The Impact of Peer-to-peer Ridesharing on Travel Mode: Empirical Study of Uber Effects on Travel Mode in Seattle

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Abstract

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Peer-to-peer ridesharing, as a new travel mode, could be a potential solution to two major transportation issues: congestion and air pollution by reducing inefficient driving and promoting public transit ridership. Uber, as one of the leader transport network company, launched in San Francisco in 2010 and expanded around the world. This new travel mode could affect transportation situation, however, its impact is still not clear. The results from this study are based on current research to test the impact of this new travel mode in Seattle through the difference-in-differences analysis. This thesis could help policymakers to forecast the future transportation demand by estimating the commuters of different commute mode choice within the effects of this new travel option on commuting.

According to past studies, peer-to-peer ridesharing could reduce driving alone demand but its impact on public transit is not clear. This thesis analyzes the impacts of peer-to-peer ridesharing on driving alone and public transit to commuting controlling for socio-demographic factors. In addition, it studies the different impact of peer-to-peer ridesharing within the different socio-demographic factors through Cluster analysis.

This thesis collects 143 census tract data of Seattle from 2010-2016 as the study sample. Through the difference-in-differences analysis and the dynamic coefficient robustness test, this thesis measures the impacts of peer-to-peer ridesharing in Seattle. Then, this thesis divides 143 census tracts into three clusters through the K-mean Cluster analysis and studies the different impact of peer-to-peer ridesharing on commute mode across these clusters.

Key word: peer-to-peer ridesharing, difference-in-differences analysis, transportation demand

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1 Introduction

In America, commuting through driving alone is a major part of daily travel behavior. There are more than 255 million cars in America, nearly 797 cars per thousand people. While private cars have many benefits, they are the main causes of many problems in the United States today (Johansson, 2017). It contributes major part of air pollution emissions (Kijewska, 2016; Office of the Assistant Secretary for Transportation Policy, 2009). Transportation is also a big expense for American families. The average American household devotes 18% of income to driving around (Bailey, 2004). This could be a large expense especially for people in lower-income class. They have to spend a lot of money on owning and maintenance a car instead of improving life quality (Ortega, 2005; Waller, 2005; Ortega, 2005).

In most cities, local governments have suggestions on how their cities are managing transportation demand to reduce car ownership. Transportation Demand Management (TDM) became a popular policy as a solution to transportation issues, i.e. transportation congestion and air pollution. Governments and transit agencies have identified a range of policy tools that can be used to improve the efficiency of transportation service. They usually determine to improve public transit infrastructure and reduce individual driving demand, however, these solutions are not efficient. According to past academic studies, there could be two reasons. One is low residential density areas that public transit cannot efficiently serve (Victoria Transport Policy Institute, 2018). The second is that privately owned vehicles are better and more flexible than almost any other forms of public transit (Downs, 2004). In many cities, inefficient transportation planning causes higher traffic demand, while local government cannot afford enough transportation services for citizens due to limited budget and other social issues (Waller, 2005). Thus most bus services are overcrowded, undependable, slow, and inconvenient uncoordinated.

Peer-to-peer ridesharing, as a new transportation mode, may contribute to TDM and solve transportation issues. In general, peer-to-peer ridesharing could be regarded as a special ridesharing which is any means of transportation in which multiple people use the same car, truck, van, or vehicle to arrive at a similar destination (Riderster, 2013). Peer-to-peer ridesharing is a service that riders could request real-time transportation service. This travel mode is growing fast, around 20% annual increase of pick-up in 2017 (Soper, 2017). Uber is the first company offering this new travel mode in 2010, following with Lyft, Wingz and the like (Rayle, 2014).

Peer-to-peer ridesharing is quite different from past travel modes. This new travel mode including the "private" characteristics of driving alone and "public factor" of transit could be a potent solution to transportation issues by reducing the rate of driving alone. This new travel mode is cheaper than owning a personal car and much faster than the major of public transit (Altshuler, 2017; Cyganski, 2016; Huang, 2004). With the combination of "driving alone" and "public transit", this new travel mode could be more efficient in low residential density neighborhood and provide a more comfortable travel mode than public transit (Victoria Transport Policy Institute, 2018). Therefore, this new travel mode could promote TDM purposes, promoting public transit and reduce driving alone demand.

1.1 Research Objectives

The main objective of this thesis is to help researchers define the impacts of peer-to-peer ridesharing and measure its impacts on travel mode choice within the different socio-demographic factors. This thesis examines whether such peer-to-peer ridesharing could effectively alter travel mode choice. It could contribute to the literature on new travel mode by evaluating its influences on driving alone and public transit ridership. In addition, the results from this study could provide a detailed analysis of different types of areas in a city within the different socio-demographic factors, a consideration not focused on current literature. Therefore, it looks into the impact of peer-to-peer ridesharing on different commute mode choice with the following points:

1. Define the impact of peer-to-peer ridesharing on commute mode in Seattle;

2. Explore the different impacts within different social-demographic factors of Seattle.

1.2 Research Hypotheses

This thesis focuses on analyzing the impact of peer-to-peer ridesharing on commute mode choice in Seattle. The change in peer-to-peer ridesharing is the Uber launch time point in Seattle. This change is hypothesized to be the cause of commuting mode shift. e.g. from individual driving to public transportation or in turn. The degree of change for different areas would differ according to different socio-demographic factors, as well as their current transportation commute mode choice. The following sections describe the research hypotheses and relevant research questions in this thesis.

1.2.1 Peer-to-peer Ridesharing Could Reduce Driving alone

During the past decades, researchers have done a lot of studies about this new transportation mode. Generally, peer-to-peer ridesharing could reduce congestion and driving alone (Jung, 2018; Shaheen, 2012; Shared-Use Mobility Center, 2016). In these studies, peer-to-peer ridesharing could reduce car ownership and therefore alleviate congestion over time. It could also provide an alternative mode choice for those who do not want to drive to work and lack of public transit accessibility.

1.2.2 Peer-to-peer Ridesharing Could Promote Public Transit Ridership

This new travel mode could also encourage more people to take public transit (Shared-Use Mobility Center, 2016). This could be a travel choice for the last mile to expand the public transit service area. Although this new faster travel mode could be an alternative choice of public transit, because of its higher price than traditional public transit, it may not affect the low-income commuters as a major part of public transit ridership (Martin, 2011). In some studies, the low-income class places a relatively low value on commute time so that they do not want to spend extra expense for faster service.

1.2.3 Effects of Peer-to-peer Ridesharing Vary across Neighborhoods with Different Socioeconomic Characteristics

The effect of peer-to-peer ridesharing could be different within socio-demographic factor because of differences in the elasticity. According to past studies, income, gender, and age could be significant. Economically, because of the higher expense than public transit, this new travel mode may have differential effects across different income classes (AlisarAoun, 2013; Chan, 2012; Neoh, 2018; Park, 2018; Hallock, 2015; Amirkiaee, 2018; Deakin, 2014). Peer-to-peer ridesharing may not contribute to the low-income class who usually live in neighborhoods with less public transit access and more elastic on travel time. The low-income class put less value on their schedule and could be sensitive to the extra expense of peer-to-peer ridesharing. Gender and age could also be significant. In some studies, the areas with higher male percentage and lower median age could be more driving alone (Chandra, 2005). In addition, current travel behavior, car ownership, average commuting time and subjective travel attitude could also affect commute mode choice (Morckel & Terzano, 2014).

1.3 Thesis Outline

The next chapter, Chapter 2, focuses on past academic studies to define the measurement of commute mode in this thesis, peer-to-peer influences on commute choice, and the impact of socio-demographic factors on commute choice. Chapter 3 entails the data statistical description. The sample is 143 census tract data of Seattle from 2010 to 2016. Related data is from the American Community Survey 5-year estimates. Chapter 4 focuses research methodology in this thesis: difference-in-differences analysis, dynamic coefficient robustness test, k-mean cluster analysis and other goodness fit test. Dynamic coefficient robustness analysis is to measure the multi-collinearity to test the difference-in-differences analysis. To define the impact of peer-to-peer ridesharing within different socio-demographic factors like income and commuter through different mode, K-mean cluster analysis is used to classify census tract. Chapter 5 provides the results: overall analysis and special analysis for three different clusters results. Chapter 6 assesses the impacts on commuting mode choice in Seattle based on the results. Chapter 7 is the last Chapter about conclusion and limitations.

2 Literature Review

2.1 Commute Choice

Daily commute could be divided into rigid travel and flexible travel (Zhou, 2006). Such rigid travels as going to work, school, etc., due to the repetition of their daily routines, would form less flexible travel mode. In this case, the choice of travel mode of rigid travel is easy to determine. Rigid travel is also a major part of the daily commute. In this thesis, rigid travel to work is the measurement of the commute mode choice.

The specific travel mode for residents when traveling should be related to many factors. It is related to the willingness to travel, expenses, and the level of transportation infrastructure construction (Li W. , 2017). Any change in any one of these factors may result in travel mode change. Providing a more diversified travel mode could reduce the use of personal cars and reduce the demand for car ownership (Clewlow R. , 2017; Cyganski, 2016; Boll, 2018; Transport and Environment, 2017; University College London, 2011). In addition, there are a number of academic studies focused on the effect of neighborhood characters on reducing car use for commuting particularly. They found that individuals living in a mixed land use neighborhood drive less than those who live in low density and suburban area (Frank, 1994).

Other studies, however, have the different opinion about the effects of built environment. They think while the built environment could affect commute and commute length, socio-economic characters and lifestyle could also be important. The terrain, features, and traffic volume should also be important factors. Additionally, the relationship between the built environment and commute choice may not be a direct factor. Dr. Schwanen studied the differences in commuting method choices in terms of inconsistency between residential areas and neighbor types. He found the influence of neighborhood type inconsistencies interacts with commuters' beliefs about personal driving (Schwanen, 2005).

The average commuting time to work is also significant. Commuters through driving alone would spend less commuting time compared to the commuters through public transit (Wang, 2013; Jaffe, 2014). In turn, the commuters living farther from the workplace may prefer to drive alone to work. Besides, the effect of the policy could not be ignored (Rotaris, 2014; Hendricks, 2007; Victoria

Transport Policy Institute, 2017; Winters, 2010). In general, through promoting public transit and setting limitations of driving alone, TDM could reduce driving alone significantly.

2.2 The Impact of Peer-to-peer Ridesharing

Peer-to-peer ridesharing inevitably affects the travel behavior and change the habits (Huang, 2004). This new travel mode improves the urban traffic situation, reduce congestion, and ease air pollution. Peer-to-peer ridesharing can reduce the consumption of non-renewable energy sources, and eliminate harmful pollution caused by automobiles. It could promote more economical modes of travel and enhance awareness of environmental protection (Pojani, 2015). It could increase the utilization rate of the car and reduce the vehicle ownership, which contributes to the improvement of urban traffic (Clewlow R. , 2017). In addition, commuters using peer-to-peer ridesharing may use also public transit more, own fewer cars and spend less money on transportation (Shared-Use Mobility Center, 2016; Jung, 2018). Public transit and peer-to-peer ridesharing mode should complement one another by serving different trip types. Public transit could be a major mode for daily commute and peer-to-peer ridesharing is most commonly used for recreation (Shared-Use Mobility Center, 2016; Li Z. , 2016; Shaheen, 2012).

A report published by University of California, Davis, offers a different view that peer-to-peer ridesharing could not change the personal attitude to own a car (Clewlow R. , 2017). In addition, with more efficiency usage, peer-to-peer ridesharing could reduce the fixed cost of vehicle use (Victoria Transport Policy Institute, 2018). This more efficient car usage leads to promote car ownership and reduce public transit demand (Altshuler, 2017; Circella, 2018). Specifically, peer-to-peer ridesharing attracts people away from bus service and light rail services (Clewlow R. M., 2017; Kodransky, 2014; Lewis, 2017; Linden, 2016; Smith O. , 2018; Liedtke, 2018; Mchugh, 2016).

It is worth noting that studying the short-term and long-term effects of these new travel modes, and the equivalence of commuting modes - such as travel modes to be replaced and why people are moving from previous modes – is a complex task. Although there is extensive information on these transportation network companies, Uber and Lyft, on the Internet, due to the privacy protection of customers, it is still difficult to obtain relevant data, including average travel time, average waiting time, destination and pick-up address, and driver information. It is still important to understand the impact of these new commuting modes on traffic. Without proper data, it may be difficult to clearly measure these effects.

2.3 Socio-demographic Factors and Peer-to-peer Ridesharing

The growth of the peer-to-peer ridesharing has shifted consumption habits of individuals and how they approach transportation (Kitchel, 2017). Peer-to-peer ridesharing mode could reduce transportation congestion and air pollution (Li Z. , 2016; Shaheen, 2012; D.Contreras, 2017), but its influences are affected by socio-demographic factors. There are a lot of studies that focus on travel mode across socio-demographic factors (Kelly, 2005; Schwanen, 2005; Krol, 2005; Abou-Zeid, 2011). Low-income groups are affected by the extra expense. They have more flexible schedule and be more sensitive to the extra expense so that they may not choose peer-to-peer ridesharing. The median-income groups tend to have less flexible work schedules, so that they tend to place a relatively high value on commute time (Shaheen, 2012). They may choose peer-to-peer ridesharing because they could be willing to spend a little more money on much faster transportation service.

The empirical studies indicate the similar opinion. In San Francisco, a survey based on a 6281 respondent shows an overall decline in public transit use that was statistically significant (Martin, 2011; Gehrke, 2018). In this survey, these peer-to-peer ridesharing customers are median-income class and live in neighborhoods with abundant public transit access. In addition, a study in New York presents over 70% peer-to-peer ridesharing pickup locations originate in Manhattan (Fischer-Baum, 2015). This could also be an evidence for median-income class travel through peer-to-peer ridesharing more.

Theoretically and empirically, lower income commuters tend to be more sensitive to the expense and could change their behavior. Besides, other socio-demographic factors could also affect commute mode choice and the peer-to-peer ridesharing influence on commute mode (Papaioannou, 2015; Clewlow R. M., 2017; Park, 2018). In general, there could be more driving alone to work in areas with lower median ages and higher male percentages because the old may not have the ability to drive around and because male commuters prefer to drive around more (Morckel & Terzano, 2014).

2.4 Summary

According to past literature, travel mode could be affected by several factors: built environment, socio-demographic characters, new travel mode choice, and transportation policy. For instance, higher road density and lower residential density promote car ownership and better public transportation accessibility promote public transit ridership. The socio-demographic factors may directly determine the commute choice in some circumstances, such as the income, lifestyle preference, age and gender, the purpose of travel, travel distance, and travel expenses. Commuters with low levels of income tend to choose transport modes with lower expense and slower speeds. They are reluctant to exchange higher economic expenditures for time savings. In addition, the effect of transportation policies such as TDM could also be significant. According to past studies, these policies could reduce driving alone demand by improving public transit infrastructure and raising the driving alone cost.

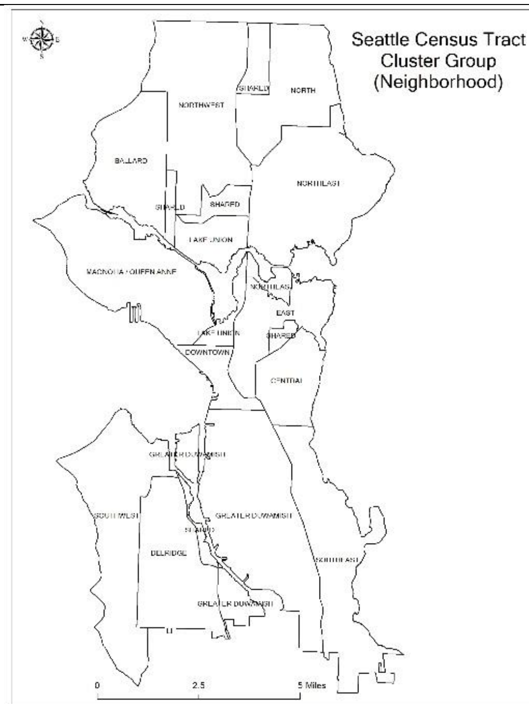
New travel mode may also be important by providing more commute choice to shift commuters' attitudes. Based on current transportation theories, most commuters choose to travel in a way to achieve passenger space movement with minimum cost and high quality (Pojani, 2015). The "cost" here mainly refers to travel expenses, while the "high quality" is speed supplemented by safety, comfort, punctuality, and reliability. Peer-to-peer ridesharing is less "cost", compared to driving alone, and more "high quality", compared to public transit, could shift commute mode significantly. In addition, the policy effect could also be significant such as pricing parking and congestion area policy.

3 Data

3.1 Study Area

According to U.S. Census data, in 2018, there are 3.87 million people living in Seattle Metropolitan areas which rank as the 15th-largest around America. Seattle is the largest city and most important seaport in this metropolitan area or even in Northwestern America. Currently, 704,352 people living in Seattle with 3.1% annual increase. According to University of Washington GIS Center record, there are 14 neighborhoods districts (Wagda, 2012) (Table 3-1). They are Downtown, East, Central, Magnolia/Queen Anne, Northwest, Northeast, Lake Union, Southwest, Ballard, Delridge, Greater Duwamish, Southeast, and North.

Table 3-1 Seattle 13 Neighborhood

Seattle Neighborhood	**Name**	
	Ballard	
	Central	
	Delridge	
	Downtown	
	East	
	Greater Duwamish	
	Lake Union	
	Magnolia/Queen Anne	
	North	
	Northeast	
	Northwest	
	Southeast	
	Southwest	
	Shared Neighborhood*	

* Shared neighborhood means these areas covered by more than one neighborhood.

From 2015 to 2018, with annual 3.1 percentage of population growth, Seattle ranks as the fastest growing city in America (Figure 3-1) (Balk, 2017). Seattle exemplifies the powerful current of economic vitality (Brownstein, 2017). With Internet companies expansion, there 2.4 percentage job growth during that time (Washington State Economic and Revenue Forecast Council, 2017). The tech talent is in high demand. Washington State Employment Security Department estimates these high tech jobs growth is expected to be 4.34 percent in 2017 (Employment Security Department, 2018), so did these jobs relating to professional and business services. The median income is also increasing. In 2017, a median household income is $83,476, a 2.91% increase compared with 2016, much higher than American median household income, $59,000 with3.2% from a year earlier in 2017.

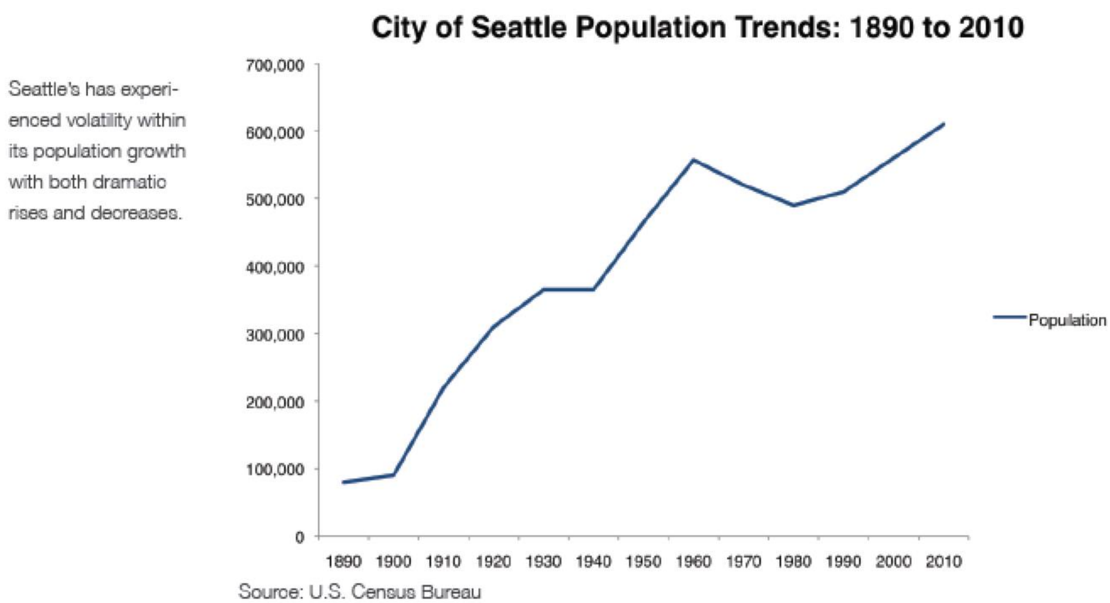


Figure 3-1 Seattle Population Trend

Source: Lake Union Laboratory http://lulab.be.washington.edu/omeka/items/show/1120

Although the employment and income are increasing, there still are problems. The first is increasing daily cost including food, housing, and transportation. In particular, the real estate is increasing rapidly. Median price per home is up 15.2% in 2017 (Reynolds, 2017). With rapid economic development, however, the gap of income is also obvious. In 2016, Seattle Gini index jumped to 50.4 as the second biggest increase in America (Balk, 2017).

Secondly, increasing traffic congestion is also a problem in Seattle (Berube, 2018; Jiao, Dozens of U.S. Cities Have ‘Transit Deserts’ Where People Get Stranded, 2018). Dr. Junfeng Jiao studied this issue. He introduced a concept, transit desert, to measure transportation demand and supply. He defined the demand of public transit outpaces supply as the “transit desert”. According to his study, although the whole Seattle public transit is fine, Rainier Valley and parts of West Seattle rank second in this desert category.

The purpose of this thesis is to analyze the impact of peer-to-peer ridesharing on travel mode controlling for the effect of socio-demographics.

- Dependent variables: the number of commuters through driving alone, the number of commuters through public transit.
- Controlling variables: the number of commuters, median earning, median commuter age, gender, average commute time, and car ownership.

The number of commuters should be more important than population as a control variable because the main of transportation service users are people over 16. This commuter’s number could be better than using normal population as the demand for transportation. The number of commuters driving alone refers the people commute through an individual car, truck or van. The number of commuters taking public transit refers the commuters commute through the public transit system excluding taxicab.

In this thesis, the sample is 143 census tracts in Seattle with data from 2010 to 2016 (1001 observations). The census tract data in 2010 and 2011 is from the 2007-2011 American Community Survey 5-year estimates and the census tract data from 2012 to 2016 is from the 2012-2016 American Community Survey 5-year estimates provided by U.S. Census Bureau. These following sections introduce a statistical description of all variables.

3.2 Dependent Variables

Table 3-2 depicts the statistical description of dependent variables including drive alone and public transit. The number of driving alone in Seattle from 2010 to 2016 ranges from 81 to 3037 with 1408 as the mean per census tract. The number of public transit ridership in Seattle from 2010 to 2016 ranges from 29 to 1993 with 508 as the mean of per census tract. Figure 3-2 and Figure 3-3 present the histograms of commuters driving alone and commuters taking public transit. The driving alone histogram indicates that the commuters through driving alone fit a normal distribution and the commuters through public transit have a left-skewed distribution and fit poorly to a normal distribution.

Table 3-2 Dependent Variable Statistical Description

Variable	Mean	S.D.	Min	Max	Observation	Description
Drive alone	1408	593.1	81	3037	1001	number of commuters driving alone (count)
Transit	508	287.7	29	1993	1001	number of commuters taking transit (count)

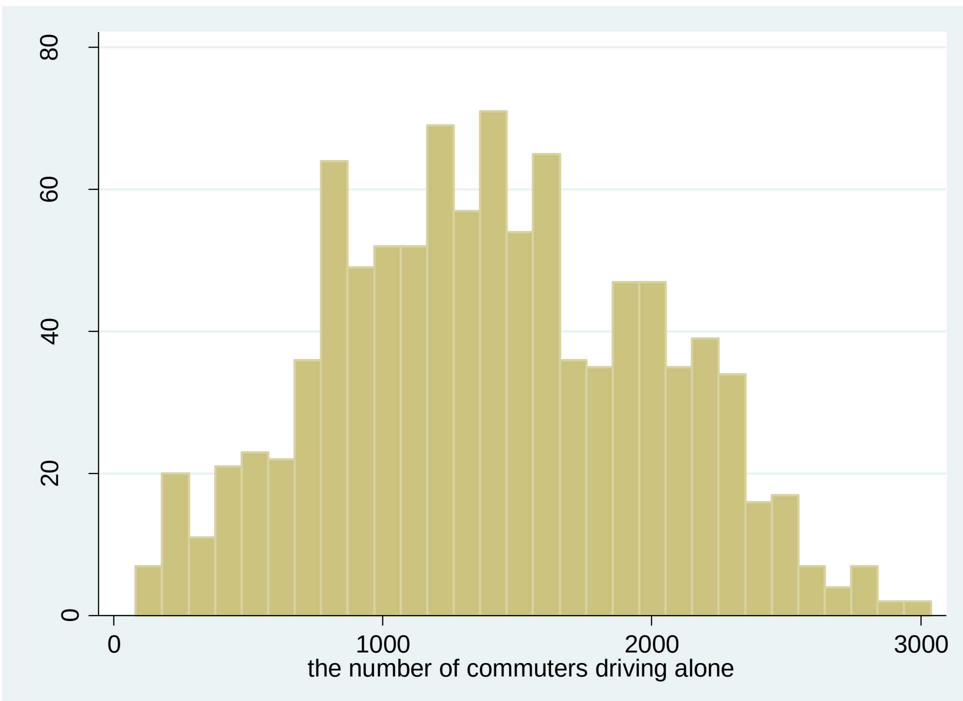


Figure 3-2 The Count of Driving Alone to Work Histogram

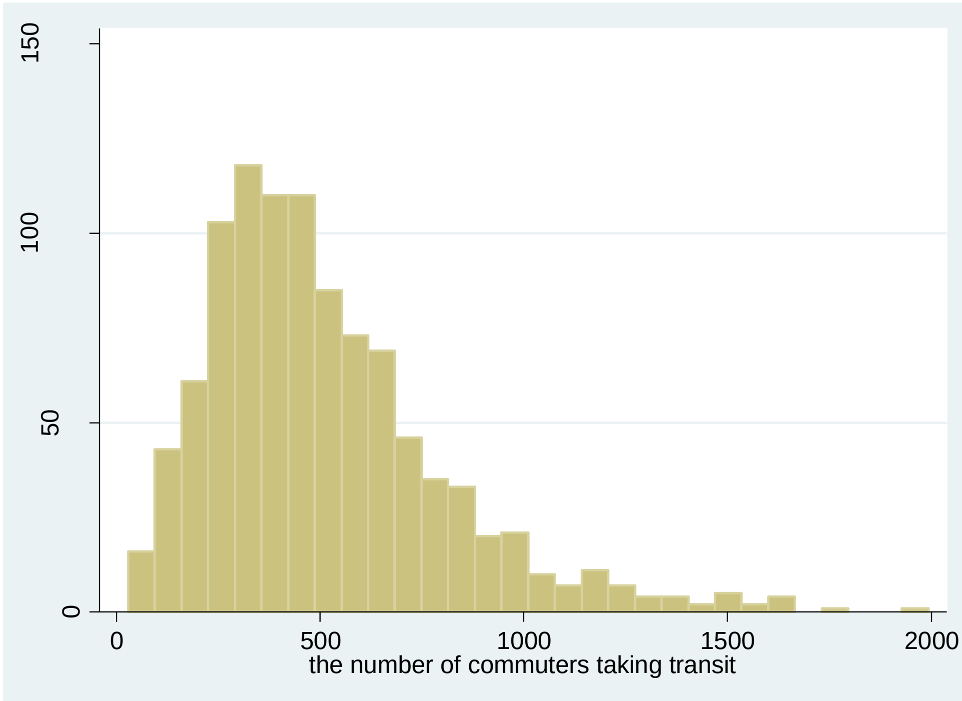


Figure 3-3 The Count of Taking Public Transit to Work Histogram

3.3 Uber Entry and Control Variables

There are a lot of studies about these new transport companies (Hall, 2017; Basu, 2018; Uber: Advanced Technologies Group, 2017). To eliminate this effect, Uber launch time could be a good treatment point in this thesis.

Uber entry is a dummy variable with “0” (before treat) and “1” (after treat), with “0” as the reference group and “1” as the treatment. The treatment time point is 2011 (Broderick, 2011). Before and in 2011, treat is “0” and after 2011, treat is “1”.

Table 3-3 presents the statistical description of Uber entry and control variables. The number of commuters from 2010 to 2016 ranges from 636 to 6039 with 2516 as the mean per census tract. The median earning ranges from 2557 to 102948 with 44868 as the mean per census tract. The median earning ranges from 2557 to 102948 with 44868 as the mean per census tract. The average age ranges from 19.7 to 55 with 38.77 as the mean per census tract. The male percentage ranges from 29% to 68% with 52% as the mean per census tract. The average commute time ranges from

16.2 to 38.6 with 25.8 as the mean per census tract. The average car ownership percentage ranges from 41% to 100% with 91.4% as the mean per census tract.

Figure 3-4 depicts the histograms of these six controlling variables. Most of controlling variables fit a normal distribution except car ownership percentage. It is right-skewed significantly.

Table 3-3 Independent Variable and Controlling Variables Statistical Description

Variable	Mean	S.D.	Min	Max	Observation	Definition
Treat	0.714	0.452	0	1	1001	Uber entry
Commuters	2516	954.9	636	6039	1001	Number of commuters (count)
Earning	44868	14228	2557	102948	1001	Commuters annual median earning (dollars)
Median age	38.77	5.691	19.7	55	1001	Commuters median age (year)
Male percentage	0.526	0.047	0.29	0.68	1001	Male commuters percentage
Commute time	25.88	3.264	16.2	38.6	1001	Mean commute time to work (minute)
Car ownership percentage	0.914	0.11	0.41	1	1001	Percentage people with at least one car

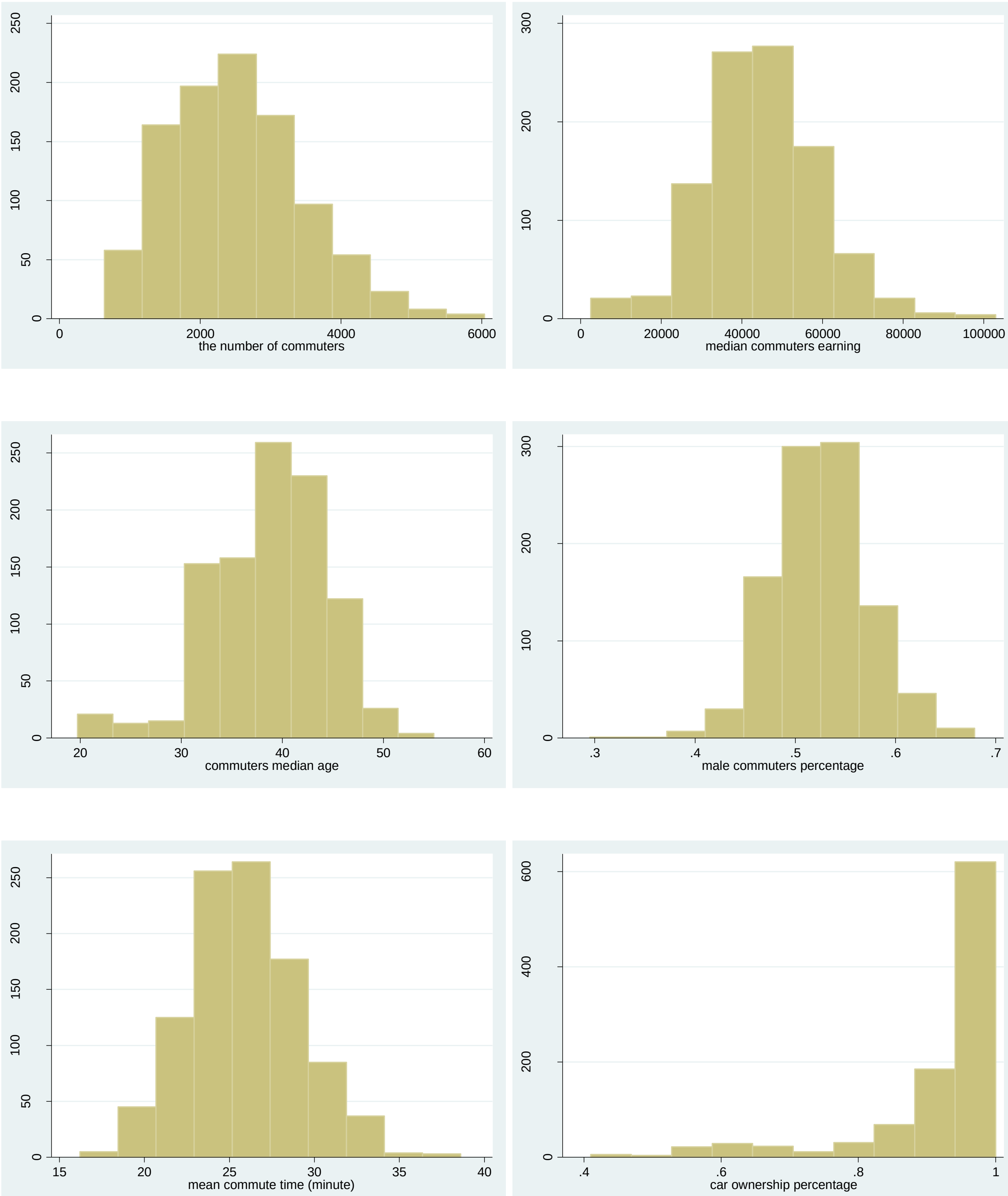


Figure 3-4 Uber entry and control variables histogram

3.4 Summary

All this data across 143 census tracts in Seattle from 2010 to 2016 is from American Community Survey by U.S. Census Bureau. Since the primary goal of this thesis is to measure the impact of peer-to-peer ridesharing on travel mode choice, the dependent variables include the number of commuters driving alone to work and the number of commuters taking public transit to work. The independent variable is a dummy variable coded as Uber entry with "0" in 2010 and 2011 and "1" after 2011. Controlling variables include the number of commuters, median earning, median commuter age, gender, average commute time, and car ownership.

4 Research Methods

In Chapter 3, the data is time-series heterogeneous census tract data in Seattle from 2010 to 2016 (Jeffery, 2002). This type of dataset is collecting data from a certain area at different times. Each observation at the same time should be independent and does not affect each other. Figure 4-1 depicts research frame. The key is to assess the impact of peer-to-peer ridesharing with controlling group on travel mode choice. In this chapter, I introduce the methodology: Difference-in-differences analysis, Cluster analysis and measures of Model Goodness of fit.

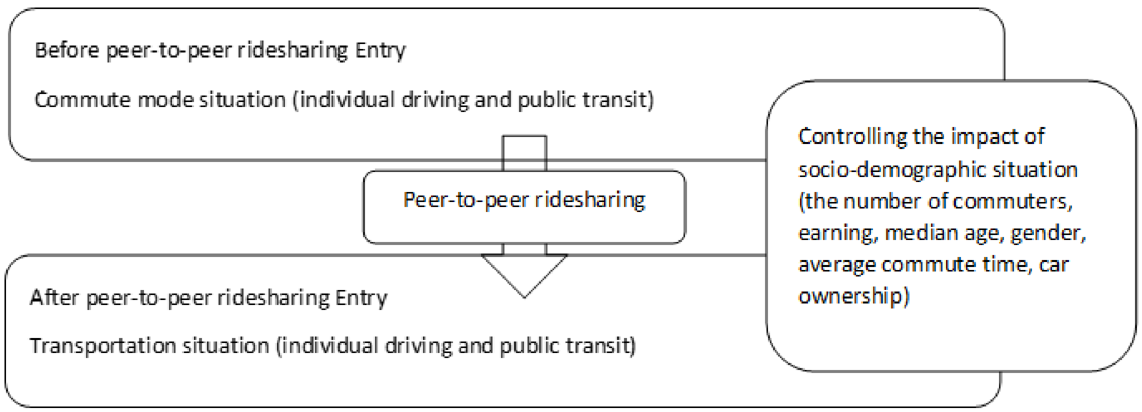


Figure 4-1 Research Framework

4.1 Difference-in-differences analysis

This research uses difference-in-differences (DID) (M, 2004). This is a popular method to analysis the intervention impact by comparing to control group. In terms of evaluation of intervention effects, the DID model effectively combines some of the factors and the intervention factors by controlling the "before and after differences" and "with or without differences" based on cross-sectional regression in which the variables are associated with one period or point in time (Roberts, 2004). The covariates further controlled some "suspicious" influencing factors in the intervention group and the control group to supplement the defect that the "natural experiment" in the sample allocation could not be completely randomized, so as to obtain a real evaluation of the intervention effect. So that, there are few conditions that the structural model needs to meet, which is a reason why the model is widely used in the econometric analysis (Abadie, 2005; Imbens, 2009).

4.1.1 DID Definition

DID requires data about the treatment group and control group before and after a certain treat time. Before using the DID model, the data should meet three hypotheses (Feldstein, 1996):

(1) The development of the intervention group project had no influence on the relevant research variables of the control group. The project implementation only resulted in the change of the relevant research variables of the intervention group.
(2) During the project period, the macro environment (other than project implementation factors) has the same impact on the intervention group and the control group.
(3) Some important features of the intervention group and the control group are stable and do not change with time throughout the project.

The core of the DID model is the estimator. The following formula is obtained by combining the simple before-after comparison and the simple cross-sectional comparison (O'Neill, 2016):

$$\begin{aligned} DID\ estimator &= E\ (Y \mid T = 1) - E\ (Y \mid T = 0) = \Delta\, y = \Delta\, Y\ treatment - \Delta\, Y\ control \\ &= (Y\ treatment, t1 - Ytreatment, t0) - (Y\ control, t1 - Y\ control, t0) \end{aligned}$$

where $\Delta\, y$ means the estimator of DID. Y means the average of result. $treatment$ and $control$ mean the treat group and control group. t 1 and t 0 mean after and before the treatment.

Combing the different time data, it can increase the sample size to obtain more precise estimates and more efficient test statistics. It can also add new variables before and after the intervention. Based on this type of data, the equation for this thesis is given by:

$$DID\ estimator\ it = b\ 0 + b\ 1 * T\ i, t + b\ 2 * A\ i, t + \ \varepsilon\ i, t$$

where $DID\ estimator$ is dependent variable. $T\ i, t$ is dummy variables to define before or after the treatment. $A\ i, t$is the controlling variables. $\varepsilon\ i, t$ means residual error. i means the ID of each individual. t means different time point.

4.1.2 Dynamic Coefficient Robustness Analysis

Through DID, there is a risk of multi-collinearity on time series data. So it is necessary to do a robustness test. Dynamic analysis is a good way to test the possibility of adverse causality (Yusof, 2014; Bertrand M. , 2003).

$$\gamma\ i,t = b\ 0 + b\ 1 * Current^{0}\ i,t + b\ 2 * After^{1}\ i,t + b\ 3 * After^{2}\ i,t + b\ 4 * After^{3}\ i,t + b\ 5 * After^{4}\ i,t + b\ 6 * After^{5}\ i,t + b\ 7 * A\ i,t + \varepsilon\ i,t$$

where $Current^{0}$ means the treatment year. If this year is the treatment year, $Current^{0}$ equals 1, otherwise 0. $After^{i}$ equals 1 if this is the i year after the treatment, otherwise 0. Others characters follow the rule of above DID equation.

This analysis indicates the dependent variables in each year in and after 2011 compared to 2010 within controlling variable. Each estimated coefficient refers to the dependent variable change compared to before treatment. The change of $b\ i$ could be a strong evidence of treatment influence.

4.2 Cluster analysis

Cluster analysis is based on certain requirement**s** and rules. Through cluster analysis, a dataset without a category label could be divided into several subsets (classes), so that similar objects are classified as a class, and dissimilar objects are divided into different classes. The cluster analysis can effectively discover the data distribution characteristics implied in the dataset (Williams, 2011) (Torgo, 2010).

In this thesis, K means could be fine to classify this dataset. The K-means clustering algorithm expresses the model as a set of k-means. Each object in the data set is associated with the class represented by the k-means that is the nearest mean, and thus divide the data set into k subset classes. To measure the nearest mean, Distance Square Sum (DSS) should be important. This refers to the sum of squared errors of all objects in the dataset:

$$\mathrm{Ep} = \sum_{k=0}^{n} \sum p \in Ci\ \ |p - mi\ |^{2}$$

where p is a point of the dataset, referring the given data object. mi is the average value of cluster Ci (both p and mi are multidimensional).

DSS is an important indicator of K-means clustering. By choosing different cluster number to find the division that minimizes the DSS function value, the local optimum is generally achieved. That is, the algorithm will eventually minimize the DSS. This approach attempts to make the generated result cluster compact and independent. “In k-means clustering, the user specifies the number of clusters to create using an iterative process. Each observation is assigned to the group whose mean is closest, and then based on that categorization, new group means are determined.” (Kaufman, 1990)

Therefore, the research on k-means will mainly focus on the method of defining the mean of different measurements of each attribute in the data set, the method of determining the number of clusters k, and so on. In order to influence the measurement unit of the excluded object attribute, it is generally required to perform dimensionless processing on each attribute before the clustering algorithm is implemented.

4.3 Measures of Model Goodness-of-Fit

4.3.1 Adjusted Pseudo R^2

The Pseudo R^2 and adjusted Pseudo R^2 are used to measure the capability of a model to explain the variability of the dependent variable. The log likelihood of the base model is a total sum of squares indicating the variability of the dependent variable, and the log likelihood of the converged model is the total sum of squared errors indicating the variability of the dependent variable that is not predicted by the model (Institute for Digital Research and Education, 2011; Freese, 2006). R^2 shows how well terms fit the estimate regression.

$$R^2 = 1 - \frac{Sum\ Squared\ Regression\ Error}{Sum\ Squared\ Total\ Error}$$

$$\boldsymbol{Adjusted\ Pseudo\ R^2 = 1 - \frac{(1-R^2)(n-1)}{n-k-1}}$$

where n is the number of points in your data sample. k is the number of independent regressors.

4.3.2 Calinski/Harabasz pseudo-F Index

Calinski/Harabasz pseudo-F Index is a method to test the model goodness of K-mean cluster analysis. An informal indicator of the "best number" of clusters is suggested in this index (Caliński, 1972; Wilkinson, 2013).

$$Calinski/Harabasz\ pseudo - F\ = \frac{(GSS)/(K-1)}{(WSS)/(N-K)}$$

where N is the number of observations, K is the number of clusters at any step in the hierarchical clustering, GSS is the between-group sum of squares, and WSS is the within-group sum of squares.

5 Result

In this chapter, the results are estimated in Stata. This software includes data management, statistical analysis, graphics, simulations, regression, and programming (Stanford Library, 2018).

From above chapters, the range and scale of each variable are different and the data is time-series data section which may lead to less stationary, the collinearity and heteroscedasticity. The natural logarithm transformation is a commonly method to these problems (Feng, 2014; Nau, 2018). This thesis took the approach to transform the variables into their logarithms. For instance, if there is a dependent variable Y and independent variable X. After logarithmic transformation, the linear regression equation is given by:

$$\ln Y = a + b \ln X$$

where a is constant and b is the coefficient.

From exponentiating both sides of the equation, it is given by:

$$Y = e^{a} X^{b}$$

This equation means with 1% additional X, there could be b % increase in Y.

In this thesis, the transformed equation is:

$$New\ variables = \ln Raw\ variables$$

This transformation could help to improve model stability and elastic coefficients. “drive alone” (the number of commuters driving alone), “transit” (The number of commuters taking transit), “commute time” (Mean commute time to work), “commuters” (The number of commuters), “earning” (Median commuters earning), and “median age” (Median commuters age) are log-transformed.

5.1 Overall Result

As above section, there are 143 census tracts in Seattle from 2010 to 2016. This independent pooled cross-sectional data could be analyzed by DID (Davies, 1995; Baltagi, 1995). In addition, the control group and the treated group are the same census tracts but at different time point:

- Treated group: Seattle 143 census tracts after 2011
- Control group: Seattle 143 census tracts before and in 2011

Overall, note that the estimate of the impact of Uber on the drive alone is negative statistically significant while on transit is positive statistically significant (Table 5-1). This result indicates Uber could reduce drive alone and promote public transit usage. This is consistent with the existing literature that people using ride-sharing more may reduce drive alone to work and increase public transit (Shared-Use Mobility Center, 2016). It is worth noting that for the control variables, as the commute time increase, there will be fewer cars and more public transit usage.

$$\begin{aligned}\ln(Driving\ alone) &= -0.88 - 0.023 \times Uber\ Entry \\ &+ 0.92\ln(commuters) + 0.24\ln(median\ age) - 0.16\ln(commute\ time) \\ &+ 0.33\ln(\ Car\ ownership)\end{aligned}$$

$$\begin{aligned}\ln(Public\ transit) &= -3.7 + 0.02 \times Uber\ Entry \\ &+ 1.1\ln(commuters) + 1.2\ln(commute\ time) - 0.7\ln(Car\ ownership)\end{aligned}$$

Table 5-1 DID Overall Result

	ln (drive alone)	ln (public transit)
Uber entry	-0.023**	0.020*
	(-2.93)	(2.65)
ln (commuters)	0.92***	1.1***
	(12.7)	(6.00)
ln (earning)	0.053	-0.133
	(0.97)	(-1.19)
ln (median age)	0.24*	-0.41

	(2.64)	(-1.33)
ln (commute time)	-0.16*	1.2***
	(-2.10)	(7.71)
ln (Male percentage)	-0.064	0.089
	(-0.57)	(0.57)
ln (Car ownership percentage)	0.33*	-0.70**
	(2.24)	(-2.76)
Cons	-0.88	-3.7
	(-1.11)	(-1.59)
N	1001	1001
Adj. R-square	0.497	0.460

T statistics in parentheses
* P < 0.05, ** P < 0.01, *** P < 0.001

In order to explore the impact of other factors, there is a robustness test: dynamic coefficient analysis (Table 5-2). As mentioned above, people using ride-sharing more may reduce drive alone to work and increase public transit, however, this relationship could be denied by parallel trend assumption (Branas, 2011; Bertrand M. , 2003; Bertrand M. , 2004).

Table 5-2 depicts the detail result of the dynamic coefficient analysis. It indicates the commute mode change rate after the treatment compared to 2010 number within socio-demographic characters. In $ln\ (drive\ alone)$ column, $b\ 1, 2, 3, 4, 5, and\ 6$ are negative and the absolute values are increasing. In $ln\ (public\ transit)$ column, it is worth noting that $b\ 1, 2$ are negative. $b\ \ 3, 4, 5, and\ 6$ are positive.

Table 5-2 Dynamic Coefficient Result

	ln (drive alone)	ln (public transit)
Current (2011)	-0.007	-0.011
	(-1.122)	(-0.563)
After 1 (2012)	-0.014	-0.014
	(-1.626)	(-0.634)
After 2 (2013)	-0.028**	0.032**
	(-2.775)	(2.517)
After 3 (2014)	-0.033*	0.041**
	(-2.491)	(2.705)
After 4 (2015)	-0.035**	0.061
	(-2.611)	(1.549)

After 5 (2016)	-0.052***	0.084*
	(-4.086)	(2.084)
ln (commuters)	0.937***	1.100***
	(12.405)	(5.234)
ln (earning)	0.081	-0.217
	(1.238)	(-1.750)
ln (median age)	0.241*	-0.418
	(1.950)	(-1.332)
ln (commute time)	-0.110	1.041***
	(-1.405)	(6.856)
ln (Male percentage)	-0.063	0.094
	(-0.579)	(0.616)
ln (Car ownership percentage)	0.299	-0.617*
	(1.974)	(-2.497)
Cons	-1.503	-1.93
	(-1.626)	(-0.736)
N	1001	1001
Adj. R-square	0.505	0.465

T statistics in parentheses
* P < 0.05, ** P < 0.01, *** P < 0.001

5.1.1 Interpretation of Impact on Driving Alone

Uber entry and 4 controlling variables are observed to be significant in DID result, respectively. The impacts of the number of commuters, median age, commute time, and car ownership are significant and are consistent with findings in literature.

1) Peer-to-peer ridesharing could reduce driving alone

In DID result, the coefficient of Uber entry is negative 0.023. This suggests from 2012 to 2016, after Uber entry, $ln\ (drive\ alone)$ decreases by 0.023, 2.3% less driving alone commuters compared before Uber launch. Likewise, Dynamic coefficient result suggests that for After 2 (2013), the coefficient is -0.028 and statistically significant. This means controlling for other socio-demographic characters including the commuters number, driving alone commuters could relatively decrease compared to 2010, before Uber entry. Through the $ln\ (drive\ alone)$ column, the absolute value of each coefficient in each year is increasing, which means during this period, Uber entry had an increasing impact. Overall, the dynamic coefficient analysis indicates $ln\ (driving\ alone)$ decreased by 0.028 in 2013, 0.033 in 2014, 0.035 in 2015 and 0.052 in 2016 compared to driving alone commuters in 2010 controlling for other characters including commuters. This means driving alone commuter could decrease by 2.8% in 2013, 3.2% in 2014, 3.4% in 2015 and 5.1% in 2016 relatively.

2) Socio-demographic factors affect travel mode choice

The coefficient of $ln\ (commuters)$ is 0.92. This indicates driving alone commuter number could increase by 0.92% for 1% additional commuters. The coefficients of $ln\ (median\ age)$ and $ln\ (commute\ time)$ are 0.24 and -0.16, which indicates driving alone increase by 0.24% for 1% additional median age and decrease 0.16% for additional commuting time. The coefficient of car ownership percentage is 0.33 which indicates driving alone commuter count increase by 0.33% for 1% additional car ownership.

5.1.2 Interpretation of Impact on Public Transit

1) Peer-to-peer ridesharing could promote public transit ridership

In DID result, the coefficient of Uber entry is 0.02. This indicates that Uber entry could promote public transit ridership, increasing 0.02 $ln\ (public\ transit)$, 2% more public transit ridership compared before Uber launch. Dynamic coefficient result indicates that after 2012, commuting through public transit started to increase. The 2013 coefficient is 0.032 which means commuters through public transit could have increased compared to 2010. Overall, the dynamic coefficient analysis indicates $ln\ (public\ transit)$ could increase by 0.032 in 2013, 0.041 in 2014, 0.061 in 2015 and 0.084 in 2016 compared to public transit commuters in 2010 and controlling for other characters including commuters. This means public transit commuter could increase by 3.3% in 2013, 4.2% in 2014, 6.3% in 2015 and 5.3% in 2016 compared to public transit commuters in 2010 relatively. Besides, it is worth noting the coefficients in 2011 and 2012 are insignificant and negative, which may mean that the effect of Uber on public transit has a time lag.

2) Socio-demographic factors affect travel mode choice

The coefficient of $ln\ (commuters)$ is 1.1. This suggests public ridership increases 1.1% for additional 1% commuters. Individuals spending more time on commuting prefer to take public transit. The coefficient of $ln\ (commute\ time)$ is 1.2 which means public transit ridership increases 1.2% for 1% additional commuting time. The coefficient of $ln\ (car\ ownership)$ is -0.7%, which indicates public transit ridership decreases 0.7% for 1% additional car ownership.

5.2 Different Types of Census Tracts Results

Cluster analysis is to regroup these 143 census tracts according to four factors including the number of commuters through driving alone, the number of commuters through public transit, mean commute time, and median commute earning in 2016 through K-mean cluster analysis. All these variables are logarithms transformed in order to influence the measurement unit of the excluded object attribute. According to Calinski and Harabasz index (M. Halkidi, 2001), these 143 tracts are divided into three groups (Table 5-4, and Figure 5-1). Table 5-3 depicts the statistical description.

Table 5-3 Detail of Clustering Result

		Drive alone	Transit	Mean Travel Time	Median earning
Cluster 1	Mean	1431	459.5	25.46	74161
Cluster 2	Mean	1551	648.8	27.17	52932
Cluster 3	Mean	1360	590.1	28.43	34518
Total	Mean	1458.9	592.6	27.33	49967

Table 5-4 Summary Result of Clustering Result

	Drive alone	Transit	Travel time	Median earning	Observations
Cluster 1	Average	Low	Low	High	26
Cluster 2	High	High	Average	Average	64
Cluster 3	Low	Average	High	Low	53

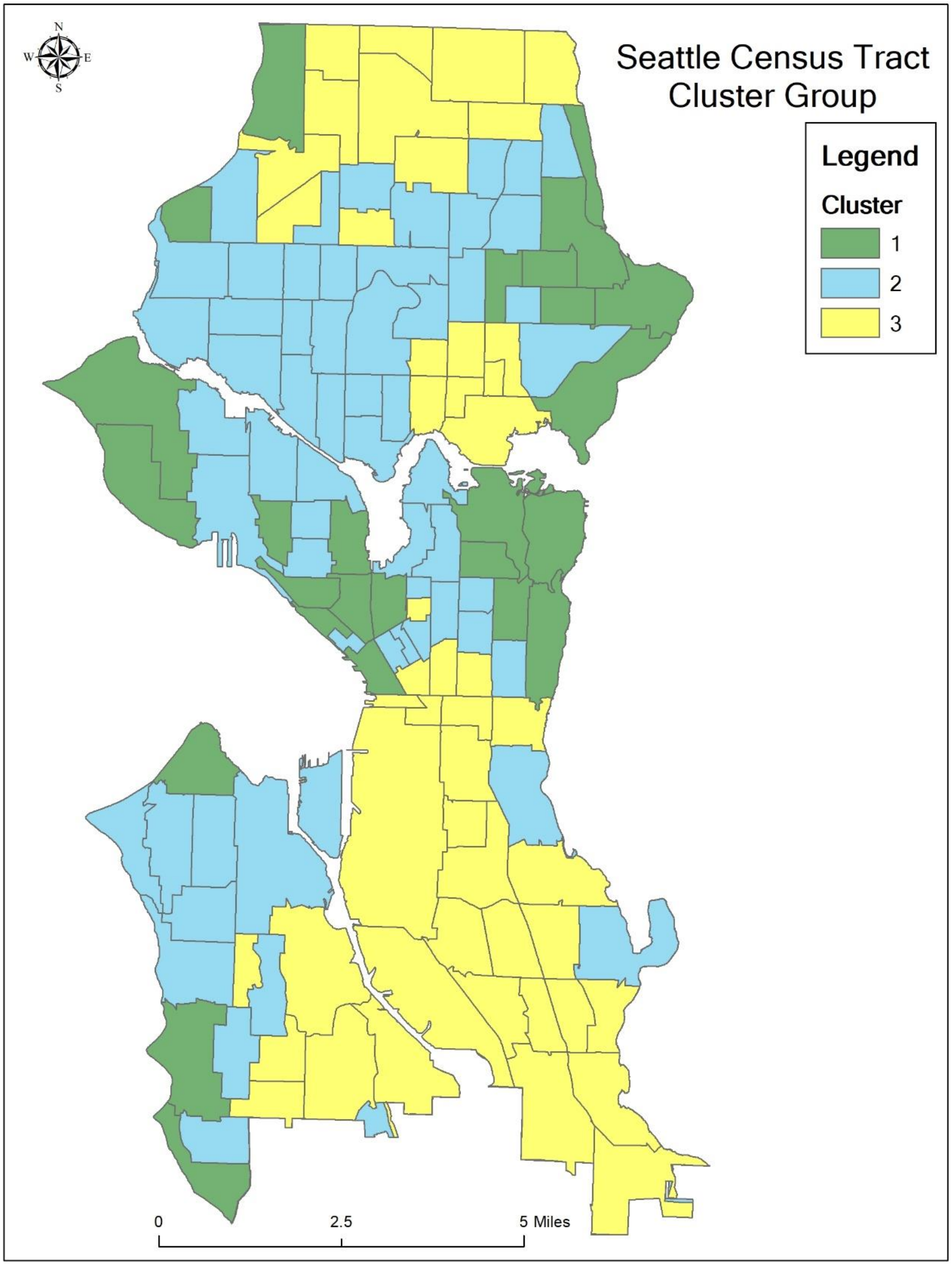


Figure 5-1 Seattle Census Tract Cluster Analysis

5.2.1 Cluster 1

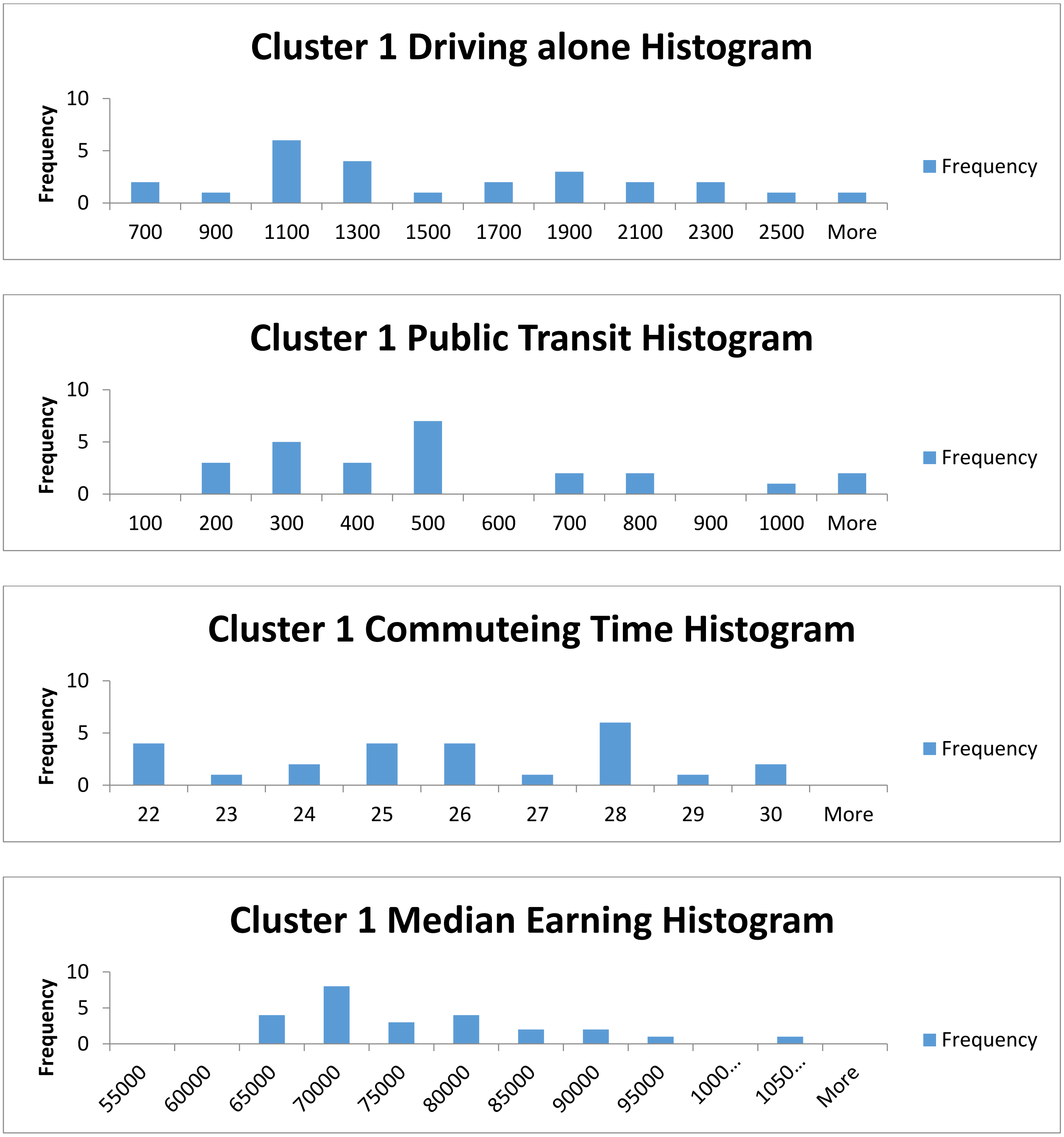


Figure 5-2 Cluster 1 Four Factor Histogram

Cluster 1 is the area with average drive alone workers, fewer transit workers, less travel time and high median earning. Figure 5-2 depicts the histograms of these four factors: commuters through driving alone, commuters through public transit, median earning, and average commuting time.

Table 5-5 indicates there is not the statistically significant effect of Uber on travel mode (either driving alone or public transit). While it is worth noting that in Cluster 1 situation, higher median earning could reduce driving alone and higher commute time could promote more people taking transit. Then test this result through Marianne Bertrand's method as mentioned (Table 5-6). According to the dynamic coefficient analysis result, all b 1~6 are not statistically significant.

$$\ln(Driving\ alone) = -0.31 + 0.85\ln(commuters) - 0.15\ln(mean\ earning) + 0.55\ln(median\ age)$$

$$\ln(Public\ transit) = -6.56 + 0.73\ln(commuters) + 1.44\ln(commute\ time)$$

Table 5-5 Cluster 1 DID Result

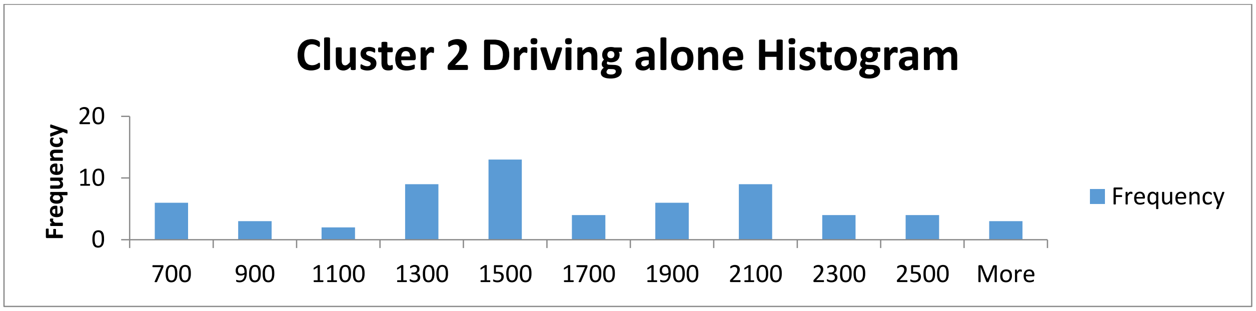
	ln (drive alone)	ln (public transit)
Uber entry	-0.010	0.013
	(-0.586)	(0.397)
ln (commuters)	0.854***	0.733***
	(4.884)	(3.515)
ln (earning)	-0.154*	0.225
	(-2.313)	(1.675)
ln (median age)	0.552*	-0.061
	(2.195)	(-0.102)
ln (commute time)	0.123	1.444**
	(0.782)	(3.598)
ln (Male percentage)	-0.238	0.389
	(-1.792)	(0.837)
ln (Car ownership percentage)	0.485	-1.208
	(1.674)	(-0.997)
Cons	-0.307	-6.563*
	(-0.174)	(-2.407)
N	182	182
Adj. R-square	0.553	0.389
T statistics in parentheses		
* P < 0.05, ** P < 0.01, *** P < 0.001		

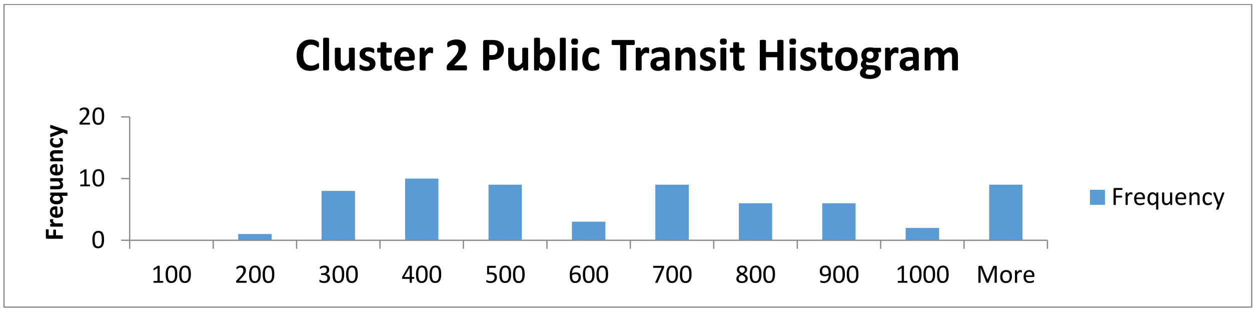
Table 5-6 Cluster 1 Dynamic Coefficient Analysis Result

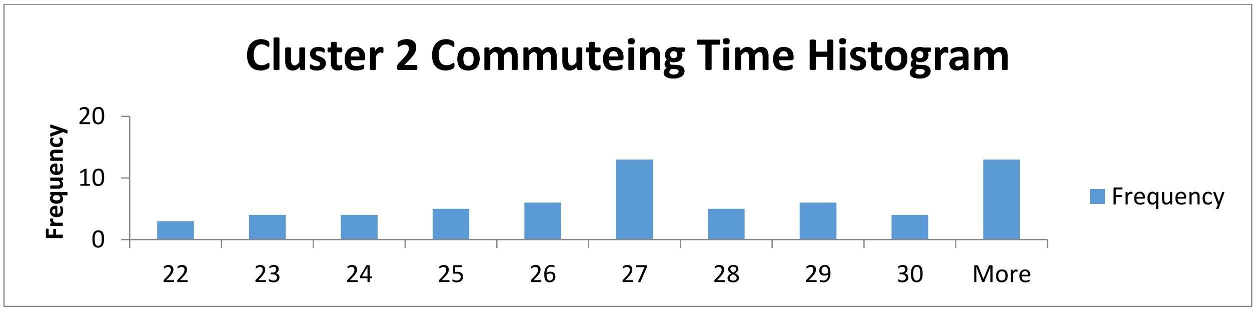
	ln (drive alone)	ln (public transit)
Current (2011)	-0.030	-0.000
	(-1.190)	(-0.003)
After 1 (2012)	-0.028	-0.030
	(-1.167)	(-0.596)
After 2 (2013)	-0.020	0.041
	(-0.894)	(0.906)
After 3 (2014)	-0.014	0.016
	(-0.640)	(0.271)
After 4 (2015)	-0.028	0.030
	(-1.137)	(0.411)
After 5 (2016)	0.003	-0.058
	(0.086)	(-0.622)
ln (commuters)	0.849***	0.768*
	(4.845)	(2.719)
ln (earning)	-0.197**	0.292
	(-2.332)	(1.871)
ln (median age)	0.543	0.061
	(2.000)	(0.103)
ln (commute time)	0.085	1.485***
	(0.485)	(4.710)
ln (Male percentage)	-0.238	0.318
	(-1.787)	(0.655)
ln (Car ownership percentage)	0.502	-1.374
	(1.587)	(-1.215)
Cons	0.383	-8.197*
	(0.184)	(-2.196)
N	182	182
Adj. R-square	0.556	0.393

T statistics in parentheses
* P < 0.05, ** P < 0.01, *** P < 0.001

5.2.2 Cluster 2







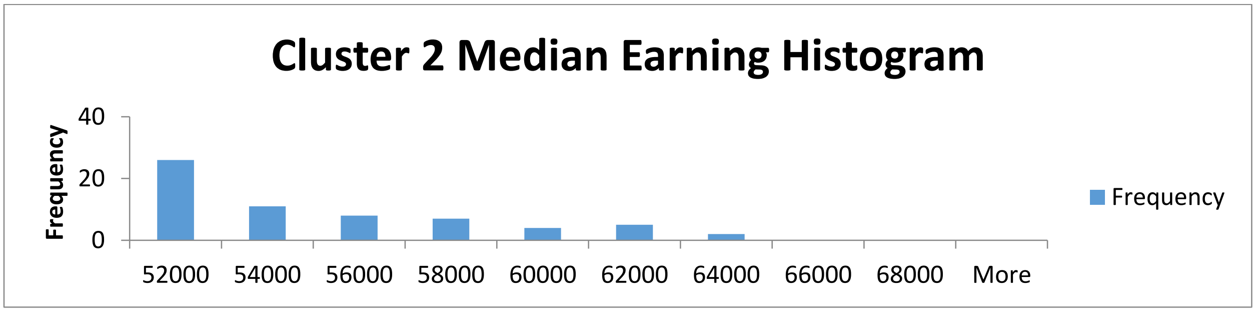


Figure 5-3 Cluster 2 Four Factor Histogram

Cluster 2 is the area with more drive alone workers, more transit workers, average travel time and average median earning. Figure 5-3 depicts the related four factors histograms. There are 64 census tracts of Cluster 2, as 44.8% of Seattle 143 census tracts.

Table 5-7 indicates the result matching overall result: people using ride-sharing more may reduce driving alone to work.

$$\ln(Driving\ alone) = -1.7 - 0.025 \times Uber\ Entry + 0.94 \ln(commuters) + 0.19 \ln(mean\ earning) - 0.24 \ln(commute\ time)$$

$$\ln(Public\ transit) = -4.5 + 1.6 \ln(commuters) - 0.4 \ln(mean\ earning) + 1.3 \ln(commute\ time)$$

Table 5-7 Cluster 2 DID Result

	ln (drive alone)	ln (public transit)
Uber entry	-0.025*	-0.004
	(-2.360)	(-0.153)
ln (commuters)	0.937***	1.633***
	(9.802)	(10.650)
ln (earning)	0.194*	-0.403*
	(2.250)	(-2.002)
ln (median age)	0.060	-0.500
	(0.362)	(-1.072)
ln (commute time)	-0.235**	1.251***
	(-3.023)	(5.440)
ln (Male percentage)	-0.025	0.116
	(-0.115)	(0.497)
ln (Car ownership percentage)	0.274	-0.465
	(0.892)	(-1.087)
Cons	-1.704	-4.474
	(-1.466)	(-1.891)
N	448	448
Adj. R-square	0.493	0.566

T statistics in parentheses
* P < 0.05, ** P < 0.01, *** P < 0.001

Table 5-8 presents the result of the dynamic coefficient analysis. In $ln(drive\ alone)$ column, $b\ 1, 2, 3, 4, 5, and\ 6$ are negative and the absolute values are increasing. In $ln(public\ transit)$ column, the mathematic signs of coefficients are not stable. In 2011, 2012, 2014 and 2015, the coefficients are negative while in 2013 and 2016 are positive.

Table 5-8 Cluster 2 Dynamic Coefficient Analysis Result

	ln (drive alone)	ln (public transit)
Current (2011)	-0.017*	-0.013
	(-2.152)	(-0.421)
After 1 (2012)	-0.026*	-0.010
	(-2.512)	(-0.287)
After 2 (2013)	-0.037**	0.001
	(-2.778)	(0.030)
After 3 (2014)	-0.038*	-0.010
	(-2.269)	(-0.207)
After 4 (2015)	-0.056	-0.042
	(-1.677)	(-0.875)
After 5 (2016)	-0.070**	0.063
	(-3.255)	(1.109)
ln (commuters)	0.960***	1.607***
	(8.944)	(9.676)
ln (earning)	0.250*	-0.538*
	(2.191)	(-2.345)
ln (median age)	0.041	-0.455
	(0.117)	(-0.946)
ln (commute time)	-0.194*	1.222***
	(-2.360)	(5.573)
ln (Male percentage)	-0.033	0.149
	(-0.158)	(0.657)
ln (Car ownership percentage)	0.210	-0.316
	(0.643)	(-0.710)
Cons	-2.472	-2.858
	(-1.603)	(-1.008)
N	448	448
Adj. R-square	0.497	0.573
T statistics in parentheses		
* P < 0.05, ** P < 0.01, *** P < 0.001		

5.2.3 Cluster 3

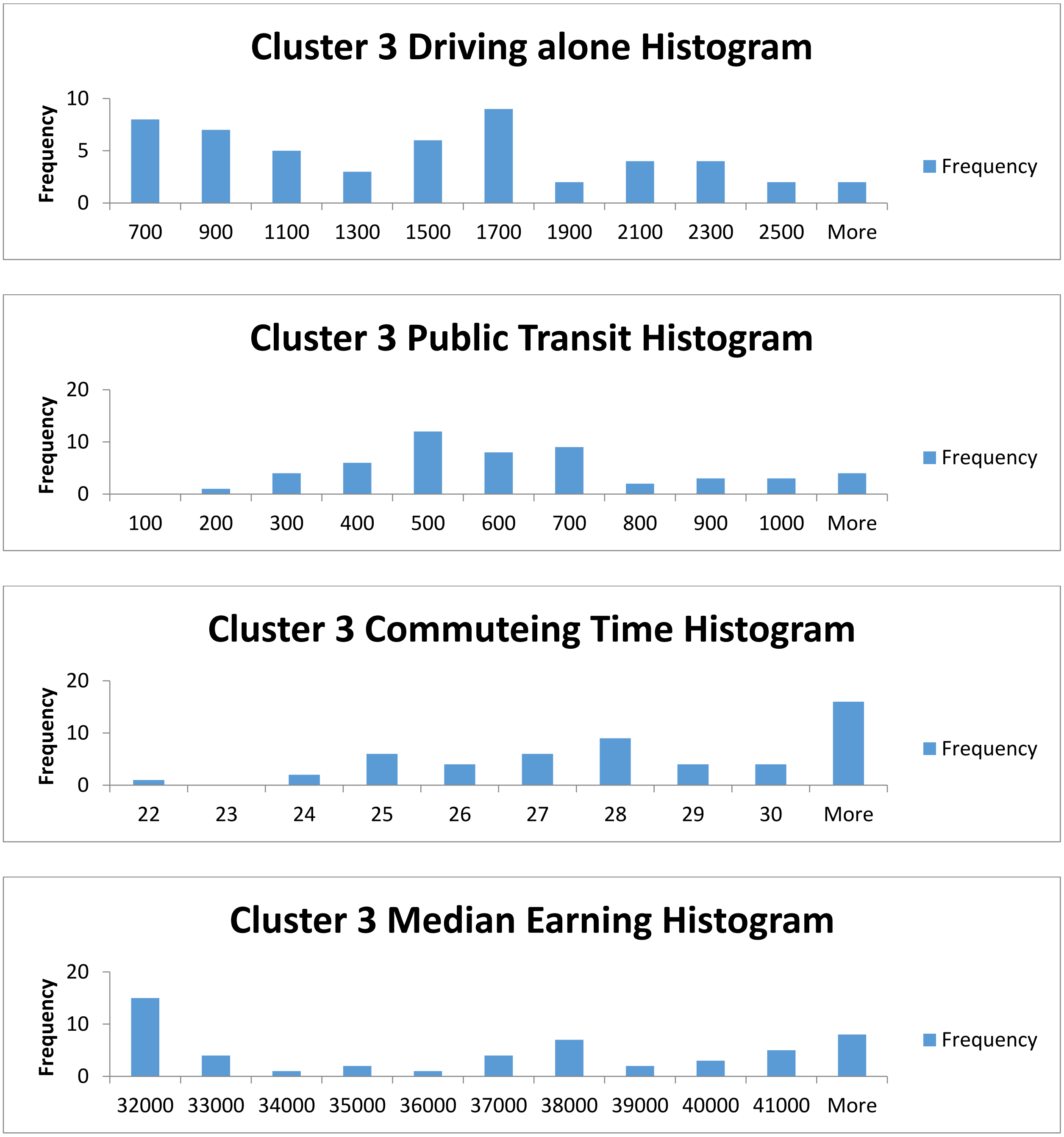


Figure 5-4 Cluster 3 Four Factor Histogram

Cluster 3 is the area with less drive alone workers, average transit workers, high travel time and less median earning. Figure 5-4 presents the four factors histograms. There are 53 census tracts in cluster 3, 37.1% of Seattle. The result (Table 5-9) indicates the effect of treat is statistically significant.

$$\ln(Driving\ alone) = -0.69 - 0.024 \times Uber\ Entry + 0.96 \ln(commuters)$$

$$\ln(Public\ transit) = -0.58 + 0.033 \times Uber\ Entry + 0.79 \ln(commuters) + 1.1 \ln(commute\ time)$$

Table 5-9 Cluster 3 DID Result

	ln (drive alone)	ln (public transit)
Uber entry	-0.024*	0.033*
	(-2.159)	(2.612)
ln (commuters)	0.956***	0.792***
	(11.506)	(2.892)
ln (earning)	0.063	-0.142
	(0.875)	(-1.096)
ln (median age)	0.132	-0.452
	(0.771)	(-1.567)
ln (commute time)	-0.222	1.080***
	(-1.726)	(5.305)
ln (Male percentage)	-0.008	-0.053
	(-0.068)	(-0.268)
ln (Car ownership percentage)	0.250	-0.630
	(1.534)	(-2.004)
Cons	-0.691	-0.577
	(-0.654)	(-0.238)
N	371	371
Adj. R-square	0.514	0.415
T statistics in parentheses		
* P < 0.05, ** P < 0.01, *** P < 0.001		

Table 5-10 presents the dynamic coefficient analysis. In $ln(drive\ alone)$ column, b 1 and 2 are positive. b $3, 4, 5, and$ 6 are negative. In $ln(public\ transit)$ column, b 1 and 2 are negative. b $3, 4, 5, and$ 6 are positive.

Table 5-10 Cluster 3 Dynamic Coefficient Analysis Result

	ln (drive alone)	ln (public transit)
Current (2011)	0.013	-0.014
	(0.957)	(-0.567)
After 1 (2012)	0.008	-0.020
	(0.535)	(-0.677)
After 2 (2013)	-0.015*	0.036*
	(-0.994)	(1.747)
After 3 (2014)	-0.033*	0.042***
	(-1.231)	(1.602)
After 4 (2015)	-0.023**	0.056*
	(-2.888)	(1.832)
After 5 (2016)	-0.055**	0.142**
	(-2.888)	(3.511)
ln (commuters)	0.981***	0.714**
	(11.028)	(2.765)
ln (earning)	0.093	-0.247
	(1.198)	(-1.789)
ln (median age)	0.132	-0.425
	(0.738)	(-1.498)
ln (commute time)	-0.135	0.870***
	(-1.091)	(4.362)
ln (Male percentage)	0.007	-0.077
	(0.060)	(-0.418)
ln (Car ownership percentage)	0.184	-0.507
	(1.021)	(-1.125)
Cons	-1.474	1.691
	(-1.099)	(0.270)
N	371	371
Adj. R-square	0.525	0.448

T statistics in parentheses

* P < 0.05, ** P < 0.01, *** P < 0.001

5.2.4 Interpretation of Cluster Result

Through the cluster analysis and DID for each cluster, the results suggest the impact of Uber entry is different within socio-demographic factors. The following sections indicate the detail interpretations of these 3 cluster types.

1) Cluster 1

In Cluster 1, DID result (Table 5-5) indicates Uber entry effect is not significant, either on driving alone or on public transit. In $ln\ (drive\ alone)$ column, the coefficient of $ln\ (commuters)$ is 0.85, 0.85% driving alone increasing by 1% additional commuters. The coefficient of $ln\ (earning)$ is -0.15, 0.15% driving alone decreasing by 1% additional mean earning. The coefficient of $ln\ (median\ age)$ is 0.55, 0.55% driving alone increasing by 1% additional median age. Dynamic coefficient analysis result is consistent with DID result. It also presents controlling for other socio-demographic characters including commuters, the coefficient in each year is similar besides 2016 and all of them are not statistically significant.

In $ln\ (public\ transit)$ column, 1% additional commuters could increase by 0.73% public transit and 1% additional commuting time increases by 1.44% public transit ridership. These are consistent with hypotheses. Dynamic coefficient analysis result is also consistent with the DID result. It indicates that the effect of Uber entry in Cluster 1 could not be significant.

2) Cluster 2

In Cluster 2, DID results (Table 5-7) indicates Uber effect is significant on $ln\ (driving\ alone)$ that decreases by 0.025 compared to before Uber entry but may not be significant on public transit commuters. In $ln\ (drive\ alone)$ column, with 1% additional commuters, there could be 0.94% more driving alone commuters. With 1% additional mean earning, there could be 0.19% more driving alone commuters. With 1% additional average commuting time, the commuters through driving alone could decrease by 0.24%. These are consistent with hypotheses. Dynamic coefficient analysis result is consistent with DID result. The coefficient of each year is negative and its absolute value is increasing. For instance, controlling for other socio-demographic characters including commuters, in 2011, the $ln\ (driving\ alone)$ could decrease by 0.017 compared to 2010 and decrease by 0.026 in 2012 also compared to 2010. In 2013, it could decrease by 0.037, 0.038

in 2014 and 0.07 in 2016. These indicate driving alone commuter could decrease 1.7% in 2011, 2.6% in 2012, 3.6% in 2013, 3.7% in 2014 and 6.8% in 2016 relatively. This result could be an evidence that Uber entry helps to reduce driving alone commuters.

In $ln\ (public\ transit)$ column, the Uber effect is not statistically significant. Dynamic coefficient analysis result also is consistent with DID result. Controlling for other socio-demographic characters, all coefficients are not statistically significant. Besides, 1% additional commuters could increase 1.6% public transit commuters. For every 1% more median earning, the public transit ridership could decrease by 0.40%. For every 1% more commuting time, the public transit ridership could increase by 1.3%.

3) Cluster 3

DID result indicates Uber entry affects either driving alone or public transit ridership significantly. Uber entry reduces 0.024 $ln\ (driving\ alone)$, 2.4% less driving alone commuters, and promotes 0.033 $ln\ (public\ transit),$ 3% more public transit commuters. In $ln\ (drive\ alone)$ column, for every 1% additional commuters, driving alone increase 0.96%. Dynamic coefficient analysis indicates controlling for other characters, in 2013, the $ln\ (driving\ alone)$ could decrease by 0.015, 0.033 in 2014, 0.023 in 2015 and 0.055 in 2016 compared to 2010 driving alone commuters. These mean driving alone commuter could decrease by 1.5% in 2013, 3.2% in 2014, 2.3% in 2015 and 5.4% in 2016 compared to 2010 relatively. These changes could be an evidence that Uber entry could help to reduce driving alone commuters.

In $ln\ (public\ transit)$ column, public transit increase by 0.79% with 1% additional commuters. For every 1% more commuting time, the public transit ridership could increase by 1.1%. Dynamic coefficient analysis result indicates public transit commuter could increase by 0.036 in 2013, 0.042 in 2014, 0.056 in 2015 and 0.142 in 2016 compared to public transit commuter number in 2010. These mean public transit commuter could increase by 3.7% in 2013, 4.3% in 2014, 5.8% in 2015 and 15.3% in 2016.

6 Impacts on Future Commuting Mode Choice and Planning Implications

In Seattle Comprehensive Plan 2035 (Office of Planning & Community Development, Seattle, 2015), there are two important principles: “Promoting public transportation through fewer parking options” and “Making the region more connected via public transportation”. While according to current public transit heat map, it is hard for current public transit system to serve whole Seattle urban area efficiently, leading to high driving alone demand. In addition, because the number of commuters is increasing (Figure 6-3), the demand for public transit is also increasing.

With the urbanization, traffic congestion has become increasingly serious, and traditional public transportation based on fixed lines has been criticized for its low quality of service. In the view of this, peer-to-peer ridesharing containing public and private could be a solution. To alleviate congestion, it is important to clarify the impact of peer-to-peer ridesharing on travel mode. In addition, planners solve this increasing demand with the limited budget and complicated impact of peer-to-peer ridesharing for Seattle.

In addition, TDM requires the planners forecasting future different commute mode demand to address the serious increasing demand outpaces supply. The data about commuting bases on the *American Community Survey: Commuting/ Journey to Work* (U.S. Department of Commerce, 2018). There are two methods for forecasting commuter-adjusted population estimates in American Community Survey 5-year (U.S. Department of Commerce, 2017):

Method 1: Total resident population + (total workers working in area - workers who lived and worked in same area) - (total workers living in area - workers who lived and worked in same area);

Method 2: Total resident population + Total workers working in area - Total workers living in area.

These two methods are reasonable in past, however, these ignore the effect of new travel mode on commute mode choice. This thesis could provide a forecasting modification considering the impact of peer-to-peer ridesharing.

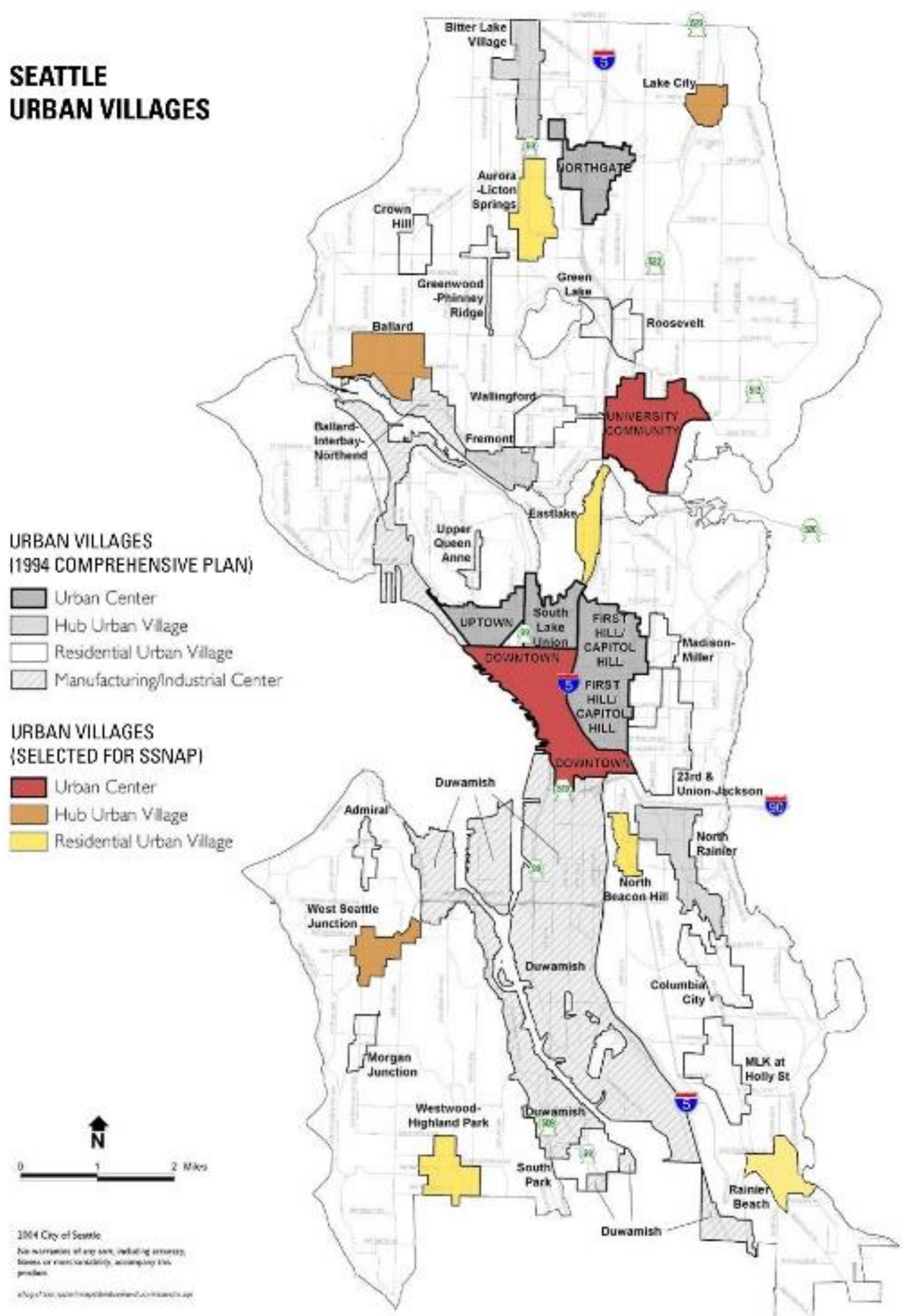


Figure 6-1 Seattle Urban Village Planning

Source: The Northwest Urbanist https://thenorthwesturbanist.com/2015/02/03/civic-indicators-highlight-seattles-progress-challenges/

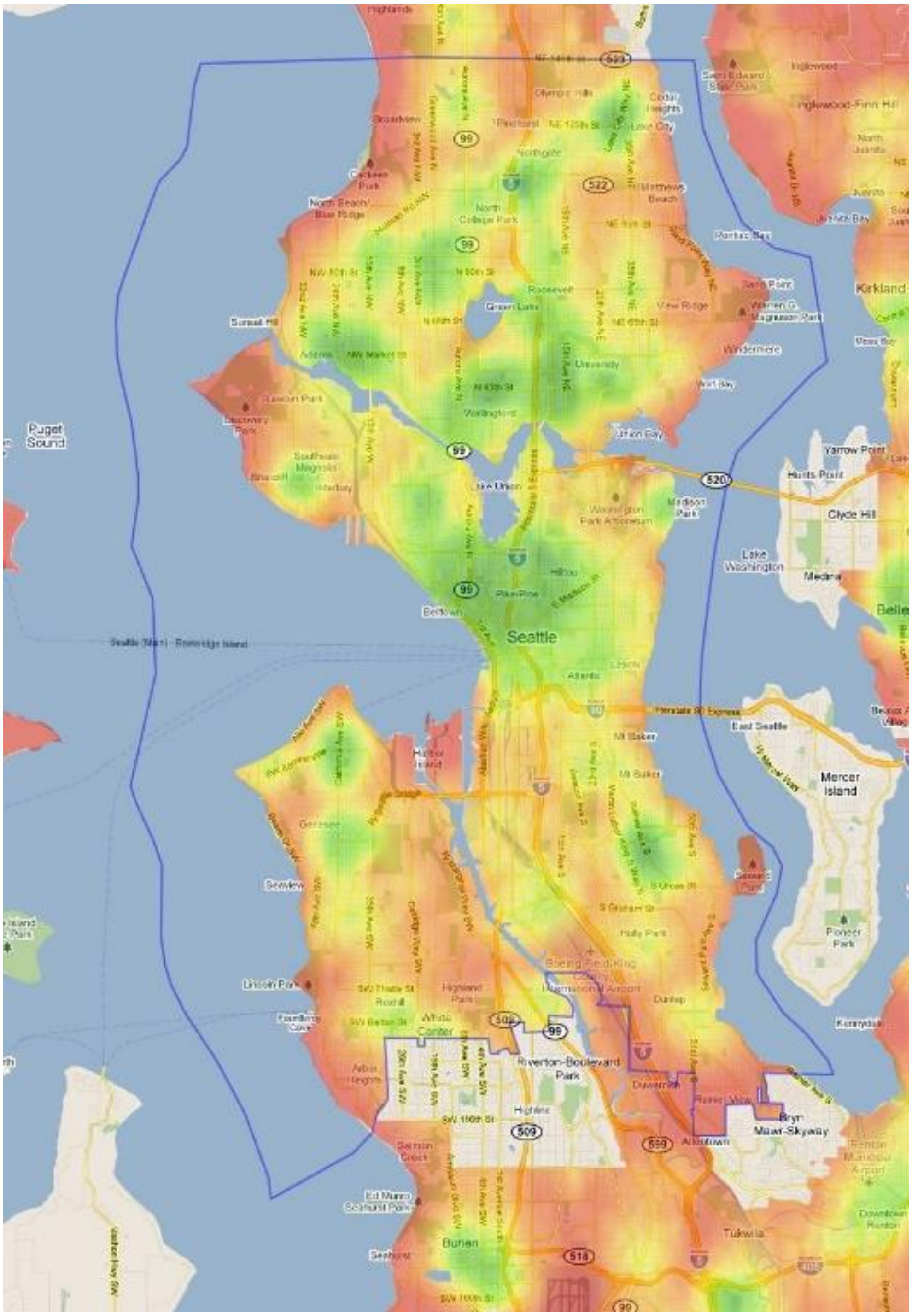


Figure 6-2 Seattle Public Transit Accessibility Map

Source: Multi-family Executive http://www.multifamilyexecutive.com/property-management/marketing/download-of-the-week-q-a-with-walk-score-ceo-josh-herst

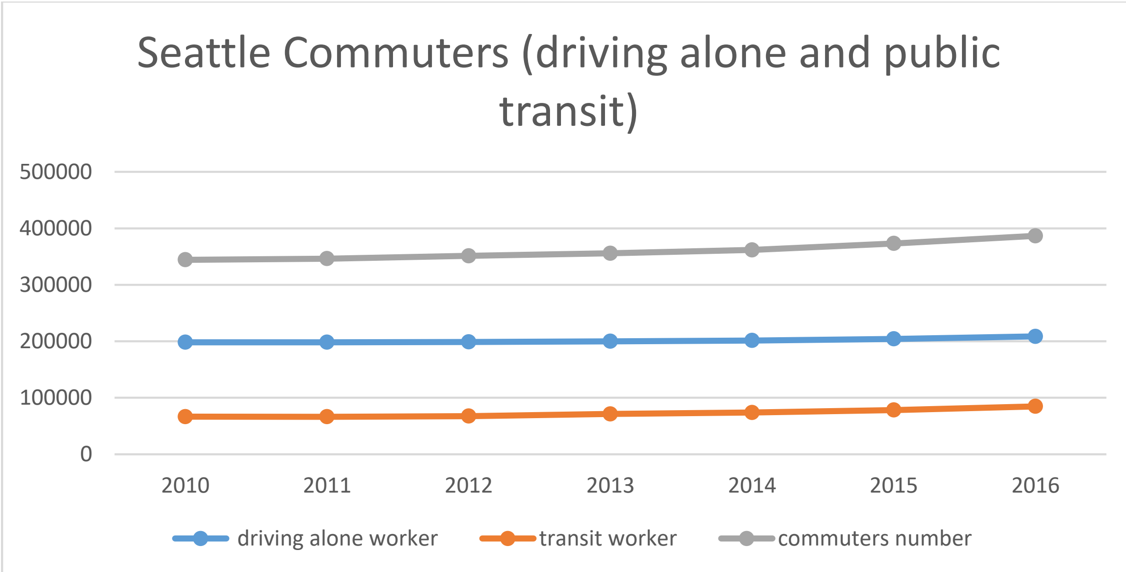


Figure 6-3 Seattle Commuter Category

In Chapter 5, peer-to-peer ridesharing could reduce driving alone and promote public transit overall. It helps to reduce 2.3% driving alone and increase 2% public transit ridership overall relatively. In particular, its effects on travel mode are affected by socio-demographic factors. The following sections provide detail forecasting modification to estimate future commuting mode choice based on average annual increasing rate and the impact of peer-to-peer ridesharing.

6.1 Seattle Census Tract Commuting Mode

In 2016, there are 386,669 commuters in Seattle, 208,625 driving alone to work and 84,754 taking public transit to work. Figure 6-4 presents the distribution of commuters driving alone percentage and Figure 6-5 presents commuters taking public transit.

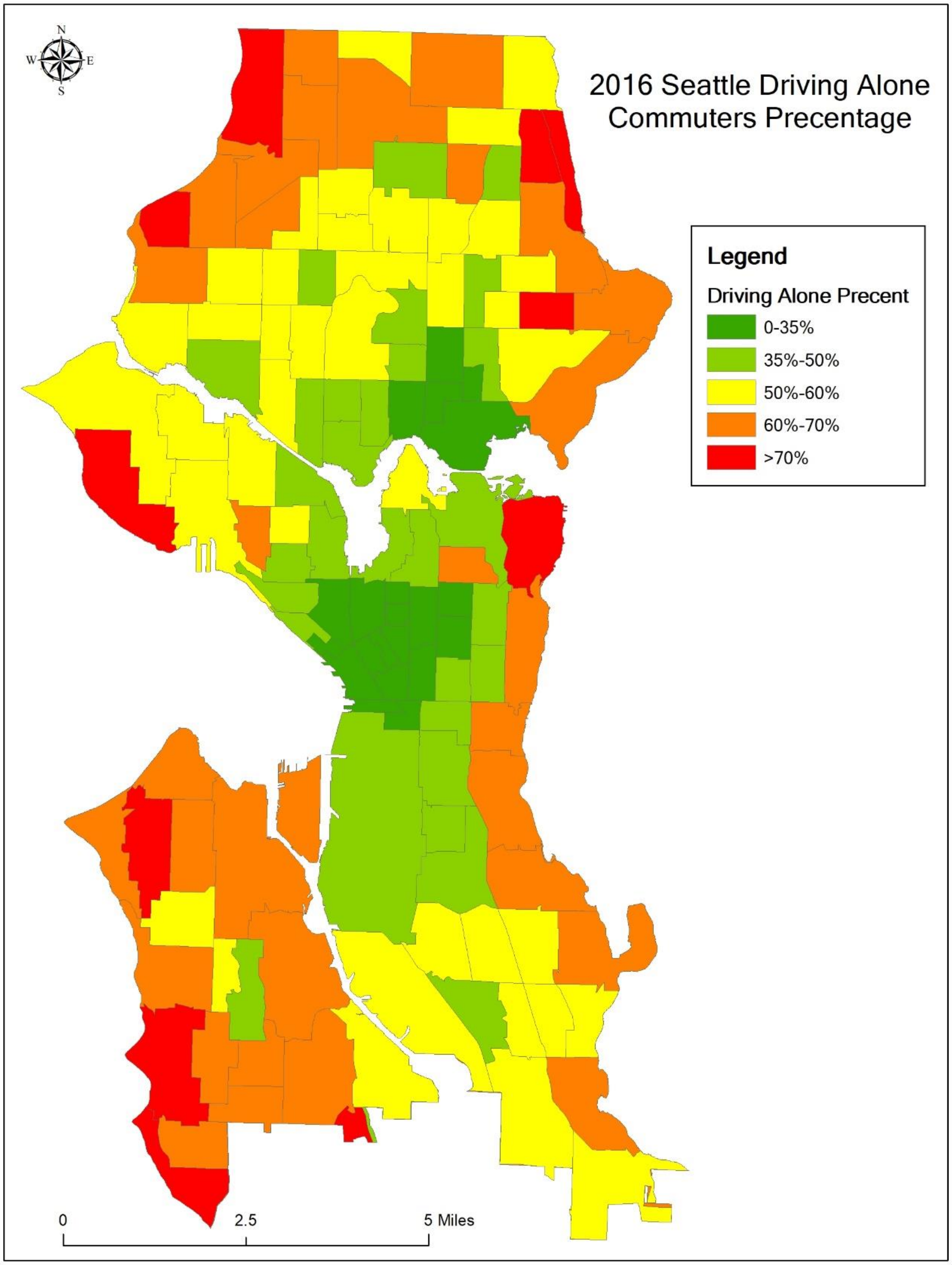


Figure 6-4 Commuters through Driving Alone Percentage

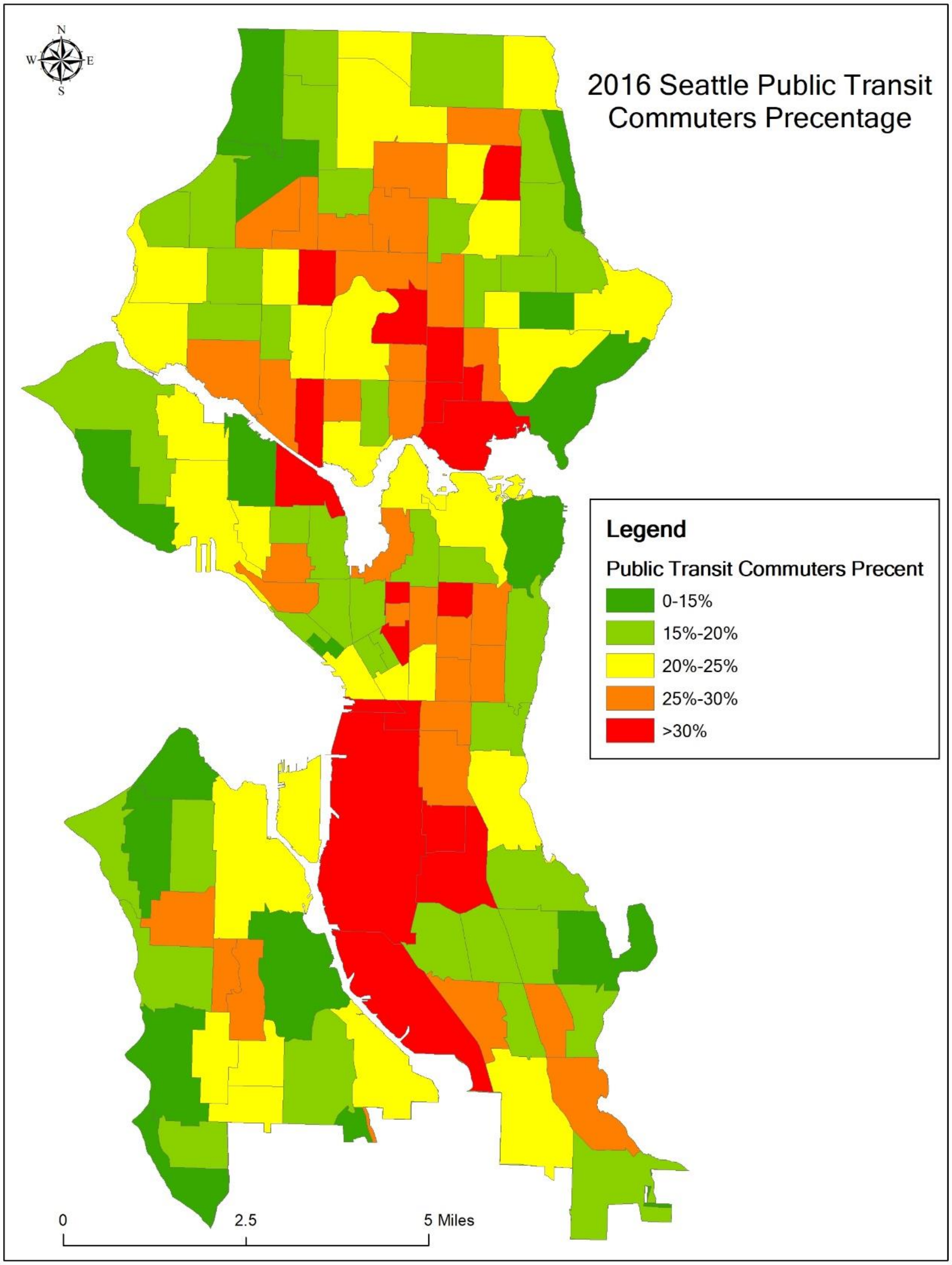


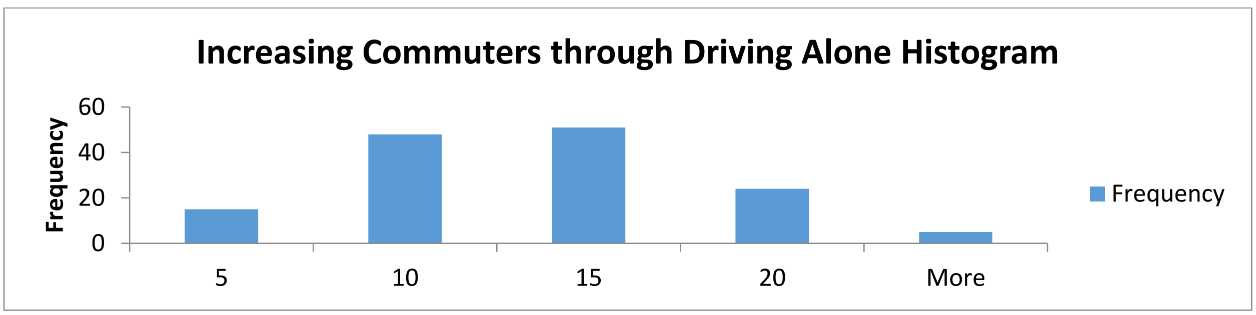
Figure 6-5 Commuters through Public Transit Percentage

Through Figure 6-4 and Figure 6-5, the driving alone percentage is lower in Downtown area where there is relatively higher public transit percentage. In the edge of Seattle, there would be a higher driving alone percentage and lower public transit percentage relatively.

From 2010 to 2016, Seattle is growing. In 2010 there were 344,326 commuters in Seattle, 198,230 commuters driving alone and 66,543 commuters taking public transit. Assuming this increasing rate will be stable in 3 years after 2016. The equation for average annual increase rate is given by:

$$Commuter\ increase\ rate\ = \frac{(2016\ commuters - 2010\ commuters)}{2010\ commuters * 7}$$

Thus the average annual commuters increase rate is 1.8%. The average annual commuters driving alone increase rate is 0.75% and the average annual commuters taking public transit increase rate is 3.91%. Thus, the increasing commuters through driving alone and public transit in 2017 could be estimated without the impact of peer-to-peer ridesharing. Figure 6-6 presents the histograms of driving alone and public transit.



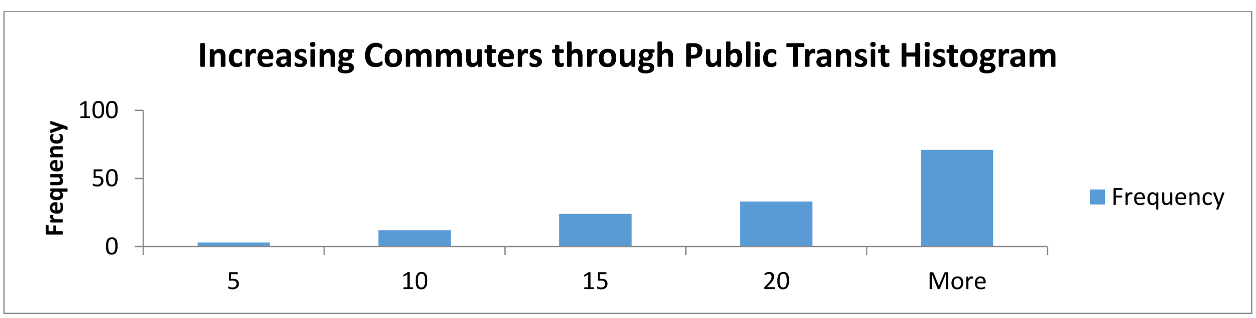


Figure 6-6 Increasing Commuters Histograms

6.2 Peer-to-peer Ridesharing Impacts

Introducing the impact of peer-to-peer ridesharing, the increasing commuter number would be modified. In Chapter 5, the impact of peer-to-peer ridesharing is measured: Uber entry could decrease 2.3% driving alone and increase 2% public transit ridership overall. Across different cluster types, the impact could be different. In Cluster 1, 26 census tracts, Uber entry could not affect driving alone and public transit for commuting significantly. In Cluster 2, 64 census tracts, Uber entry could reduce 2.5% driving alone but could not affect public transit significantly. In Cluster 3, 53 census tracts, Uber entry affects both driving alone and public transit significantly. It could reduce 2.4% driving alone and increase 3% public transit ridership. Table 6-1 depicts the Uber entry effects.

Table 6-1 Uber Entry Effects

	Increasing Commuters Type	Uber entry effect
Cluster 1 (26)	Driving Alone	*
	Public Transit	*
Cluster 2 (64)	Driving Alone	-2.5%
	Public Transit	*
Cluster 3 (53)	Driving Alone	-2.4%
	Public Transit	3.0%
Seattle (143)	Driving Alone	-2.3%
	Public Transit	2.0%
Census Tract Count in parentheses		
*means not statistical significant		

Overall, in Seattle area, Uber could help to reduce driving alone commuters and increase public transit commuters, but it is also worth noting that the impact of Uber entry on the different types of areas should be different. In Cluster 1 with average drive alone workers, fewer transit workers, less travel time and high median earning, Uber entry effect is not significant either on driving alone or on public transit. The reason could be Uber entry, as a faster and cheaper commute mode, may not shift the rich commuters' commuting preference. In Cluster 2 with more drive alone workers, more transit workers, average travel time and average median earning, Uber entry could affect driving alone commuters significantly. The reason may be the middle-income class are willing to shift from driving alone to taking Uber because of less cost. However, those who take public transit to work may not be willing to take Uber or could not afford Uber due to its relatively higher expense than traditional public transit. In Cluster 3 with less drive alone workers, average transit workers, high travel time and less median earning, Uber effects on both driving alone and public transit are significant. It could reduce driving alone and promote public transit ridership. In the view of this, planners may need to improve the public transit system in Cluster 3. According to Figure 5-1, Figure 6-4 and Figure 6-5, North Seattle, Industrial District and University District should be the priority to improve public transit services because they are of Cluster 3 and there are relatively high public transit commuter percentages in these areas.

Besides, TDM requires the planners forecasting future different commute mode demand to address the serious increasing demand outpaces supply while current forecasting does not consider the new commute mode impact. American Community Survey 5-year still forecasts different commute demand through commuters working place. This thesis may be a simple but useful step to measure the new mode effects on transportation demand.

7 Conclusion and Limitations

7.1 Conclusion

This thesis introduces that the peer-to-peer ridesharing, as a new travel mode, could affect local transportation behavior. This thesis chooses Seattle as the study area and chooses Uber launch as the treatment. It explores the influence of peer-to-peer ridesharing on travel modes. Based on the difference-in-differences analysis (DID) using data for years 2010-2016, this paper analyzes the impact of peer-to-peer ridesharing on travel mode, driving alone and public transit. Considering the effects of socio-demographics, this thesis classifies the 143 census tracts in Seattle in 2016 through Cluster analysis and define the different impacts in three cluster types.

Overall, peer-to-peer ridesharing could change individuals commute choice by reducing driving alone and promoting public transit. Robustness test proves this result. In addition, the socio-demographic factors could also affect travel mode choice. 143 census tracts are divided into three clusters across different socio-demographic factors and different travel mode in 2016 through K-means Cluster analysis. Cluster 1 includes 26 census tracts with relatively average drive alone workers, fewer transit workers, less travel time and higher median earning. Cluster 2 includes 64 census tracts with relatively more drive alone workers, more transit workers, average travel time and average median earning. Cluster 3 includes 53 census tracts with relatively less drive alone workers, average transit workers, high travel time and less median earning. DID and robustness indicate the impact of peer-to-peer ridesharing in Cluster 1 is not significant on commute mode. In Cluster 2, the impact on driving alone commuting is significant and in Cluster 3, the impacts on both driving alone and public transit are significant. Based on these findings, this thesis suggests Seattle government may need to consider the effect of peer-to-peer ridesharing and the difference effects within different socio-demographic characters.

It is worth noting that socio-demographic characters play a significant role in commute mode choice. Overall, higher median age and higher car ownership could promote more driving alone commuters and commute time correlates to driving alone commuters positively. Commute time correlates to public transit commuters negatively and higher car ownership could reduce commuters through public transit. In addition, the socio-demographic characters effects in the different cluster are different. The mean earning effects on driving alone in Cluster 1 and 2 are different. In Cluster 1, higher earing commuters may drive less for commuting while in Cluster 2, the higher earning commuters may prefer to drive alone to work.

7.2 Limitations

1. Data limitations

Due to limited resources, no primary data was collected in this study. All data is from American Community Survey 5-year estimation. Travel modes selected by the thesis include driving alone and public transport, however, in actual situations, there are also some other forms of public transportation, such as carpool. In the model, more public transport modes can be considered based on the actual conditions of urban transport mode to verify the applicability of the model.

2. Model limitations

This difference-in-differences model is not flawless. This thesis chooses socio-demographic characters including the number of commuters, the median income of commuters, the median age of commuters, the gender, average commute time for daily work, and the percentage of car ownership as controlling variables. According to past studies, other factors could also affect commute mode choices such as residential density, public transit accessibility, and road infrastructure. In addition, this thesis adopts difference-indifferences analysis based on cross-section regression. This regression is under the risk of the endogeneity. The solution to this issue is building an instrumental variable. This could be an important part of future research.

This thesis chooses Uber entry as the independent dummy variable ignoring other transport network companies and transportation policy effects. For example, although the overall result of DID is significant and is consistent with dynamic coefficient analysis, there could also be some interferences such as Seattle light rail Link System expansion to University of Washington and new parking pricing policy. Besides, the goodness-fit test could also be improved by introducing AIC and BIC.

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