August 2021

Analysis of Relative Frequency of Commuting Modes During COVID-19 Pandemic"

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ANALYSIS OF RELATIVE FREQUENCY OF COMMUTING MODES DURING COVID-19 PANDEMIC

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfilment
of the Requirements for the Degree
Master of Science
Civil Engineering

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by
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August 2021

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ABSTRACT

At the end of December 2019, a new coronavirus spread in Wuhan, China, and worldwide and the World Health Organization (WHO) declared this outbreak of the COVID-19 virus a pandemic on March 11, 2020. Different states and cities implemented various strategies including school closure, working from home, and restaurant and shop closures to control the virus spread, resulting in reduced travel demand. COVID-19 provided an opportunity to understand the differential impacts of a pandemic on travel demand. This study investigates the changes in the U.S. transportation mode use and factors influencing changes in mode use frequency for commuting during the coronavirus pandemic compared to pre-coronavirus period. Researchers conducted three waves of surveys in four metropolitan areas: New York, Washington D.C, Miami, and Houston in the United States and received 2800 responses from each wave. For this thesis, respondents had to commute at least one day/week to be included in the analysis. Ordered logistic models for relative frequency of use of commuting modes such as owned/leased vehicles, rideshare, bus and walk were created. Larger household size was positively associated with the more frequent use of owned/leased vehicles. Coronavirus risk perception was negatively associated with more frequent use of buses. Vehicle ownership was negatively associated with more frequent use of rideshare mode.

Keywords: COVID-19, Commuting modes

DEDICATION

This thesis report is dedicated to God, my loving family and supporting husband who has helped me to grow constantly through my journey.

ACKNOWLEGMENTS

This study is a part of a larger project funded by The National Science Foundation grant #1822436. The National Science Foundation is an independent agency of the United States government that supports fundamental research and education in all the non-medical fields of science and engineering. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of The National Science Foundation and the U.S. Government assumes no liability for the contents or use thereof.

First, I would like to thank my research advisor, Dr. Pamela Murray-Tuite for her continued assistance in the creation of this thesis, as well as her guidance throughout the process of performing academic research. I would also like to thank my committee members, Dr. Mashrur 'Ronnie' Chowdhury, and Dr. Jennifer Ogle, for their comments and assistance through this process. Third, I would like to thank members of my research team Dr. Kris Wernstedt, Dr. Seth Guikema, and Dr. Ed Fox for their assistance through the entirety of this project. Fourth, I would like to thank Emmanuel Adjei and Jamal Nahofti Kohneh for their assistance navigating the research world. Fifth, I would like to thank the faculty and staff of the Glenn Department of Civil Engineering for their constant support throughout my academic career.

Finally, I would like to thank the friends and family who assisted in this project by giving a different approach, providing feedback on my ideas. I truly could not have done it without all your support.

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CHAPTER ONE

INTRODUCTION

1.1 Introduction

At the end of December 2019, a new coronavirus spread in Wuhan, China, and worldwide. The World Health Organization (WHO) declared this outbreak of the COVID-19 virus a pandemic on March 11, 2020, because of the widespread among many people in various nations (WHO, 2020). Globally, the scale is 178 million cases and 3.8 million deaths as of June 17, 2021 (Worldometer, 2021). However, the global pandemic declaration responses were not uniform and consistent throughout the countries depending on wealth, availability of healthcare and medicine, public awareness, and the extent of authoritarianism in the government (Kates et al., 2020) Government directions in the United States have changed over time, starting with voluntary stay-at-home requests and restrictions on large public gatherings and eventually leading to virtual statewide lockdowns. After the declaration of a national emergency in March 2020, California was the first state in the United States of America to give the orders of stay-at-home except to go for essential needs so that the curve (number of new diagnosed COVID-19 cases) could be flattened (AJMC, 2020). The Centers for Disease Control and Prevention (CDC) recommended practicing social distancing and self-quarantine starting from early February 2020 to deal with the pandemic and flatten the curve. Past studies have shown that human mobility and interaction patterns, especially during pandemics, directly contributed to the spread of infectious diseases (Funk et al., 2010; Peixoto et al., 2020). Different states and cities implemented various strategies with the intent to control the virus spread. With the known mechanism of COVID-19 transmission and increasing risks of getting infected with it, public awareness and adherence to government policies became the critical factor during COVID-19's onset. Travel demand dropped as strategies including school closure, working from home, restaurant and shop closures, remote teaching, and the travel ban were implemented in March 2020 (Parr et al., 2020 and Mogachi, 2020).

Implementation of social distancing policies and stay-at-home orders had significant effects on activity participation. These orders affected the employment status of many people, increased work from home, and canceled most out-of-home (leisure) activities. As a result, travel demand decreased, and many countries observed a spectacular drop in vehicle traffic and a decrease in public transport ridership, leading to less frequent services (Carrington, 2020). Because of the collective nature of its mobility, public transportation is especially vulnerable to disruptions and shocks from pandemics. Social distancing and unprecedented restrictions on the use of public transportation decreased demand for many public transit systems in the United States (Liu et al., 2020).

Ives et al. (2009) conducted a study of health care staff using focus groups and interviews and asked about their attitudes toward working during pandemic Influenza. Several participants suggested that they were hesitant to use public transport due to fear of infection and, as a result, more people would start commuting in private cars. Aligned with these findings, Blendon et al. (2008) published findings from a national survey conducted in the U.S. to examine public opinion on community prevention measures for pandemic influenza, where 89% of respondents replied that they would restrict the use of public transport (buses and trains). In addition, 85 percent of them stated that when schools were closed, they would not encourage their children to use public transport. During the COVID-19 pandemic, travelers' behavior was also significantly influenced by fear of infection and perceived danger, and the impact varied depending on the most infected locations where people live and the demographic characteristics (Abdullah et al., 2020).

Individuals have different travel needs. Their trips can range from shopping for groceries to commuting to work. Depending on employment status, family members, and other demographics, such as age, ethnicity, education, and occupation, the types of trips and the use of transport modes differ (Abdullah et al., 2020). Governmental requests for travel limitations and public isolation affected individuals' travel behavior. During pandemic circumstances, understanding and predicting travel behaviors are essential for transport planning, decision making, and policymaking based on people's travel needs. Government officials could use such knowledge to reschedule public transport operations, and taxi operators and ride-sharing companies could better manage their services using such information.

The COVID-19 disease had unique challenges and forced the U.S. government to historic lockdowns and shutdowns after the declaration on National emergency in March 2020 (Farivar, 2020). These lockdowns and social distancing policies influenced travel mode choice and affected commuting patterns. Many businesses were closed, or employees were offered the ability to work from home during the pandemic.

Furthermore, public health concerns impacted travel behavior, and people started avoiding public transport and preferred active transport modes (e.g., bike, walk) for recreational activity or shorter commutes or private cars during the pandemic (De Vos, 2020). COVID-19 provided an opportunity to understand the differential impacts of a pandemic on travel demand. Studying the changes in the U.S. transportation mode use and factors influencing changes in mode use frequency during the coronavirus pandemic is necessary. This research investigates the influence of traveler characteristics and other factors on the relative frequency of commuting mode use.

1.2 Goals and Objectives

The insights gained from this study could help the transportation agencies prepare, make decisions, and make transport policies during pandemic situations based on people's travel behavior. The following objective helped to pursue these goals: to identify the factors associated with changes in relative frequency of commuting mode use during COVID-19 compared to the pre-COVID period. Three waves of survey data from the four metropolitan areas of New York, Washington D.C., Miami, and Houston supported the analyses.

1.3 Intellectual Contribution

Several studies explored the effects of COVID-19 on travel behavior (Menon et al., 2020 and Shakibaei et al., 2021), the mode shift from public transport to private or active transport during COVID-19 (Das et al., 2021 and Abdullah et al., 2020), the relation between perception of risk and the change in travel behavior (Beck and Hensher, 2020), and the influence of demographics such as age, gender, income on mode choice (Abdullah et al., 2020). However, little existing work focuses on the relative frequency of commuting mode in the U.S. during COVID-19 in late Summer 2020. Abdullah et al. (2020) clarified that the trip's intent, the choice of mode, the distance traveled, and the frequency of the primary trip before and during the pandemic were significantly different.

From the modeling perspective, Eeshan et al. (2020) created models to quantify the effect of the travelers' socio-demographic characteristics on the mode-specific trip frequencies before (January 2020) and during the early stages of COVID-19 spread in India (March 2020). Taylor et al. (2020) determined that about 72 percent (7 out of 10 respondents) of respondents surveyed in a sample of 1,000 residents of New York State would not like to use public transport (e.g., train, bus, ferry) over private vehicles even after the removal of social distancing constraints. Among pre-COVID-19 public transit users still commuting at the time of a survey in June 2020 in Canada, public transit remained the most used commuting mode during the pandemic. However, personal motor vehicle reliance was substantial among the sample population and exceeded active modes of travel during the pandemic (Harris et al., 2021). Overall, the public changed the frequency of using the commuting modes during the coronavirus pandemic. Based on the existing literature, this study is working to bridge the gap between these existing works to study the influence of travel behavior characteristics on the relative frequency of commuting modes in the U.S. during the COVID-19 period.

This study used data originally collected to examine changes in travel behavior at different times during the COVID-19 pandemic. Three survey waves in the year 2020 were conducted to understand residents' experiences during the coronavirus pandemic in four metropolitan cities in the United States- New York, Washington D.C., Miami, and Houston. The first wave was conducted from August 20, 2020, to September 02, 2020, the second wave from October 09, 2020, to October 22, 2020, and the third wave from December 11, 2020, to December 26, 2020. The collected data was used to create ordinal regression models for commuting modes to identify significant characteristics influencing change in the use frequency of transportation modes such as owned or leases vehicles, ride-sharing services such as Uber or Lyft, bus, and walk.

1.4 Outline of Thesis

The remaining thesis is organized into five chapters. Chapter 2 provides a brief overview of the literature that is important to this project, such as traveler characteristics and commuting modes, while introducing project hypotheses. Chapter 3 provides an overview of the data sources for this thesis and the process of obtaining the data. Chapter 4 describes the procedure used for data analysis and modeling. Chapter 5 presents and discusses the modeling results. Finally, Chapter 6 provides a summary as well as conclusions and recommendations for future studies.

CHAPTER TWO

LITERATURE REVIEW

2.1 Background

Overall, travel behavior has changed due to the spread of the COVID-19. De Vos (2020) explained that due to COVID-19, people reduced their travel and preferred to use active modes or cars over public transport to avoid physical contact. In the USA, population mobility was reduced by 7.87% after the first official stay-home orders on March 19, 2020 (Engle et al., 2020). The traffic volume reduction is an effect of the reduction in human mobility. For example, by March 22, 2020, traffic volumes in Florida were 47.55% lower than they were at the same time in 2019 (Parr et al., 2020). A trend of traffic volume recovery was observed across all examined states by the end of May 31, 2020, but still, most states, including Florida, were in the range of about 25% to 30% below the 2019 traffic volumes (Parr et al., 2021). The states implemented different stay-at-home and reopening policies. People often plan and perform out-of-home activities to maintain or enhance well-being, but reduced activity participation due to social distancing could negatively affect subjective well-being (De Vos, 2020)

In a survey conducted in New York with a sample of 1000 residents, about 72% (7 of 10) of participants indicated that they would not prefer to use public transportation (e.g., plane, train, bus, or cruise ship) over private cars (Taylor et al., 2020) even after social distancing restrictions lifted later in 2020. Furthermore, in a research study, respondents prioritized the factors related to infection, e.g., passengers' faces covered with a mask, social distancing, and hygiene, while choosing a travel mode during COVID-19 (Abdullah et al., 2020). In Washington DC, Metrorail ridership declined by 90%, and bus ridership declined by 75% by the end of March 2020 (WMATA, 2020). A similar trend was observed in Seoul, South Korea, with a 40% reduction in subway ridership in the first week of March 2020 compared to January 2020 due to the risk perceptions of COVID-19 (Park, 2020). However, a report by Lime Micro-mobility (Thigpen, 2020) observed a positive shift towards active modes, where 23% of all respondents already purchased a bike or e-bike by June 2020 because of the COVID-19 crisis for commuting, and most of the respondents might shift to more flexible, short-distance modes, such as bicycles or e-bikes or walking more in the future even if the COVID-19 crisis is over.

In New York state, stay-at-home orders were relaxed at the end of July 2020, but there was a prohibition of social gatherings even after the relaxation of these orders (COVID-19 guidance, 2020), so people might have walked, jogged, or cycled as a recreational activity, to maintain a certain level of subjective well-being. As a result, walking (as a primary mode of transportation) for short trips increased by 7% during COVID-19 to avoid social contact during travel (De Vos, 2020 & Abdullah et al., 2020).

In a literature review on working from home and commuting, a study showed a considerable fall in the number of commuting trips compared to the pre-coronavirus period (Beck et al., 2020) due to an increase in the number of days working from home. A couple of studies investigated workplace closure due to COVID-19 restrictions that ultimately affected the commuting mobility pattern. For example, during the lockdown in Spain, mobility to workplaces dropped 80% compared with pre-COVID-19 trends

(Google, 2020 & MITMA, 2020). The most affected mode in Spain was public transport rather than private cars (Apple, 2020). However, in a Boston city survey, among 4200 respondents, 30% reported the subway (blue line and red line in Boston) as their commuting mode, and 22% reported the Commuter rail (the purple line which goes into suburbs in various directions) as their commuting mode in the pre-covid period (Rivera et al., 2020). The telework frequency among the respondents has changed from 7% to 60% for five days per week during the pandemic (Rivera et al., 2020). Thus, the increase in the number of days working from home significantly impacted respondents' commuting patterns.

Furthermore, in a literature review on risk perception, when there was an increased perceived risk of contracting influenza in stores respondents were more likely to avoid public places and more likely to avoid transit if there was a perceived risk of getting infected in the transportation system and increased their stay at home (Hotle et al., 2020). Thus, psychological constructs changed the activity-travel behavior during the pandemic. Parady et al. (2020) also discovered a similar result during the outbreak in the Kanto Region, Japan, where risk perception, fear, and anxiety related to the pandemic and social influence all substantially impacted the frequency of in-store shopping, outside eating, and leisure activities.

In terms of socio-demographic variations, females lost many jobs as they were more likely to have worked in places closed during the pandemic (Beck et al., 2020 & Alon et al., 2020). It also has been observed that income has some relation with travel patterns. For example, due to a larger probability of being essential workers with no chance to work remotely, Lio et al. (2020) revealed that people with lower income did not or could not reduce their travel during the COVID-19 pandemic. In contrast, higher-income households and more educated respondents are more likely to be given flexibility or directed to work from home (Jay et al., 2020; Kochharn, 2020). This restriction or flexibility affects the commuting patterns. Due to the COVID-19 pandemic in Washington, USA, the reduction in travel frequencies was significantly lower among the lower-income and less-educated individuals (Brough et al., 2020).

Another demographic is age; several previous studies have linked older age with avoidance behavior, e.g., avoidance of large gatherings and crowded public transit, particularly during pandemics (Jones et al., 2009). However, older travelers tend to travel less than young people even during the outbreak of H1N1 (Leggat et al., 2009; Sharangpani et al., 2011). Since the beginning of the COVID-19 pandemic, public transportation use has dropped among people with non-physical occupations (Liu et al., 2020). That is, people who can work from home avoid taking public transportation; others who cannot work from home must rely on it (Liu et al., 2020).

The frequency of public transit operations throughout the U.S. decreased after the emergency declaration in March 2020 as public transport services strongly depended on revenues from fares, and due to plummeting revenues, transport services faced financial difficulties (Badger, 2020). Buying a car for low-income households is not a feasible option due to financial constraints, and thus they must rely on public transit even though the frequency of transit operations decreased, and public transit is not safer than a private vehicle (Housing matters, 2020).

2.2 Literature Gaps

At the time of this writing, COVID-19 was still an ongoing crisis in many countries. Despite the vast amount of data gathered, this review of COVID-19 scientific papers revealed relatively limited studies on the effects of the COVID-19 pandemic on transportation (Awad-Nunez et al., 2021). Most of the researchers previously focused on the impacts of COVID-19 on travel behavior, mode preferences, and factors affecting travel behavior changes during COVID-19. However, the relative frequency of commuting modes during COVID-19, compared to pre-pandemic conditions at the individual level, has received little attention. Mathijs et al. (2020) suggested applying qualitative studies to understand how and why people's behavior changed because of the coronavirus crisis. Siliang Luan et al. (2021) suggested investigating people's psychological changes towards travel behavior before the emergence of COVID-19 and comparing the changes with the responses collected in a survey about travel behaviors during the COVID-19.

Travel behaviors and mode preferences were significantly different during pandemic events than in pre-pandemic settings due to governmental restrictions and individual fear of infection (Abdullah et al., 2020). Therefore, a research gap may be identified about how frequently the transport mode has been used for commuting during the COVID-19 period compared with the pre-COVID-19 period and the factors influencing it; this is the gap addressed in this thesis.

2.3 Research Hypotheses

This study investigates the relative frequency of different commuting modes such as private vehicle, rideshare, bus, walk and the factors influencing it. We developed the following hypotheses based on previous literature to help with the selection of variables to model relative frequency of commuting modes.

H1: Respondents who are concerned about getting sick with a coronavirus infection are more likely to use owned or leased vehicles/motorcycles more often for commuting than the pre-coronavirus period.

The number of individuals getting infected with coronavirus increased significantly daily after the declaration of the COVID-19 pandemic in March 2020 (Worldometer). Given that COVID-19 is significantly more fatal than seasonal flu or pneumonia, Basu et al. (2020) anticipated that people's concern towards coronavirus infection would be one of the most critical factors influencing travel behavior. Based on a descriptive analysis of a risk perceptions survey conducted in Ohio, Basar et al. (2021) reported that individuals perceived private cars safer than shared modes when it comes to COVID-19 exposure. Shakibaei et al. (2021) also observed an increase in the number of people who started driving their own cars instead of taking public transportation. We, therefore, anticipate that respondents who are concerned about getting sick with a coronavirus infection are more likely to use owned or leased vehicles/motorcycles more often for commuting than the pre-coronavirus period.

H2: Respondents who are working from home for a greater number of days in a week are less likely to use owned or leased vehicles/motorcycles more often for commuting than the pre-coronavirus period.

After the declaration of a pandemic, the decision to work from home (WFH) and cease commuting was driven mainly by mandated government directives. Companies that followed the workplace closure policy allowed people to telework. As per the statistics (Statista report, 2020), 17 percent of U.S. employees worked from home five days or more per week before the coronavirus pandemic, i.e., before March 2020. The share increased to 44 percent during the pandemic in April 2020. The suppression of travel activity and the increase in working from home have significantly impacted commuting behavior (Beck et al. 2020). Mokhtarian et al. (1995) also found that telecommuting reduced commute and non-commute travel (measured in person-miles). We anticipate that the use of private vehicles has decreased during the COVID-19 period due to the increased working from home days per week compared to the pre-coronavirus period.

H3: Respondents with more household vehicles are more likely to use the owned or leased vehicles more often for commuting.

Households with more private vehicles are more likely to have access to these resources when changing travel patterns during pandemics. In one German survey, when asked about vehicle ownership, one-third of individuals in car-free households reported that they missed owning a car during the lockdown in April 2020 (Eisenmann et al., 2021). An IBM survey of 10,000 Americans in late April 2020 observed similar results where some statistical evidence suggested that many people who did not see the need for using a personal vehicle before the pandemic indeed saw the benefits of using it during the pandemic (NADA, 2020). Therefore, the respondents with more household vehicles are more likely to use them more often for commuting during coronavirus as the pandemic had the effect of making drivers who already had cars realize that they would depend on them more (Mark, 2021).

H4: Respondents with larger households are more likely to use the owned vehicle or motorcycle more often compared to the pre-coronavirus period.

Household size closely correlates to living arrangements, i.e., we may expect households with children to be the households of a larger size (Borgoni et al., 2002), and households with children are more likely to use a car than single person households (Cheng et al., 2014). Individuals can share the car with other household members and drive other family members during their commutes. Also, driving with other family members allows more time for communication that eventually might help to improve individuals' mental well-being, especially during the coronavirus crisis (De Vos, 2019a). Therefore, we anticipate that commuters from larger households are more likely to use the owned vehicle or motorcycle more often than in the pre-coronavirus period.

H5: Older respondents are more likely to use the bus less often for commuting during the pandemic than in the pre-coronavirus period.

Old-aged people are disproportionately affected by the COVID-19 pandemic (Richardson et al., 2020). Therefore, they are more worried and are perceived to be at higher risk than younger people (Gerhold, 2020; CDC guidelines, 2020). In addition, several previous studies have explained that older age is linked with avoidance behaviors such as avoidance of public transport, particularly during pandemics (Jones & Salathe, 2009). The Centers for Disease Control and Prevention (CDC) guidelines also stated that older adults are at the highest risk for severe illness with COVID-19. We, therefore, anticipate that older respondents are more likely to use the bus less often for commuting than the pre-coronavirus period.

H6: Respondents concerned about getting sick with a coronavirus infection are more likely to use the bus less often for commuting than the pre-coronavirus period.

Public transport is considered a hotspot for viruses as it might be difficult to avoid contact with other passengers (Troko et al., 2011). Individuals may contract the COVID-19 virus by touching a virus-infected surface or object and then touching their face, mouth, nose, or eyes (CDC, 2021). However, the perception of getting a coronavirus infection can be one of the reasons that over 42% of the participants in an Australian survey (Beck and Hensher, 2020) referred to the bus as the least comfortable mode. Overcrowding and hygiene or cleanliness were reported as the significant factors for avoiding commutes by bus and influencing the mode switching behavior of respondents

(Li and Hensher, 2011, 2013). We, therefore, anticipate that respondents concerned about getting sick with a coronavirus infection are more likely to use the bus less often for commuting than the pre-coronavirus period.

H7: Respondents with more household vehicles are more likely to use the (transit) bus less often for commuting than the pre-coronavirus period.

According to a survey conducted for 3000 American workers (cars.com), 65% of bus riders have stopped riding the bus, shifted to private cars, or rode the bus less frequently during the pandemic. In the same survey, respondents with vehicle ownership reported that they are no longer willing to use the bus as their commuting mode even if they have used the bus more often before the COVID-19 pandemic (Paul, 2020). It has been observed in the city center in China that if a family owns a car, it would almost certainly be used for daily commuting (Chen, 2021). We, therefore, anticipate that the respondents with more household vehicles are more likely to use the (transit) bus less often during the coronavirus period.

H8: Households with shorter commutes are more likely to walk more often during the pandemic as compared to the pre-coronavirus period.

During the pandemic, the well-being of individuals is a more critical factor, and to enhance physical activities, De Vos (2020) reported that active modes such as walking play an essential role. Grudgings et al. (2021) presented additional health benefits of walking by enabling social distancing compared to public transport modes. Along with this, active transport is also considered a feasible option for short city trips (Beck and Hensher, 2020). Early studies into the impacts of COVID-19 on travel behavior in Toronto's greater area have found that one-third of the respondents preferred active and sustainable modes such as walking for the commute during the pandemic (Loa et al., 2021). Therefore, we anticipate that households with shorter commutes are more likely to walk more often for commuting than in the pre-coronavirus period.

CHAPTER THREE

DATA

3.1 Data Acquisition and Preparation

The President of the United States declared a public health emergency on January 31, 2020, and a national emergency on March 13, 2020, concerning the coronavirus disease 2019 (COVID-19) pandemic (NCSl.org, 2020). The community mitigation strategies such as stay-at-home orders and avoidance of close person-to-person contact were widely implemented to reduce population movement and community spread of COVID-19 (Moreland, 2020). Hence, the states and territories experienced a decrease in population movement after the mandatory stay-at-home orders in most counties.

The researchers, therefore, surveyed respondents from four metropolitan areas: New York, Washington DC, Houston, TX, and Miami, FL, to understand residents' experiences during the COVID-19 period and the factors involved in their behavioral changes. The data required for this study came from a survey conducted by the larger research team designed to explore changes in travel, use of electronic communication, and electric power dependence. Three waves of surveys were conducted in 2020 following the national emergency declaration on March 13, 2020. The research team wanted to capture the possible changes approximately over two-months period between each two surveys, so the survey period for wave 1 was from August 20, 2020, to September 02, 2020, wave 2 from October 09, 2020, to October 22, 2020, and wave 3 from December 11, 2020, to December 26, 2020. In each wave, the survey questionnaire was assembled into different major blocks of questions:

- Current and Pre-coronavirus Employment status
- Risk perceptions
- Travel activities and commuting patterns
- Power perceptions
- Socio-demographics

The survey research firm Ovation was employed to administer the online survey through their panels. Ovation typically uses social media and other avenues to recruit potential respondents into a panel. The research team created a web survey using the Qualtrics survey platform and then sent the URL to Ovation. Ovation then embedded the URL in its system and sent email invitations to its panel members to complete the survey in the Ovation system. These respondents were directed to the survey's Qualtrics URL, where they entered their responses. These responses were saved in our Qualtrics database, and the Ovation system kept track of the respondents. Furthermore, Ovation provided the team with some basic respondent characteristics (such as gender, age, income) to avoid asking those questions in the survey.

Before taking the survey, certain factors were taken into consideration, including:

1. Minimum age: The respondents had to be 18 years or older.
2. Employment: Most of them need to have worked outside the home before COVID-19 (the research team controlled for that with a survey quota)

The research team set the maximum number of respondents in the survey design who did not work outside the home to 10% of total respondents (0.1*2800=280) in each of the three waves. The research team did this with a quota based on responses to a screening question by asking each respondent if they worked outside the home at the beginning of the survey, and when 280 responses were received from respondents who indicated "no," the survey quota function automatically terminated the survey for any additional people who came into the survey and answered "no" to the question. The team used the same principle to control the quota for responses from each metropolitan area. The total number of responses was limited to 2800 in each survey wave from within the four metropolitan areas: 1000 responses from New York and 600 responses each from Washington D.C, Miami, and Houston.

The research team chose to implement skip patterns under different scenarios based on the respondents' answer choices to shorten the survey.

The respondents' demographic characteristics from all three waves for four metropolitan cities are summarized below from Table 3.1 - 3.4.

The estimates from the U.S. Census Bureau for the year 2019 are compared with the wave one survey sample data and combined waves survey data. The comparisons are shown in the following Tables.

Table 3.1: Demographic comparisons for New York Metropolitan area

Demographic	Choices	Survey Sample % Wave 1	Survey Sample % Combined waves	Census%
Race:	White	74.7%	77.6%	60.21%
	Black	12.0%	11.2%	20.9%
	Native American	0.5%	1.0%	0.19%
	Asian	5.9%	5.0%	15.22%
	Native Hawaiian	0.5%	0.4%	0.0%
	Pacific islander	0.7%	0.6%	0.02%
	Other races	3.6%	2.3%	0.96%

	Two or more races	2.0%	2.0%	2.46%
Hispanic:	Yes	16.1%	17.1%	25.0%
	No	83.9%	82.9%	75.0%
Gender:	Male	58.5%	62.4%	48.0%
	Female	41.5%	37.6%	52.0%
Age*:	18-29	24.3%	21%	17.9%
	30-59	72.9%	76.6%	52.56%
	59+	2.8%	2.5%	29.52%
Average annual income:	Less than $50,000	21.5%	22.5%	31.7%
	$50,000-$100,000	22.4%	23.8%	25.4%
	$100,000-$200,000	31.4%	38.7%	26.8%
	Over $200,000	16.5%	15.1%	16.1%
* Census % redistributed to account for age 18+ survey sample				
Source: 2019 American Community Survey 1-Year Estimates				

As shown in Table 3.1, the notable different demographic from U.S. Bureau Census data is the White race and Asian race for the New York metropolitan area. The survey data sample had more respondents with White race and fewer respondents with Asian race than the U.S. Census Bureau reported. The other demographic characteristics, such as age, are intentionally oversampled with more focus on the younger age group because of the desired to capture commuting behavior.

Table 3.2: Demographic comparisons for Washington D.C Metropolitan area

Demographic	Choices	Survey Sample % Wave 1	Survey Sample % Combined waves	Census%
Race:	White	74.9%	74.2%	53.36%
	Black	14.5%	14.5%	29.73%
	Native American	0.5%	0.6%	0.28%
	Asian	3.8%	4.5%	12.27%
	Native Hawaiian	0.00%	0.1%	0.00%
	Pacific islander	0.2%	0.4%	0.05%
	Other races	3.6%	1.6%	0.42%

	Two or more races	4.0%	4.0%	3.88%
Hispanic:	Yes	10.4%	10.8%	16.3%
	No	89.6%	89.2%	83.7%
Gender:	Male	60.7%	55.6%	49%
	Female	39.3%	44.4%	51%
Age*:	18-29	22.8%	23.4%	17.85%
	30-59	73.0%	72.0%	56.36%
	59+	4.2%	4.6%	25.77%
Average annual income:	Less than $50,000	26.4%	26.3%	21.5%
	$50,000-$100,000	25.8%	25.8%	25.5%
	$100,000-$200,000	38.5%	37.2%	32.7%
	Over $200,000	9.3%	10.7%	20.3%
* Census % redistributed to account for age 18+ survey sample				
Source: 2019 American Community Survey 1-Year Estimates				

As shown in Table 3.2, the notable different demographic from U.S. Bureau Census data is the White race and Black race for Washington D.C metropolitan area. The survey data sample had more respondents with White race and fewer respondents with Black race than the U.S. Census Bureau. The other demographic characteristics, such as age, are intentionally oversampled with more focus on the younger age group.

Table 3.3: Demographic comparisons for Miami Metropolitan area

Demographic	Choices	Survey Sample % Wave 1	Survey Sample % Combined waves	Census%
Race:	White	69.8%	71.7%	54.67%
	Black	17.8%	17.8%	37.12%
	Native American	2.5%	1.7%	0.24%
	Asian	2.5%	1.7%	4.6%
	Native Hawaiian	0.2%	0.4%	0%
	Pacific islander	1.0%	0.6%	0.07%
	Other races	4.4%	3.9%	0.71%
	Two or more races	1.8%	2.2%	2.58%
Hispanic:	Yes	33.2%	33.2%	46.1%
	No	66.8%	66.8%	53.9%

Gender:	Male	52.0%	51.7%	49%
	Female	48.0%	48.3%	51%
Age*:	18-29	24.0%	27.5%	15.87%
	30-59	70.3%	67.3%	52.1%
	59+	5.7%	5.2%	32.03%
Average annual income:	Less than $50,000	40.6%	38.4%	42.1%
	$50,000-$100,000	24.6%	26.3%	29.5%
	$100,000-$200,000	22.9%	23.0%	20%
	Over $200,000	12.0%	12.5%	8.3%
* Census % redistributed to account for age 18+ survey sample				
Source: 2019 American Community Survey 1-Year Estimates				

As shown in Table 3.3, the notable different demographic from the U. S Census Bureau data is the White race and Black race for the Miami metropolitan area. The Survey data sample had more respondents with the White race and fewer respondents with the Black race than the U.S. Census Bureau. The other demographic characteristics, such as age, are intentionally oversampled, focusing on the younger age group.

Table 3.4: Demographic comparisons for Houston Metropolitan area

Demographic	Choices	Survey Sample % Wave 1	Survey sample % Combined waves	Census%
Race:	White	60.0%	62.3%	56.59%
	Black	22.4%	20.4%	27.15%
	Native American	2.9%	2.4%	0.34%
	Asian	6.7%	6.3%	12.56%
	Native Hawaiian	0.3%	0.2%	0.0%
	Pacific islander	0.0%	0.3%	0.07%
	Other races	4.5%	4.2%	0.33%
	Two or more races	3.0%	3.9%	2.94%
Hispanic:	Yes	23.5%	21.9%	38%
	No	76.5%	78.1%	62%
	Male	54.8%	43.6%	49.5%

Gender:	Female	45.2%	56.4%	50.5%
Age*:	18-29	34.7%	35.1%	19.38%
	30-59	62.2%	61.3%	56.68%
	59+	3.2%	3.6%	23.94%
Average annual income:	Less than $50,000	43.1%	44.8%	36.4%
	$50,000-$100,000	29.8%	28.0%	29.1%
	$100,000-$200,000	18.4%	20.3%	24.2%
	Over $200,000	8.6%	6.9%	10.3%
* Census % redistributed to account for age 18+ survey sample				
Source: 2019 American Community Survey 1-Year Estimates				

As shown in Table 3.4, the notable different demographic from the U.S. Bureau Census data is the White race for the Houston metropolitan area. The survey data sample had more respondents of the White race than the U.S. Census Bureau. The other demographic characteristics, such as age, are intentionally oversampled, focusing on the younger age group. The research team did not weight the survey sample data as the only notable different demographic from U.S. Bureau Census data is the White race in all four metropolitan areas.

After receiving the survey results through Qualtrics, the sample data was reviewed, and the team did some necessary recoding. We created numerous dummy variables during the analysis process to test for the influence of the presence of specific characteristics. For example, the binary dummy variable for New York City indicates whether the respondent is from New York City or not. Variables such as income and frequency of activities not related to work and percentage of risk perception were recoded into semi-continuous forms, and variables such as number of days per week working from home, number of days commuting per week were recoded into continuous forms.

For the income variable, the midpoint of each income range was considered while recoding in the survey analysis.

This study analyzes the relative frequency of commuting modes for wave one survey data and combined waves survey data. The transport options given to the respondents for commuting in the survey questionnaire were owned vehicle/motorcycle, rented vehicle/motorcycle, carpool, ridesharing services such as Uber/Lyft, taxi, bus, metro rail/ light rail/ commuter rail, bike, walk, ferry, and others. The relative frequency of commuting modes question was provided with choices such as use the commute mode from the transport options less, same, or more as compared to the pre-coronavirus period. The responses from wave 1 survey data were used to analyze the relative frequency of owned vehicle/motorcycle mode of transportation for commuting. However, the responses for other modes were not sufficient to closely look at the change in relative frequency, and therefore, wave 1, wave 2, and wave 3 survey data were combined into a single wave for further analysis. The commuting modes such as owned/leased vehicle, rideshare, bus, and walk were then used as dependent variables to create the models.

Table 3.5 presents the frequencies of commuting modes used as dependent variables to create models.

Table 3.5: Commuting modes frequencies

Transport mode	Use this less now than pre-coronavirus period	Use this same now than pre-coronavirus period	Use this more now than pre-coronavirus period
Wave 1			
Owned vehicle/motorcycle	373 (13.3%)	449 (16.0%)	254 (9.1%)
Combined waves			
Owned vehicle/motorcycle	1160 (13.8%)	1550 (18.5%)	755 (9.0%)
Carpool	130 (1.5%)	139 (1.7%)	88 (1.0%)
Rideshare	270 (3.2%)	312 (3.7%)	194 (2.3%)
Taxi	262 (3.1%)	245 (2.9%)	163 (1.9%)
Bus	273 (3.3%)	277 (3.3%)	135 (1.6%)
Rail	133 (1.6%)	184 (2.2%)	83 (1.0%)
Bike	110 (1.3%)	145 (1.7%)	114 (1.4%)
Walk	93 (1.1%)	189 (2.3%)	179 (2.1%)

As shown in Table 3.5, a greater number of respondents used private vehicles during the coronavirus pandemic compared to other modes of transportation. The overall percentage of using all modes less frequently is more than the same and less frequent except for bike and walk mode during the pandemic compared with the pre-pandemic period. Preliminary analysis was performed on the sample data using SPSS to help with the selection of variables. The sample had a significantly greater number of responses for work outside the home during the pandemic than working from home, and a greater number of responses for employed than unemployed or retired as the survey was conducted in a way where only the respondents commuting for work at least one day/week were presented with the commuting mode question. Summary statistics of all the selected variables for the final models are presented in Table 3.6 and Table 3.7 for wave 1 survey data, and combined waves survey data, respectively.

Table 3.8 and Table 3.9 present the correlation data for the variables included in the analysis for wave 1 sample data and combined waves sample data, respectively.

Table 3.6: Summary statistics of selected variables for wave 1 survey data

Variables	Number of responses	Min.	Max.	Mean	Standard deviation
Dependent variable					
Current vs. pre-corona commute w/ owned vehicle/motorcycle (0-Less, 1- Same, 2- More)	1076	0	2	0.89	0.756
Independent variable					
Number of household members (above 18 years)	2796	1	5	3.06	1.223
Education level-Graduate and above (0-No, 1-Yes)	2800	0	1	0.42	0.493
Current Employment Status (0-Unemployed or retired, 1- employed)	2797	0	1	0.97	0.159
Extremely disruptive 8hr Power outage (0-No, 1-Yes)	2779	0	1	0.39	0.487
More likely to leave the home during an 8-hour power outage in home today than during an 8-hour power outage in home this time last year (1- agree, 0 otherwise)	2791	0	1	0.44	0.497
Members of household have become more dependent on electric power during the Coronavirus period (1- agree, 0 otherwise)	2795	0	1	0.66	0.474
Age in years (continuous)	2800	18	65	37.16	10.966
Race Asian (0-No, 1-Yes)	2781	0	1	0.06	0.229
Latin Origin (0-No, 1-Yes)	2793	0	1	0.21	0.409
Occupation Professionals (0-No, 1-Yes)	2715	0	1	0.28	0.449
Number of days working from home (continuous)	2723	0	7	3.3	2.169
Current frequency of online meetings days/week (semi-continuous)	2778	0	6.5	2.39	1.96
Current frequency of online entertainment days/week (semi-continuous)	2789	0	6.5	3.53	2.267
Have children below 16 yrs. of age (0-No, 1-Yes)	2433	0	1	0.68	0.465
Self at risk for getting sick with coronavirus infection (0-No, 1-Yes)	2790	0	1	0.55	0.497

Variables	Number of responses	Min.	Max.	Mean	Standard deviation
Started attending events more than 4 weeks ago (0-No, 1- Yes)	2660	0	1	0.08	0.27
Gender (0-Male, 1-Female)	2800	0	1	0.45	0.498
Obtain Grocery frequency/week any method (semi-continuous)	2798	0.50	8.00	1.8247	1.498
Grocery curbside pickup only (0-No, 1-Yes)	2796	0	1	0.07	0.257
Change time/day of week obtain groceries w/ coronavirus (0-No, 1-Yes)	2093	0	1	0.65	0.477
Frequency of activities not related to work (semi-continuous)	2798	0.00	8.50	2.692	2.00
Percent Risk of getting infected if eat in crowded restaurant now (semi-continuous)	2787	0.05	30.00	12.60	10.892
Indicator variable for NY (0-No, 1-Yes)	2800	0	1	0.36	0.479
Indicator variable for Washington DC (0-No, 1-Yes)	2800	0	1	0.21	0.410
Indicator variable for Houston (0-No, 1-Yes)	2800	0	1	0.21	0.410
Indicator variable for Miami (0-No, 1-Yes)	2800	0	1	0.21	0.410

Table 3.7: Summary Statistics of selected variables for combined waves survey data

Variables	Number of responses	Min.	Max.	Mean	Standard deviation
Dependent variables					
Current vs. pre-corona commute w/ owned vehicle/motorcycle (0-Less, 1- Same, 2- More)	3465	0	2	0.88	0.734
Current vs. pre-corona commute w/ ride share (0-Less, 1- Same, 2- More)	776	0	2	0.90	0.768
Current vs. pre-corona commute w/ bus (0-Less, 1-Same, 2- More)	685	0	2	0.80	0.746
Current vs. pre-corona commute w/ walk (0-Less, 1-Same, 2- More)	461	0	2	1.19	0.746
Independent variables					
Number of people in household (above 18 years)	8389	1	5	3.12	1.223
Occupation Professionals (0-No, 1-Yes)	8145	0	1	0.27	0.443
Number of days per week currently commute to work (continuous)	4615	0	7	3.86	1.746
Number of days per week currently work at home (continuous)	8172	0	7	3.17	2.189
Transit operated slower than normal (0-No, 1-Yes)	941	0	1	0.38	0.486
Changed transit route/time for transit crowding/congestion (0-No, 1-Yes)	929	0	1	0.74	0.441

Variables	Number of responses	Min.	Max.	Mean	Standard deviation
Time takes for one-way commute to work in minutes (semi-continuous)	4417	15.00	95.00	33.80	17.63
Number of Vehicles/Motorcycle in household	8390	0	3	1.48	0.794
Self at risk for getting sick with coronavirus infection (0-No, 1-Yes)	8363	0	1	0.55	0.498
Events never stopped attended (0-No, 1-Yes)	8382	0	1	0.04	0.206
Events not yet attended (0-No, 1-Yes)	8382	0	1	0.48	0.500
Percent Risk of getting infected if eat in crowded restaurant (semi-continuous)	8353	0.05	30.00	12.52	10.94
Have children below 16 yrs. of age (0-No, 1-Yes)	8019	0	1	0.65	0.478
Race White (0-No, 1-Yes)	8336	0	1	0.74	0.436
Race Asian (0-No, 1-Yes)	8336	0	1	0.05	0.223
Race Black (0-No, 1-Yes)	8336	0	1	0.17	0.376
Native American (0-No, 1-Yes)	8336	0	1	0.02	0.146
Grocery curbside pickup only (0-No, 1-Yes)	8389	0	1	0.07	0.258
Grocery home delivery only (0-No, 1-Yes)	8389	0	1	0.13	0.335
Obtain Grocery frequency/week any method (semi-continuous)	8388	0.05	8.00	1.74	1.54
Changed time/day groceries for more schedule flexibility	4035	0	1	0.40	0.491
Frequency of activities not related to work times/week (semi-continuous)	8391	0.00	9.00	2.73	2.003
Extremely disruptive 8hr Power outage (0-No, 1-Yes)	8349	0	1	0.38	0.486
Gender (0- Male, 1- Female)	8398	0	1	0.45	0.498
Education level-Graduate and above (0- No, 1-Yes)	8399	0	1	0.43	0.495
Age in years (continuous)	8399	18	65	37.04	10.900
Indicator variable for wave 2 survey (0-No, 1- Yes)	8399	0	1	0.33	0.471
Indicator variable for wave 3 survey (0-No, 1- Yes)	8399	0	1	0.33	0.471
Indicator variable for NY (0-No, 1-Yes)	8399	0	1	0.36	0.479
Indicator variable for Washington DC (0-No, 1-Yes)	8399	0	1	0.21	0.410
Indicator variable for Miami (0-No, 1-Yes)	8399	0	1	0.21	0.410

Table 3.8: Correlation matrix of independent variables for wave 1 survey data

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	HHnumber	1.000																							
2	edu_gradplus	.228**	1.000																						
3	Employed	0.012	.075**	1.000																					
4	pow8hrextrm	-.069**	0.004	-0.031	1.000																				
5	powerleaving agree	.106**	.199**	.040*	.081**	1.000																			
6	Powdepent	.107**	.181**	0	0.033	.347**	1.000																		
7	age	0.025	.214**	-0.011	.058**	0.015	.073**	1.000																	
8	asian	-0.011	-.075**	0.01	-0.002	-0.029	0.011	-0.035	1.000																
9	Latin origin	-0.014	-.174**	-0.008	0.002	-.055**	-.101**	-.177**	-0.031	1.000															
10	OccProfess	0.011	.091**	.	-0.023	-.053**	0.022	-0.003	.059**	-.044*	1.000														
11	homedays	.080**	.164**	.	0.015	.097**	.138**	0.002	-0.027	-.044*	.063**	1.000													
12	online meet	.149**	.274**	.122**	0.031	.175**	.151**	-0.002	-0.008	-.059**	.111**	.360**	1.000												
13	online entertn	.066**	0.012	-.040*	0.022	-0.006	.084**	-.102**	0.021	-0.028	.051**	.088**	.178**	1.000											
14	coronarisk	-0.012	.045*	0.033	.090**	.071**	.087**	.107**	-0.003	.049**	-0.006	-0.03	0.014	-0.016	1.000										
15	Evnt_4wkNY	0.017	0.019	0.003	0.003	0.027	0.035	-0.015	-0.016	0.006	0.026	0.018	-0.002	0.019	0	1.000									
16	gender	-.196**	-.323**	-.077**	.038*	-.196**	-.106**	-.178**	.074**	.125**	.070**	-.122**	-.198**	.083**	-.045*	0.021	1.000								
17	groceryfreq	.148**	.110**	0.031	-.049**	.159**	.051**	-0.028	-.077**	-.069**	-0.035	.099**	.106**	0.035	0.013	.067**	-.116**	1.000							
18	grocerycurb	-.075**	-.065**	0.002	-0.022	-.046*	-.086**	-.101**	0.013	.131**	-0.032	-0.025	0.005	-.042*	.049**	-0.018	0.016	-0.02	1.000						
19	grocerychang	.122**	.239**	0.028	0.037	.212**	.151**	-0.031	-0.023	0.018	-0.003	.211**	.274**	-0.006	.234**	-0.012	-.174**	.079**	.	1.000					
20	activityfreq	0.029	.043*	0.019	-0.001	.169**	0.034	-0.021	-0.023	-0.031	-0.017	.102**	.099**	.054**	.059**	.093**	-.081**	.356**	-0.026	0.034	1.000				
21	riskpercent	0.021	.053**	-0.034	.080**	.044*	.142**	0.013	0.021	0.006	.055**	.076**	.072**	.093**	.189**	-0.001	.054**	-0.005	0	.077**	-.052**	1.000			
22	NY	.113**	.110**	0.005	-.050**	.049**	.093**	-0.006	0.02	-.039*	.040*	0.013	.062**	0.034	0.025	.237**	-.056**	0.025	-.055**	.073**	.076**	0.007	1.000		
23	D.C	-.040*	.075**	-0.002	0.033	.041*	0.011	.075**	-0.004	-.138**	-0.035	.069**	0.022	0.007	0.029	-.094**	-.062**	-0.007	-0.022	0.037	-0.015	0.02	-.389**	1.000	
24	Miami	0.006	-.050**	0.014	0.001	-.050**	-0.015	0.023	-.061**	.155**	-0.009	-0.012	0	-.048*	-0.036	-.096**	0.029	-0.017	-0.008	-0.038	-0.035	0.016	-.389**	-.273**	1.000
**Correlation is significant 0.01 level (2-tailed)																									
*Correlation is significant 0.05 level (2-tailed)																									

Table 3.9: Correlation matrix of independent variables for combined waves survey data

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	HHnum	1.000																									
2	occuprofess	0.005	1.000																								
3	commuteday	.068**	-0.019	1.000																							
4	homedays	.072**	.062**	-.196**	1.000																						
5	tranrtchange	.121**	0.016	-.136**	.283**	1.000																					
6	Comt_min	.067**	.034*	-.065**	.218**	0.039	1.000																				
7	vehnum	.161**	.039**	.033*	0.006	.286**	-0.008	1.000																			
8	coronarisk	-.038**	0	-.100**	-.064**	.149**	.084**	.037**	1.000																		
9	eventsnot	-.045**	.058**	.057**	-0.007	-.224**	-.127**	-.041**	-0.012	1.000																	
10	percentrisk	0.016	.038**	.043**	.073**	0.058	.064**	0.016	.217**	.084**	1.000																
11	Asian	-.029**	.062**	-0.003	-.025*	-.124**	-0.015	-.035**	-0.007	.050**	0.016	1.000															
12	Black	-.115**	-.037**	0.008	-0.018	-.109**	-0.018	-.106**	-.075**	-0.02	-0.01	-.062**	1.000														
13	Native	-.025*	-0.015	-0.024	-0.011	-0.002	-0.002	-.039**	0.002	-.026*	-.022*	-0.006	0.013	1.000													
14	curbpickup	-.080**	-.032**	-.081**	0.007	0.054	.060**	.024*	.041**	-.070**	-0.012	0.01	.082**	.071**	1.000												
15	homedelivery	.092**	.024*	-0.009	.152**	-0.038	-0.009	-0.003	-.076**	.075**	.045**	-.042**	-.060**	-.023*	-.107**	1.000											
16	Groc_freq	.158**	-0.018	.115**	.099**	.223**	.126**	.077**	-0.007	-.191**	0.02	-.063**	0.007	-0.008	-0.004	-.026*	1.000										
17	activityfreq	.051**	-0.016	.101**	.087**	.177**	.133**	.047**	0.016	-.249**	-.046**	-.037**	-0.007	0.008	0.011	-.150**	.339**	1.000									
18	powextrm	-.032**	-.031**	-.068**	0.003	0.038	0.017	-0.002	.095**	.022*	.059**	0	-0.019	-.040**	-.030**	-.071**	-.045**	-0.001	1.000								
19	gender	-.176**	.072**	.058**	-.127**	-.249**	-.154**	-.091**	-0.02	.106**	.056**	.070**	.163**	.043**	0.021	-.097**	-.124**	-.079**	0.018	1.000							
20	edugradplus	.198**	.098**	-.113**	.171**	.301**	.134**	.116**	.042**	-.067**	.035**	-.069**	-.226**	-.081**	-.076**	.131**	.100**	.042**	.029**	-.323**	1.000						
21	age	0.009	.022*	0.018	.027*	0.033	.037*	.051**	.086**	.105**	.024*	-.042**	-.244**	-.083**	-.095**	0.014	-0.012	-.032**	.050**	-.185**	.240**	1.000					
22	wave_2	.065**	-.041**	-0.028	.029**	0.033	.032*	.050**	0.006	-.032**	-.024*	-.045**	-.083**	-.048**	-0.018	.035**	.024*	.022*	0.016	-.113**	.150**	.097**	1.000				
23	wave_3	-.029**	0.021	0.017	-.070**	-0.035	-.044**	-.034**	-0.009	0.004	0.015	.036**	.073**	.057**	0.021	-.048**	-0.016	-0.006	-.022*	.116**	-.139**	-.104**	-.500**	1.00			
24	NY	.104**	.025*	-.066**	.046**	0.055	.146**	-.067**	0.018	-.057**	0.002	0.007	-.096**	-.031**	-.062**	.060**	.025*	.035**	-.028*	-.117**	.164**	.040**	0	0	1.000		
25	DC	-.057**	0.001	-.083**	.039**	0.034	-0.001	0.009	.038**	.039**	.031**	0.014	0	-.030**	-.025*	-0.013	-.028**	-.039**	.043**	-0.01	.066**	.053**	0	0	-.389**	1.000	
26	Miami	0.006	-0.006	.044**	-0.003	-0.04	-.048**	0.021	-.045**	.026*	-0.003	-.067**	.034**	0.004	-0.006	0.003	0.018	0.005	-.024*	.031**	-.085**	-0.009	0	0	-.389**	-.273**	1.0

**Correlation is significant 0.01 level (2-tailed)

*Correlation is significant 0.05 level (2-tailed)

3.2 Timeline for COVID-19

A resident from Washington state became the first person in the United States with a COVID-19 confirmed case on Jan 21, 2020 (AJMC, 2020). Since then, several regional and national policies have shaped the metropolitan area, impacting the population's travel behavior. However, each state or territory had the authority to enact its policies to protect the public's health, and jurisdictions varied widely in the type and timing of orders issued related to stay-at-home requirements. Tables 3.10 - 3.13 shows the timeline of government responses in the four metropolitan areas in our study. Our survey waves were conducted during the coronavirus pandemic, and therefore it is essential to examine the changes in people's travel behavior due to lockdowns and reopening policies implemented by local government officials.

The government responses timeline for COVID-19 in the New York metropolitan area (New York state, New Jersey State, Connecticut state) is presented in Table 3.10 (Husch Blackwell, 2021).

Table 3.10: Timeline for COVID-19 in New York Metro area

Date	Events
March 7, 2020	New York State of emergency declaration
March 8, 2020	Events with more than 500 people banned
March 13, 2020	WHO declared the outbreak a pandemic
March 15, 2020	Gatherings of 50+ banned
March 16,2020	New York city (NYC) public school closed, bars and restaurants closed,
March 22, 2020	PAUSE program began/closure for all non-essential business/stay-at-home orders
April 06, 2020	NY state’s stay-at-home order extended
April 30, 2020	NYC subway closure from 1 a.m. to 5 a.m.
May 01, 2020	School closed for the remainder of the academic year
May 23, 2020	Gatherings allowed up to 10 with social distancing

Date	Events
June 08, 2020	NYC phase 1 reopening/ reopening of selected business that can offer curbside pickup
June 15, 2020	Non-essentials gatherings allowed up to 25 people
June 22, 2020	NYC phase 2 reopening/ outdoor dining, salons, cleaning services opened, Limit on outdoor gatherings increases to 250 people in New Jersey (NJ) state.
July 06, 2020	NYC phase 3 reopening/schools reopened with state guidance, entertainment with 33% capacity, gatherings up to 25 people
July 20, 2020	Phase 4 reopening in almost all regions of New York state allows schools and low-risk arts, entertainment, and recreation businesses to reopen. Gatherings of up to 50 people will also be allowed.
July 20, 2020	Phase 2 reopening in New Jersey state and Connecticut state (entertainment and events up to 50 people)
Sept 09, 2020	Malls in NYC reopened at 50% capacity
Sept 29, 2020	Elementary students returned to classrooms across NYC
Sept 30, 2020	Indoor dining resumed with 25% occupancy
Oct 19, 2020	Movie theatres reopened with 50% capacity and no more than 50 people per screen
Nov 11, 2020	All indoor and outdoor gatherings at private residences limited to no more than 10 people.

The government responses timeline for COVID-19 in Washington D.C. metropolitan area is presented in Table 3.11 (Husch Blackwell, 2021).

Table 3.11: Timeline for COVID-19 in Washington D.C metro area

Date	Events
March 13, 2020	Gatherings of 50+ banned
March 16, 2020	Restaurants, bars closed
May 15, 2020	Limited D.C government operations
May 29, 2020	D.C phase 1 reopening/ outdoor dining in restaurants opened/ curbside pickup
June 22, 2020	D.C phase 2 reopening/ restaurants indoor dining opened with 50% capacity
Nov 24, 2020	Indoor occupancy of restaurants reduced from 50% to 25%

The government responses timeline for COVID-19 in the Miami metropolitan area (Florida state) is presented in Table 3.12 (Husch Blackwell, 2021).

Table 3.12: Timeline for COVID-19 in Miami metro area

Date	Events
March 09, 2020	State of emergency declaration
March 20, 2020	Only take-out and delivery services from restaurants allowed
April 01, 2020	Statewide stay-at-home orders
April 17, 2020	Florida beaches allowed to reopen if done safely
May 18, 2020	Miami Dade county phase one of reopening
May 27, 2020	Restaurants reopened for dine-in
June 01, 2020	Hotels and pool reopened
June 03, 2020	Chances of gyms, fitness center, youth activities to reopen
June 29, 2020	Issued Emergency order to close all beaches
July 30, 2020	Extended the declaration of State of local emergency
Oct 28, 2020	Again, extended the declaration of State of local emergency

The government responses timeline for COVID-19 in the Houston metropolitan area (Texas state) is presented in Table 3.13 (Husch Blackwell, 2021).

Table 3.13: Timeline for COVID-19 in Houston metropolitan area

Date	Events
March 13, 2020	State of emergency declaration/WHO declared the outbreak a pandemic
March 16, 2020	Bars in Houston closed
March 19, 2020	Gatherings of 10 people allowed
March 25, 2020	Closure for all non-essential business/stay-at-home orders
April 03, 2020	CDC recommended cloth face coverings
May 01, 2020	Several businesses reopened
May 08, 2020	Salons reopened with 25% capacity
May 22, 2020	Bars reopened/restaurants reopened with 50% capacity
June 03, 2020	Almost all businesses reopened with 50% occupancy
June 12, 2020	Restaurants started operating with 75 % capacity
June 26, 2020	Bars shut down again and restaurant capacity backed to 50% capacity
July 03, 2020	Prohibited outdoor gatherings of more than 10 people
Sept 17, 2020	Occupancy levels increased to 75% from 50% for restaurants, museums, gyms
Oct 09, 2020	Indoor occupancy limited to 50%

As shown in Table 3.10 and Table 3.12, the New York state and Florida state declared an emergency before the National emergency declaration on March 13, 2020. Metropolitan areas in the U.S. followed the state policies. This timeline for COVID-19 helped to understand the respondents' travel behavior during the pandemic. The timeline was useful in the modeling process since it allowed us to choose variables depending on when respondents first started attending events in each metropolitan area. For example, the timeline for New York metropolitan area helped to select the interaction term of respondents from the New York metro area and started attending events with more than ten people before the end of July 2020 as, before that period, New York State continued phase 3 reopening with gatherings up to 25 people. New Jersey state and Connecticut state also continued the phase 2 reopening policies where events were allowed to attend with not more than 50 people before the end of July 2020. The first wave of the COVID-19 survey period was from August 20, 2020, to September 02, 2020. As per the timeline people started attending the events with more than 10 people in New York metropolitan area (New York state, New Jersey state and Connecticut state) more than four weeks before our first survey wave. Therefore, in this way, the timeline helped us in selecting the variables from our survey data and examined the individual's travel patterns during the pandemic.

As shown in Table 3.10 to Table 3.13, during wave 1 survey, i.e., from August 20, 2020, to September 02, 2020, the New York metropolitan area was in phase 4 of reopening, and the Washington D.C. metropolitan area was in phase 2 of reopening. In contrast, the Miami and Houston metropolitan areas were still under restrictions.

However, a few changes were observed during the wave 2 survey, from October 09, 2020, to October 22, 2020, where indoor capacity in the Houston metropolitan area reduced from 75% to 50%. Similarly, before the wave 3 survey, i.e., from December 11, 2020, to December 26, 2020, Washington D.C. reduced the indoor restaurant capacity from 50% to 25%. These changes in the reopening phases in all four metropolitan areas could have affected the travel behavior response of people in three waves of COVID-19 surveys.

CHAPTER FOUR

METHODOLOGY

4.1 Ordinal Logistic (OL) Modeling

This study analyzed the survey data of commuting respondents using the ordered logit regression method. The dependent variable includes three relative frequency type choices (less, same, more) representing how frequently respondents currently use modes such as their owned or leased vehicle/motorcycle; bus; ride-sharing service, such as Uber or Lyft; taxi; Metrorail/light rail/commuter rail; bike; and walk for commuting during the coronavirus period compared to the pre-coronavirus period. These responses have an intuitive order and are reported as 1, 2, and 3 (less, same, and more). However, these are not equivalent to any mathematical representation. The difference in the behavior between 1 and 2 is not necessarily equal to that between 2 and 3. An ordered logit (or probit) model is the most suitable and commonly used methodology for the dependent variable with such properties, and therefore ordered logit was used for this study (Long and Freese, 2006).

Let Y_i be an ordinal outcome variable with C categories for the i^{th} subject, alongside a vector of covariates x_i (Grilli et al., 2014). Ordinal regression models are usually not expressed in terms of probabilities of the categories, but they refer to a convenient one-to-one transformation, such as the cumulative probabilities. The last cumulative probability is necessarily equal to 1, so the model specifies only C-1 cumulative probabilities. The parameters α_c are called thresholds or cutoff points, and C-1 is the number of thresholds. The models in this study have a C equal to 3, and thus two cutoff thresholds, one between the responses less and same and the other between the responses same and more (Williams and Quiroz, 2020).

The cumulative probability for category c is (Willaims, 2018),

$$P(Y = 3) = \frac{1}{1+\exp(-\alpha_3+\beta' x_i)} \tag{1}$$

$$P(Y = 2) = \frac{1}{1+exp(-\alpha_2+\beta' x_i)} \tag{2}$$

$$P(Y = 1) = 1 - P(Y = 2) - P(Y = 3) \tag{3}$$

where,

$\beta' x_i = \beta_1 x_{1+} \beta_2 x_{2+} \beta_3 x_3$

β= estimated co-efficient in the model

α_c = estimated cutoff points, c=1,2 (Williams, 2018)

The ordinal logistic regression modeling should follow and test the assumptions in the order: a) the dependent variable is ordered, b) one or more of the independent variables are continuous, categorical, or ordinal, c) no multicollinearity, and d) proportional odds. The first two assumptions were already tested before selecting the type of model (Menard, 2002). Multicollinearity occurs when there is a high correlation among two or more independent variables in a multiple regression model. Ordered logistic regression requires little or no multicollinearity among the independent variables as it can undermine the statistical significance of an independent variable. To avoid multicollinearity, Spearman correlation coefficients were determined for each pair of independent variables. Variables with correlation coefficients exceeding 0.4 were not permitted in the same model as they were considered moderately correlated (Hinkle et al., 2003)

The last assumption of the ordered logistic regression is that the relationship between each pair of outcome groups of the dependent variable is the same. In other words, ordered logistic regression assumes that the coefficients that describe the relationship between less versus the same and more outcome categories of the dependent variable are equal to those that describe the relationship between the less and same versus more. This is called the proportional odds assumption or the parallel regression assumption. If the relationship between the coefficients of all the pairs of groups is the same, then there is only one model (Williams, 2006; Williams and Quiroz, 2020). Brant's test (Long and Freese, 2006) allows examination of whether the assumption of parallel lines was violated. For Brant's test, the proportional odds assumption is considered to hold if the probability (p-values) for all variables is greater than alpha=0.05. The assumption of proportional odds is strongly affected by sample size and the number of covariate patterns and hence often violated, leading to the need for a generalized ordered logit model, as used in this study.

The generalized ordered logit model extends the ordered logit model (also known as proportional odds model) (Grilli et al., 2014) by relaxing the assumption of proportional odds. In a generalized ordered logit, unlike the ordered logit, an independent variable can have C-1 betas. The formulas for the generalized ordered logit model and the ordered logit model are the same, except that in the ordered logit model, the β's (but not the α's) are the same for all the values of 'c' (Williams, 2006). The equation that shows how to calculate the probabilities based on the generalized ordered logit model is

$$P(Y_i > c) = \frac{exp(\alpha_c + x_i\beta_c)}{1 + exp\,(\alpha_c + x_i\beta_c)}, c = 1,2 \qquad (4)$$

where,

α_c = estimated cutoff points, c=1,2

C= number of outcomes/categories (Grilli et al., 2014).

4.2 Modeling Process

The developed hypotheses based on previous literature helped guide the selection of variables to model the relative use frequency of different modes of transportation for commuting. To help narrow the possible list of additional (non-hypothesis) variables for use in the multivariable modeling process, the significance level of all the independent variables was checked in univariate models, akin to Hosmer and Lemeshow's purposeful selection (Hosmer et al., 1999 and Hosmer et al., 2000). Though there is no statistical justification of univariate screening (Sun et al., 1996), we considered the threshold value for significance (p-value) of variables as 0.25. Variables with p-values less than this threshold were considered for the multivariable (generalized) ordered logit model. NLOGIT software, an extension of the econometric and statistical software package LIMDEP, was used to create (generalized) ordered logit models. After adding all the potential variables, the model was created using a backward elimination approach in NLOGIT software, where the least significant variable was eliminated at each step. This process was repeated until a significance level of 0.05 was reached for a 95% confidence level that the parameter estimate was different from zero for all the variables in the model as recommended for large sample sizes created using wave 1 survey data (Heinze et al., 2018; Dunkler et al., 2014). However, for the combined wave (wave 1+wave 2+ wave 3), the same data was used repeatedly to create the series of models for different modes. Some independent variables were selected multiple times for the analysis using the same sample set. In such models, the process of the backward elimination approach was repeated until the significance level of 0.01 was reached (Heinze et al., 2018). The improvement of the model from one to the next was determined by checking the McFadden pseudo R^2. It was used to indicate the goodness of fit of the model. Larger values of McFadden's pseudo R^2 are better than smaller ones, but typically ordered logistic regression has low values and should not be interpreted as the R^2 for linear regression models (Grilli et al., 2014).

CHAPTER FIVE

RESULTS AND DISCUSSION

5.1 Modeling Results

Following the methodology described in Chapter 4, four (generalized) ordered logit models for private vehicle commuting mode are presented in Table 5.1. Two models are presented for wave 1 survey data, and two for the combined waves survey data. The combined wave data was also used for ordered logit models for other commuting modes (rideshare, bus, and walk). Two models for each of these modes are presented in Tables 5.2, 5.3, and 5.4, leading to ten models in all. The Full model (Model F) contains hypothesis variables that may or may not be statistically significant along with other statistically significant variables. Model S contains only statistically significant variables. Model S is presented with marginal effects. Results of the relative frequency of commuting modes are presented below.

5.1.1 Owned or leased vehicle/motorcycle

Model F is a generalized ordered logit model with 1014 observations for wave 1 data and 3410 observations for models developed with the combined waves data. McFadden Pseudo R-squared values are usually used to indicate the model's goodness of fit. However, this value is low in the case of ordered logistic regression. Previous studies reported that this value ranges between 0.012 to 0.138 (Hotle et al., 2020). The McFadden Pseudo R-squared value is 0.089 for the wave 1 model and 0.084 for the combined waves model.

Model S for the relative frequency of using the owned or leased vehicle has six significant variables for the model based on wave one survey data with 1017 observations and four significant variables for the model developed with the combined waves data with 3442 observations. The McFadden Pseudo R-squared value is 0.070 for the wave 1 model and 0.063 for the combined wave model.

5.1.1.1 Wave 1 Survey data

For wave 1 survey data, the significant variables are the number of household members, an interaction term of residing in the New York City metropolitan area and starting to attend events with more than ten people more than four weeks before the end of the survey period, i.e., before Sep 02, 2020, an indicator for respondents who consider themselves at any risk for getting sick from coronavirus infection, number of days working from home during the survey period, frequency of participating in non-work-related activities, and number of vehicles in the household. As shown in Table 5.1, an additional household member increases the likelihood of using the owned or leased vehicle more by 3.43% and decreases the likelihood of using the owned vehicle less by 4.13%. Respondents who have started attending the events more than four weeks before the end of the survey period and belong to the New York City metropolitan area are 18.02% more likely to use the owned or leased vehicle more. Individuals who consider themselves at any risk of getting sick from coronavirus infection are 9.55% less likely to use the owned or leased vehicle more. An increase in the number of times per week working from home decreases the likelihood of using the owned or leased vehicle more by 4.26% per additional day and increases the likelihood of using it less by 5.14%. An increase in the number of times per week non-work outings are undertaken increases the likelihood of using the owned or leased vehicle more by 1.74% per day. The increase in the number of vehicles in the household decreases the likelihood of using the owned or leased vehicle more by 5.45% per vehicle and increases the likelihood of using it less by 6.58%.

5.1.1.2 Combined waves survey data

For combined wave survey data, the significant variables are the number of household members, frequency of obtaining groceries in a week (any method), whether they consider themselves at any risk for getting sick from coronavirus infection, and the number of days currently working from home. As shown in Table 5.1, an increase in the number of household members increases the likelihood of using the owned or leased vehicle more by 1.8% per additional person and decreases the likelihood of using the owned vehicle less by 2.22%. An increase in the number of times per week to obtain groceries increases the likelihood of using the owned or leased vehicle more by 2.67% per additional day. Individuals who consider themselves at any risk of getting sick from a coronavirus infection are 8.07% less likely to use the owned or leased vehicle more and 9.58% more likely to use the vehicle less than in pre-COVID-19 times. An increase in the number of times per week working from home decreases the likelihood of using the owned or leased vehicle more by 4.33% per day and increases the likelihood of using it less by 5.34%. Out of all the significant variables, the number of household members, respondents' consideration of any risk for getting sick with coronavirus infection, and the number of days currently working from home are consistent with the significant variables of wave 1 survey data.

5.1.2 Rideshare

Model F for the relative frequency of rideshare commuting mode is a generalized ordered logit model with 753 observations based on the combined waves data. In this model, the McFadden Pseudo R-squared value is 0.046.

Model S for the relative frequency of rideshare commuting mode has four significant variables for the model developed with the combined waves data with 765 observations. McFadden's Pseudo R-square value for this model is 0.029.

The significant variables in model S for the rideshare commuting mode are frequency of participating in non-work-related activities, the number of vehicles in the household, Asian race, and American Indian/ Native American or Alaska Native race. As shown in Table 5.2, an increase in the number of times per week non-work outings are undertaken increases the likelihood of using the rideshare more by 3.21% per day. An increase in the number of vehicles in the household decreases the likelihood of using the rideshare more by 6.62% per vehicle and increases the likelihood of using it less by 8.03%. Individuals of the Asian race are 14.36% less likely to use the rideshare more. Individuals of American Indian/ Native American or Alaska Native race are 16.41% less likely to use the rideshare more.

5.1.3 Bus

Model F for the relative frequency of bus commuting mode is a generalized ordered logit model with 622 observations based on the combined waves data. McFadden's Pseudo R-squared value for this model is 0.052.

Model S for the relative frequency of bus commuting mode has three significant variables for the model developed with the combined waves data with 678 observations. McFadden's Pseudo R-square value for this model is 0.023.

For combined wave survey data, the significant variables in model S for the bus commuting mode are frequency of participating in non-work-related activities, total time it takes from home to reach the work location in minutes, and whether the respondent changed transit routes to decrease the likelihood of crowding or congestion. As shown in Table 5.3, an increase in the number of times per week non-work outings are undertaken increases the likelihood of using the bus more by 2.04% per day. An increase in the time to reach the work location from home increases the likelihood of using the bus more by 0.18% per minute. Individuals who changed the route they took to commute to decrease crowding or congestion are more likely to use the bus less by 13.8%.

5.1.4 Walk

Model F for the relative frequency of walk commuting mode is a generalized ordered logit model with 448 observations based on the combined waves data. In this model, McFadden Pseudo R-squared value is 0.045

Model S for the relative frequency of walk commuting mode has two significant variables for the model developed with the combined waves data with 459 observations. McFadden's Pseudo R-square value for this model is 0.019.

The significant variables in the model for the walk commuting mode are the number of days commuting to work per week and the frequency of online meetings for work in a week. As shown in Table 5.4, an increase in the number of days per week commuting to work increases the likelihood of walking more by 3.64% per additional day and decreases the likelihood of it less by 2.42%. An increase in the number of days per week attending online meetings for work increase the likelihood of walking more by 3.29%. Interestingly as per the results, the effect of the frequency of attending meetings online on the use of walk mode for commuting was opposite than anticipated before adding the variable in the model.

Table 5.1: Models for owned or leased vehicle commuting mode

	Wave 1 survey data							Combined waves (wave 1+wave 2+wave 3) survey data						
Variables	Full Model Model F		Significant Model Model S		Marginal effects			Full Model Model F		Significant Model Model S		Marginal effects		
	Less vs Same & More	Less & Same vs More	Less vs Same & More	Less & Same vs More	Less	Same	More	Less vs Same & More	Less & Same vs More	Less vs Same & More	Less & Same vs More	Less	Same	More
HHnumb	0.171*** (0.064)	-0.080** (0.034)	0.185*** (0.060)	-0.128*** (0.034)	-4.13%	0.71%	3.425	0.097*** (0.034)	-0.077*** (0.019)	0.102*** (0.031)	-0.093*** (0.017)	-2.22%	0.42%	1.80%
Grofreq	0.067 (0.045)	0.067 (0.045)						0.125*** (0.023)	0.125*** (0.023)	0.150*** (0.021)	0.150*** (0.021)	-3.28%	0.62%	2.67%
EvntNY	0.791** (0.365)	0.791** (0.365)	0.832** (0.338)	0.832** (0.338)	-15.82%	-2.19%	18.01%							
Cornarisk	-0.474*** (0.151)	-0.105 (0.088)	-0.503*** (0.144)	-0.163* (0.086)	10.98%	-1.43%	-9.55%	-0.438*** (0.080)	-0.144*** (0.048)	-0.445*** (0.076)	-0.185*** (0.044)	9.58%	-1.51%	-8.07%
Homeday	-0.24*** (0.038)	-0.131*** (0.02)	-0.231*** (0.037)	-0.167*** (0.023)	5.14%	-0.08%	-4.26%	-0.233*** (0.021)	-0.135*** (0.013)	-0.244*** (0.020)	-0.187*** (0.012)	5.34%	-1.00%	-4.33%
Actyfreq	0.078** (0.036)	0.078** (0.036)	0.094*** (0.033)	0.094*** (0.033)	-2.1%	0.36%	1.74%	0.046** (0.018)	0.046** (0.018)					
Grocurb	-0.035 (0.258)	-0.035 (0.258)						-0.028 (0.156)	0.116 (0.081)					
Age	-0.011* (0.005)	-0.011* (0.005)						0.0002 (0.004)	0.007*** (0.002)					
Occprofs	-0.142 (0.137)	-0.142 (0.137)						-0.044 (0.075)	-0.044 (0.075)					
Edugrad	-0.033 (0.156)	-0.423*** (0.102)						-0.085 (0.086)	-0.295*** (0.054)					
Vehnum	-0.274*** (0.094)	-0.274*** (0.094)	-0.295*** (0.092)	-0.295*** (0.092)	6.58%	-1.12%	-5.45%	0.074 (0.056)	0.154*** (0.336)					
Gender	0.182 (0.153)	0.200** (0.090)						0.068 (0.083)	0.159*** (0.050)					
Riskpcnt	0.008 (0.006)	0.008 (0.006)						0.006 (0.003)	-0.002 (0.002)					

Table 5.1: (Cont.)

	Wave 1 survey data							Combined waves (wave 1+wave 2+wave 3) survey data						
Variables	Full Sample Model Model F		Significant Model Model S		Marginal effects			Full Sample Model Model F		Significant Model Model S		Marginal effects		
	Less vs Same & More	Less & Same vs More	Less vs Same & More	Less & Same vs More	Less	Same	More	Less vs Same & More	Less & Same vs More	Less vs Same & More	Less & Same vs More	Less	Same	More
NY	0.099 (0.177)	0.099 (0.177)						-0.180* (0.106)	-0.306*** (0.064)					
DC	0.022 (0.187)	0.022 (0.187)						-0.256** (0.114)	-0.219*** (0.067)					
Miami	0.064 (0.183)	0.064 (0.183)						-0.056 (0.109)	-0.1099* (0.059)					
Wave 2								-0.100 (0.083)	0.111* (0.059)					
Wave 3								-0.014 (0.082)	-0.014 (0.082)					
Constant	1.274*** (0.381)	1.295*** (0.135)	1.117*** (0.252)	1.473*** (0.115)				0.811*** (0.220)	1.022*** (0.122)	0.934*** (0.123)	1.477*** (0.064)			
Observations	1014	1014	1017	1017				3410	3410	3442	3442			
AIC	2030.8		2055.0					6666.3		6845.7				
McFadden Pseudo R-squared	0.089		0.070					0.084		0.063				

Note: Standard errors in parentheses, ** *p< 0.001, **p< 0.05, *p< 0.10.

Table 5.2: Models for Rideshare commuting mode

	Combined waves (wave 1+wave 2+wave 3) survey data						
Variables	Full Model Model F		Significant Model Model S		Marginal effects		
	Less vs Same & More	Less & Same vs More	Less vs Same & More	Less & Same vs More	Less	Same	More
Hhnumb	0.070 (0.069)	0.070 (0.069)					
Grofreq	0.0516 (0.044)	0.0516 (0.044)					
Actyfreq	0.148*** (0.038)	0.148*** (0.038)	0.174*** (0.034)	0.174*** (0.034)	-3.91%	0.68%	3.21%
Pcntrisk	0.013* (0.0072)	0.013* (0.0072)					
Comumint	-0.0011 (0.0041)	-0.0011 (0.0041)					
Coronraisk	0.043 (0.147)	0.043 (0.147)					
Vehnumb	-0.393*** (0.104)	-0.393*** (0.104)	-0.359*** (0.092)	-0.359*** (0.092)	8.03%	-1.42%	-6.62%
Comdays	0.036 (0.048)	0.036 (0.048)					
Freqmeet	0.051 (0.037)	0.051 (0.037)					
Asian	-0.885** (0.413)	-0.885** (0.413)	-1.023*** (0.369)	-1.023*** (0.369)	24.81%	-10.45%	-14.36%
Native	-1.393** (0.545)	-1.393** (0.545)	-1.273*** (0.492)	-1.273*** (0.492)	30.78%	-14.37%	-16.41%
Age	0.0088 (0.0086)	0.0088 (0.0086)					
Gender	0.097 (0.158)	0.097 (0.158)					
Wave2	-0.396** (0.193)	-0.254** (0.111)					
Wave3	-0.249 (0.175)	-0.249 (0.175)					
NY	-0.413** (0.233)	-0.156 (0.102)					
DC	00085 (0.252)	00085 (0.252)					
Miami	0.043 (0.231)	0.043 (0.231)					
Constant	0.119 (0.464)	0.758*** (0.071)	0.694*** (0.177)	1.800*** (0.091)			
Observations	753	753	765	765			
AIC	1598.5		1619.3				
McFadden Pseudo R-squared	0.046		0.029				

Note: Standard errors in parentheses, ***p< 0.001, **p< 0.05, *p< 0.10

Table 5.3: Models for Bus commuting mode

	Combined waves (wave 1+wave 2+wave 3) survey data						
Variables	Full Model Model F		Significant Model Model S		Marginal effects		
	Less vs Same & More	Less & Same vs More	Less vs Same & More	Less & Same vs More	Less	Same	More
Actyfreq	0.095** (0.044)	0.095** (0.044)	0.131*** (0.035)	0.131*** (0.035)	-3.123%	1.08%	2.04%
comumint	0.015*** (0.003)	0.015*** (0.003)	0.0114*** (0.004)	0.0114*** (0.004)	-0.27%	0.09%	0.18%
Coronarisk	0.046 (0.170)	0.046 (0.170)					
Comdays	0.044 (0.054)	0.044 (0.054)					
Grofreq	-0.026 (0.054)	-0.026 (0.054)					
Freqshop	0.109*** (0.040)	0.109*** (0.040)					
Asian	-0.745* (0.384)	-0.745* (0.384)					
Chldnumb	0.021 (0.085)	-0.110** (0.052)					
Gender	-0.008 (0.190)	0.289** (0.114)					
Tranchng	-0.578*** (0.200)	-0.578*** (0.200)	-0.606*** (0.187)	-0.286** (0.114)	13.8%	-3.57%	-10.32%
Pcntrisk	-0.007 (0.007)	-0.007 (0.007)					
Grocurb	0.244 (0.363)	0.244 (0.363)					
Age	0.006 (0.009)	0.006 (0.009)					
Timehome	-0.141 (0.253)	-0.141 (0.253)					
Raceblack	0.099 (0.214)	0.099 (0.214)					
Vehnumb	-0.036 (0.112)	-0.036 (0.112)					
edugrad	-0.024 (0.197)	-0.024 (0.197)					
Wave2	-0.03 (0.199)	-0.03 (0.199)					
Wave3	0.279 (0.197)	0.279 (0.197)					
NY	-0.091 (0.269)	-0.091 (0.269)					
DC	0.297 (0.317)	0.297 (0.317)					
Miami	0.156 (0.311)	-0.148 (0.143)					

Table 5.3: (Cont.)

	Combined waves (wave 1+wave 2+wave 3) survey data						
Variables	Full Sample Model Model F		Significant Model Model S		Marginal effects		
	Less vs Same & More	Less & Same vs More	Less vs Same & More	Less & Same vs More	Less	Same	More
Constant	-0.634 (0.603)	0.739*** (0.110)	0.0013 (0.222)	0.829*** (0.094)			
Observations	622	622	678	678			
AIC	1293.3		1406.0				
McFadden Pseudo R-squared	0.052		0.023				

Note: Standard errors in parentheses, ***p< 0.001, **p< 0.05, *p< 0.10

Table 5.4: Models for Walk commuting mode

	Combined waves (wave 1+wave 2+wave 3) survey data						
Variables	Full Model Model F		Significant Model Model S		Marginal effects		
	Less vs Same & More	Less & Same vs More	Less vs Same & More	Less & Same vs More	Less	Same	More
HHnumb	-0.051 (0.080)	-0.051 (0.080)					
Actyfreq	-0.014 (0.051)	-0.014 (0.051)					
Pcntrisk	0.003 (0.009)	0.003 (0.009)					
Comumint	-0.003 (0.005)	-0.003 (0.005)					
Comdays	0.192*** (0.065)	0.192*** (0.065)	0.153*** (0.055)	0.153*** (0.055)	-2.42%	-1.22%	3.64%
Freqmeet	0.173*** (0.049)	0.173*** (0.049)	0.139*** (0.041)	0.139*** (0.041)	-2.19%	-1.11%	3.29%
Gender	0.342* (0.206)	0.342* (0.206)					
Coronarisk	-0.206 (0.202)	-0.206 (0.202)					
White	0.300 (0.236)	0.300 (0.236)					
Native	4.062 (7.637)	0.969 (1.469)					
Grofreq	-0.009 (0.057	-0.009 (0.057					
Grodelivery	-0.401 (0.420)	-0.401 (0.420)					
Timehome	-0.436 (0.293)	-0.436 (0.293)					
Age	0.006 (0.014)	0.011* (0.007)					
Wave2	-0.014 (0.231)	-0.014 (0.231)					
Wave3	-0.052 (0.224)	-0.052 (0.224)					
NY	0.340 (0.263)	0.340 (0.263)					
DC	0.291 (0.323)	0.291 (0.323)					
Miami	0.007 (0.298)	0.007 (0.298)					
Constant	0.278 (0.716)	0.256 (0.249)	0.429 (0.267)	1.883*** (0.121)			
Observations	448	448	459	459			
AIC	950.6		959.1				
McFadden Pseudo R-squared	0.045		0.019				

Note: Standard errors in parentheses, ***p< 0.001, **p< 0.05, *p< 0.10

5.2 Hypothesis Revisited

This discussion is based on the results of ordered logit models in the multi-variable context. Each hypothesis variable is included in the model and the relationship between independent variable and dependent variable are discussed below by revisiting the hypotheses.

H1: Respondents who are concerned about getting sick with a coronavirus infection are more likely to use owned or leased vehicles/motorcycles more often for commuting than the pre-coronavirus period.

Coronavirus risk perception was previously found to be a critical factor influencing travel behavior (Basu et al., 2020). In our study, the coronavirus risk indicator variable was statistically significant for both wave 1 survey data ($p<0.05$) and combined waves survey data ($p<0.01$). However, the effect was opposite that hypothesized, rejecting the hypothesis. The increase in coronavirus risk concern was anticipated to increase the frequency of using the private vehicle more often for commuting than the pre-coronavirus period. Therefore, it was anticipated that people who were probably using different modes for commuting before the pandemic had changed their commuting mode to private vehicles because of the fear of infection. It is possible that the structure of the survey's skip patterns did not well capture mode shifts. In our model, for an increase in coronavirus risk concern, there was a decrease in the use of vehicles. Potentially, this shows that the respondents concerned about getting sick with the coronavirus infection preferred to use the private vehicle less for commuting even though the private cars are safer than any other mode. It is possible because of the overall change in the commuting pattern during the pandemic, and people started to avoid unnecessary travel, or they have shifted to active modes for the health and well-being.

H2: Respondents working from home for a greater number of days in a week are less likely to use owned or leased vehicles/motorcycles more often for commuting than the pre-coronavirus period.

The number of days working from home variable was statistically significant for both wave 1 survey data ($p<0.05$) and combined waves survey data ($p<0.01$). An increase in the number of days working from home per week was statistically significant in both Model S and Model F, with the direction of effect as hypothesized for both datasets failing to reject this hypothesis. The results of the models indicate that respondents who are working a greater number of days in a week from home are less likely to use private vehicles more often for commuting than the pre-coronavirus period. However, it should be noted that respondents should have to commute at least one day/week to record the answer for the relative frequency of commuting modes. Harris et al. (2021) found that all out-of-home commute modes, including private vehicles in Canada, declined during COVID-19, with increasing telework. The percentage of people working from home for at least one day a week had increased from 30% to 60% and working for five days a week from home increased from 7% to 30% in Australia (Beck and Hensher, 2020). Potentially, this shows that our dataset includes the respondents who worked from home for more days, and hence the private vehicle has been used less often during the pandemic than the pre-coronavirus period.

H3: Respondents with more household vehicles are more likely to use the owned or leased vehicles more often for commuting.

The number of household vehicles was statistically significant for the model built with wave 1 survey data ($p<0.05$). However, the household vehicle number shows no statistical significance for the model built with the combined waves survey data and stricter significance level ($p>0.01$). However, the hypothesis that more household vehicles increase the likelihood of using the vehicle more often during the pandemic was rejected since the direction of effect was opposite that hypothesized. Owning more cars during the pandemic was anticipated to be a resource, especially for those who did not see the need to use it before the pandemic (NADA, 2020). It could be possible that the ability to travel in the desired way is associated with access to transport resources (e.g., owning a car) but, with travel barriers or travel restrictions, it's use is affected (Khaddar et al., 2021). Regardless of having access to these transport resources, travel restrictions could have resulted in low travel demand and limited to no use of preferred commuting modes.

H4: Respondents with larger households are more likely to use the owned vehicle or motorcycle more often compared to the pre-coronavirus period.

Household size was statistically significant for the models built with wave 1 survey data ($p<0.05$), and the combined waves survey data ($p<0.01$). The hypothesis that an increase in the number of household members increases the likelihood of using the private cars more often was not rejected in the full model (with hypothesis variables) or the significant model (with significant variables). It has been observed that traveling alone results in a lower level of travel satisfaction than traveling with a companion (De Vos, 2019a). According to research, car dependency increases in households with young children (Ryley, 2006; Scheiner, 2014). Therefore, we anticipated that the household members would be more willing to share the car with other members and drive them during commutes. The literature mainly was conclusive in explaining why household size is significantly associated with the frequent use of private cars. However, larger households are known to travel more (Kim, Anorve, & Tefft, 2019) and commute further (Crane, 2007). Our survey's respondents may have driven other family members more often than pre-COVID times (e.g., driving children to school instead of having them use the school bus), which could have encouraged trip chaining on the way to work and the use of personal vehicles. Hence, the household size is positively associated with the individuals' frequent use of vehicles.

H5: Older respondents are more likely to use the bus less often for commuting during the pandemic than in the pre-coronavirus period.

The respondent's age was statistically non-significant (p>0.01), rejecting this hypothesis for the combined waves survey data. It was anticipated that age is positively associated with avoidance behavior, with older people more willing to avoid social contact than younger people, particularly during pandemics (Gerhold, 2020), resulting in commuting less often by bus. Social distancing may be seen more with older people while commuting during pandemics. However, when the respondents were segmented according to age, the data for the over 30 groups showed a higher preference for cars over public transport, while the under 30 groups preferred public transport during regular commute trips (Das et al., 2021). In our dataset, more than 50% of the respondents' ages are between 30-59 years; thus, age was expected to be a significant factor for the modeling. However, it was not statistically significant.

H6: Respondents concerned about getting sick with a coronavirus infection are more likely to use the bus less often for commuting than the pre-coronavirus period.

The coronavirus risk variable was statistically non-significant ($p>0.01$), rejecting this hypothesis for the combined waves survey data. Public transport such as buses was considered the hotspot for many viruses (Troko et al., 2011), and coronavirus transmission could be one of them. Our dataset had 55% of respondents who showed concern about getting infected with coronavirus infection, out of which 10% of respondents commuted to work by bus during the survey period. Potentially, our respondents commuting by bus did not have viable alternative modes.

H7: Respondents with more household vehicles are more likely to use the (transit) bus less often for commuting than the pre-coronavirus period.

The number of household vehicles was statistically non-significant for the combined waves survey data ($p>0.01$), rejecting the hypothesis. A recent survey conducted by Pillai (2020) revealed that 55% of Indian shared transport users were more likely to own private cars soon when the study was conducted, reflecting increased car sales and skepticism over public transport use. Nineteen percent of commuters having a car in their household reported using public transport as their normal commute mode before lockdown, but there was a reduction to 6% in public transport services during the pandemic (Das et al., 2021). However, from the model results, it could be seen that vehicle ownership is not a good predictor of the relative frequency of bus mode for commuting as respondents overall reduced their travel by bus irrespective of vehicle ownership rejecting this hypothesis.

H8: Households with shorter commutes are more likely to walk more often during the pandemic than in the pre-coronavirus period.

The time it took for the respondents to reach the work location from home (in minutes) variable was statistically not significant for the combined waves dataset ($p>0.01$), rejecting the hypothesis. Previous literature found a positive association between shorter commutes and active modes such as walking (Lin et al., 2015) to maintain an individual's health and well-being (Bergman and Bergman, 2019). Based on our sample, approximately 40% of the respondents who walked to work during the survey reported that they walked more during the coronavirus period than the pre-coronavirus period, but there was no significant effect of shorter commute time.

CHAPTER SIX

CONCLUSIONS

6.1 Summary and Relevance

This study is among the first to examine changes in the U.S.' relative commuting transportation mode use frequency during the COVID-19 period based on survey data. The study used survey data collected from three waves, with the first wave starting in Aug 2020 and the third wave ending in Dec 2020. The research team examined the existing literature and circumstances of COVID-19 situations in the year 2020 in four metropolitan areas: New York, Washington D.C., Houston, and Miami, and then drafted the survey. The research team desired a geographic mix of metropolitan areas across the U.S. for various reasons, including different state political environments and significant transit shares. It is important to note that the survey data used in this thesis came from respondents who were commuting at least for 1 day/week during the pandemic. The survey data was used to create (generalized) ordered logit models to determine the relative frequency of different commuting modes in all four metropolitan areas.

The significant empirical findings are discussed later in section 6.2. Our study examined the various factors such as coronavirus risk perception, commuting patterns, socio-demographics, and work from home policies that influenced the decision of respondents to commute more by private cars, ride-share, bus, and walking during the pandemic. These factors are associated with the frequency of using different modes of transportation for commuting during the pandemic. The disruption created by COVID-19 has significantly changed people's perception of commuting modes (World bank blogs, 2020), leading many decision-makers to rethink the role of all modes of transport. This study aims to help the U.S. transportation authorities to make decisions during pandemic situations based on people's travel behavior and the factors associated with it.

The objectives of this study were to examine the changes in transportation mode use during the COVID-19 period and study the influence of travel behavior characteristics on the relative frequency of commuting modes in the four metropolitan areas New York, Washington D.C., Miami, and Houston, during the COVID-19 period.

6.2 Conclusions and Limitations

COVID-19 lockdown and reopening played an essential role in the employment status, work-from-home policies, and travel behavior (Vyas et al., 2021). Around 96% of the respondents in our dataset were employed during the survey (either full-time, part-time, or self) and commuted at least one day per week. This work developed an analysis based on ordered logit models and helped identify the factors influencing the relative frequency of commuting modes. The significant variables and their relationship with frequency of use of commuting modes is discussed below.

6.2.1 Demographics

Several demographic variables were tested for their association with the relative frequency of commuting modes such as private vehicles, rideshare, bus, and walk. Two models were created for the private vehicle mode using wave 1 survey data and two for the combined waves survey data. For the rest of the modes, combined survey data was used for the analysis.

In our study, income, and education with graduate-level or higher were highly correlated with each other; therefore, both could not be included simultaneously in any models. Based on this dataset, education was not a significant factor associated with the relative frequency of use of any mode during the coronavirus pandemic.

The household size was found to positively affect the relative use frequency of private vehicles with additional household members increasing the likelihood of using the private cars more often during the coronavirus period than the pre-coronavirus period.

Age was anticipated to be a significant factor for determining the relative frequency of bus use, but it was not associated with the relative frequency for any commuting mode.

For rideshare, vehicle ownership was found to be a significant factor. Respondents with more vehicles in their households were more likely to use the rideshare mode less often during the pandemic compared with the pre-pandemic period.

While exploring the racial demographic, it was found that respondents of Asian and American Indian/Native American/Alaska Native race are more likely to use the rideshare less often during the coronavirus pandemic than the pre-coronavirus period.

Factors such as employment status and gender had no significant influence on our models.

6.2.2 Commuting

Increased work from home days had a negative impact on the use of vehicles, with people using this mode less during the pandemic compared to the pre-pandemic period. The number of days commuting per week is positively associated with more walking to work during the coronavirus period compared to the pre-pandemic period.

Shorter commutes were anticipated to be significant for the walk mode. However, in the model results, shorter commutes were found insignificant for walk mode, and longer commutes were found to be a significant factor for bus mode.

6.2.3 Risk Perception

A dummy indicator variable for Coronavirus risk perception was a significant factor for private vehicle commuting mode. It shows a negative association with the frequency of use of private vehicles. Respondents concerned about getting sick with coronavirus infection were less likely to use the private vehicle more often during the pandemic.

6.2.4 Non-work activities

The interaction term of respondents residing in the New York metropolitan area and starting to attend events more than four weeks before the first wave survey period Sep 02, 2020, with more than ten people was positively associated with the relative frequency of private vehicle use. Respondents from the New York metropolitan area starting to attend the events were more likely to use the private vehicle more often during the pandemic compared to pre-pandemic period. Furthermore, the frequency of activities undertaken not related to work was a significant factor in determining the relative frequency of private cars and buses with an increase in the number of times per week non-work outings are undertaken increasing the likelihood of using private cars and buses more per day.

Coronavirus pandemic has impacted people's perception of commuting modes (Abdullah et al., 2020). The key findings of this study indicate some policies and suggestions to implement. From our results, we found that the respondents are more likely to walk more for an increase in the number of days commuting to work. To support these commuters, policymakers and transport planners can try to stimulate and promote active modes such as walking and cycling by (temporarily) allocating less-used street space to cyclists and pedestrians (King and Krizek, 2020).

There are some limitations to consider. It is important to note that the wave 2 and wave 3 surveys asked additional questions from the wave 1 questionnaire due to the time difference in the survey period. When the wave 1 survey took place in late Aug 2020, schools and colleges either just started online or in-person or were about to start. However, only Wave 2 and wave 3 captured the change in behavior concerning children going to in-person school or attending online classes. This study used a combination of three waves (wave 1+wave 2+wave 3), and it, therefore, does not allow considering the additional school-related questionnaire present in wave 2 and wave 3.

Similarly, regarding the survey, considering the completion time, the research team designed it in such a way that respondents must be employed (full time, part-time, self-employed) and commute at least 1 day/week during the pandemic to answer the dependent variable question on how frequently they used the specific mode for commuting during the survey period. Also, the survey design leading to the relative commuting mode use did not identify the respondents' responses who had commuted regularly before the pandemic and were now commuting for 0 days/week during the survey period even if, by definition of relative frequency, respondents are commuting less. However, more advanced modeling can address this issue in the future.

If the respondents selected owned vehicle/motorcycle as their commuting mode, the survey design omitted the non-vehicle respondents in the ordered logit model for relative frequency in vehicle/motorcycle use. This issue is analogous to self-selection (Kamruzzaman et al., 2015 & Clarke et al., 2020). For example, suppose we are modeling only those who commute to work one or more days per week and only those currently using a vehicle to commute. In that case, we have an omitted variable related to mode choice that likely correlates with the independent variables we include (which violates assumptions about the error term). For example, suppose we included income as one of our independent variables in the ordered logit regression. Income likely influences mode choice, so by excluding observations on those who do not commute by personal vehicle, we may bias the coefficient estimate of income in the ordered model since the sample is biased.

Finally, this study was directed at four metropolitan areas- New York, Washington DC, Miami, and Houston. Other regions or nations may have different results for a COVID-19 survey due to political environments, the difference in lockdowns and reopening policies, and available transport modes in the specific regions. The metropolitan areas with significant transit shares (e.g., New York and Washington D.C) were included to examine the possible differential responses in commuting under the COVID-19 period when transit was available.

6.3 Future Directions

Considering the pandemic's rapid evolution in many nations at the time of this writing, there are many possibilities for future work and dimensionality. For example, the data for this study were collected before the launch of any vaccines for COVID-19. Moreover, as of July 03, 2021, around 23.8% of the world's population received at least one dose of the COVID-19 vaccine, but only 1.0% of people received at least one dose of the COVID-19 vaccine in low-income and developing countries (Vaccination statistics, 2021). Therefore, future surveys should be conducted in the vaccinated regions to capture differential responses and people's behavior towards commuting. In addition, the stated preference type of survey could be helpful to capture people's preference for commuting modes after the end of the COVID-19 crisis.

Future surveys could ask about behavior such as

1. Anticipated travel behavior after vaccination for COVID-19.
2. Intended purchase of a vehicle in the future; and

3. Preference for working from home more frequently even after the COVID-19 crisis is over.

This change in travel behavior may have implications on various lifestyle decisions, including residential location, e-commerce, and future travel behavior. The research team will investigate some of these potential impacts and their implications for future planning and policymaking.

Another suggestion is to explore the respondents' opinions on autonomous vehicles considering the COVID-19 pandemic. For example, future surveys can capture the public's willingness to use autonomous vehicles on the ride-hailing platform for commuting to avoid contact with drivers. Therefore, it may be worthwhile to investigate with this study (and future studies) the impact of the pandemic on the future adoption of autonomous vehicles and the market penetration of these emerging transportation technologies.

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