix to accumulate the scores over the game period. The player with higher score would be able to influence opponents to cooperate. The payoff matrix for EPD is shown in Table 3.2.

Table 3.2: A numerical example of payoff matrix in evolutionary prisoner's dilemma

		Player 2	
		Cooperate	Defect
Player1	Cooperate	3, 3	0, 5
	Defect	5, 0	1, 1

As players are allowed to play multiple games consecutively, their strategies specify agents' actions in any situations that may arise. There are four strategies possible, namely, always cooperating (ALLC), Tit-for-Tat (TFT), Anti-Tit-for-Tat (ATFT), and always defecting (ALLD). ALLC is a strategy that an agent always cooperates, while an agent with ALLD strategy always defects. Tit-for-Tat is a decision rule to cooperate in the first move and then do whatever the opponent does in the last encounter. In other words, if its opponent cooperates in this round, the player will cooperate in the next round. To put in layman's terms, it means "if you are nice to me this time, I will be nice to you the next time we meet." Anti-Tit-for-Tat is simply the opposite of Tit-for-Tat.

Among these four strategies, Tit-for-Tat is found to be the best strategy because it gives the highest payoffs (Axelrod, 1984; Nowak and May, 1992; Cohen *et al.*, 1999). As Power (2009) puts it, "altruism strategies tend to outperform greedy ones over the long run."

3.2.4 Evolutionary Prisoner's Dilemma In Agent-Based Model

The notion of EPD has be applied to many studies using agent-based modeling (see Cohen *et al.* (1999) and Gulyás & Platkowski (2004), for example). The strategies in the EPD can be used to characterize agent relationship in the agent-based model. Following Cohen *et al.* (1999), the ABM in this study employs a decision rule of the agent using "binary" strategy; the strategy may vary in two factors: the probability of cooperating after the other cooperate (p) and the probability of cooperating after the other defect (q). Since on the first play, there is no history of previous encounters to draw upon. The probability of agent cooperating in the first move (denoted as i) also need to be specified. With these variations in (i, p, q) combinations, agents are restricted to one of these four types:

- $i = p = 1$, $q = 1$: ALLC
- $i = p = 1$, $q = 0$: TFT
- $i = p = 0$, $q = 1$: ATFT
- $i = p = 0$, $q = 0$: ALLD

At the beginning of the simulation, agents are divided equally into these four types of strategies. As the simulation proceeds, the fraction of agents in each (i, p, q) combination varies, but no new combination is created. These binary strategies are deterministic so that agents can immediately determine the payoffs of any numbers of plays. To illustrate this, payoff matrix of four-move games is shown in Table 3.3. The sum of four-move payoffs is shown in the parenthesis.

Table 3.3: Individual and four-move payoffs from interactions of all strategies

		Player 2			
		ALLC	TFT	ATFT	ALLD
Player 1	ALLC	3333 (12)	3333 (12)	0000 (0)	0000 (0)
	TFT	3333 (12)	3333 (12)	0153 (9)	0111 (3)
	ATFT	5555 (20)	5103 (9)	1313 (8)	1000 (1)
	ALLD	5555 (20)	5111 (8)	1555 (16)	1111 (4)

Note: Sum of payoffs are shown in parenthesis

Generally, no best strategy exists independently of the strategy used by the other player. For example, ATFT and ALLD may do better than TFT and ALLC for player 1 when the opponent's (player 2's) strategy is ALLC, but it is the opposite when player 2's strategy is TFT. In this sense, the variation in opponent's strategy that a player encounters is a crucial role in the emergence of cooperative regimes. Consequently, the system dynamics do not depend directly on global proportions of strategy types, but rather on an agent's adaptive behavior and on meetings of agents, i.e., who is interacting with whom, at a local scale.

From the seminal work of Cohen *et al.* (1999), context preservation is found to be crucial for "sustaining cooperation for interaction process" for adaptive agents. According to Cohen *et al.* (1999), conditions that preserve the neighborhood of interacting players often maintain cooperation among players or allow cooperation to emerge. Context preservation also tends to increase local influencing (i.e., frequently-interacted players become similar over time) and homophily (i.e., tendency to interact among the same players). Context preservation may refer to an agent's neighborhood. The more likely that the agents will meet again, the more they cooperate. Thus, the environment on which agents interact is one of the key factors in the emergence of cooperation.

In Cohen *et al.* (1999), the basic ABM model consists of 256 agents who are categorized equally into four strategies: ALLC, TFT, ATFT, and ALLD. Each agent is randomly allocated in a 16x16 grid in torus space so that agents of any strategies have an equal chance of meeting other agents with different strategies. In each iteration, each agent plays four games with its four adjacent neighbors in the north, east, south, and west—also known as a von Neumann neighborhood. In addition, the agents are adaptive, meaning that they change their strategies based on the interactions they previously have with other agents. An agent first compares its score to its neighboring agents during the current period. If the best score of neighboring agents is higher than or equal to the agent's own score, the agent then adapt by imitating the strategy of neighboring agent with the highest score. The agent simply imitates its own strategy when its score is equal to the best score of its neighbors. At time 100, all agents adopt Tit-for-Tat strategy, which supports the earlier finding that Tit-for-Tat is the best among the other three strategies.

3.2.5 Congestion Game

Levinson (2005) sets up the game theory model for a congestion game, using a simple two-player (or vehicle) interaction. A decision made by one traveler—such as departure time or vehicle maneuver—affects the journey delay and arrival times experienced by other travelers. The model assumes that players are instrumentally rational and have perfect knowledge of the game. It is also assumed that there is common knowledge of rationality as well as consistent alignment of beliefs. A payoff matrix in the two-player congestion game represents costs by incorporating a penalty for early arrival (E), late arrival (L), and journey delay (D). Hence, both players try to minimize the costs for each scenario. Each vehicle has three options: to depart early, to depart on-time, or to depart late. If both players depart at the same time, both players have an equal chance of suffering from the incurred penalty costs, and there will be congestion. For example, if both vehicles depart early, there will be only one that arrives early while the other will suffer journey delay. Thus, each player has a 50% chance of being early or suffering journey delay (see Levinson (2005)). The payoff matrix is described in Table 3.4. As can be seen, the equilibrium solution depends on the values of E, L, and D. Several plausible solutions are discussed in Levinson (2005).

Table 3.4: Payoff matrix of two-player congestion game

		Player 2		
		Early	On-time	Late
Player 1	Early	0.5*(E+D), 0.5*(E+D)	E, 0	E, L
	On-time	0, E	0.5*(L+D), 0.5*(L+D)	0, L
	Late	L, E	L, 0	L+0.5*(L+D), L+0.5*(L+D)

Source: Levinson (2005)

The concept of the construction of the payoff matrix is simple, yet powerful, in describing driving behavior and congestion from micro-behavioral perspective. Nonetheless, it still lacks the sense of space and mobility dimension. This analysis, therefore, adopts the concept of two-player congestion game within the framework of the evolutionary prisoner's dilemma. Space and mobility are introduced and play an important role in the emergence of congestion.

3.3 Methodology

Unlike previous studies of EPD, this study employs a more realistic spatial geographic space—one where agents locate and interact— in GIS. The framework of this spatial EPD model is based on RepastCity2 model developed by Malleson (2011). Built in Repast Simphony modeling system 2.0 beta software by Argonne National Laboratory, the model comprises two major types of objects (known as "contexts" in Repast technical terminology): city context and agent context, of which their spatial locations are contained in a GIS projection. The city context represents physical geographies—or built environments—and consists of three sub-contexts: building, road, and junction contexts, the latter two of which form a road network. The building context contains building footprints, representing a spatial extent of the building configuration. The other component of the model, the agent context, contains autonomous and self-interested agents whose spatial locations are stored in a GIS projection. The model structure diagram is shown in Figure 3.1. These model components are fully described in the following sections.

One of many advantages of using Repast Simphony as a modeling platform is that it is fully equipped with a wide variety of libraries in Java, particularly simplifying programming and enabling a link between agent-based modeling and GIS. For instance, GIS topology is fully integrated in Repast Simphony. The tools used in linking GIS to agent-based modeling are in JTS Topology Suite, provided by Vivid Solutions. In addition, Repast Simphony's Graphical User Interface (GUI) simplifies a model display and setting, making it visually appealing to end users. A user can program in a pure Java language or in a built-in graphic model builder.[2] The Java programming of the agent context is included in the Appendix.

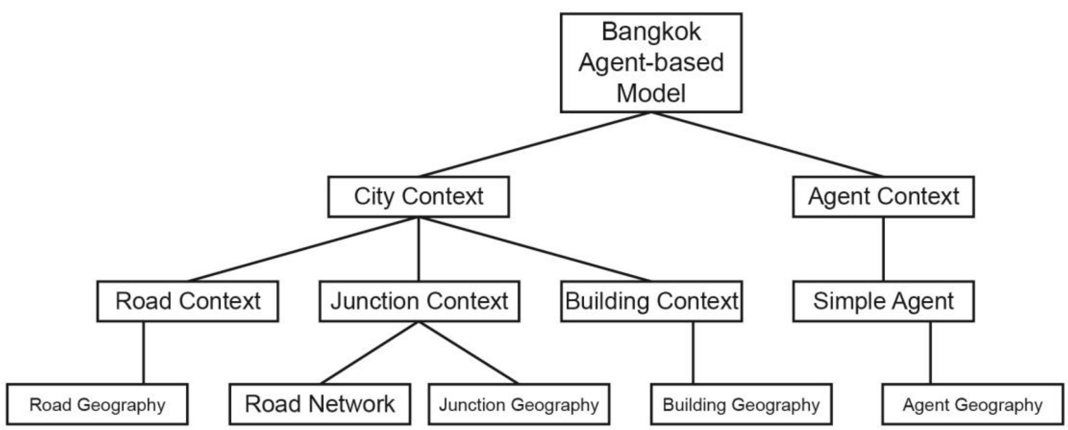


Figure 3.1: The structure of spatial agent-based model of Bangkok

[2] See Repast Documentation for more detail (http://repast.sourceforge.net/docs.html).

The study area in this study is the city center of Bangkok, Thailand. The GIS layers consist of roads, building footprints, and point locations of agents (or motorist in this case), which will be described in the following section. Although Bangkok is used in this study, the model platform is flexible and modifiable to incorporate different study areas—with different GIS inputs.

3.3.1 City Context

The city context contextualizes the actual physical surroundings—within which agents move and interact—in a GIS geography; it is comprised of road, junction, and building contexts (See Figure 3.1). Roads and buildings, which are the two GIS inputs, are prepared in ArcGIS. The road shapefile is a simple representation of road centerline, and the building shapefile is a polygon shapefile of building parameters. Using Repast "shapefile loader" tool, shapefile layers of roads and buildings are read, importing their geographies into the model. The road geography is stored in the road context, while the building geography is contained in the building context. The last component of the city context is the junction context. It contains road junction (nodes) and a road network. The junction context is constructed based on road geography from the input GIS road shapefile. During the model initialization process, topological relationships of junctions and roads are built into a road network. Through iterating all road objects, junctions are created where two roads meet, and these junctions are added to the junction context and the road network projection. Meanwhile, the edge (or arc) connecting two nodes are created and added to the road network. The relationship of road objects in the road geography and road edges in the road network projections is kept, linking the GIS projection to the network projection. By default, the map coordinate system of input GIS layers must be the geographic coordinate system.

Thus, the coordinate system of all input GIS shapefiles in the model is in World Geodetic System (WGS) 1984.

Figure 3.2: The spatial extent of City Context

The extent of city context encompasses around 4 square miles, or around 10 square kilometers, in Pathumwan district. As illustrated in Figure 3.2, roads are shown in black, and buildings are in grey. The study area covers one of the busiest areas in Bangkok, with several intersections and commercial/office buildings. For simplicity, all roads in the city context represent two-way roads with one lane in each direction.

3.3.2 Agent Context

The agent context contains all agents, which are adaptive and autonomous, playing EPD to each other. Each agent is an object in the agent context, representing a motorist on the road. The geographical locations of all agents are also acquired from a GIS input, as in the city context, in the form of a point shapefile.

Following Cohen *et al.* (1999), the strategy is deterministic, that is, it is error-free and noiseless. It is assumed that all players are rational and know perfectly the values of one's payoff matrix as well as each other's. There are four strategies: ALLC, TFT, ATFT, and ALLD. Once having interacted with its neighbors, the agent adapts to the best strategy. Suppose T denotes a time period (or the number of turn) in the simulation. In each turn, an agent can decide whether to cooperate or defect with its neighboring agents, of which the number may vary throughout the simulation period. The agent's strategy is driven by the agent's memories and lessons learnt from the previous encounter in the period $T-1$.

In period 0, population is split, with equal probability, into four types of strategies: ALLC, TFT, ATFT, and ALLD. The initial location of each individual agent is at the center of a building in the city context. In every period afterward, each individual agent randomly chooses a building and route of travel to that destination. While traveling, an agent encounters other individuals, which are considered to be the agent's neighbors if located within a certain distance. Once the agent's neighbors are determined, the agent plays multiple EPD games with its neighbors and accumulates the payoff values. Since the agent is mobile, it is possible that the agent may have no neighbors at a certain point in time. If the agent has no neighbors, the agent will not play any games in that turn. The details of the agent's movement rule are described in Section 3.3.2.1. Then, the neighborhood criteria are discussed in detail in Section 3.3.2.2. Finally, the rule of agent interaction is fully described in Section 3.3.2.3.

3.3.2.1 Agent's Movement Rule

Figure 3.3 illustrates the overall flow of agents' movement in a simulation. At the beginning of each trip, each agent chooses a random destination, which is one of the buildings in the building context. Once a destination is selected, the route is formed, and the agent travels along the road to its destination. In a simulation, the agents are allowed to move only along the roads via nodes or junctions. In other words, the agents' movement is restricted only on the road.

Following Malleson (2011), the algorithm of an agent's movement along the road involves a few steps. Suppose an agent starts at his/her home, and a random destination is selected. The first step is to identify the nearest junctions of an agent's origin position and destination. When these junctions are identified, a route is determined. To form a route between the origin and destination locations, a list of edges in the road network projection is generated using Dijkstra's shortest path algorithm. Once the route has been formed, a list of coordinates through which the agent must pass when traveling from the origin to the destination is also formed. To generate a list of coordinates, all the edges that make up the route are iterated over to find their corresponding road objects in the road geography and eventually to add all the coordinates which form the geometry of these road objects to the list. As such, the agent's movement from its origin to its destination is restricted only to roads.

After the list of coordinates along the route is generated, in each turn the agent can only move a certain distance from its current position. If the agent is currently not on a road segment, for example, the agent may be inside a building, the agent is first moved to the nearest junctions (or nodes). The maximum distance of agent movement in each tick is exogenously defined. Virtually, this defines the "speed" of agent's movement. Currently, the maximum movement distance allowed in each tick is set at 5 meters, or around 16 feet. Thus, if one tick is equivalent to one second in real-time, an agent's speed is 18 kilometer per hour, which is approximately an average speed in Bangkok city center. If an agent cannot move from one coordinate to the next in one turn (in other words, the distance between the two coordinates is greater than the maximum allowable travel distance), it will move toward the next coordinate by the defined maximum distance in one turn and continue the remaining distance toward the next coordinate in the following turn.

In addition, before beginning to move in each turn, each agent performs several checks, including determining the number of neighboring players and their locations. As shown in Figure 3.3, decisions and actions shown on gray background are decisions needed to be determined prior to moving in each turn. If an agent has at least one neighbor, it will interact with its neighbors, which is described in the following section. If not, the agent performs further checks, which are special movement features added in the model. For example, to avoid collision, an agent may pause traveling if they have a vehicle in front of them. At the intersection, an agent also temporarily stops moving when a traffic light is red and continues traveling when a traffic light turns green. For simplicity in programming, the traffic light control at intersection allows vehicles moving from one direction at a time. For instance, at an intersection, only vehicles from the east may travel while vehicles from the north, west, and south have to stop. The model also allow for the possibility of having an accident, depending on strategy of an agent. Agents with ALLD strategy have higher probability of having an accident than agents with other strategies. If an agent is involved in an accident, it temporarily stops moving.

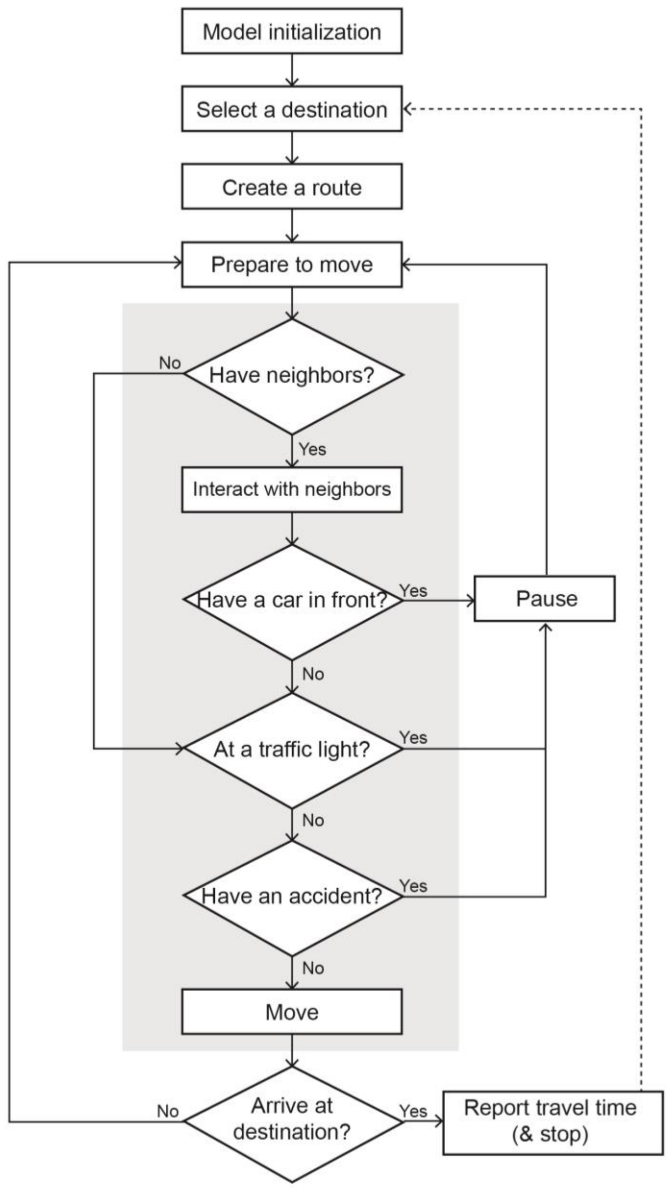


Figure 3.3: The flow diagram of agent-based model of Bangkok

3.3.2.2 Agent's Neighborhood

As previous works have shown that context preservation is an important factor for the emergence of cooperation, the agents' neighborhood is a crucial component since local influence can largely affect and sustain the cooperation. The neighborhood of an agent, in fact, can be defined in many different ways, depending on the environmental context employed in the model. If an agent is located in a 2-dimensional grid system, its neighbors can comprise four cells (von Neumann) or eight cells (Moore) surrounding the agent.[3]

Alternatively, an agent's interacting neighbors can be defined based on their proximity to other agents. If the distance between two agents is less than some threshold distance set by the analyst, these two agents are considered to be neighbors. The most commonly defined distance is straight-line or Euclidian distance. Using GIS layers for geographic locations of agents, an interaction neighborhood can be defined as agents situated within a specified radius buffer from Agent A (see Figure 3.4 (b)). Agents that are located outside of the buffered area are not considered the neighbor of Agent A, and thus will not interact with Agent A.

The major difference between grid space and GIS space is the variation in the number of agent's neighbors. While an agent in the grid may have a constant number of neighbors, four neighbors in this example, the neighbor of an agent in GIS space may vary, depending on an agent's and its neighboring agents' current position. This difference in the number of neighbors certainly affects the interaction pattern of the agent.

[3] The four-cell neighborhood is known as von Neumann neighborhood after mathematician John von Neumann, while the eight-cell neighborhood is also known as Moore neighborhood after mathematician and computer scientist Edward F. Moore.

(a) von Neumann Neighbors (b) Neighbors within 5-meter Buffer

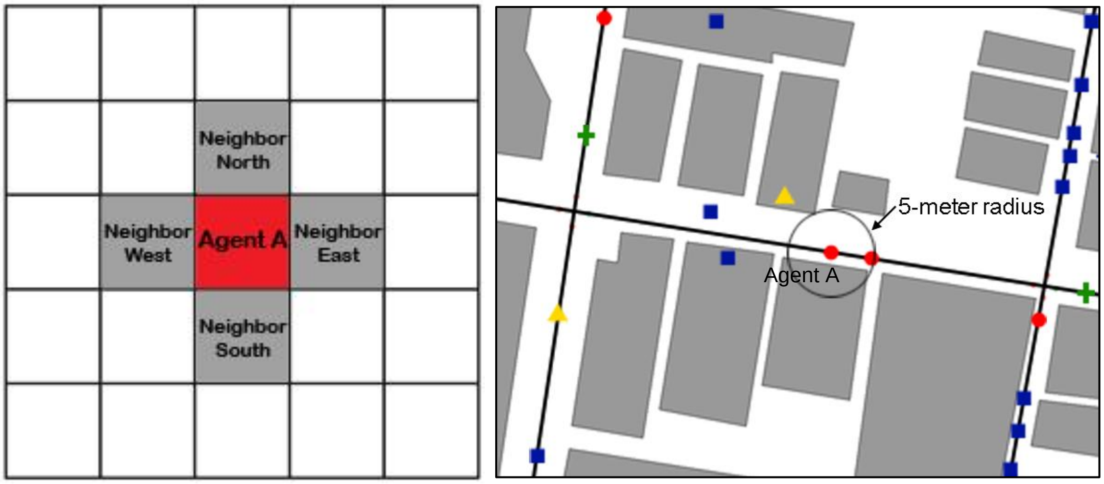


Figure 3.4: A comparison of agent's neighborhood in grid context (a) and in Geographic Information Systems (b)

In the model, agents are said to be neighbors if they are located within a certain Euclidian distance from each other. That distance is currently set to be 5 meters, which is approximately the length of a car. In every turn, as an agent moves along the road, its neighbor would change, depending on the agent's current position. It is also possible that at some turns an agent may not have a neighbor at all. An agent itself is always included as its neighbor. So, in every turn, an agent will always have at least one neighbor, that is the agent itself.

3.3.2.3 Agent's Interaction Rule

After its neighbors are determined, an agent interacts with its neighbors to accumulate payoff—representing travel costs. In each turn, and agent will play N number of EPD games with its neighbor, where N denotes the number of neighbors. Since every agent is assumed to be rational and know perfectly the value in the payoff matrix, the payoff is deterministic. The agent's strategy determines how it interacts with its neighbors.

The emergence of cooperation depends largely on local influence, that is, "the mix of encounter." Unlike in Cohen (1999), however, the number of neighbors of an agent may vary because of the movement of the agent.

The construction of a payoff matrix adopts the concept of congestion game of Levinson (2005). At the simplest form, players may choose to cooperate (driving responsibly, following traffic regulation, for example) or to defect (such as violating traffic regulations or drive negligently). Each player's decision takes into account the penalty—measured in terms of the value of time loss—of journey delay (C_d), involving in an accident (C_a), and being fined by traffic police (C_f). Table 3.5 shows a payoff matrix of the congestion game. When both players choose to cooperate, each encounter an equal chance of incurring costs of journey delay. If a player chooses to cooperate while the other defects, this player has to bear the cost of journey delay as well as the cost of having an accident with some probability. The other player that defects not only bears the cost of potential accidents but also the possibility of being fined by the traffic police because of its reckless driving behaviors, for example, moving traffic violation. If both players defect, each will bear all cost of journey delay, accidents, and being fined. The elements in the payoff matrix are defined as follows:

$$F_1 = 0.5*C_d, \tag{1}$$

$$F_2 = C_d + (P_a*C_a), \tag{2}$$

$$F_3 = (P_a*C_a) + (P_f*C_f), \tag{3}$$

$$F_4 = (0.5*C_d) + (P_a*C_a) + (P_f*C_f), \tag{4}$$

where C_d denotes costs of journey delay = 0.0083 THB/sec,

C_a denotes costs of accident = 770 THB/case,

C_f denotes traffic violation fines = 400 THB,

P_a denotes the probability that an accident can occur in each turn

= 0.00000004, and

P_f denotes the probability of receiving a traffic violation fine in each turn

= 0.00000012.

The numerical values in the payoff matrix are derived from stylized facts, statistics reports, and previous studies related to transportation in Bangkok. As agents make decisions in every encounter, these values are normalized in a monetary value per second of time. The cost of journey delay per second (C_d) is estimated to be 0.0083 THB or around US $0.0003. It derives from the study of Dissanayake and Morikawa (2010) that estimates the hourly value of time of Bangkok commuters is 30 THB, which gives the value of 0.0083 THB per second. The cost of an accident is calculated from a recent statistical report from the Royal Thai Police Central Information Technology Center. In 2011, there were 4,669 traffic accident cases reported to the police, and it was estimated that the damage from these accidents was 3,598,000 THB, or around 770 THB (US $25) per case ($C_a$). An average fine for traffic violation in Bangkok is 400 THB, thus the value of C_f. The probability of accident occurring (P_a) is calculated from the ratio of the number of cars involved in accidents to total number of cars registered in Bangkok in 2011. Finally, the probability of receiving a traffic violation fine (P_f) is derived from the ratio of the number of cases the fine issued (Dailynews, 2012) to the total number of vehicle registered in Bangkok. The value in the payoff matrix from these stylized facts is shown in Table 3.6. Since the payoff represents costs, the value is shown in negative numbers. As can be seen, the matrix is one example of the prisoner's dilemma; each agent individually has an incentive to defect, but it is more socially optimal if both cooperate.

Table 3.5: The payoff matrix of congestion game

		Player 2	
		Cooperate	Defect
Player1	Cooperate	F_1, F_1	F_2, F_3
	Defect	F_3, F_2	F_4, F_4

Table 3.6: The numerical payoff matrix of congestion game

		Player 2	
		Cooperate	Defect
Player1	Cooperate	-0.00415, -0.00415	-0.00830, -0.00008
	Defect	-0.00008, -0.00830	-0.00423, -0.00423

3.4 Simulation Results

To examine congestion as a consequence of motorists' interactions, the analysis consists of simulations with three different initial conditions: (1) when all motorists always cooperate, (2) when all always defect, and (3) when all four strategies are mixed. A case when all agents always cooperate serves as a baseline when all motorists behave nicely, while a condition when all always defect serves as an extreme case when everyone behaves badly. The hypothesis tested here is that when an increasing number of motorists behave recklessly (i.e., choose to defect) to save travel time, inadvertently creating more congestion. The model simulation allows for testing such hypotheses. Congestion is evaluated using average travel time in every 50-tick interval. For each initial condition, a simulation is run for 5,000 ticks. The travel time in milliseconds is reported and recorded when agents reach its destination and complete a trip.

In the simulation graphic interface, each type of agent is symbolized differently both in terms of colors and shapes. Agents with ALLC, TFT, ATFT, and ALLD are shown in blue circle, green cross, red square, and yellow triangle, respectively. If an agent changes its strategy, its graphic representation also changes. Figure 3.5 illustrates the simulation interface at time 0 and 50 for the mixed strategy initial condition. As can be seen, all agents start at the internal point inside buildings and gradually move toward the nearest road and continue moving on the road afterward.

(A) (B)

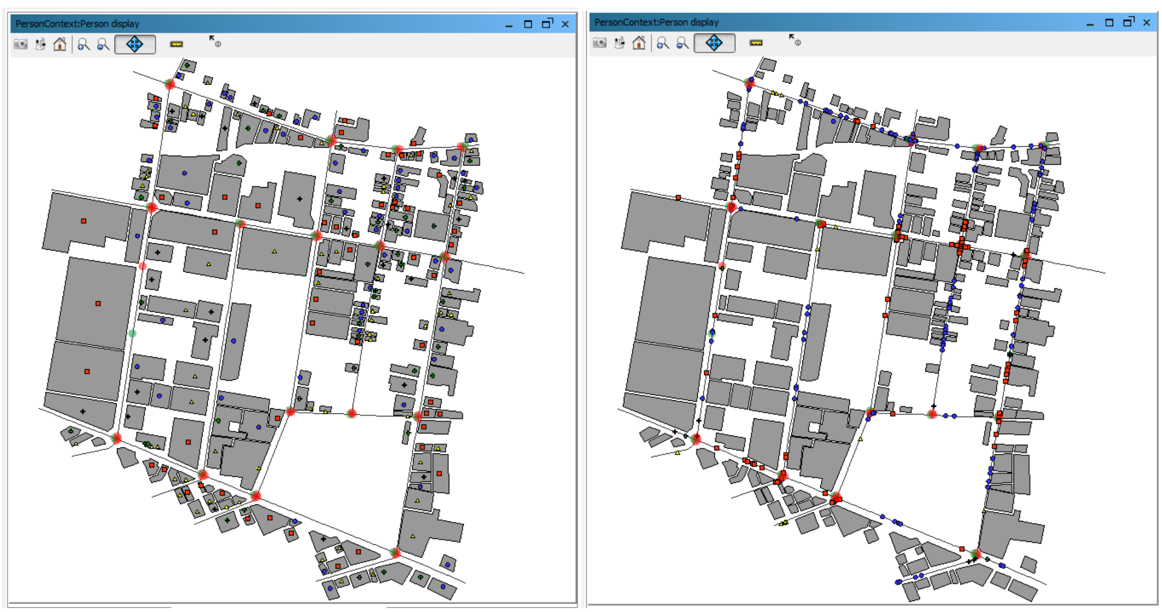


Figure 3.5: Simulation interface at tick 0 (A) and 50 (B)

Figure 3.6 illustrates average travel time for each initial condition. As can be seen, although the results are based on one simulation for each condition, a condition with all ALLD agents overall has the highest average travel time. On average, the travel time in scenario with ALLD agents is 102,629.72 milliseconds, while the travel time of ALLC and mixed strategies are 79,921.02 and 85,469.56 milliseconds, respectively. It suggests that when pursuing its own interest, an agent who always defects makes the society as a whole worse off. By driving negligently to avoid traffic, agents paradoxically create more congestion, and congestion emerges as a result of spatial interaction of motorists.

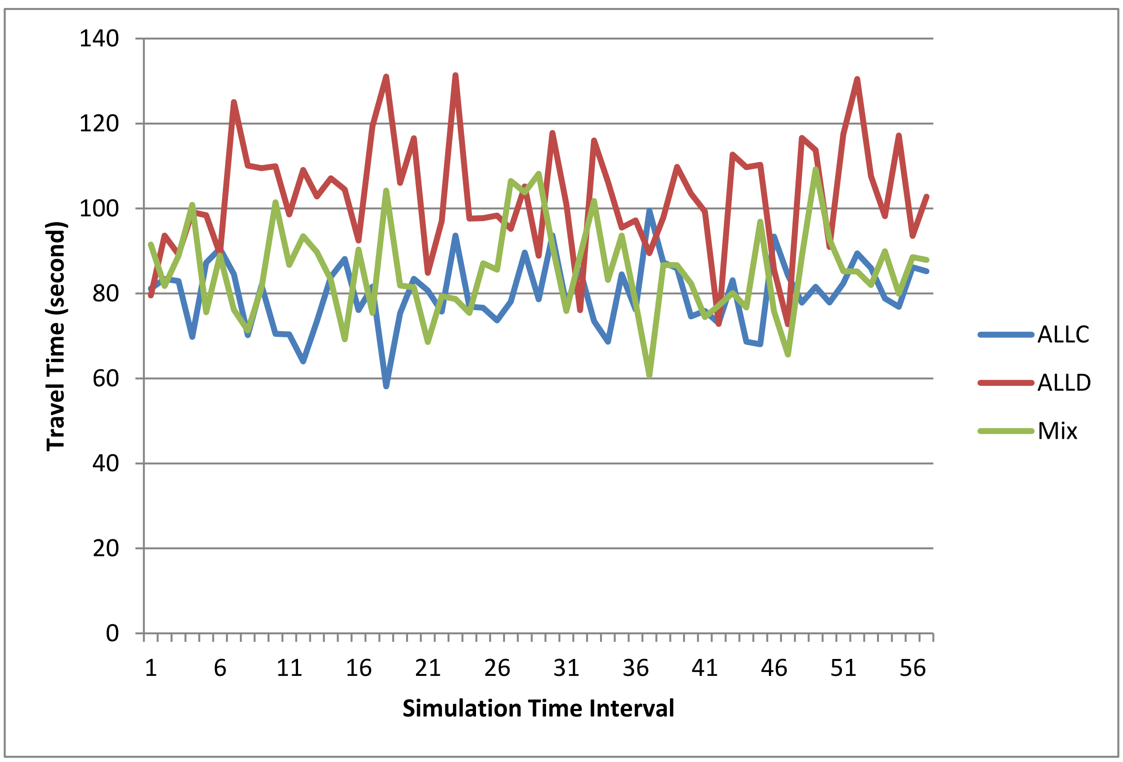


Figure 3.6: Average travel time with three different initial conditions

3.5 Conclusions and Further Studies

Prisoner's dilemma is one extension of Game Theory that has long been used to analyze phenomena when individuals acting in their self-interest become worse off than if they cooperate. Evolutionary Prisoner's Dilemma (EPD), in particular, incorporates adaptive agents in iterated games. In the EPD, context preservation is found to play a key role in the emergence of cooperation since cooperation tends to emerge if players are likely to encounter each other again in the future. Therefore, for each player the interaction dynamic at the local scale is more important than what happens at the global scale. In this sense, the neighborhood of agents is a key factor in the emergence of cooperation.

This paper develops visual representation tools to analyze strategic behaviors in game theoretic perspective when spatial interactions and movement are possible. It extends the conceptual framework of EPD to examine road users' behaviors in the setting of roads in Bangkok city center. The analysis assumes that while traveling an agent's decisions take into account costs associated with journey delay, accidents, and traffic violation fines. This paper argues that motorists violate traffic regulations—intentionally act negligently—because of the belief that doing so save travel times. Paradoxically, if enough motorists share the belief the result is even more congestion. In comparison to scenarios when more drivers behave responsibly, overall traffic is much slower when all motorists behave irresponsibly—or always defect. Congestion, thus, emerges as a result of strategic time-saving behavior.

This modeling framework of travel behavior can be extended in several possible ways. Further extensions include incorporating road networks in the model and allow for agent's heterogeneity such as types of vehicle or characteristics of drivers. The model can also potentially incorporate the number of policy analyses such as an increase in traffic violation fines, effectiveness of traffic law enforcement, and congestion pricing.

APPENDIX

Agent Context

```
public class PersonContext extends DefaultContext<SimplePerson> {

    public PersonContext() {
        super("PersonContext"); // This must match the context name in
context.xml

        if (ContextCreator.debug) System.out.println("PersonContext: building
person context and projections");

        // Create the PersonGeography projection:
        GeographyParameters<SimplePerson> geoParams = new
GeographyParameters<SimplePerson>();
        Geography<SimplePerson> personGeography =

GeographyFactoryFinder.createGeographyFactory(null).createGeography("PersonGe
ography", this, geoParams);

        /* Read in the shapefile data and add agents to the context and
geography */
        File personFile = null;
        ShapefileLoader<SimplePerson> personLoader = null;
        try {
            personFile = new File(GlobalVariables.PEOPLE_SHAPEFILE);
            personLoader = new ShapefileLoader<SimplePerson>(
                    SimplePerson.class, personFile.toURL(), personGeography,
this);
            personLoader.load();
        } catch (java.net.MalformedURLException e) {
            System.err.println("Malformed URL exception when reading
peopleshapefile.");
            e.printStackTrace();
        }
    }
}
```

Simple Agent

```
public class SimplePerson  {

    private int id;
    private String name;
    private Route route;    // A Route object controls where this person goes
and moves them around the city.

    private String category;    // an attribute read from the agent shapefile
(agent or light)
    private String direction;
    private String stopsign;    // an attribute read from the agent shapefile
    private int NIntersect;     // an attribute read from the agent shapefile
for the number of traffic lights at an intersection
    private int number;         // an attribute read from the agent shapefile
for the ID number of traffic light

    private int looprun1= 0;
    private int looprun2= 0;

    private House destinationHouse;
    private Coordinate destinationCoord;

    public static double currentTime;
    private double startTime;   // trip start time
    private double endTime;     // trip end time

    // return total travel time once an agent finishes a trip
    public int sumTravelTime= 0;
    public double getSumTravelTime(){
        return sumTravelTime;
    }
    // return total number of trip
    public int sumNumTrip= 0;
    public int getSumNumTrip(){
        return sumNumTrip;
    }

    // accident related variables
    private double prAccident= Math.random();
    private double timeAccident; // used to record a time when accident
occurs (that is when this.accident becomes true
    private boolean accident= false;
    private int pauseInterval= 5000;

    Iterable<SimplePerson> otherMotorist;

    public SimplePerson() {
    }

    public void step() {
        currentTime = System.currentTimeMillis();
        try {
                this.getCurrentLocation();

                if (this.category.equals("agent")) {
                    if (this.route==null)  {// create a new route if the
route is null
```

```
                        House h =
ContextCreator.getHouseContext().getRandomObject();
                        this.route = new Route(this,

ContextCreator.getHouseGeography().getGeometry(h).getCentroid().getCoordinate
(), h);
                        startTime= System.currentTimeMillis();
                        this.destinationHouse= h;
                        this.destinationCoord=
ContextCreator.getHouseGeography().getGeometry(h).getCentroid().getCoordinate
();
                    }
                    if (!this.route.atDestination()){   // if an agent does
not arrive at destination, keep moving
                        if (this.getNumNeighbors() > 1) {
                            this.game();
                        }
                        if (this.hasCarInFront()==false &&
this.atTrafficLight()==false){ // travel if this agent has no car in front
and is not at traffic light
                            if (this.hasAccident()==false){
                                if (this.Atype== ALLD){

this.route.travel(1.05*GlobalVariables.TRAVEL_PER_TURN);
                                } else if (this.Atype== ATFT || this.Atype==
TFT ){

this.route.travel(1.025*GlobalVariables.TRAVEL_PER_TURN); // This will move
the person towards their destination
                                } else
{this.route.travel(GlobalVariables.TRAVEL_PER_TURN);}
                            } else {
                                if (this.getNumNeighbors() > 1){
                                    this.route.travel(0);
                                } else if (this.Atype== ALLD){

this.route.travel(1.05*GlobalVariables.TRAVEL_PER_TURN);
                                } else if (this.Atype== ATFT || this.Atype==
TFT ){

this.route.travel(1.025*GlobalVariables.TRAVEL_PER_TURN); // This will move
the person towards their destination
                                } else
{this.route.travel(GlobalVariables.TRAVEL_PER_TURN);}
                            }
                        }
                    } else { // if an agent arrives at destination, report
travel time and create a new trip
                        endTime= System.currentTimeMillis();
                        sumNumTrip= sumNumTrip+1;
                        sumTravelTime= sumTravelTime + (int)(endTime-
startTime) ;

                        // create a new route
                        House h =
ContextCreator.getHouseContext().getRandomObject();
                        this.route = new Route(this,

ContextCreator.getHouseGeography().getGeometry(h).getCentroid().getCoordinate
(), h);
                        startTime= System.currentTimeMillis();
                        this.destinationHouse= h;
```

```
                        this.destinationCoord=
ContextCreator.getHouseGeography().getGeometry(h).getCentroid().getCoordinate
();
                        }
                }
            }
            catch (Exception e) {
                    System.err.println("Person "+this.id+" ("+this.name+") had an
error while travelling:");
                    e.printStackTrace();
            }
            if (ContextCreator.debug) System.out.println("TOTAL STEP
TIME("+this.id+"): ("+(System.currentTimeMillis()-
SimplePerson.currentTime)+"ms)\n\n");

    }

// ********************************************************************** //
// ************************ Evolutionary Game ************************ //
// ********************************************************************** //

      // Constants for agent strategies
      final int ALLC = 0;   // shown as red circle
      final int TFT = 1;    // shown as blue cross
      final int ATFT = 2;   // shown as green rectangle
      final int ALLD = 3;   // shown as black triangle

      // Constants for actions
      final int C = 1;             // Cooperate
      final int D = 0;             // Defect
      // Conversion array from action to String
      final String[] actionToString = {"D", "C"};

      // Action matrices
      // The x_PARAMS[] matrices define the behavior for each of the four
strategies
      // (i.e., ALLC, TFT, ATFT, ALLD, respectively).
      public final int I_PARAMS[] = {C, C, D, D}; // First action
      public final int P_PARAMS[] = {C, C, D, D}; // Action if opponent
cooperated
      public final int Q_PARAMS[] = {C, D, C, D}; // Action if opponent
defected

      // The agent's internal variables
      int x, y;                             // The player's location on the
grid
      private SimplePerson other;           // Handle to the opponent
      private int Atype;                    // The agent's strategy
      int newType;                          // The agent's calculated
strategy during adaptation
      //int[][] prefs= { {1,5},             // Payoff / Preference matrix
      //          {0,3} };                      // (this one is PD)
      double[][] prefs= { {-42.3,-1.0},             // Payoff / Preference
matrix
              {-83,-41.5} };
      int action;                           // The current action
      int memory;                           // The opponent's last action
      double cumulPayoff;                       // The agent's cumulated
payoff
      int numPlays;                         // Number of games played (for
statistics)
```

```java
	Iterable<SimplePerson> otherList ;			// List of opponents
	private Coordinate currentLocation= null;	// Current location

	// a dummy variable used to count each type
	// return 1 if being an agent of that type, 0 otherwise
	int ALLCd= 0;
	int TFTd= 0;
	int ATFTd= 0;
	int ALLDd= 0;

	  // initial number of each type (= (total number of agent)/4)
	  public static int IntialNum= 52;

	  public static int IntNumALLC= IntialNum;
	  public static int IntNumTFT= IntialNum;
	  public static int IntNumATFT= IntialNum;
	  public static int IntNumALLD= IntialNum;

	// Storing the opponent's last action
	// (Same as that in SimpleIPD.)
	public void remember() {
	  memory = other.action;
	}


////////////////////////////////////////////////////////////////////////

	// The agent's decision-making.
	// This is the main behavioral method that uses one of the x_PARAMS[][]
	// matrices depending on whether the move is the first one or the other
player
	// cooperated. The actual move is also dependent on the agent's type.
	// The move is recorded in the player's action variable.
	//
	// The play method is identical to that in SimpleIPD except that the
numPlay
	// counter has to be incremented. (It is identical to that in
GraphIPD.)
	public void play() {
	  // Keeping track of the number of games played
	  numPlays++;
//	 if (time == 1)
//	    action = I_PARAMS[Atype];	// This call is moved to
initialType()
//	  else
	    if (memory == C)
	      action = P_PARAMS[Atype];
	  else
	      action = Q_PARAMS[Atype];
	}

////////////////////////////////////////////////////////////////////////

	// Administering the payoff.
	// Updates the cumulative payoff by adding the payoffs from the
preference
	// matrix as a function of both sides' moves .
	// (Same as that in GraphIPD.)
	public void addPayoff() {
	  cumulPayoff =  (cumulPayoff - prefs[action][other.action]);
	}
```

```
//////////////////////////////////////////////////////////////////////////

      // In this pair of methods the player updates the strategy to that of
the
      // most successful player encountered (based on the otherList).
      // (They are the same as those in GraphIPD, except the randomization
      // of the neighbor-list in adapt().)

      // Calculating the agent's new strategy
      public void adapt() {
            // We use double-buffering by storing the result in newType which
will later
            // be used to update type (but we can't to do that until we've
gone through
            // all players):
            newType = Atype;

            // We use uniform random number to draw a random number
            // and with probability pAdapt we let the player execute
            // the body of method
            if (Math.random() < GlobalVariables.pAdapt ) {

                // We make sure we are not biased by the order in which we
check the
                // neighbors
                //Collections.shuffle((List<?>) otherList);

                double bestPayoff= getAveragePayoff();
                for (SimplePerson act : otherList) {
                    if (act.id != this.id){
                        double payoff= act.getAveragePayoff();
                        if (payoff > bestPayoff) {
                            bestPayoff= payoff;
                            // Set the new type to the best known (up to now)
                            newType = act.Atype;
                        }
                    }
                }
            }
      }

      // Complete double-buffering by updating the strategy type
      // to the recently calculated value
      public void updateType() {
        Atype = newType;
      }

//////////////////////////////////////////////////////////////////////////

      // Helper function returning the agent's average pay off.
      public double getAveragePayoff() {
        if (numPlays == 0)
            //return -1.0;              // Extreme value as an 'error
message'
            return 0.0;              // Extreme value as an 'error message'
        else
          return (double)cumulPayoff/(double)numPlays;
      }

//////////////////////////////////////////////////////////////////////////

      // An agent playing a game with its neighbor
```

```java
        public void game() {

            this.getNeighbors();
            // 1. if an agent has neighbor that is not itself
            // play a game with each neighbor
            if (getNumNeighbors() > 1){
                for (SimplePerson act : otherList) {
                    if (act.id != this.id &&
                            this.category.equals("agent") &&
                            act.category.equals("agent")){ // only play with
other agent
                        this.other = act;
                        this.play();
                        this.remember();
                        this.addPayoff();

                        // 2. adapt to new strategy
                        this.adapt();
                        this.updateType();
                    }
                }
            }
        }

          // get a type of an agent
          public int getType() {
              return Atype;
          }

          /**
           * @param id the iD to set
           */
          public void setType(int type){
              this.Atype = type;
          }

          /**
           * set an agent's type randomly.
           * This method is called at time 0.
           */
          public void resetRandomType() {
              double r= Math.random();
              if (this.category.equals("light")){
                  Atype= 99; // set initial type of the traffic light to 99
              }
              else {
                  if (r >= 0 && r < 0.25) {
                      Atype= ALLC;
                  }
                  else if (r >= 0.25 && r < 0.5){
                      Atype= TFT;
                  }
                  else if (r >= 0.5 && r < 0.75){
                      Atype= ATFT;
                  } else {
                      Atype= ALLD;
                  }

                  // set agent's initial action and memory
                  this.action = I_PARAMS[Atype];
                  //this.remember();
              }
```

```
        }

        public void setType(){
            if (this.category.equals("light")){
                Atype= 99; // set initial type of the traffic light to 99
            }
            else Atype= ALLD;
            //else Atype= ALLC;
        }

        /**
         * set an agent's current location to Coord
         */
        public void setCurrentLocation(Coordinate coord) {
            this.currentLocation= coord;
        }

        /**
         * = an agent's current location in coordinates
         */
        public Coordinate getCurrentLocation() {
            Geography<SimplePerson> agentGeography =
ContextCreator.getPersonGeography();
            this.currentLocation=
agentGeography.getGeometry(this).getCoordinate();
            return currentLocation;
        }

        /**
         * find an agent's neighbors and add neighbors to otherList
         */
        public void getNeighbors(){
            // get an agent's geography
            GeometryFactory geomFac= new GeometryFactory();
            Geography<SimplePerson> agentGeography =
ContextCreator.getPersonGeography();
            Point coordGeom = geomFac.createPoint(this.currentLocation);
            this.otherList=
agentGeography.getObjectsWithin(coordGeom.buffer(GlobalVariables.PERSON_BUFFE
R).getEnvelopeInternal());
        }

        // = the number of neighbor
        public int getNumNeighbors(){
            this.getNeighbors();
            ArrayList<SimplePerson> tmpList = new ArrayList<SimplePerson>();
            for (SimplePerson act : otherList) {
                 tmpList.add(act);
             }
            return tmpList.size() ;
      }

        // count each type of agent
        /** = 1 if this agent is of type ALLC, 0 otherwise
         */
        public int getALLCd() {
            if (this.Atype == 0){
                return 1;
            }
            else return 0;
        }
```

```java
        /** = 1 if this agent is of type TFT, 0 otherwise
         */
        public int getTFTd() {
            if (this.Atype == 1){
                return 1;
            }
            else return 0;
        }

        /** = 1 if this agent is of type ATFT, 0 otherwise
         */
        public int getATFTd() {
            if (this.Atype == 2){
                return 1;
            }
            else return 0;
        }

        /** = 1 if this agent is of type ALLD, 0 otherwise
         */
        public int getALLDd() {
            if (this.Atype == 3){
                return 1;
            }
            else return 0;
        }


// ******************************************************************* //
// ************************ Congestion Model ************************ //
// ******************************************************************* //
    /**
     * A method to check if any neighbors are moving in the same direction
     * @return true if there is at least one neighbor moving in the same
direction, false otherwise.
    */
        public boolean isCongestedNext(){
            // First, get neighbors and its current location.
            ArrayList<SimplePerson> tmpList = new ArrayList<SimplePerson>();
            Geography<SimplePerson> agentGeography1 =
ContextCreator.getPersonGeography();

            //compare the movement direction to its neighbors
            if (this.getNumNeighbors() > 1 && this.route != null){
              for (SimplePerson act : otherMotorist) {

                    Coordinate coord=
agentGeography1.getGeometry(act).getCoordinate();
                     // compare the movement direction of the agent and its
neighbor
                     if (    act.route != null &&
                             Route.angle(this.currentLocation,
this.route.route.get(0))== Route.angle(coord, act.route.route.get(0))){

                         if (this.route.route.get(0).x <
act.route.route.get(0).x &&
                                 this.route.route.get(0).y <
act.route.route.get(0).y){ //this.travelDirection() == "Q1" &&
                             tmpList.add(act);
                         }
                         else if (this.route.route.get(0).x >
act.route.route.get(0).x &&
```

```
                                this.route.route.get(0).y <
act.route.route.get(0).y){ // this.travelDirection() == "Q2" &&
                            tmpList.add(act);
                        }
                        else if (this.route.route.get(0).x >
act.route.route.get(0).x &&
                                this.route.route.get(0).y >
act.route.route.get(0).y){ //this.travelDirection() == "Q3"  &&
                            tmpList.add(act);
                        }
                        else if (this.route.route.get(0).x <
act.route.route.get(0).x &&
                                this.route.route.get(0).y >
act.route.route.get(0).y){ // this.travelDirection() == "Q4" &&
                            tmpList.add(act);
                        }
                    }
                }
            }
            return tmpList.size() > 0 ? true : false;
        }


        public boolean hasCarInFront(){
            // get an agent's geography
            this.travelDirection();

            GeometryFactory geomFac= new GeometryFactory();
            Geography<SimplePerson> agentGeography =
ContextCreator.getPersonGeography();
            Point coordGeom = geomFac.createPoint(this.currentLocation);

            // get agents within a buffer
            Iterable<SimplePerson> otherMotorist=
agentGeography.getObjectsWithin(coordGeom.buffer(0.0001).getEnvelopeInternal(
));

            ArrayList<SimplePerson> tmpList = new ArrayList<SimplePerson>();
             for (SimplePerson act : otherMotorist) {
                 //if (RoadContext.onRoad(this.getCurrentLocation()) ){
                     act.travelDirection();
                     if (this.id != act.id &&
this.direction.equals(act.direction) ){
                         // case 1
                         if (this.direction == "Q1" &&
                                 (this.currentLocation.x <
act.currentLocation.x )) { //|| this.currentLocation.y <
act.currentLocation.y
                             //System.out.println("this agent has " + act.id
+" in front of it in Q1 direction");
                             tmpList.add(act);
                         }
                         // case 2
                         if (this.direction == "Q2" && this.currentLocation.x
> act.currentLocation.x) { //&& this.route.route.get(0).x >
act.route.route.get(0).x
                             //System.out.println("this agent has " + act.id
+" in front of it in Q2 direction");
                             tmpList.add(act);
                         }
                         // case 3
                         if (this.direction == "Q3" &&
```

```
                                  (this.currentLocation.x >
act.currentLocation.x )) { //|| this.currentLocation.y >
act.currentLocation.y
                            // System.out.println("this agent has " + act.id
+" in front of it in Q3 direction");
                             tmpList.add(act);
                         }
                         // case 4
                         if (this.direction == "Q4"  &&
this.currentLocation.x < act.currentLocation.x) { //&&
this.route.route.get(0).x < act.route.route.get(0).x
                             //System.out.println("this agent has " + act.id
+" in front of it in Q4 direction");
                             tmpList.add(act);
                         }
                     }
                // }
             }

            return tmpList.size() > 0 ? true : false;
        }


        /**
         * A method to check the movement direction in quadrants
         * @return Q1, Q2, Q3, Q4.
        */
        public void travelDirection(){
            if (this.category.equals("agent") ) {
                this.getCurrentLocation();
                if (!this.route.atDestination() && this.route != null) {
                    if (this.route.route.get(0).x > this.currentLocation.x &&
this.route.route.get(0).y > this.currentLocation.y ){
                        this.direction= "Q1";
                    }
                    else if (this.route.route.get(0).x <
this.currentLocation.x && this.route.route.get(0).y > this.currentLocation.y
){
                        this.direction= "Q2";
                    }
                    else if (this.route.route.get(0).x <
this.currentLocation.x && this.route.route.get(0).y < this.currentLocation.y
){
                        this.direction= "Q3";
                    }
                    else {this.direction= "Q4";}
                }
            }
        }


        /**
         * A method that return whether an agent is having an accident.
         * @return true or false.
        */
        public boolean hasAccident() {
            if (accident==true){
                prAccident= Math.random()+0.7;
            } else {
                prAccident= Math.random();
            }
            if (this.Atype==ALLD){
```

```
                accident= (prAccident > 0.90 ) ? true : false;  //previously
0.93
            } else if (this.Atype == TFT || this.Atype == ATFT){
                accident= (prAccident > 0.96 ) ? true : false;
            } else {
                accident= (prAccident > 0.99 ) ? true : false;
            }
            return accident;
        }

        /**
         * A method to set traffic light. The traffic lights at intersection
         * alternate between red and green.
        */
            public void trafficLight(){
                double currenttime = System.currentTimeMillis();
                int time= (int) ( currenttime - ContextCreator.startTime);
                int interval= 5000; // time interval for green light
                int n= 4;           // number of traffic lights at
intersections
                if (this.category.equals("light")) {

                    ////// Four traffic lights //////
                    if (this.getNIntersect()==4){
                        // case 4Q1
                        if (this.stopsign.equals("Q1")) {
                            // set a traffic light to red
                            if (time >= looprun1*interval && time <
(n*looprun1*interval)+interval ){
                                this.direction= this.getStopsign();
                                this.Atype= 98;     //for visualization (98=
red)
                                looprun1= looprun1+1;
                            }
                            // set a traffic light to green
                            if (time >= (n*looprun2*interval)+interval &&
time < (n*looprun2*interval)+(n*interval) ){
                                this.direction= "NA";
                                this.Atype= 99;     //for visualization (99=
green)
                                looprun2= looprun2+1;
                            }
                        }
                        // case 4Q2
                        if (this.stopsign.equals("Q2")) {
                            // set initial cycle
                            if (time >= 0 && time < 2*interval) {
                                this.direction= this.getStopsign();
                                this.Atype= 98;     //for visualization
                            }

                            // set a traffic light to red
                            if (time >= looprun1*interval+interval && time <
(n*looprun1*interval)+interval+interval ){
                                this.direction= this.getStopsign();
                                this.Atype= 98;     //for visualization (98=
red)
                                looprun1= looprun1+1;
                            }
                            // set a traffic light to green
```

```
                                if (time >=
(n*looprun2*interval)+interval+interval && time <
(n*looprun2*interval)+(n*interval)+interval ){
                                    this.direction= "NA";
                                    this.Atype= 99;     //for visualization (99=
green)
                                    looprun2= looprun2+1;
                                }
                            }

                            // case 4Q3
                            if (this.stopsign.equals("Q3")) {
                                // set initial cycle
                                if (time >= 0 && time < interval) {
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization
                                }
                                if (time >= 2*interval && time < 3*interval) {
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization
                                }

                                // set a traffic light to red
                                if (time >= looprun1*interval+2*interval && time
< (n*looprun1*interval)+interval+2*interval ){
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization (98=
red)
                                    looprun1= looprun1+1;
                                }
                                // set a traffic light to green
                                if (time >=
(n*looprun2*interval)+interval+2*interval && time <
(n*looprun2*interval)+(n*interval)+2*interval ){
                                    this.direction= "NA";
                                    this.Atype= 99;     //for visualization (99=
green)
                                    looprun2= looprun2+1;
                                }
                            }

                            // case 4Q4
                            if (this.stopsign.equals("Q4")) {
                                // set initial cycle
                                if (time >= 0 && time < interval) {
                                    this.direction= "NA";
                                    this.Atype= 99;     //for visualization (99=
green)
                                }
                                if (time >= interval && time < 4*interval) {
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization
                                }


                                // set a traffic light to red
                                if (time >= looprun1*interval+3*interval && time
< (n*looprun1*interval)+interval+3*interval ){
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization (98=
red)
                                    looprun1= looprun1+1;
```

```
                    }
                    // set a traffic light to green
                    if (time >=
(n*looprun2*interval)+interval+3*interval && time <
(n*looprun2*interval)+(n*interval)+3*interval ){
                        this.direction= "NA";
                        this.Atype= 99;     //for visualization (99=
green)
                        looprun2= looprun2+1;
                    }
                }
                }

            ////// Two traffic lights //////
            else if (this.getNIntersect()==2){
                // case 2Q1
                if (this.stopsign.equals("Q1")) {
                    // set a traffic light to red
                    if (time >= looprun1*interval && time <
(2*looprun1*interval)+interval ){
                        this.direction= this.getStopsign();
                        this.Atype= 98;     //for visualization (98=
red)
                        looprun1= looprun1+1;
                    }
                    // set a traffic light to green
                    if (time >= (2*looprun2*interval)+interval &&
time < (2*looprun2*interval)+(2*interval) ){
                        this.direction= "NA";
                        this.Atype= 99;     //for visualization (99=
green)
                        looprun2= looprun2+1;
                    }
                }
                // case 2Q3
                if (this.stopsign.equals("Q3")) {
                    // set a traffic light to red
                    if (time >= looprun1*interval+interval && time <
(2*looprun1*interval)+interval+interval ){
                        this.direction= this.getStopsign();
                        this.Atype= 98;     //for visualization (98=
red)
                        looprun1= looprun1+1;
                    }
                    // set a traffic light to green
                    if (time >=
(2*looprun2*interval)+interval+interval && time <
(2*looprun2*interval)+(2*interval)+interval ){
                        this.direction= "NA";
                        this.Atype= 99;     //for visualization (99=
green)
                        looprun2= looprun2+1;
                    }
                }
            }
            ////////// 3 traffic lights ////////////
            else {
                if (this.getNumber()==11) {
                    // case 3Q2
                    if (this.stopsign.equals("Q2")) {
                        // set a traffic light to red
```

```
                                if (time >= looprun1*interval && time <
(3*looprun1*interval)+interval ){
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization
(98= red)
                                    looprun1= looprun1+1;
                                }
                                // set a traffic light to green
                                if (time >= (3*looprun2*interval)+interval &&
time < (3*looprun2*interval)+(3*interval) ){
                                    this.direction= "NA";
                                    this.Atype= 99;     //for visualization
(99= green)
                                    looprun2= looprun2+1;
                                }
                            }
                            // case 3Q3
                            if (this.stopsign.equals("Q3")) {
                                // set initial cycle
                                if (time >= 0 && time < interval) {
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization
                                }
                                // set a traffic light to red
                                if (time >= looprun1*interval+interval &&
time < (3*looprun1*interval)+interval+interval ){
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization
(98= red)
                                    looprun1= looprun1+1;
                                }
                                // set a traffic light to green
                                if (time >=
(3*looprun2*interval)+interval+interval && time <
(3*looprun2*interval)+(3*interval)+interval ){
                                    this.direction= "NA";
                                    this.Atype= 99;     //for visualization
(99= green)
                                    looprun2= looprun2+1;
                                }
                            }

                            // case 3Q4
                            if (this.stopsign.equals("Q4")) {
                                // set initial cycle
                                if (time >= interval && time < 2*interval) {
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization
                                }
                                // set a traffic light to red
                                if (time >= looprun1*interval+2*interval &&
time < (3*looprun1*interval)+interval+2*interval ){
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;     //for visualization
(98= red)
                                    looprun1= looprun1+1;
                                }
                                // set a traffic light to green
                                if (time >=
(3*looprun2*interval)+interval+2*interval && time <
(3*looprun2*interval)+(3*interval)+2*interval ){
                                    this.direction= "NA";
```

```
                                        this.Atype= 99;     //for visualization
(99= green)
                                        looprun2= looprun2+1;
                                    }
                                }
                            }

                            else if (this.getNumber()==6) {
                                // case 3Q1
                                if (this.stopsign.equals("Q1")) {
                                    // set a traffic light to red
                                    if (time >= looprun1*interval && time <
(3*looprun1*interval)+interval ){
                                        this.direction= this.getStopsign();
                                        this.Atype= 98;     //for visualization
(98= red)
                                        looprun1= looprun1+1;
                                    }
                                    // set a traffic light to green
                                    if (time >= (3*looprun2*interval)+interval &&
time < (3*looprun2*interval)+(3*interval) ){
                                        this.direction= "NA";
                                        this.Atype= 99;     //for visualization
(99= green)
                                        looprun2= looprun2+1;
                                    }
                                }
                                // case 3Q2
                                if (this.stopsign.equals("Q2")) {
                                    // set initial cycle
                                    if (time >= 0 && time < interval) {
                                        this.direction= this.getStopsign();
                                        this.Atype= 98;     //for visualization
                                    }
                                    // set a traffic light to red
                                    if (time >= looprun1*interval+interval &&
time < (3*looprun1*interval)+interval+interval ){
                                        this.direction= this.getStopsign();
                                        this.Atype= 98;     //for visualization
(98= red)
                                        looprun1= looprun1+1;
                                    }
                                    // set a traffic light to green
                                    if (time >=
(3*looprun2*interval)+interval+interval && time <
(3*looprun2*interval)+(3*interval)+interval ){
                                        this.direction= "NA";
                                        this.Atype= 99;     //for visualization
(99= green)
                                        looprun2= looprun2+1;
                                    }
                                }

                                // case 3Q4
                                if (this.stopsign.equals("Q4")) {
                                    // set initial cycle
                                    if (time >= interval && time < 2*interval) {
                                        this.direction= this.getStopsign();
                                        this.Atype= 98;     //for visualization
                                    }
                                    // set a traffic light to red
```

```
                                        if (time >= looprun1*interval+2*interval &&
time < (3*looprun1*interval)+interval+2*interval ){
                                            this.direction= this.getStopsign();
                                            this.Atype= 98;     //for visualization
(98= red)
                                            looprun1= looprun1+1;
                                        }
                                        // set a traffic light to green
                                        if (time >=
(3*looprun2*interval)+interval+2*interval && time <
(3*looprun2*interval)+(3*interval)+2*interval ){
                                            this.direction= "NA";
                                            this.Atype= 99;     //for visualization
(99= green)
                                            looprun2= looprun2+1;
                                        }
                                    }
                                }

                                else if (this.getNumber()==3 || this.getNumber()==12)
{
                                    // case 3Q1
                                    if (this.stopsign.equals("Q1")) {
                                        // set a traffic light to red
                                        if (time >= looprun1*interval && time <
(3*looprun1*interval)+interval ){
                                            this.direction= this.getStopsign();
                                            this.Atype= 98;     //for visualization
(98= red)
                                            looprun1= looprun1+1;
                                        }
                                        // set a traffic light to green
                                        if (time >= (3*looprun2*interval)+interval &&
time < (3*looprun2*interval)+(3*interval) ){
                                            this.direction= "NA";
                                            this.Atype= 99;     //for visualization
(99= green)
                                            looprun2= looprun2+1;
                                        }
                                    }
                                    // case 3Q3
                                    if (this.stopsign.equals("Q3")) {
                                        // set initial cycle
                                        if (time >= 0 && time < interval) {
                                            this.direction= this.getStopsign();
                                            this.Atype= 98;     //for visualization
                                        }

                                        // set a traffic light to red
                                        if (time >= looprun1*interval+interval &&
time < (3*looprun1*interval)+interval+interval ){
                                            this.direction= this.getStopsign();
                                            this.Atype= 98;     //for visualization
(98= red)
                                            looprun1= looprun1+1;
                                        }
                                        // set a traffic light to green
                                        if (time >=
(3*looprun2*interval)+interval+interval && time <
(3*looprun2*interval)+(3*interval)+interval ){
                                            this.direction= "NA";
```

```
                                        this.Atype= 99;     //for visualization
(99= green)
                                        looprun2= looprun2+1;
                                    }
                                }

                                // case 3Q4
                                if (this.stopsign.equals("Q4")) {
                                    // set initial cycle
                                    if (time >= interval && time < 2*interval) {
                                        this.direction= this.getStopsign();
                                        this.Atype= 98;     //for visualization
                                    }
                                    // set a traffic light to red
                                    if (time >= looprun1*interval+2*interval &&
time < (3*looprun1*interval)+interval+2*interval ){
                                        this.direction= this.getStopsign();
                                        this.Atype= 98;     //for visualization
(98= red)
                                        looprun1= looprun1+1;
                                    }
                                    // set a traffic light to green
                                    if (time >=
(3*looprun2*interval)+interval+2*interval && time <
(3*looprun2*interval)+(3*interval)+2*interval ){
                                        this.direction= "NA";
                                        this.Atype= 99;     //for visualization
(99= green)
                                        looprun2= looprun2+1;
                                    }
                                }
                            }

                            else if (this.getNumber()==4 || this.getNumber()==10)
{
                                // case 3Q1
                                if (this.stopsign.equals("Q1")) {
                                    // set a traffic light to red
                                    if (time >= looprun1*interval && time <
(3*looprun1*interval)+interval ){
                                        this.direction= this.getStopsign();
                                        this.Atype= 98;     //for visualization
(98= red)
                                        looprun1= looprun1+1;
                                    }
                                    // set a traffic light to green
                                    if (time >= (3*looprun2*interval)+interval &&
time < (3*looprun2*interval)+(3*interval) ){
                                        this.direction= "NA";
                                        this.Atype= 99;     //for visualization
(99= green)
                                        looprun2= looprun2+1;
                                    }
                                }
                                // case 3Q2
                                if (this.stopsign.equals("Q2")) {
                                    // set initial cycle
                                    if (time >= 0 && time < interval) {
                                        this.direction= this.getStopsign();
                                        this.Atype= 98;     //for visualization
                                    }
                                    // set a traffic light to red
```

```
                                if (time >= looprun1*interval+interval &&
time < (3*looprun1*interval)+interval+interval ){
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;      //for visualization
(98= red)
                                    looprun1= looprun1+1;
                                }
                                // set a traffic light to green
                                if (time >=
(3*looprun2*interval)+interval+interval && time <
(3*looprun2*interval)+(3*interval)+interval ){
                                    this.direction= "NA";
                                    this.Atype= 99;      //for visualization
(99= green)
                                    looprun2= looprun2+1;
                                }
                            }

                            // case 3Q3
                            if (this.stopsign.equals("Q3")) {
                                // set initial cycle
                                if (time >= interval && time < 2*interval) {
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;      //for visualization
                                }
                                // set a traffic light to red
                                if (time >= looprun1*interval+2*interval &&
time < (3*looprun1*interval)+interval+2*interval ){
                                    this.direction= this.getStopsign();
                                    this.Atype= 98;      //for visualization
(98= red)
                                    looprun1= looprun1+1;
                                }
                                // set a traffic light to green
                                if (time >=
(3*looprun2*interval)+interval+2*interval && time <
(3*looprun2*interval)+(3*interval)+2*interval ){
                                    this.direction= "NA";
                                    this.Atype= 99;      //for visualization
(99= green)
                                    looprun2= looprun2+1;
                                }
                            }
                        }
                            }

                    }
            }


        /**
         * A method to check if an agent is at the traffic light
         * @return true or false.
         */
        public boolean atTrafficLight(){
            GeometryFactory geomFac= new GeometryFactory();
            Geography<SimplePerson> agentGeography =
ContextCreator.getPersonGeography();
            Point coordGeom = geomFac.createPoint(this.currentLocation);

            // get agents within a buffer
```

```
            Iterable<SimplePerson> otherMotorist=
agentGeography.getObjectsWithin(coordGeom.buffer(0.0001).getEnvelopeInternal(
));
            ArrayList<SimplePerson> tmpList = new ArrayList<SimplePerson>();
             for (SimplePerson act : otherMotorist) {
                 act.trafficLight();
                 if (act.category.equals("light") &&
this.direction.equals(act.direction)) {
                     tmpList.add(act); //add to tmpList only the traffic
light
                 }
             }
            return tmpList.size() > 0 ? true : false;
        }

// ******************************************************************** //
    /**
     * @return the iD
     */
    public int getId() {
        return id;
    }

    /**
     * @param id the iD to set
     */
    public void setId(int id) {
        this.id = id;
    }

    /**
     * @return the name
     */
    public String getName() {
        return name;
    }

    /**
     * @param name the name to set
     */
    public void setName(String name) {
        this.name = name;
    }

    // = this agent id, name, and current location
    @Override
    public String toString() {
        return "SimplePerson [id= " + this.id + ", type= " + this.Atype + ",
at " + this.currentLocation + "]";
    }

    public void setCategory(String category) {
        this.category = category;
    }

    public String getCategory() {
        return category;
    }

    public void setStopsign(String stopsign) {
        this.stopsign = stopsign;
    }
```

```java
    public String getStopsign() {
        return stopsign;
    }

    public void setNIntersect(int nIntersect) {
        NIntersect = nIntersect;
    }

    public int getNIntersect() {
        return NIntersect;
    }

    public void setNumber(int number) {
        this.number = number;
    }

    public int getNumber() {
        return number;
    }


}
```

REFERENCES

Axelrod, R. M. (1984). *The evolution of cooperation*. New York: Basic Books.

Banks, J. H. (2002). *Introduction to transportation engineering*. McGraw-Hill.

Bazzan, A. L. C., Bordini, R. H., & Campbell, J. A. (2002). Evolution of agents with moral sentiments in an iterated prisoner's Dilemma exercise. In S. Parsons, P. Gmytrasiewicz & W. Michael (Eds.), *Game Theory and Decision Theory in Agent-based Systems* (pp. 43-64). Norwell: Kluwer Academic.

Cohen, M. D., Riolo, R. L., & Axelrod, R. (1999). The emergence of social organization in the prisoner's dilemma: How context-preservation and other factors promote cooperation. *Santa Fe Institute Working Papers*, 99-01-002.

Dissanayake, D., & Morikawa, T. (2010). Investigating household vehicle ownership, mode choice and trip sharing decisions using a combined revealed preference/stated preference Nested Logit model: case study in Bangkok Metropolitan Region. *Journal of Transport Geography*, 18(3), 402-410.

Gulyás, L., & Płatkowski, T. (2004). On Evolutionary 3-Person Prisoner’s Dilemma Games on 2-D Lattice Cellular Automata. In P. Sloot, B. Chopard & A. Hoekstra (Eds.), (Vol. 3305, pp. 831-840): Springer Berlin / Heidelberg.

Hilderbrand, M. Prentice, B., Lipnowski, I. (1990). Enforcement of highway weight regulations: a game theoretic model. Journal of the Transportation Research Forum 30(2), 442-452.

Levinson, D. (2005). Micro-foundations of congestion and pricing: A game theory perspective. *Transportation Research Part A: Policy and Practice*, *39*(7-9), 691-704.

Littlechild, S. C., & Thompson, G. F. (1977). Aircraft landing fees: a game theory approach. *The Bell Journal of Economics*, 8, 186-203.

Liu, H., Xin, W., Adam, Z., & Ban, J. (2007). *A game theoretical approach for modeling merging and yielding behavior at freeway on-ramp section*. Paper presented at the 17th International Symposium on Transportation and Traffic Theory, London, UK.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation, 4*(3), 151-162.

Malleson, N. (2011). *RepastCity: A Demo Virtual City*. Retrieved August 2011 from http://portal.ncess.ac.uk/wiki/site/mass/repastcity.html

Nowak, M. A., & May, R. M. (1992). Evolutionary games and spatial chaos. *Nature*, 359(6398), 826-829.

Ostrom, E. (1990). *Governing the Commons: The Evolution of Institutions for Collective Action*. Cambridge University Press, Cambridge.

Ostrom, E. (2000). Collective Action and the Evolution of Social Norms. *Journal of Economic Perspectives*, 14, 137-158.

Power, C. (2009). A spatial agent-based model of n-person Prisoner's Dilemma cooperation in a socio-geographic community. *Journal of Artificial Societies and Social Simulation, 12*(1), 8.

Repast Organization for Architecture and Design (2008). *Repast Documentation*. http://repast.sourceforge.net/docs/docs_main.html

Repast Organization for Architecture and Design (2010). *Repast Simphony 2.0 Beta*. Retrieved August 2011 from http://repast.sourceforge.net/.

Royal Thai Police Central Information Technology Center (2011). *Accident Statistics Report*. Retrieved May 2012 from http://statistic.police.go.th/traff_main.htm. (in Thai)

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of mathematical sociology, 1*(2), 143-186.

Tay, R. (2002). The prisoner's dilemma and vehicle safety: Some policy implications. *Journal of Transport Economics and Policy*, 491-495.

Traffic Violation Tickets Issued in Bangkok Plummeted by 70% (2012, September 22). Dailynews. Retrieved from http://www.dailynews.co.th/thailand/155061 (in Thai).

Zou, X., & Levinson, D. (2006). A multi-agent congestion and pricing model. *Transportmetrica*, 2(3), 237-249.