Global Disruptions in the Transportation Sector: The Effect of Ridehailing Services and the COVID-19 Pandemic

By

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Abstract

Enabled by information and communication technologies (ICT) and based on the principles of the shared/gig economy, ridehailing services (e.g., Uber, DiDi, Ola) are transforming the travel patterns and the lifestyle patterns of people around the world. Other new technologies based on the same principles, including smartphone app connectivity and access to mobility services for multiple users on an on-demand basis (e.g., food delivery services, micromobility), can potentially have similar transformative impacts. It is thus important to study these services and their impacts carefully to leverage these technologies in creating a more inclusive, sustainable, and resilient transportation system.

In the last two years, the COVID-19 pandemic has created an even bigger disruption to the transportation sector (including life in general). While there is a general consensus among the research community that the pandemic is fundamentally transforming the transportation sector, the post-pandemic future of the transportation system remains to be seen. What social and transportation inequities occurred during the disruption of the pandemic? And how can the post-pandemic transportation sector be shaped to become more inclusive, resilient and sustainable?

The goal of my dissertation is to create a deeper understanding of these two major disruptions in the transportation sector. I do this by analyzing survey data collected in cities of the United States, Canada, Germany, Chile, Mexico, Brazil, India and China, in combination with socio-demographic and geospatial datasets available in these countries.

In the first two studies (Chapter 2-3) I focus on California. First, I explore the factors that affect the use of ridehailing services (Uber, Lyft) as well as adoption of shared (pooled) ridehailing (UberPOOL, Lyft Share) by estimating a semi-ordered bivariate probit model. The model reveals the similarities and differences in the markets for each of the two services. Among the main findings from the study, I find that being white and living in a higher-income household is associated with a higher likelihood of being a frequent user of non-shared ridehailing but does not have statistically significant

effects on the likelihood of adopting shared ridehailing. While the likelihood of using both non-shared ridehailing and shared ridehailing is higher in urban areas, residents of neighborhoods with higher intersection density are found to be more likely to only adopt shared ridehailing.

Next, I estimate an integrated choice and latent variable (ICLV) model to develop an in-depth understanding about the effect of the built-environment on ridehailing use for non-work purposes while accounting for confounding effects such as the preference to own a vehicle and to live in urban locations. My analysis confirms that failure to consider the latent preferences for residential location can lead to biased results. This analysis results in two major findings: 1. individuals living in vibrant and walkable neighborhoods are more likely to replace other modes (possibly active modes) with ridehailing, 2. previous studies may have misestimated the relationships between public transit and ridehailing by ignoring confounding effects.

In the following two studies, I move to an international perspective on the impacts of these services and other disruptions in the transportation sector. First, I focus on the adoption of ridehailing in developing countries. To do this, I compile survey datasets from Mexico City, Sao Paulo, Beijing, and Mumbai and estimate a binary logit model of the adoption of ridehailing with discrete segmentation for each country. My analysis shows that younger respondents are more likely to adopt these services in all locations. A number of other factors are found to have significant effects only in selected regions. Among other findings, in Mumbai, respondents who live in zero-vehicle households are more likely to use ridehailing, probably as an effect of social status, while this is not true in the other regions. Women are more likely to use ridehailing than men in Sao Paulo and Beijing, and this effect is significantly stronger in Mumbai. However, in Mexico City, an opposite effect was observed, i.e., men are more likely to use these services than women.

In the final study, I focus on the disruption that the COVID-19 pandemic brought to society starting in early 2020. To do this, I focus on one of the major components of disruption the pandemic has caused, the heavy shift to telecommuting. I aim to understand the influence of household and individual socio-demographic characteristics on two related dependent variables: the decision to exclusively telecommute and the frequency of physical commute to work (if not exclusively telecommuting) during the *first wave* of the pandemic in Canada, Chile, Germany and the U.S. I jointly model the two decisions while accounting for confounding effects, including those associated with different recruiting and sampling methods for each country and unobserved country-specific attributes (e.g., COVID-19 response). In all countries, affluent workers (i.e., high-income, high-educated, or non-essential-workers) are found to have a higher propensity to exclusively telecommute and to report to work at a lower frequency if commuting physically. I also uncover that the effects of a few selected sociodemographic characteristics differ greatly by country, including household size, full/part-time worker status, gender, and vehicle ownership. This study contributes to the academic literature by comparing how the response to the global COVID-19 pandemic (in terms of telecommuting behavior) depended on the local context. Finally, the last two studies converge on one finding from my dissertation – context matters while studying individual behaviors, and it is not always easy to generalize findings and transfer the lessons learned from one location to others.

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1. Introduction

The emergence of new mobility technologies is changing travel patterns, with important implications for transportation sustainability. New shared mobility services include a broad range of services. Ridehailing services (e.g., Uber/Lyft) are perhaps the most popular of all new mobility services offered so far. Transportation Network Companies (TNCs) (or ridehailing services) bring together the supply and demand of the taxi services by connecting passengers to 'taxi' drivers using a smartphone app. By the end of the year 2017, Uber announced the completion of one billion trips, and in 2019 the number reached 5 billion (Uber, 2019b). Nearly 10% of the U.S. population has reported that they use ridehailing at least once a month (M. Conway, Salon, & King, 2018). There is a growing body of literature on the factors influencing the adoption and usage of ridehailing (Alemi, 2018; Alemi et al., 2018; Dias et al., 2017; Lavieri & Bhat, 2019). However, the prominence of these services in the current transportation system and the promises they hold for future urban mobility (i.e., mobility-as-a-service, shared autonomous vehicles) merit a much deeper investigation.

In addition, starting in early 2020, the COVID-19 pandemic has been a shock to the transportation system and to society in many ways (Beck & Hensher, 2020; Eisenmann, Nobis, Kolarova, Lenz, & Winkler, 2021; Shamshiripour, Rahimi, Shabanpour, & Mohammadian, 2020). One of the key steps to contain the spread of the infectious disease is to minimize physical contact between people. As a result, many people in the U.S. (and other countries) 'stayed-at-home' voluntarily, on the orders of their workplace and/or due to the restrictions imposed by the government (Cheng, Barceló, Hartnett, Kubinec, & Messerschmidt, 2020). In April 2020, during the first peak of the pandemic, the daily vehicles miles travelled (VMT) in the U.S. was almost 60% of the value expected had there been no pandemic (Bureau of Transportation Statistics, 2020). It is still a matter of speculation how the new 'normal' in the transportation sector will look like once the pandemic is over. This uncertainty about the future can have a big implications for the relevance of the understanding of the changing travel behavior and lifestyle in the past decade.

In this dissertation, I intend to fill some of the important research gaps of how the disruptions engendered by ridehailing services and the COVID-19 pandemic are reshaping travel behavior. First, I examine the use of shared ridehailing services (UberPool and Lyft Share) and how the use of ridehailing services, in general, is influenced by the built environment. I then investigate how the adoption of ridehailing services varies with the context, in particular the context of the city where these services are being used. I also investigate how the COVID-19 has impacted commute trip generation patterns. Table 1-1 shows the details of the research questions answered in each chapter of my dissertation, together with the dataset and methodology used, and the central dependent variable(s) in each analysis.

In the first study (Chapter 2 of this dissertation) I explore the factors affecting the adoption of shared ridehailing services. Shared ridehailing (such as UberPool/Lyft Share) is a type of ridehailing service that enables unacquainted riders, travelling in the same direction, to share rides. In exchange for increased travel time and the disutility of sharing the ride with a stranger, the riders are offered a discount of up to 40-50% (Shaheen, Cohen. Adam, & Bayen. Alexandre, 2018; Shaheen & Cohen, 2019; Sperling, 2018). At least in theory, shared (or pooled) ridehailing brings together the public interest of promoting high occupancy vehicles with private business interests. The barriers to the adoption of shared ridehailing is still an under-researched area in the literature. Thus, I investigate what observable factors influence 1) the adoption of shared ridehailing services, 2) the frequency of usage of ridehailing services after accounting for unobserved factors which influence both in the metropolitan regions of California (San Francisco, Los Angeles and San Diego). The observable factors include the socio-demographic characteristics and individual attitudes, data on which were collected using a survey of California residents. The survey also asked the information about the use patterns of ridehailing services. The survey also asked respondents to report their home location, enabling me to use external data sources to post process and characterize the built environment of the residential location, another observable factor that I use in the analysis.

I estimate a semi-ordered bivariate probit model (Greene & Hensher, 2009). The two dependent variables are the frequency of usage of ridehailing (ordinal) and the adoption of shared ridehailing services (binary). I assume the error terms associated with the two dependent variables are correlated and follow a bivariate normal distribution, implying that some unobserved factors influence both dependent variables. The model demonstrates how the socio-demographic and built environment variables have a different effect on the use of the two services. For instance, being white and living in a higher-income household is associated with a higher likelihood of being a frequent user of regular ridehailing but does not have statistically significant effects on the likelihood of adopting shared ridehailing. Residents of urban neighborhoods are found to be more likely to use ridehailing often than the residents of suburban and rural neighborhoods. This effect of the neighborhood type is not significant for the adoption of shared ridehailing when individual attitudes are included in the model. In addition, I also show that perceived longer travel times and lack of privacy can be a barrier to use shared ridehailing services.

In the next study (Chapter 3), I systematically review and critique the literature on the effect of the built environment on the use of ridehailing. I find contradictory results in the studies on the topic published to date. For instance, *intersection density* has been observed to have both negative (Sabouri, Park, Smith, Tian, & Ewing, 2020) and positive (Yu & Peng, 2019) relationships with ridehailing demand. After noting similar contradictory reported influences of other built environment measures on the use of ridehailing, I argue that inaccurate conclusions have been drawn in previous studies due to four methodological limitations. These include:

1. Ignoring the effect of built environment on the total number of trips made by an individual;
2. Ignoring the supply differences of ridehailing between urban and non-urban areas;
3. Ignoring the effect of the underlying attitudes which also influence residential choice (urban versus non-urban) (i.e., residential self-selection) and household choice of whether to own a vehicle; and

4. The use of general built environment measures – D's (density, diversity, design etc.) instead of more behaviorally meaningful accessibility measures which reflect the 'potential to travel' from an individual's perspective.

I try to account for these concerns by estimating an integrated choice and latent variable (ICLV) model which consists of six main dependent variables estimated simultaneously. First, I model two types of binary choices for all respondents: residential location type (urban or non-urban), and car ownership (yes or no). The remaining dependent variables are of two types: the total number of trips (made using all modes) for non-work purposes, and the share of these trips made by ridehailing. I model these responses conditional on neighborhood type of the home-location of the respondents' (urban or non-urban). This yields four dependent variables, where only two of the four are observed for each respondent. I estimate latent variables, using attitudinal measures, to control for the underlying pro-urban and car-lover attitudes. These latent variables are used for estimating residential location choice, vehicle ownership, total trips and ridehailing mode-share (hence controlling for residential self-selection). I also develop my own accessibility measures (e.g., proximity to restaurants, movie theaters) and use third-party accessibility measures (e.g., Walkscore, Job accessibility via. Transit), which I use in the Integrated Choice and Latent Variable (ICLV) model to get an unbiased estimate of the influence of the built-environment on ridehailing use (which in this case is the mode share of ridehailing). Apart from the methodological contribution, this analysis results in two main policy insights: 1) shorter trips made by ridehailing in urban areas must be priced to discourage the substitution of walking, 2) policies related to ridehailing and public transit must be reconsidered. Previous studies may have overestimated the complementary or substitution relationships between the two modes by ignoring confounding effects.

After building a good understanding of how ridehailing services are used in California, I investigate how a change in the *context* affects the way this service is used. By context I mean the presence of alternative modes of transportation in a given region, vehicle ownership trends, urban form characteristics, and the general societal and travel culture of any given region. These factors are often ignored when the scope of a study is limited to a homogenous region (much like in the previous two chapters of my dissertation where I focus solely on California), as these factors remain constant for all the individuals whose behaviors are being investigated. However, ignoring the contribution of these factors in affecting the observed behaviors can give a false confidence in the generalizability of the study results.

In Chapter 4 of this dissertation, I conduct an international comparison on how the effect of the factors influencing the adoption of ridehailing differs across four cities in developing countries of Asia and Latin America – Beijing, Mumbai, Mexico City and Sao Paulo. The data was collected through cross-sectional surveys using a mix of sampling approaches – online opinion panels and intercept surveys. I estimate a binary logit model with the adoption of ridehailing services as the dependent variable, and a discrete segmentation of the effect of the independent variables in each country. The explanatory variables in the model include socio-demographic characteristics of the respondents, their household structures, vehicle ownership status and their attitudes about technologies. The survey also asked respondents to report their home-location which I used to create accessibility measures using external data sources. These measures were also included in the model. The findings from the study showed how the effects of almost all of the variables change with the city. This confirms the importance of the assumption I made in my dissertation that context indeed matters when studying the use of ridehailing services. That is, in each context, not only are the motivating factors different, but the effect of the same characteristics on the probability to use ridehailing services is also highly dependent on the context. My analysis shows that women and younger respondents are more likely to adopt these services in all locations, but the magnitude of respective coefficients in the model varies by the location. A number of other factors are found to have significant effects only in selected regions. Among other findings, in Mumbai, respondents who live in zero-vehicle households are more likely to use ridehailing, while this is not true in the other regions. The study provides useful information to help in understanding the transportation planners and practitioners in the developing countries how these services are changing mobility in these quickly growing urban regions, and the way they interact with other traditional transportation options.

In the final study of this dissertation (Chapter 5), I shift the focus to the structural changes in the transportation sector brought by the COVID-19 pandemic. This crisis is unique because it is dramatically transforming the ways in which people engage in activities almost everywhere across the globe. Thus, I focus on four countries – Canada, Germany, Chile, and the United States of America – spanning over three continents. The diversity in the local contexts (including transportation and digital infrastructure, COVID-19 response policies etc.) allow me to compare how people have been reacting similarly (or differently), by adjusting their behavior, to the pandemic. The COVID-19 pandemic is transforming every aspect of transportation. However, in this study, I focus on how the commute patterns are evolving during the pandemic with the increased adoption of telecommuting. More specifically, I identify the population segments that did not telecommute despite a strong signal from most governments and employers, or that could not telecommute. Among those who did not telecommute I investigate how frequently they physically commuted to work.

For this study I collaborated with researchers in Chile and Germany who conducted online surveys in their countries roughly at the same time as when our research team at the UC Davis conducted surveys in Canada and the US. In each of these countries, surveys were conducted immediately after the pandemic became serious enough to prompt strong government policies from the respective governments. I compile the datasets from the four different countries and jointly model the individuals' decision to 1) exclusively telecommute from home and 2) the frequency of physical commute (if not exclusively telecommuting). The independent variables in the study include household and individual socio-demographic characteristics. Other important variables – individual attitudes and built environment – could not be included in the model as they were not consistently asked in the three surveys. I also allow scale parameters to be unique to each country to account for the variance differences between countries. A number of factors could have led to these variance differences including the differences in the data collection methods, contextual differences and the transportation infrastructures in these countries. This research inquiry can help to identify sources of social inequity among the employed population, especially in emergencies in which public health risks are larger than usual. Finally, I also include descriptive statistics about whether these behaviors will persist after the pandemic is over. This question can have implications for several transportation-related and other lifestyle issues. These include changes in travel demand, which eventually affect the return of the investments in transportation infrastructure as well as any downstream impacts of the transportation sector, and housing patterns (e.g., urban sprawl). Even though I do not directly focus on new mobility in this study (which has been the topic of the previous sections in my dissertation), my research, which identifies who are the main adopters of telecommuting during the pandemic, still can provide a basis for future studies investigating how use of new mobility has changed during the pandemic.

Table 1-1 Datasets and methodologies for research questions identified

Research Question	*Dataset*	*Methodology*	*Dependent Variables*	*Reason for selecting the methodology*	*Chapter*
RQ1: What factors affect the use of solo-ridehailing services vs. shared ridehailing in Californian metro-regions - San Francisco, San Diego and Los Angeles?	California Mobility Panel Survey (2018 dataset)	Semi-bivariate probit model	1. Frequency of usage of ridehailing services (ordinal) 2. Adoption of Shared ridehailing services (binary)	To account for unobserved effects which affect both adoption of shared ridehailing and frequency of ridehailing use	2
RQ2: What is relationship between built environment and non-work ridehailing use after accounting for confounding effects such as attitudes about home location and vehicle ownership?	California Mobility Panel Survey (2018 dataset)	Integrated Choice Latent Variable Model	1. Log of total non-work trips (linear) 2. Log odds of ridehailing use (linear) 3. Home location (urban vs. non-urban) (binary) 4. Vehicle Ownership status (binary)	To meaningfully account for residential self-selection bias while estimating the effect of the built environment on ridehailing use	3
RQ3: Who adopts ridehailing services in four cities from developing countries around the world?	Survey in four mega-cities in Asia and Latin America (2018-2019)	Binary logit model with interaction of explanatory variables with dummy variables for each city	Adoption of ridehailing services (binary)	The dummy variable interaction is a way to understand the observed taste heterogeneity in adoption of RH in the different cities.	4
RQ4: Who worked exclusively from home or reduced their commute frequency during the first wave of the pandemic in the U.S., Canada, Chile and Germany?	Cross-sectional surveys conducted in the U.S., Canada, Chile and Germany during the first wave of the pandemic in 2020	Joint estimation of binary logit and ordered logit models with scale parameters for each country.	1. Working exclusively from home or not (binary) 2. Frequency of commute travel (ordinal)	The scale parameters accounts for the difference in the variance of each dataset which can be accounted unobserved effects such as culture of the country, data collection method etc.	5

2. Exploring the Factors that Affect the Frequency of Use of Ridehailing and the Adoption of Shared Ridehailing in California

2.1. Abstract

In this study we explore the factors that affect the use of ridehailing services (Uber, Lyft) as well as adoption of shared (pooled) ridehailing (UberPOOL, Lyft Share) using data collected in California in fall 2018 using cross-sectional travel surveys. We estimate a semi-ordered bivariate probit model using this dataset. Among other findings, the model results show that better-educated, younger individuals who currently work or work and study are more likely to use shared ridehailing services compared to other individuals, and in particular members of older cohorts. Being white and living in a higher-income household is associated with a higher likelihood of being a frequent user of regular ridehailing but does not have statistically significant effects on the likelihood of adopting shared ridehailing. With respect to the factors limiting the use of shared ridehailing services, we found that increased travel time and lack of privacy decreases the likelihood of adoption of shared ridehailing. We also find evidence that some land use features affect the likelihood of using both types of services. While the likelihood of using both ridehailing and shared ridehailing is higher in urban areas, residents of neighborhoods with higher intersection density are found to be more likely to only adopt shared ridehailing. However, some of the land-use variables become insignificant after introducing individuals' attitudes related to land-use into the model. This is an indication of residential self-selection, and the potential risk of attributing impacts to land-use features if individual attitudes are not explicitly controlled for.

2.2. Introduction

Travel demand in the U.S. has been going through a structural change since the last 15 years. Total and per-capita vehicle miles traveled (VMT) increased during the 20th century and until the mid-2000s, when total VMT almost became stagnant, and there was a decline in per-capita VMT. However, since 2015, there has been an increase in both VMT and per-capita VMT (Circella, Tiedeman, Handy, Alemi, & Mokhtarian, 2016). This change is reflected in the vehicle ownership which reached a 'peak' in 2008 (with 243 million vehicles), followed by decline of 4 million vehicle in the period of 2008-2011, before rebounding again to 241 million by 2013 (Circella et al., 2016).

Several possible explanations have been proposed to these changes in travel behavior. Some of them include fluctuations in fuel prices, change in household compositions, the economic recession, change is lifestyle, and new mobility services enabled by information and communication technology (Circella et al., 2016; Newman & Kenworthy, 2011). On one hand, the information and communication technology made it possible to share real-time locational data and provided access to internet through smart phones. At the same time, the so-called sharing economy, allows individuals to share resources without the need to own. Together they have introduced new ways to travel which do not include a fixed cost of vehicle ownership, provide cheaper options of travel, and reduce travel uncertainty.

The new shared mobility services have brought a range of services to the market. These include fleet-based carsharing services, bikesharing, e-scooter sharing, and ridehailing services. Ridehailing, also known as ridesourcing (SAE, 2018) or the services provided by transportation network companies (TNCs) such as Uber and Lyft, brings together the supply and demand typical of taxi services through modern smartphone apps. The matched drivers pick up the users from their location and drive them to desired destinations in exchange of monetary compensation. Ridehailing is quickly gaining popularity in the U.S. and other markets around the world. By the end of the year 2017 Uber announced the completion of 1 billion trips, and in 2019 the number reached to 5 billion (Uber, 2019b). Nearly 10% of the U.S. population has reported that they use ridehailing at least once a month, according to the recent National Household Travel Survey (NHTS) data (M. Conway, Salon, & King, 2018). In San Francisco, ridehailing services account for nearly 15% of the trips made within the city. This translates to almost 20% of the total VMT with in the city. In New York City, ridehailing services accounted for 600 million VMT in the period of 2014-17 (Schaller Consulting, 2017).

After a few years of experimentation, in 2014, Uber launched UberPOOL, and Lyft launched Lyft Line (later rebranded to Lyft Share). The purpose of these services is to enable unacquainted riders, travelling in same direction, to share rides. The computer algorithm optimizes the route of their vehicles in real time to allow new pickups along a trip by minimizing the detours for each rider. In exchange of increased travel time and the disutility of sharing the ride with a stranger, the riders are offered a discount of up to 40-50% (Sperling, 2018). These services are only offered in dense urban areas such San Francisco and New York City. Shared ridehailing or pooling services bring together public interest of promoting high occupancy vehicles with private business interests. For the service providers, shared ridehailing brings in new prospects of increasing profits by increasing the utilization rate of resources (labor and capitol). By decreasing the costs of the trips, they can make ridehailing more accessible to various segments of the market and for new trip purposes. Shared ridehailing services provide an avenue to increase efficiency of a trip (as opposed to a trip made by a single occupant vehicle). However, overall, these services may have positive, neutral or negative impact on the VMT in the transportation system depending on the modes replaced and how successfully multiple passengers are matched in single trip without much detours (Alemi, 2018). This builds a case to further investigate the adoption and impacts of shared ridehailing in more detail. In order to increase the market share of shared ridehailing it is important to understand the right balance of decreased costs and increased disutility for various segments of the market.

The objective of this study is to understand the factors that affect the frequency with which travelers living in California use ridehailing and their eventual adoption of shared ridehailing services. We identify the differences in the factors that encourage the use of each type of service, through the estimation of a semi-ordered bivariate probit model of the adoption of shared ridehailing and frequency of use of ridehailing as dependent variables. Since shared ridehailing is not available everywhere in California, we focus on the subsample of individuals living in regions of the state where shared ridehailing services are available.

The remainder of the chapter is organized as follows. In the next section, we discuss the literature on ridehailing adoption and use. In section 2.4., we summarize our data collection efforts, our conceptual model and the details of the semi-ordered bivariate model. In section 2.5., we discuss the results from the model estimation, and in the final section 2.6. we present conclusions and implications for future research.

2.3. Literature Review

Traditional carpooling has been often promoted as a strategy to reduce the number of vehicles on the roads. It allows travelers to share a ride to a common destination, and has numerous societal benefits such as reductions in VMT, greenhouse gases (GHG) emissions, congestion and need for parking infrastructure (Shaheen et al., 2018). The share of carpooling to work reached its maximum in 1970s (20% of all commute trips), during the energy crisis, which lead to a 23% reduction in VMT. The main takers of carpooling were households with low income and more workers than vehicles in the household (Shaheen & Cohen, 2019). Younger individuals, immigrants and blue collar employees in the U.S. are still more likely to carpool than other demographics (Blumenberg & Smart, 2010; Neoh, Chipulu, & Marshall, 2017). Reduction in congestion, environmental concerns, reduction in travelling costs, incentives from the employers, access to special parking spots and HOV (high occupancy vehicles) lanes, and an opportunity to socialize are some of the motivating factors which have led to adoption of carpooling. The other factors that lead to more carpooling are situational variables such as having a fixed commute schedule and residence in urban areas. Typically, carpooling is more successful for commute trips as opposed to non-commute trips which require extensive coordination and planning (Cools, Tormans, Briers, & Teller, 1998; Ferguson, 1997; Neoh et al., 2017). Carpooling saw a sharp decline as a mode of transportation in 1980s – soon after the end of shortage of oil in the U.S. (Ferguson, 1997). There are many reasons which have made Americans stop carpooling. Perhaps some of the most important barriers are the difficulty in coordinating the time of trip with other non-households members, the difficulty (and anxiety) about sharing a ride with strangers (Cools et al., 1998), and the low-density patterns of U.S. cities, which make origins and destinations not convenient for pooling. Strategies which penalize driving alone such as congestion pricing have been unsuccessful in promoting carpooling in American households (Baldassare, Ryan, & Katz, 1998). Therefore, ever since 1980's single occupancy vehicles have been the most preferred mode of transportation in the US.

Information and Communication Technology (ICT) solutions along with the application of the shared economy to transportation have now opened doors to new ways of travel, including the ability to share rides with others in a more efficient way. Ridehailing is probably the most relevant type of new mobility services in this regard. Some studies have explained how ridehailing can potentially be used as a travel demand management strategy (Rodier, Alemi, & Smith, 2016). On average, the use of ridehailing is much higher in mid-sized and large US cities (M. Conway, Salon, & King, 2018). The users of ridehailing services are young individuals with medium to high income (Alemi, Circella, Handy, et al., 2018; Alemi, Circella, Mokhtarian, & Handy, 2018; M. Conway, Salon, & King, 2018). Individuals who make frequent long-distance trips are more likely to use such services, possibly to access and egress airport. Moreover, individuals with pro-environment attitudes and those who easily embrace new technologies are more likely to use such services (Alemi, Circella, Handy, et al., 2018).

But a bigger debate has been on - do ridehailing services help reduce VMT and congestion, or do they further increase them? Certainly, the answer lies in how ridehailing interacts with other modes of transportation and the way users adjust their activities and travel schedules as a result of the use of ridehailing. Babar & Burtch (2017) examined public transit ridership data in the U.S. and showed how ridehailing on one hand replaces the services provided by city buses but compliments the services provided by subway and commuter rail. Another study analyzing the NHTS dataset in the U.S. reported that in the absence of ridehailing services many trips currently made using ridehailing would have been completed using public transit (15-50%) or active modes (12-24%), or they would not have been made at all (2-22%) (Schaller, 2018). At the same time, ridehailing replaces private modes in areas with high parking charges (Schaller, 2018). At this point there is not much consensus on the impact of ridehailing on transportation, as well as, more particularly, its impact on VMT and GHG emissions. Li, Hong, & Zhang (2016) analyzed the traffic congestion data in cities of the U.S. before and after introduction of ridehailing services and found evidence that ridehailing could reduce congestion by reducing vehicle ownership. But, there has also been evidence from simulation and survey based studies suggesting that the introduction of ridehailing leads to an increase in VMT in the transportation system (Anderson, 2014; Henao & Marshall, 2018; Schaller Consulting, 2017; Tirachini & Gomez-Lobo, 2019). Many reasons have been cited to explain such an increase in VMT: the deadheading of drivers in search of passengers, eventual induced travel and replacement of trips to be made by transit and active modes (Henao & Marshall, 2018; Tirachini & Gomez-Lobo, 2019). For example, Erhardt et al. (2019) analyzed data scrapped from API services of Uber and Lyft, and show how ridehailing services have led to increase in congestion and VMT in San Francisco.

Ridehailing companies also provide a platform for sharing the ride without much effort through their shared (pooled) services: this may lead to a higher vehicle occupancy leading to an overall reduction in VMT and per-capita emissions of greenhouse gases (Sperling, 2018; Tirachini & Gomez-Lobo, 2019), depending on the conditions in which services are “consumed” by travelers. Still, so far the acceptance of shared ridehailing services has been low – 13% to 20% of the trips made using the online ridehailing platform (Gehrke, Felix, & Reardon, 2018; Henao & Marshall, 2018). To authors’ knowledge, not many studies have investigated the barriers to using shared ridehailing services. Lavieri & Bhat (2019) conducted a survey in Dallas, Texas and jointly modeled the usage of shared ridehailing services in present and future preference of shared autonomous vehicles. The study showed that there are two main factors affecting the use of shared vehicles – extra time with new passenger and presence of a new passenger in the car. In the current study we analyze how factors influencing the adoption of shared ridehailing services differ from frequency of use of regular ridehailing – which has been very popular so far. In the next section we describe the dataset used to answer this question.

2.4. Data and Method

2.4.1. Data Collection

The dataset used for this analysis is a part of a larger research effort carried out at the Institute of Transportation Studies (ITS) of the University of California, Davis. As part of a longer longitudinal mobility study, our research team administered two waves of surveys in California with, among other objectives, the goal to better understand the adoption and impacts of new mobility services. The data from the first wave (2015) was used to create an initial understanding of ridehailing services (Alemi, Circella, Handy, et al., 2018; Alemi, Circella, Mokhtarian, & Handy, 2019; Alemi, Circella, Mokhtarian, et al., 2018). In this chapter, we use the data from the second round of data collection, completed in fall 2018 (Circella, Matson, Alemi, & Handy, 2019) to create a deeper understanding of the differences between factors influencing use of ridehailing and shared ridehailing services.

The full 2018 dataset consisted of 4,071 completed surveys, before data cleaning. We employed a combination of sampling strategies to recruit respondents in 2018, including:

a) Mail survey: we mailed out 30,000 paper surveys to randomly selected residential addresses in the state. To ensure representation from entire California, a stratified random sampling approach was used. California was divided into six regions, and the sampling rates were adjusted according to the populations in these regions. The respondents had the option of mailing back the completed questionnaire or complete the survey through an online link. A total of 1,992 respondents (1,620 via mail and 372 online) completed the survey through this channel. In order to encourage more responses, we entered the respondents into a drawing for the chance to win one of ten $100 gift cards or one of five hundred $10 gift cards from Amazon. Respondents who mailed back the survey (incomplete or complete) or those who provided contact details at the end of the online survey were eligible for the drawing.

b) Recontact of 2015 respondents: We recalled all the respondents who completed the previous survey in 2015 using the same commercial online opinion panel from that data collection. Unfortunately, only 246 of the previous respondents completed the survey in 2018.

c) New online opinion panel recruitment: We also refreshed the panel by adding a group of participants in this wave of data collection, recruiting them through another online opinion panel company. The opinion panel company compensates survey respondents with points that can be converted into airline miles, gift cards etc., with the number of the accrued points commensurate to the length of the specific survey. We recruited these additional respondents to make up for the natural dropping out of respondents from the panel. We used quota sampling by California region and neighborhood type (urban, rural, etc.) for this recruitment, and established socio-demographic targets for age, gender, children in the household, household income, race, ethnicity, work status and school status. The quotas and targets were set using the most recent 5-year estimates from the American Community Survey (ACS). A total of 1,833 respondents completed this survey through this channel.

The survey was designed to collect information on respondent’s attitudes and preferences; use of technology in life; their lifestyle – formation of the household, number of vehicles, work status, home and work location; current travel patterns; usage of emerging transportation services – ridehailing; perception about autonomous vehicle; and background information. The survey was designed to be completed in 30 to 40 minutes.

The goal of this study is to understand the factors affecting the use of shared ridehailing services. Since shared ridehailing services are only available in eight counties (San Francisco, San Mateo, Santa Clara, Alameda, Contra Costa, Marin, Los Angeles and San Diego) in the state of California, we only focus on responses from individuals living in these areas. This left us with 1,592 complete cases. The information about availability of shared ridehailing service in particular county is not publicly available. We used price estimators from Lyft and Uber to identify the counties where shared ridehailing services were offered (Lyft, 2019; Uber, 2019a). We entered random origin/destination in each county to find out if Uber or Lyft provided pooling services.

2.4.2. Data Description

Dependent variables: in the survey we asked respondents to report how frequently they used ridehailing and shared ridehailing services by asking them to choose one option from – "I am not familiar with it", "It's familiar but I've never used it", "I used it in the past, but not anymore", and several categories for "I use it…" "…less than once a month", "…1-3 times a month", "…1-2 times a week", and "…3 or more times a week".

We use two dependent variables in our model – adoption of shared ridehailing (binary variable) and frequency of use of ridehailing services (ordinal variable). We grouped respondents who reported that they have never used or heard about shared ridehailing services into '*non-users*' category, and those who reported they had used service in past but not anymore, use it less than once a month, 1-3 times a month, 1-3 times a week or more than 3 times a week were categorized as '*users*'. Nearly one-third of the respondents from the selected counties reported to have used shared ridehailing services at least once. We want to point out that initially we wanted treat this as an ordinal variable. However, very few numbers of respondents (less than 5%) reported using shared ridehailing on weekly basis. Thus, we collapsed this into a binary variable.

For the frequency of use of ridehailing, respondents who had never heard about or used it, or had used in past but not anymore were regrouped as 'never'. Individuals who responded by saying they used it less than once a month were categorized as 'occasional' users. The 'monthly' category is for individuals who said they use ridehailing for 1 to 3 times a month. Finally, respondents who claimed they use ridehailing services for more than once a week were all grouped together as 'weekly' users. About 7.6% of the respondents from the selected counties reported using ridehailing on a weekly basis. The proportion is twice higher in comparison with the entire dataset. Nearly 46% of the respondents in the subsample used for this analysis said they never used ridehailing services. This number is as high as 60% for the entire 2018 California dataset.

To identify the factors that affect the use shared ridehailing and ridehailing, we first explored the differences between specific groups of users and non-users of these services by examining the distribution of potential explanatory variables in each group. We divided these explanatory variables into four main groups (socio-demographics, built environment, lifestyle and personal attitudes), and we tested different variable transformations in each group to identify the variables most closely associated with the use of shared ridehailing and ridehailing services. Table 2-1 summarizes the distribution of these variables in the eight selected counties and in entire California. Table 2-2 summarizes the distribution of the explanatory variables used in the model across the two dependent variables. The four groups of variables are as follows:

Socio-demographic variables: we conducted chi-square tests on various socio-demographic variables such age, gender, race, education, income and country of birth with the hypothesis that these variables impact the frequency of use of ridehailing services and adoption of shared ridehailing services. The result of these exploratory tests showed that age, income, education and race were statistically significant in explaining the variation in the frequency of use of these services. For age, we have three categories – 'Millennials and younger', 'Gen X' and 'Baby Boomers and older' – with all three categories having an equal representation in the selected subsample used for this analysis. We define 18 to 37 years old as 'Millennials and younger'; 38 to 53 years old as 'GenX; and 54 years or older as 'Baby Boomers and older'. We use a dummy variable (White or not) to control for race; a categorical variable to control for household income that consists of three levels low-income household (household with annual income of less than $50k), medium-income household (household with annual income of $50k to $100k), and high-income households (households with annual income of more than $100k); a dummy variable for the level of education based on information on the highest attained educational level (we define individuals with a bachelor's degree or more as highly-educated individuals). As shown in table 2-1, we found that respondents living in the eight counties of interest are more likely to be higher educated and to live in high-income households. This was expected because the selected counties represent affluent regions of California, in and around San Francisco, Los Angeles and San Diego.

Lifestyle: the lifestyle of an individual can be measured in different ways. For example, Salomon & Ben-Akiva (Salomon & Ben-Akiva, 1983) describe individual's lifestyle in form of their participation in the work force, household formation and how they spend time in leisure activities. This definition has been used widely in many transportation related studies (El Zarwi, Vij, & Walker, 2017; Kitamura, 2009; Van Acker, Mokhtarian, & Witlox, 2014). We tested many indicators, which serve as a measure of lifestyle, which could explain individuals' choice of using ridehailing services. These included – presence of children in the household, household size, interaction of age and gender with employment. We found that variables describing the employment status and student status of the respondents could statistically explain their behavior of using these services. In the selected subset of the sample, 70% of the respondents have a full-time, part-time job, or they do some volunteering work. The same sample has about 10% of the respondents who are students and also have a job.

Built-environment: the location where the respondent lives and work have a high association with their travel choices (Guerra, 2014; S. Handy, Tal, & Boarnet, 2014; A. E. Lee & Handy, 2018; Nazari, Noruzoliaee, & Mohammadian, 2018; Sisson, Lee, Burns, & Tudor-Locke, 2006; Tiwari, Jain, & Ramachandra Rao, 2016; Van Acker et al., 2014). Thus, it is important to control for built environment characteristics of the neighborhood where the respondent lives. We geocoded the home location of the respondents using the Google API (Google Developers, 2019). We used this geocoded information to obtain the census tract and block group ID of the home locations using the census API (Recht, 2019). We then used external datasets to bring in information about the built environment to our final dataset. One of these additional data sources was the classification of various neighborhoods, developed by Salon (Salon, 2015) who classified all census tract in California into five neighborhood types – central city, urban, suburban, rural-in-urban and rural. We collapsed these five levels to three levels – urban (central city and urban), suburban, and rural (rural-in-urban and rural). About half of the selected subset of the sample lives in suburban neighborhoods and nearly 40% of them in live in urban neighborhoods. The other dataset that we integrate to our final dataset is the Smart Location Database maintained by the US EPA which includes information on land use density, diversity, destination accessibility, network and design for each block group in US.

We collected the walkability of the place of residence of the respondent using Walkscore.com API service (Walkscore, 2020). Walkscore ranges from 0 to 100. Where 100 indicates an extremely pedestrian friendly neighborhood, where most of the errands can be performed by walking.

Personal Attitudes: a number of studies have shown the importance of individual attitudes in predicting behavior (Ajzen, 1991; Paulssen, Temme, Vij, & Walker, 2014). In the first section of the survey, we show respondents 30 statements and ask them to indicate their level of agreement with each statement by selecting one of the five options in a Liker-type scale, from "Strongly Disagree" to "Strongly Agree". This battery of attitudinal statements was asked to measure the underlying latent constructs which can explain some of the observed behaviors of the respondents (in this case the use of ridehailing services). The statements were selected to understand respondents' attitudes towards the environment, land-use, modes of transportation etc. (see Table 2-3). Previous research suggests that each construct must have three to five measurements statements; and directionality of the statements must be diversified to discourage respondents from falling into automatic response mode (Fabrigar, Wegener, MacCallum, & Strahan, 1999; P. L. Mokhtarian, Ory, & Cao, 2009). We followed this recommendation while designing the survey.

We had three main techniques at our disposal to estimate the latent constructs from the responses to these attitudinal statements – principal component analysis (PCA), exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The primary goal of the current study is to use the latent constructs in the main choice models to explain the usage of ridehailing services. This rules out the applicability of PCA which is primarily a data reduction technique and does not attempt to model the structure of correlation among the measured variables (Fabrigar et al., 1999). PCA does not differentiate between common (latent variable) and unique (measurement error) variance of each attitudinal statement. Hence, it defeats our purpose of extracting behaviorally meaningful latent constructs. On the other hand, both CFA and EFA are based on common factor models. They attempt to preserve the correlation among measurement variables by extracting a small set of latent variables which can explain the common variances in the measurement variables.

CFA is a better approach when the goal is to test a specific theoretical hypothesis about the data. However, our goal is to extract the optimum latent variables for explaining the usage of ridehailing. Thus, we rely on EFA which is primarily a data driven approach. Unlike CFA, EFA does not make any prior assumption about the model. This is especially desirable in the current case where 30 attitudinal statements can lead to many plausible models making it impractical to test each one in the CFA framework. We conducted EFA using the 'Psych' package in R (Revelle, 2020).

While conducting an EFA, selecting the number of factors and the type of rotation are two most critical decisions which can influence the final outcome of the analysis. Fabrigar et al. explain that oblique rotation is often superior to orthogonal rotation. The latter forces the factors to be uncorrelated with one another. This is an added restriction while performing EFA. On the other hand, oblique rotation relaxes this restriction. The optimal solution of an oblique rotation can have either correlated or uncorrelated factors. Allowing the factor scores to be slightly correlated also makes sense behaviorally. For instance, one can expect a slight correlation between a latent construct about the attitude towards owning a private car and the sensitivity towards environmental issues. Thus, we resort to oblique rotation while performing factor analysis. We tested solutions using 'Oblimin' and 'Promax' rotations (both are oblique). However, the solution from 'Promax' rotation was more interpretable.

Initial rounds of EFA with oblique rotation revealed that four out of the 30 attitudinal statements did not load well on any of the factors or led to solutions with very limited interpretability (which were most likely the results of other spurious correlations, rather than true common attitudinal components). Thus, we dropped these four statements and were left with 26 attitudinal statements. Next, to decide on the number of factors for the final solution we relied on the Kaiser criterion of computing eigenvalues for correlation matrix. The rule is to keep the factor scores which have eigen values greater than value 1 (Gorsuch, 1983). This criterion suggested seven factor scores for 26 statements. However, using seven factors scores in a Promax rotation led to a solution in which multiple seemingly unrelated statements were loading on the same factor. After multiple iterations we decided on a final solution with nine factors for 26 statements. The final solution was chosen for its trade-off between explanation of variance in the data (and the criterion based on the eigenvalues) and interpretability. Fabrigar et al. explain how having fewer factors (under-factoring) can potentially lead to more severe errors compared to over-factoring. The nine factors cumulatively explain 43% of variance of the 26 statements. We included individual attitudes using the Bartlett factor scores (which produce less biased estimates as compared to regression scores (DiStefano, Min, & Diana, 2009)) that were computed through a factor analysis (Promax rotation) of the original attitudinal variables included in the dataset. The details of these factors and the attitudinal statements loading from the pattern matrix are mentioned in Table 2-3.

Towards the end of the survey, we also asked respondents to evaluate a list of shared ridehailing attributes on a Likert-type scale from "Very limiting" to "Very encouraging", and report if they perceived those attributes as barriers or enablers to use of shared ridehailing services. This question was very specific about shared ridehailing and had a different scale of measurement from the previous batch of attitudinal statements. Fabrigar et al. say – "when EFA is conducted on measured variables with low communalities, substantial distortion in results can occur". Thus, we performed a separate EFA for these limitations using 'Promax' rotation and two factor scores. The two factor scores cumulatively explain 67% variance of the six measurement variables. The results are shown in Table 2-3 as well.

This two-step approach of first estimating the latent variables and then using the factor scores in a choice model introduces a measurement error in the choice model. This is because the attitudinal statements, are not the perfect measurements of the latent constructs, but are merely indicators of the latter. Researchers sometimes jointly estimate the measurement variables and choice outcomes using the Integrated Choice and Latent Variable (ICLV) approach. However, Vij and Walker (Vij & Walker, 2016) found that in many cases ICLV models do not fit the data any better than equivalent choice model. In future, we plan to use the ICLV approach to jointly model the measurement and choice variables; and examine the added advantage of the novel approach. Nonetheless, our current analysis with EFA still holds insights about how attitudes influence the decision to use ridehailing services. Moreover, this EFA will guide our future work in defining the configuration of latent variables with the corresponding measurement variables.

Apart from the groups of variables discussed above, the long-term and medium-term travel choices of individual/ households play an important role in their current travel choices (Vij, Carrel, & Walker, 2013). These are usually measured as number of vehicles in the household, usage of public transportation, active transportation, commute distance etc. However, and somewhat surprisingly, none of these variables were significant in our models.

Table 2-1. Distribution of data in the selected counties and entire California

	Counties with Pooling services (n=1,654)	Complete Dataset (n=3,767)
Dependent Variable		
Usage of ridehailing services		
Never	46.31%	59.42%
Occasional	28.84%	24.59%
Monthly	17.17%	11.43%
Weekly	7.68%	4.56%
Usage of shared ridehailing		
Non-User	67.90%	80.36%
User	32.10%	19.64%
Socio-Demographics		
Age		
Millennials and younger (18-37 yrs. old)	31.68%	28.53%
GenX(38-53 yrs. Old)	32.41%	31.03%
Baby Boomers and older (54 yrs. or older)	35.91%	40.44%
Race		
White	74.18%	80.51%
Other	25.82%	19.49%
Household Income		
Less than $50,000	25.88%	31.18%

$50,000 - $99,999	30.29%	32.06%
More than $100,000	43.83%	36.76%
Education		
Bachelors or less	34.28%	43.23%
More than Bachelors	65.72%	56.77%
Lifestyle		
Employed		
Yes	70.62%	65.18%
No	29.38%	34.82%
Employed and Student		
Yes	10.10%	65.18%
No	89.90%	34.82%
Built Environment		
Employment Entropy		
Low [0,0.27]	20.56%	20.35%
Medium (0.27,0.65]	29.99%	29.61%
High (0.65,1]	49.46%	50.04%
Intersection Density		
Low [0,58]	26.00%	38.22%
Medium (58,1.5e+02]	58.10%	51.41%
High (1.5e+02,5.2e+03]	15.90%	10.37%
Neighborhood Type		
Urban	36.70%	19.24%
Suburban	50.67%	45.28%
Rural	12.64%	35.48%
Walkscore*	60.24 (27.87)	49.33 (29.35)

*For continuous variables, this table shows means and (in parentheses) standard deviations.

Table 2-2. Distribution of explanatory variables across dependent variables

	Shared Ridehailing		Ridehailing			
	Non-User(n=1123)	User(n=531)	Never(n=766)	Occasionally(n=477)	Monthly(n=284)	Weekly(n=127)
Socio-Demographics						
Age						
Millennials and younger	22.35%	51.41%	23.24%	31.24%	45.07%	54.33%
GenX	33.75%	29.57%	30.16%	33.54%	35.92%	33.86%
Baby boomers and older	43.90%	19.02%	46.61%	35.22%	19.01%	11.81%
Household Income						
Less than $50,000	25.82%	25.99%	34.99%	20.34%	15.85%	14.17%
$50,000 - $99,999	30.10%	30.70%	30.94%	28.51%	28.87%	36.22%
More than $100,000	44.08%	43.31%	34.07%	51.15%	55.28%	49.61%
Race						
Not white	24.40%	28.81%	27.42%	25.58%	23.59%	22.05%
White	75.60%	71.19%	72.58%	74.42%	76.41%	77.95%
Education						
Bachelors or less	35.53%	31.64%	44.13%	24.74%	25.00%	31.50%
More than Bachelors	64.47%	68.36%	55.87%	75.26%	75.00%	68.50%
Lifestyle						
Employed						
Yes	64.56%	83.43%	57.83%	76.10%	86.97%	90.55%
No	35.44%	16.57%	42.17%	23.90%	13.03%	9.45%
Work and Study						
Yes	6.59%	17.51%	5.61%	11.53%	13.38%	24.41%
No	93.41%	82.49%	94.39%	88.47%	86.62%	75.59%
Built Environment						
Employment Entropy						
Low [0,0.27]	21.82%	17.89%	23.76%	18.66%	17.96%	14.17%
Medium (0.27,0.65]	30.72%	28.44%	31.85%	27.67%	30.28%	26.77%
High (0.65,1]	47.46%	53.67%	44.39%	53.67%	51.76%	59.06%
Intersection Density						
Low [0,58]	27.87%	22.03%	26.89%	27.04%	27.11%	14.17%
Medium (58,1.5e+02]	60.82%	52.35%	61.36%	55.97%	52.46%	59.06%
High (1.5e+02,5.2e+03]	11.31%	25.61%	11.75%	16.98%	20.42%	26.77%
Neighborhood Type						
Urban	30.90%	48.96%	29.24%	38.78%	43.31%	59.06%
Suburban	55.30%	40.87%	56.79%	50.52%	41.55%	34.65%
Rural	13.80%	10.17%	13.97%	10.69%	15.14%	6.30%
Walkscore*	57.05 (27.89)	66.99 (26.64)	56.15 (27.94)	62.13 (26.77)	62.51 (28.63)	72.79 (24.87)

Table 2-3 Factor Scores for attitudinal statements

Factor Scores for Personal Attitudes	**Factor Loadings from Pattern Matrix**
Pro-Environmental Regulation	
The government should put restrictions on car travel in order to reduce congestion.	0.29
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.99
We should raise the price of gasoline to provide funding for better public transportation.	0.82
Pro-Urban	
I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.	0.79
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	0.46
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.	-0.81
Techsavvy	
I like to be among the first people to have the latest technology.	0.59
Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.	0.49
I like trying things that are new and different.	0.42
Learning how to use new technologies is often frustrating for me.	-0.61
Car Lover	
I definitely want to own a car.	0.90
I prefer to be a driver rather than a passenger.	0.41
I am fine with not owning a car, as long as I can use/rent one any time I need it.	-0.46
Pro-Environment	
I am willing to pay a little more to purchase a hybrid or other clean-fuel vehicle.	0.56
I am committed to an environmentally friendly lifestyle.	0.76
I prefer to minimize the material goods I possess.	0.39
Car Dependent	
Most of the time, I have no reasonable alternative to driving.	0.43
I am too busy to do many things I'd like to do.	0.37
My schedule makes it hard or impossible for me to use public transportation.	0.83
Car Utilitarian	
The functionality of a car is more important to me than its brand.	0.68
To me, a car is just a way to get from place to place.	0.62
Pro-Multitasking	
I try to make good use of the time I spend commuting.	0.46
My commute is a useful transition between home and work (or school).	0.54
I like to juggle two or more activities at the same time.	0.38
Pro-Luxury	
I am uncomfortable being around people I do not know.	0.32
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.	0.46
I would/do enjoy having a lot of luxury things.	0.51
Factor Scores for Attitudes Specific to Shared Ridehailing	Loading
Longer Travel Time	
Longer travel time	0.80
Longer waiting time	0.95
Unreliable travel time	0.84
Deviation from main route	0.62
Safety/Privacy	
Interacting with other passengers	0.68
Sitting next to a stranger	0.92

2.4.3. Model Estimation

In this chapter, we want to model the adoption of shared ridehailing services. At the same time, we are interested in testing the hypothesis that those who use ridehailing services with higher frequency are also more likely to be shared ridehailing users. However, using frequency of ridehailing as an independent variable to estimate the shared ridehailing adoption in a model may lead to endogeneity bias, meaning that the unobserved factors affecting the frequency of ridehailing services may also affect the use of shared ridehailing services. This may lead to over/under estimation of our estimates. One of the approaches to address the endogeneity problem is the use of two-stage least square method (2SLS), where one would estimate a univariate ordered model to estimate frequency of ridehailing; and use this estimate to model adoption of shared ridehailing services. However, as pointed out by Sajaia (Sajaia, 2008b), a bivariate ordered probit model has advantages over 2SLS, especially when the dependent variables are categorical, and when the error terms of the dependent variables are expected to have high correlation, which might be the case in modeling the two dependent variables of interest.

In this study, we estimate a semi-ordered bivariate probit model (Greene & Hensher, 2009) using the Bioprobit module in Stata (Sajaia, 2008a). For each individual i, the two dependent variables are the frequency of use of ridehailing ($y_{i,1}$) and the adoption of shared ridehailing services ($y_{i,2}$). In order to estimate a bivariate model, we defined two latent variables $y_{i,1}^*$ and $y_{i,2}^*$. These latent variables are modelled using explanatory variables $\mathbf{X}_{i,1}$ and $\mathbf{X}_{i,2}$. These explanatory variables have been described in the previous section. $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are the set of coefficients to be estimated. The error terms $\varepsilon_{i,1}$ and $\varepsilon_{i,2}$ are assumed to be correlated and to follow a bivariate normal distribution, as shown in equation (3). ρ in equation (3) is the correlation between the error terms. A value of $\rho = 0$ would imply there is no correlation between the error terms.

$$y_{i,1}^* = \boldsymbol{\beta}_1 \boldsymbol{X}_{i,1} + \varepsilon_{i,1} \tag{1}$$

$$y_{i,2}^* = \boldsymbol{\beta}_2 \boldsymbol{X}_{i,2} + \varepsilon_{i,2} \tag{2}$$

$$\binom{\varepsilon_{i,1}}{\varepsilon_{i,2}} \sim N\left[\binom{0}{0}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{3}$$

The ordinal variable $y_{i,1}$ and binary variable $y_{i,2}$ can be observed using equation (4) and (5). The unknown cut-offs satisfy the conditions $\mu_1 < \mu_2 < \mu_3$.

$$\boldsymbol{y_{i,1}} = \begin{cases} \mathbf{0}\ (\boldsymbol{Never}),\ \boldsymbol{y^*_{i,1} \leq \mu_1} \\ \mathbf{1}\ (\boldsymbol{Occassionally}),\ \boldsymbol{\mu_1 < y^*_{i,1} \leq \mu_2} \\ \mathbf{2}\ (\boldsymbol{Monthly}),\ \boldsymbol{\mu_2 < y^*_{i,1} \leq \mu_3} \\ \mathbf{3}\ (\boldsymbol{Weekly}),\ \boldsymbol{\mu_3 < y^*_{i,1}} \end{cases} \tag{4}$$

$$\boldsymbol{y_{i,2}} = \begin{cases} \mathbf{0}\ (\boldsymbol{Non\ Users}),\ \boldsymbol{y^*_{i,2} \leq \delta_1} \\ \mathbf{1}\ (\boldsymbol{Users}),\ \boldsymbol{\delta_1 < y^*_{i,2}} \end{cases} \tag{4}$$

The probability that $y_{i,1}$= j and $y_{i,2}$= k is given by equation (6). Here, Φ_2 is the bivariate normal cumulative distribution function. Please note that equation (6) is for a general ordered bivariate model. In the current case, $y_{i,2}$ is binary, which means $\delta_k = \delta_1$ and $\delta_{k-1} = 0$. These are the probabilities that enter the log-likelihood function. The model parameters $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, μ_1, μ_2, μ_3, δ_1 and ρ are estimated using the full-information maximum likelihood (FIML) estimation.

$$\Pr\left(y_{i,1} = j, y_{i,2} = k \middle| \boldsymbol{X}_{i,1}, \boldsymbol{X}_{i,2}\right) = \begin{bmatrix} \Phi_2[(\mu_j - \boldsymbol{\beta}_1\boldsymbol{X}_{i,1}), & (\delta_k - \boldsymbol{\beta}_2\boldsymbol{X}_{i,2}), & \rho] \\ -\Phi_2[(\mu_{j-1} - \boldsymbol{\beta}_1\boldsymbol{X}_{i,1}), & (\delta_k - \boldsymbol{\beta}_2\boldsymbol{X}_{i,2}), & \rho] \end{bmatrix} - \begin{bmatrix} \Phi_2[(\mu_j - \boldsymbol{\beta}_1\boldsymbol{X}_{i,1}), & (\delta_{k-1} - \boldsymbol{\beta}_2\boldsymbol{X}_{i,2}), & \rho] \\ -\Phi_2[(\mu_{j-1} - \boldsymbol{\beta}_1\boldsymbol{X}_{i,1}), & (\delta_{k-1} - \boldsymbol{\beta}_2\boldsymbol{X}_{i,2}), & \rho] \end{bmatrix} \tag{6}$$

The model estimation results are discussed in the next section.

2.5. Results and Discussions

Table 2-4 presents the results of the estimation of the semi-ordered bivariate probit models with and without attitudes. The estimated value of ρ for the model without attitudes is 0.70 and the value for the model with attitudes is 0.65. Both are significantly different from 0, allowing us to reject the null hypothesis ($\rho = 0$) and confirming that the error terms in the two equations are indeed correlated. The significance of the likelihood ratio test of independence of the two equations also show that the two equations are indeed correlated. This means that the effects of the unobserved variables on the adoption of shared ridehailing are highly correlated with those affecting the frequency of use of ridehailing. However, the reduced magnitude of ρ in the model with attitudes indicates that a part of the shared error component between the adoption of shared ridehailing and the frequency of ridehailing usage in the first model (without the attitudes) is attributable to individual attitudes (*pro-urban*, *tech-savvy*, *car dependent* and *pro-multitasking*).

We found that younger individuals are more likely to use ridehailing frequently than middle-aged and older individuals. The younger generation is also more likely to adopt shared ridehailing services than the members of the older generations. Among other sociodemographic variables, higher household income is associated with a higher frequency of using ridehailing, however household income is not a significant predictor of the propensity to adopt shared ridehailing. Our previous research studies (Alemi, Circella, Handy, et al., 2018) found a similar relationship among ridehailing, age and household income of the respondents. Individuals who self-identify as white are more likely to use ridehailing services frequently (compared to other races). However, this does not affect the propensity to adopt shared ridehailing. Lavieri and Bhat found white individuals to be more reluctant than those of other races to share rides with strangers due to privacy concerns. Higher education has positive significant coefficients for both ridehailing frequency and shared ridehailing adoption in the model without attitudes. Other studies (M. Conway, Salon, & King, 2018; Rayle, Dai, Chan, Cervero, & Shaheen, 2016; Sikder, 2019) also found that individuals with higher education (more than Bachelors' degree) are more likely to use ridehailing services. However, our study offers an added insight by comparing the results from models with and without attitudes. We observe that the education of an individual is not significant anymore when we add the *tech-savvy* factor in the model. Thus, it seems that education was acting as proxy variable for individuals who are more comfortable with using new technology, with the true effect being that individuals with such attitudes are more likely to use ridehailing services.

Among the lifestyle indicators, employed respondents are more likely to adopt shared ridehailing and to use ridehailing more frequently. It is interesting to note that employment still has a significant effect on the frequency of using ridehailing (but not on adoption of shared ridehailing) even after controlling for income in the model. As pointed out by Dias et al., (2017) this indicates that ridehailing services are possibly used for work related activities. Individuals who are employed and are students are found to be more likely to frequently use ridehailing in the model without attitudes. However, being employed and a student is not found to have significant impacts on the frequency of using ridehailing after adding the *pro-multitasking* attitude in the model.

Table 2-4 Bivariate models with and without attitudes

	Without Attitude		**With Attitude**	
	Ridehailing Frequency	Shared Ridehailing Adoption	Ridehailing Frequency	Shared Ridehailing Adoption
Socio-demographics				
Age (Ref = Millennials and younger)				
GenX	-0.3885*** (0.0705)	-0.5909*** (0.0844)	-0.3160*** (0.0708)	-0.5118*** (0.0856)
Baby Boomers and Older	-0.6507*** (0.0774)	-0.8350*** (0.0921)	-0.4964*** (0.0790)	-0.6627*** (0.0951)
Household Income (Ref = Less than $50,000)				
$50,000 to $99,999	0.3839***(0.0742)		0.4219*** (0.0742)	
$100,000 or more	0.6134***(0.0756)		0.6450*** (0.0720)	
Race (Ref = Other)				
White	0.2560*** (0.0595)		0.2899*** (0.0609)	
Education (Ref = Bachelors' or less)				
More than Bachelors'	0.1842*** (0.0668)	0.1274* (0.0769)		
Lifestyles				
Employed (Ref = No)				
Yes	0.3644*** (0.0743)	0.3612*** (0.0899)	0.3769*** (0.0763)	0.3459*** (0.0941)
Employed and Student (Ref = No)				
Yes	0.2956*** (0.0846)			
Built Environment				
Neighborhood type (Ref = Urban)				
Suburban	-0.2619*** (0.0723)	-0.2555*** (0.0785)	-0.1795*** (0.0599)	
Rural	-0.1332 (0.1198)	-0.1896 (0.1326)	-0.1128 (0.0922)	
Employment Entropy (Ref = Low)				
Medium	0.1170 (0.0829)	0.0501 (0.1025)	0.1408* (0.0830)	0.0625 (0.1041)
High	0.1775** (0.0766)	0.1691* (0.0929)	0.2473*** (0.0758)	0.1951** (0.0948)
Intersection Density (Ref = Low)				
Medium		0.0008 (0.0859)		-0.0318 (0.0806)
High		0.3715*** (0.1128)		0.3541*** (0.1048)
Walkscore	0.0032** (0.0014)			
Attitudes towards Shared Ride*				
Longer Travel Time		0.2298*** (0.0364)		0.2228*** (0.0381)
Safety/Privacy		0.1088*** (0.0363)		0.0821** (0.0379)
General attitudes				
Pro-Urban			0.1968*** (0.0270)	0.2169*** (0.0332)
Techsavvy			0.2058*** (0.0266)	0.1426*** (0.0332)
Car Dependent			-0.0602** (0.0247)	-0.0548* (0.0305)
Pro-Multitasking			0.0712*** (0.0238)	0.0818*** (0.0297)
Constants				
μ_1	0.6928*** (0.1599)		0.6773*** (0.1215)	
μ_2	1.5814*** (0.1626)		1.6103*** (0.1251)	
μ_3	2.4160*** (0.1674)		2.4904*** (0.1321)	
δ_1		0.4411*** (0.1551)		0.7105*** (0.1368)
ρ	0.6958*** (0.0437)		0.6485*** (0.0440)	
Model Specification and Goodness of Fit				

Log likelihood(null)	-2679.04	-2589.75
Log likelihood(model)	-2539.70	-2471.428
Degrees of Freedom	30	32
AIC	5139.39	5006.857
BIC	5301.72	5180.007
LR test of indep. eqns. (chi2)	278.68***	236.63***
Observations	1,654	1,654

As expected, built environment characteristics of the home location of the respondents did have some impact on the use of new mobility services. Residents of urban neighborhoods are found to be more likely to use ridehailing often than the residents of suburban and rural neighborhoods. This effect of the neighborhood type is not significant for the adoption of shared ridehailing when the factor *pro-urban* is included in the model. Among the specific characteristics of the neighborhood, the *Walkscore* of the neighborhood is significantly associated with the frequency of use of ridehailing in the model without attitudes; but this variable becomes insignificant after including the *pro-urban* factor in the model. This is an indication of residential self-selection. Previous studies have found evidence of individuals' travel choices and their residential choice being driven by same underlying attitudes (Cao, Mokhtarian, & Handy, 2009; Kitamura, Mokhtarian, & Laidet, 1997). Both studies Kitamura et al and Cao et al. followed a strategy similar to ours – they observed how land-use variables lost their significance in predicting trip frequencies by specific modes after adding attitudinal factor scores (related to residential choice) to the models. To our knowledge, none of the studies so far has examined the impact of residential self-selection while estimating demand for ridehailing services using built environment variables. This could be potentially problematic from planning perspective as it could lead to overestimation of the effect of land-use on demand for ridehailing (a form of residential self-selection bias). For instance, Yu & Peng observed a positive relationship between sidewalk density (which is another measure of walkability) of a block group and the aggregated demand for ridehailing in that block group. However, the study, by design, could not control for residential self-selection.

Further, we also evaluate the association among employment entropy (a measure of diversity), intersection density (a measure of design) of a neighborhood, and the two dependent variables (Ewing & Cervero, 2010). High employment entropy of the block is associated with a higher frequency of using ridehailing and a higher propensity to adopt shared ridehailing services. Possibly, a diversity in attractive destinations in a neighborhood induces more trips, and some of these trips are made using ridehailing services. Yu & Peng and Sabouri et al. reached a similar conclusion in their analyses about the demand for ridehailing. Intersection density can be defined as the number of intersections per acre in a block: our models show that individuals living in a neighborhood with high intersection density are more likely to adopt shared ridehailing services. High intersection density leads to easier movement of automobiles, decreasing the wait time for shared ridehailing vehicles (and increasing their popularity). It is likely that this variable also acts as a proxy for central locations where many trip origins/destinations can be found, thus increasing the likelihood of reaching the critical mass to make the shared ridehailing service attractive.

Individuals who see longer waiting time and lack of privacy in shared ridehailing services as barriers are less likely to adopt shared ridehailing services. Similar conclusion was reached by Lavieri & Bhat. Our study shows how individuals who easily embrace new technologies are more likely to both adopt shared ridehailing and to frequently use ridehailing.

2.6. Conclusion

The idea of sharing a ride was already promoted in the context of carpooling in 1970s in the United States as a way to reduce traffic congestion. However, due to lack of communication technology, coordination and planning of carpooling trips was challenging and mostly limited to commute trips with friends and family. Thanks to ICT solutions and the shared economy, ridehailing service providers now offer platforms such a Lyft Share and UberPool through which users can be matched with strangers in real time for a shared ride. Sharing a ride in the same vehicle can possibly reduce the VMT and the GHG emissions from transportation by moving more people in a single trip, as long as no counteracting impacts (such as considerable deadheading miles and mode shifts from non-auto modes) prevail. We conducted this study with a goal of understanding the factors affecting the adoption of shared ridehailing (such as UberPool and Lyft Share), and how they differ from the factors that affect the use of more conventional ridehailing

(Uber or Lyft) services. We analyzed cross-sectional survey data collected in California using a semi-ordered bivariate probit modelling approach which helped us understand the differences in the market segments and the factors affecting the use of these kinds of ridehailing services. We tested both model specifications with and without the inclusion of individual attitudes among the explanatory variables.

Among the most relevant findings, our study makes an important contribution to the literature on shared ridehailing and land use through separating the impacts of objectives measures of land-use features on the adoption of these shared mobility services from those attributable to individual attitudes. Initially, we found that the information about neighborhood type and the characteristics (walkability, in particular) of the neighborhood where the respondents live to be significant in predicting the frequency of use of ridehailing and the adoption of shared ridehailing. However, these variables lost significance after controlling for individual attitudes about land use - an indication of residential self-selection bias that would affect the analyses that do not include these attitudinal factors. Since this aspect has not been explored in other studies related to land-use characteristics and ridehailing, it is possible that the effect of land-use on ridehailing use might have been overestimated in the literature. We plan to explore this aspect in detail in future studies.

Service providers (such as Lyft and Uber in the US market) and planning agencies have strong interest in strategies which may increase the market share of shared ridehailing services to increase vehicle occupancies, respectively, as a way to grow their business models and to reduce traffic congestion and environmental impacts in central urban areas. For example, the California SB 1014 mandates the California Air Resources Board (CARB) to develop targets for 'Clean Miles Standards' that can regulate ridehailing services in California with the established goals of increasing vehicle occupancy, while at the same time promoting ridehailing electrification, reducing deadheading miles and promoting the integration of ridehailing with public transportation and active modes of travel (CARB, 2020).

Our study provides insights that can be useful to planners and policymakers to understand the responsiveness of users to new policies. Among other demographics, younger and employed individuals are found to be more likely to adopt shared ridehailing and use ridehailing frequently. However, in the current market conditions, barriers to the adoption of shared ridehailing include concerns about privacy and the increased travel times. Planning agencies and service providers can use this information to implement targeted promotional strategies to overcome these barriers. For instance, modifying the internal structure of shared ridehailing vehicles can help mitigate some of the privacy concerns. At the same time, our study shows how individuals with *pro-urban* and *tech-savvy* attitudes are more likely to use shared ridehailing services. Promotional campaigns and advertisements designed around these sentiments may further increase the uptake of these services among market segments which currently do not use these services. At the same time, expectations about the role of land-use features in affecting the adoption of these services should be somewhat tuned down, as these impacts have likely been overestimated in previous studies, due to the presence of the self-selection bias that was identified in this research.

3. A Deeper Investigation into the Role of the Built Environment in the Use of Ridehailing for Non-Work Travel

3.1. Abstract

Ridehailing has become a main-stream mobility option in many cities around the world. Many factors can influence an individual's decision to use ridehailing over other modes, and the growing need of policy makers to make built-environment and regulatory decisions related to ridehailing requires an increased understanding of these. This study develops a model that estimates how the built environment affects the decision to choose ridehailing for making non-work trips, while carefully accounting for a variety of confounding effects that could potentially bias the results (if ignored or improperly incorporated). These include: total number of trips, supply differences between urban and non-urban areas, residential choice (urban versus non-urban), and household choice of whether to own a vehicle. We use individual-level data from a California travel survey that includes detailed attitude measurements to estimate an integrated choice and latent variable (ICLV) model to properly specify these effects. We include accessibility measures used elsewhere (e.g., Walkscore) plus measures developed for this study. Our analysis estimates the effect of these measures on ridehailing mode share, and how they differ between urban and non-urban areas. We also confirm that failure to take into account, e.g., latent preferences for residential location can lead to biased results. This analysis results in two major findings: 1. individuals living in vibrant and walkable neighborhoods replace other modes (possibly active modes) with ridehailing, 2. previous studies may have overestimated the complementary or supplementary relationships between public transit and ridehailing by ignoring confounding effects.

3.2. Introduction

Ridehailing services (e.g., Uber/Lyft) have become a mainstream mobility option in many cities around the world. Uber, one of the leading ridehailing service providers, launched in 2009 had provided one billion trips by 2017. The number grew fivefold in just two more years, and it currently operates in 900 cities around the world (Uber, 2019b). Other service providers such as Lyft, DiDi and Ola have experienced similar trends (Tirachini, 2019). It is estimated that nearly ten percent of the U.S. population uses a ridehailing service at least once a month (M. Conway, Salon, & King, 2018). Policymakers in the U.S. and other countries want to regulate these services to increase the positive benefits while minimizing the negative externalities (e.g., congestion). For instance, Seattle introduced a fare of $0.51 on ridehailing trips originating in the city to reduce congestion in core urban areas and fund public transportation (Hightower, 2019). Understanding the factors affecting demand for these services can be very helpful in designing effective regulations.

With this objective in mind, a growing number of studies have aimed to improve understanding of users of these services and the factors influencing their decisions to use them (Alemi, 2018; Alemi, Circella, Handy, et al., 2018; Alemi et al., 2019; Alemi, Circella, Mokhtarian, et al., 2018; Dias et al., 2017). However, few studies have focused on the role of the built environment, even though past research has shown strong evidence that the built environment affects overall travel demand, including the choice of mode and trip distances (S. Handy, 1992). We therefore expect that the built environment also influences the demand for ridehailing services, and that this factor should therefore be taken into account when developing models and performing analyses to support policy decisions. A small number of studies examining this link have indeed found significant effects (Sabouri et al., 2020; Yu & Peng, 2019). However, as explained in detail later, these studies present mixed findings which are not consistent with each other.

This chapter investigates the influence of the built environment on – 1) the total demand for travel for non-work purposes, and 2) the degree to which ridehailing services are used to meet this demand. We use accessibility measures to characterize the built environment, including some measures that are new additions to the literature. Finally, we develop a modeling approach that takes into account latent or difficult-to-observe effects – e.g., residential self-selection, affinity for owning a personal vehicle, and shorter waiting times for ridehailing services in urban areas – that are potentially confounded with more directly-observable factors that may affect the decision to use ridehailing services. Presence of these latent/unobservable effects may bias model estimation results if not taken into account, yielding incorrect conclusions. This study uses individual-level data from a travel survey of California respondents conducted in 2018 by a research team at the Institute of Transportation Studies, University of California, Davis. We employ Integrated Choice Latent Variable (ICLV) models to address methodological issues and answer the research questions identified in this chapter.

The next section reviews relevant literature on the built environment and ridehailing, and on residential self-selection. Section 3.4 describes the data collection methods and the dataset; and provides details of the ICLV model used for analysis. Section 3.5 presents model estimation results and findings. In Section 3.6, we discuss how findings from our study contribute to the existing literature and suggest how our findings have implications for transportation planners and policymakers.

3.3. Literature Review

There have now been a number of ridehailing studies examining the behavior of users and exploring factors related to the decision to use ridehailing. Many of these focus on sociodemographic effects, but more recently some studies have started to explore the role of the built environment in influencing the use of these services. As already noted, the influence of the built environment on travel behavior has been well established, but the currently available evidence for how it influences ridehailing is less clear. Studies so far provide some evidence of a connection, but the measures used to characterize the built environment are limited, and the possibility of self-selection has not been adequately addressed.

3.3.1. Evidence on Ridehailing and the Built Environment

Research shows strong associations between ridehailing and socio-demographic characteristics. In the U.S., young individuals have a higher likelihood to use ridehailing services than older individuals. Similarly, individuals from higher income households are more likely to adopt ridehailing services than those from lower income households (Alemi, Circella, Handy, et al., 2018; M. Conway, Salon, & King, 2018; Rayle et al., 2016). Alemi, Circella, Mokhtarian, et al., (2018), employing latent class analysis, found that dependent millennials (18-34 yrs. living with parents) and older members of Gen X (42-50 yrs.) with families are both likely to adopt ridehailing services. This likelihood increases if they make frequent long-distance trips requiring air travel (implying use of ridehailing at the destination location). Low availability of vehicles in the household is also associated with the propensity to adopt ridehailing services (Conway et al., 2018). And individuals with strong pro-environmental attitudes, variety-seeking individuals and those who easily embrace technology are all more likely to adopt these services (Alemi, Circella, Mokhtarian, et al., 2018; Dias et al., 2017; Lavieri & Bhat, 2019).

Research also shows significant differences by type of place. Ridehailing use is much higher in mid-sized and large US cities (M. Conway, Salon, & King, 2018; Malalgoda & Lim, 2019) versus suburban and rural areas. This raises the question: what are the true, fundamental factors that are driving these differences in individuals' decisions? Theory suggests that many potential factors (both observable and unobservable) are highly correlated with type of place. For example, the *availability* of ridehailing services is likely to be much higher in urban areas, and there are also major differences in the built environment.

Over the past few years, a number of studies have reported evidence of a link between use of ridehailing and the built environment, after controlling for differences in socio-demographics; key findings are summarized in Table 7-1. As summarized in Table 7-2, a majority of these studies have used aggregated data on ridehailing demand from service providers such as Uber and RideAustin. Studies have explored the associations between demand for ridehailing and the built environment using measures at the census tract, TAZ or a similar aggregated levels (Gerte et al., 2018; Lavieri et al., 2018; Sabouri et al., 2020; Yu & Peng, 2019). In contrast, Alemi, Circella, Handy, et al., (2018), Alemi, Circella, Mokhtarian, et al., (2018) and Alemi et al., (2019) explored these effects using individual-level datasets collected through surveys of individuals in California.

Population density and *employment density* are consistently found to have a significant and positive relationship with demand for ridehailing, especially in the studies using aggregated data. A common explanation offered is that more activity (either in terms of population or jobs) in a location leads to more trips to that location (Sabouri et al., 2020; Yu & Peng, 2019); this is also the basis of the conventional gravity-based trip-distribution model. However, it is possible that an increase in activity increases trips by *all* modes, including ridehailing. None of the studies so far examine how demand for ridehailing changes *relative* to other modes, as a function of change in density.

Studies find that neighborhoods with a higher mix of land uses have a positive correlation with demand for ridehailing (Sabouri et al., 2020; Yu & Peng, 2019). Individuals living in such neighborhoods are more likely to adopt ridehailing than those who do not reside in such neighborhoods (Alemi, Circella, Handy, et al., 2018). In contrast, Yu & Peng (2019) and Alemi et al. (2019) found that employment-population balance (another measure of land-use mix) has a *negative* relationship with demand for ridehailing. Alemi, Circella, Mokhtarian, et al., (2018) also found a negative association between land-use mix and use of ridehailing among more car-dependent users. Yu & Peng (2019), pg. 158, offer the following explanation – "To a certain degree, the negative relationship captures a latent influence of land use on mode choice of ridesourcing, which could be explained by the extensive literature that emphasizes the role of a balanced land use planning in reducing vehicle travel and facilitating non-motorized mode choices". In other words, individuals living in neighborhoods with higher land-use mix tend to rely more on non-motorized modes and, therefore, less on ridehailing.

Studies have also looked into the relationship between the design of street networks and use of ridehailing services. Yu & Peng (2019) found a positive correlation between *sidewalk density* in a neighborhood and demand for ridehailing, showing a possible complementary relationship with active modes of travel. *Intersection density* has been observed to have both negative (Sabouri et al., 2019) and positive (Yu & Peng 2019) relationships with ridehailing demand. The former study argues that *intersection density* is positively associated with use of non-motorized modes leading to lower usage of ridehailing; the latter suggests that high *intersection density* is associated with lower waiting times and consequently *higher* use of ridehailing.

Accessibility of jobs via private cars is seen to have a negative relationship with demand for ridehailing services (Sabouri et al. 2020), possibly because ridehailing does not (as yet) compete with private vehicles as a commuting mode. Sabouri et al. (2020) also found a *negative* relationship between destination accessibility via transit and ridehailing demand, whereas Yu & Peng (2019) found this relationship to be *positive*.

Finally, the quality of transit service in a neighborhood, as measured by frequency of buses, is found to be negatively associated with ridehailing demand. Alemi, Circella, Mokhtarian, et al., (2018) investigated the relationship more closely and found that certain segments in the population (primarily car dependent) used ridehailing as substitute for transit. In contrast members of the population identified as "multimodal" used ridehailing *in combination* with transit. Evidence for this transit-ridehailing complementarity was also found by Sabouri et al. (2020).

In summary, the literature on ridehailing and the built environment has thus far produced mixed findings about the effect of latter on the use of the former. Part of the reason could be differences in the nature of the datasets (mostly aggregated). However, another potential reason is that some important methodological issues have not yet been addressed in these studies. The next sub-section summarizes these issues.

3.3.2. Methodological Issues

To our knowledge, studies so far have not addressed the following factors which may have led to inaccurate conclusions about the effect of the built environment on use of ridehailing:

- Dependent variables: In all of the studies listed in Table 7-2, the dependent variables are either the total number of ridehailing trips at the aggregated level or frequency of use of ridehailing services by individuals. The effect of the built environment variables on these dependent variables is then examined using various modelling techniques. This is problematic because the total number of trips by ridehailing (at the aggregated or individual level) is the product of total number of trips and the fraction of trips made by ridehailing services (mode share). After controlling for socio-demographics, different dimensions of the built environment affect various aspects of travel behavior. More particularly, presence and proximity to attractive destinations leads to a high travel demand which leads to a high trip frequency. The choice of mode for a trip is influenced by distance to destinations and the infrastructure which determines the 'cost' to reach a destination by a particular mode--see Handy (1992). Thus, when examining the effect of the built environment on use of ridehailing, it is important to separate the effect of the built environment on total number of trips from the degree to which ridehailing services are used to meet that demand.

- Residential self-selection (RSS) bias: Previous studies have shown that an individual's travel choices and their choice of residential location may be driven by the same underlying attitudes (Cao et al., 2009; Kitamura et al., 1997). Failure to address these effects can lead to overestimation of the influence of the built environment on travel behavior, possibly leading to misguided policy recommendations. To our knowledge the effect of residential self-selection has not yet been explored in the literature on the built environment and ridehailing use.

- Supply effect: A study by Hughes & MacKenzie (2016) shows how the average wait time for ridehailing vehicles was much lower in the urban downtown regions of Seattle as compared to non-urban regions in the outskirts. It is likely that the quality of ridehailing service will be much better in urban areas in California as well. The higher quality of service can have a direct effect on the use of ridehailing services. Since urban areas also tend to have better accessibility to activities, it is possible that we might overestimate the effect of the built environment on travel behavior if we do not correct for this 'supply' effect of ridehailing services.

- Measures of the built environment: most studies on this topic so far have characterized areas (census tracts, block group) by measuring indicators of the built environment at an aggregated level. Such studies find statistical evidence that use of ridehailing changes with the aggregated measures of the built environment in these areas. But such measures make it difficult to identify the specific aspects of these areas that influence travel behavior (S. Handy, 1996). It is more meaningful to evaluate the destination options offered to an individual and the 'cost' of reaching them as a function of the built environment. In other words, accessibility (potential for travel) is a more appropriate type of measure for modeling the impact of the built environment on travel behavior. This is still a gap in the literature when understanding the use of ridehailing services as a function of the built environment.

In the current chapter we try to address these issues while closely examining the link between use of ridehailing services and the built environment.

3.4. Methods: Data Collection, Variable Selection and Method of Analysis

In this section, after summarizing data collection we explain how we construct our dependent variables and the built environment variables to correct for the issues identified in Section 3.3. We then explain how our modeling approach accounts for long-term effects such as residential self-selection and vehicle ownership, and the supply effect of ridehailing services.

3.4.1. Data Collection

The dataset used for this analysis is a part of a larger research effort at the Institute of Transportation Studies (ITS), University of California, Davis. We launched two waves of surveys in California to understand the adoption and impacts of new mobility services. The first round was carried out in 2015. In

2018, we conducted a second round of data collection for a longitudinal study in California. For more details, see the complete report (Circella et al., 2019). We use the 2018 cross-sectional dataset in this analysis.

The final sample consisted of 4,071 completed surveys (before data cleaning). We employed a combination of sampling strategies to recruit respondents in 2018, including:

a) Address-based Mail survey: we mailed out 30,000 paper surveys to randomly selected residential addresses in the state. To ensure representation of the entire state, a stratified random sampling approach was followed. California was divided into six regions that generally correspond to areas covered by various metropolitan planning organizations – Central Valley, Metropolitan Transportation Commission, North California and others, Sacramento Area Council of Governments, San Diego Association of Governments and Southern California Association of Governments; and the sampling rates were adjusted according to populations in these regions. Respondents had the option of mailing back the filled-out (paper) survey, or they could submit their responses online by using a provided link. We received 1,992 surveys back (1,620 via mail and 372 online).

b) Recontact 2015 respondents: To conduct a panel study we attempted to recontact all respondents who completed the 2015 survey by using the same, original commercial online opinion panel. However, only 246 respondents completed the 2018 survey. This low retention rate is possibly due to the large time duration between the first and second rounds of data collection.

c) 2018 online opinion panel: We also refreshed the study by adding a group of new participants in this wave of data collection, recruiting them through another commercial online opinion panel. Again, California was divided into 6 regions as mentioned above. And, socio-demographic quotas were established for age, gender, children in the household, household income, race, ethnicity, work status, school status and the type of neighborhood (urban, rural, etc.). The quotas were set using the most current 5-year estimates from the American Community Survey (ACS) in each region. About 1,833 respondents completed this survey.

The survey was designed to collect information on respondents' attitudes and preferences; use of technology in life; lifestyle – formation of the household, number of vehicles, work status, home and work location; current travel patterns; usage of emerging transportation services – ridehailing; perception about autonomous vehicles; and background information. The survey was designed to be completed in 30 to 40 minutes.

Even though our main analysis is on the dataset describe above, we use another dataset (detailed travel diary) to empirically support how we define our hypotheses and, construct dependent variables and the built environment variables used in the models. The Sacramento Area Council of Governments (SACOG) conducted a household travel survey in 2018 in the six counties of California which come under their jurisdiction – Yolo, Sacramento, El Dorado, Placer, Sutter, and Yuba. The survey consisted of detailed trip level information of a representative sample of 4,010 households living in the region, collected over seven days. This information was collected using a smartphone app installed in the mobile phones of the respondents. The app collected passive information of each trip – origin, destination, time – and prompted respondents to enter other information such as mode used and trip purpose at the end of each trip (SACOG, 2018). For the current analysis we used a subset – only ridehailing trips – of this large dataset. We would like to point out that travel patterns in the SACOG region may be different from other regions in California. We use the SACOG travel diary dataset only to construct hypotheses which are ultimately tested using the main dataset.

3.4.2. Variable Selection

In this sub-section we summarize our rationale for constructing and selecting the dependent variables, the built environment variables, socio-demographics and attitudinal variables. Table 3-3 summarizes the distribution of these variables by urban and non-urban areas.

Dependent Variables

The analysis uses six dependent variables. First, we model two types of binary choices for all respondents: residential location type (urban or non-urban), and car ownership (yes or no). The remaining dependent variables were of two types: total number of trips (made using all modes) for non-work purposes, and the share of these trips made by ridehailing. We modeled these responses conditional on type of the neighborhood of the home-location of the respondents' (urban or non-urban). This yields four dependent variables, where only two of the four are actually observed for each respondent.

We focus on non-work trips because travelers usually have more flexibility in deciding the destination/time for discretionary trips (trips made for social, recreation, shopping and errand purposes rather than commuting). Due to this flexibility, discretionary trips are most likely to be affected by the built environment. A descriptive analysis of ridehailing trips from the California Panel 2018 study and SACOG household travel survey (see SACOG (2018) for details) from 2018 shows that a majority of trips made using ridehailing are for discretionary purposes (see Table 3-1 and Table 3-2).

The survey asked respondents to report how frequently they use private modes, active modes, public transportation and ridehailing for non-work purposes. In all, respondents were shown 12 modes. For each mode, they could select an option from a seven-point ordinal scale: 'Never' (0 days), 'Less than once a month'(0.5 days), '1-3 times a month' (2 days), '1-2 times a week' (6 days), 3-4 times a week' (14 days) and '5 times a week' (20 days). For analysis, we used a variable coded in units of "days per month" and treated it as continuous (Lee, Circella, Mokhtarian, & Guhathakurta (2019) used the same technique).

Let N be the total number of (non-work) trips estimated by summing the days-per-month frequency variables for all modes. Two of our dependent variables are $ln(N)$ for urban and non-urban respondents, respectively. As a measure of ridehailing mode share, we adopt a variable specification used by Kitamura et al., (1997)(—see this reference for more details). Let N_m be the frequency of mode m. Rather than use mode share (N_m/N) directly, we first compute the odds of using a mode versus all other modes [($N_m/(N-N_m)$)], and then take the natural log, yielding the log-odds variable

$$LogOdds_m = \ln\left({}^{N_m}/_{(N - N_m)}\right)$$

This log-odds transformation yields a continuous variable that resembles a normal distribution, suitable for a linear-in-parameters specification. If $N_m = 0$, then 0.5 is added to both numerator and denominator to avoid infinite values under the log-transformation. Kitamura et al. (1997) estimate multiple models for all the modes they were studying. In our models we are focused on the case where m = *ridehailing*.

Respondents were assigned to a home location type based on the detailed home address requested by the survey. We geocoded this home address to get the corresponding latitudes/longitudes using the *Googleways* (Cooley, 2018) package in R. We then identified the census tract number for the home location using the *Censusapi* (Recht, 2019) package in R. To assign each respondent a home location type, we relied on Salon (2015), who classified all census tracts in California into five categories – central city, urban, suburban, rural-in-urban and rural. For simplicity, we collapsed these five levels to two levels – urban (central city and urban) and non-urban (suburban, rural-in-urban and rural). This is the binary dependent variable in our analysis representing residential location choice. The survey asked respondents to report if their household owns a vehicle or not, the other binary dependent variable in our model.

Built Environment Variables

In studying travel behavior, it makes sense to evaluate the built environment from the perspective of the traveler. That is, the built environment should be evaluated with respect to the choices it offers individuals as to potential destinations and the cost, broadly defined, of reaching them (S. Handy, 2017). Accessibility measures provide a way to do this, though assumptions must be made about the distance over which destinations are relevant. Thus, while developing specific hypotheses about the influence of the built environment on use of ridehailing, it is important to rely on empirical data to get a sense of the length of the trips made by ridehailing services (and other modes) and the kinds of destinations accessed by them. Data from the SACOG Household Travel Survey (HHTS) described above provide an indication of the limit for most ridehailing trips (see Table 3-1): 75%[1] of ridehailing trips for social/recreational purposes (including visits to restaurants/cafes) in the SACOG region had trip lengths less than 5.72 miles (median 2.62 miles), while 75% of ridehailing trips for shopping/errands had trip lengths less than 7.88 miles (median 3.48 miles). In our survey (in the state of California) we asked respondents to report the trip duration of the last trip made using ridehailing services (Table 3-2). It is interesting to note that the distributions of trip duration by trip purpose in the California-2018 survey follow a very similar pattern to those from the SACOG HHTS.

Based on these numbers and our understanding of the link between travel behavior and the built environment, we hypothesize that individuals who live in vibrant neighborhoods (with destinations within walking distances) will have higher trip frequencies for non-work purposes. Moreover, these individuals can meet many of their travel needs for purposes such as eating out or visiting cafes by walking. Thus, the overall mode share of ridehailing services (for discretionary trips) will be lower for these individuals. Again, we rely on the SACOG survey to get an estimate of typical walking distances in California (although the dataset is only available for Sacramento). We observed a differential between the median lengths of home-based non-work-related walking trips in urban areas (0.48 miles) and non-urban areas (0.62 miles).

We also hypothesize that individuals who do not live in vibrant neighborhoods but have attractive destinations in the range of one to eight miles from their home locations will have the highest mode share of ridehailing services for trips with discretionary purposes. These individuals have attractive destinations in a close enough range to induce trips, but these destinations are not close enough to be reached by walking. If the neighborhood where these individuals reside does not have good transit service, we hypothesize that they will have an even higher mode share of ridehailing services.

Table 3-1 Ridehailing trip duration and length recorded by smartphones in SACOG HHTS

Trip Purpose	Percentage of Trips	**Trip Duration and Length**		
		First Quantile	Median	Third Quantile

[1] We exclude the upper quartile to prevent outliers from affecting our decisions

		Trip Duration (min)	*Trip Length (miles)*	Trip Duration (min)	*Trip Length (miles)*	Trip Duration (min)	*Trip Length (miles)*
Work/School	23.5%	10.8	*1.9*	15.0	*3.3*	23.1	*8.2*
Shopping/Errands	22.6%	9.4	*1.7*	13.9	*3.5*	23.8	*7.9*
Social/Recreation	50.1%	8.6	*1.5*	12.6	*2.6*	19.3	*5.7*
Connect with other modes	3.8%	14.0	*3.0*	15.6	*5.9*	24.6	*14.7*
Trips for all purposes (N)	864	9.4	*1.6*	13.9	*3.2*	21.4	*7.0*

Table 3-2 Self-reported ridehailing trip durations from CA Panel dataset

Trip Purpose	Number of trips	**Trip Duration in Minutes**		
		First Quantile	Median	Third Quantile
Work/School	15.3%	10.0	18.0	30.0
Shopping/Errand	16.2%	10.0	15.0	25.0
Social/Recreation	45.8%	10.0	15.0	20.0
Connect with other modes*	25.6%	15.0	20.0	30.0
Trips for all purposes (N)	1968	10.0	15.0	25.0

*Other modes include airplanes

To test these hypotheses about the effects of the built environment on ridehailing mode share for discretionary trips, we need measures that capture the *vibrancy* of the residence neighborhood, the presence of *attractive destinations* within a medium-distance range, and *connectivity* to destinations by alternative modes of transportation. A closer look at the detailed purposes for which ridehailing services are used (from the SACOG household travel survey), Figure 3-1, reveals that 22% of discretionary trips are made to access restaurants. Visits to movie theaters also form a large percentage (16%) of such trips. Trips for shopping form 7% of the discretionary trips. We used the *Googleways* (Cooley, 2018) and *Spatial Points* packages (Bivand, Pebesma, & Gómez-Rubio, 2008) in R to build the following accessibility measures for the reported home addresses:

1. Vibrant neighborhoods:
    a. For non-urban neighborhoods, our measure of vibrancy is calculated as the sum of the inverse of distance to restaurants within 1 mile of the place of residence:

$$\sum_{j=1}^{J} 1/d_{ij}$$

d_{ij} = Distance (Euclidean) to restaurant j from the home location of individual i

J = number of restaurants within a 1-mile radius of the home location of individual i

If an individual has a good variety of restaurants in close proximity, we expect them to make more non-work trips within the neighborhood by walking and rely less on alternative modes (such as ridehailing) to reach these destinations.

b. For urban neighborhoods, we observed that most home locations in our sample had a restaurant within 1-mile radius. Thus, for urban areas we include a dummy variable (0 or 1) which takes the value '1' if the home-location has a restaurant within a 0.5-mile radius (this corresponds to the threshold we observed in SACOG dataset).

c. We also include a commercial third-party measure of neighborhood accessibility: *Walkscore*[2]. *Walkscore* is another measure of neighborhood accessibility that essentially indicates how easily an individual can perform errands by walking (Walkscore, 2020). For each address, Walkscore analyzes hundreds of walking routes to nearby amenities, and awards points based on a decay function of the distance required for reaching them. Amenities within 5 minutes of walking receive maximum points while those beyond 30 minutes receive no points. The Walkscore ranges from 0 to 100, where 100 indicates an extremely pedestrian-friendly neighborhood with destinations in very close proximity, where most errands can be performed by walking.

[2] It can be used free of charge for research purposes.

2. Destinations visited occasionally by an individual, such as department stores (e.g., Target) or movie theaters, can induce more trips if they are located within a 'close' distance. But such destinations are not usually within walking distance, so it is possible that trips to these destinations will be made via ridehailing services, even more so in the absence of links via transit. We measure the following as indicators of accessibility to non-work-related activities beyond the neighborhood:
   a. Distance (Euclidean) to the nearest department store from the home location of the respondent. We specify it as a categorical variable with three levels – *less than 0.65 miles, between 0.65 miles and 8 miles* and *more than 8 miles* – for department stores in non-urban areas.
   b. All urban home locations in our sample had a nearest department store within a distance of 8 miles. Thus, for urban areas we include a dummy variable which measures if the home-location has a department store in less than 0.65 miles (again, cutoffs based on home-based non-work-related trip lengths by walking and ridehailing in SACOG dataset[3]).
   c. We also measure distance to the nearest movie theater from the home location. For non-urban areas, we categorize it into three levels - *less than 0.65 miles, between 0.65 miles and 8 miles* and *more than 8 miles*.

[3] The sample in the SACOG survey is from SACOG region. The sample used for model estimation in this study is from entire California (and it is not completely representative). Even though the cut-offs for distances to various types of destinations are in the same ballpark range, we have minor differences in the cut-offs depending on the distributions of distances from home locations to different types of destinations (and residential location type - urban/non-urban areas) in the dataset we use for model estimation.

d. For urban areas we include dummy variables which measures if the home-location has a movie-theater in 0.5-mile distance. Table 3-3 summarizes the distribution of these variables.

3. Finally, it is also important to evaluate how well served the residence neighborhood is by transit. We hypothesize that individuals living in neighborhoods with good access to destinations via transit will have a lower mode share of ridehailing services. The accessibility laboratory at the University of Minnesota has calculated the number of jobs accessible through transit in each block group in the U.S. (Owen & Murphy, 2017). We link this information to the block groups of the home locations of the respondents in our survey.

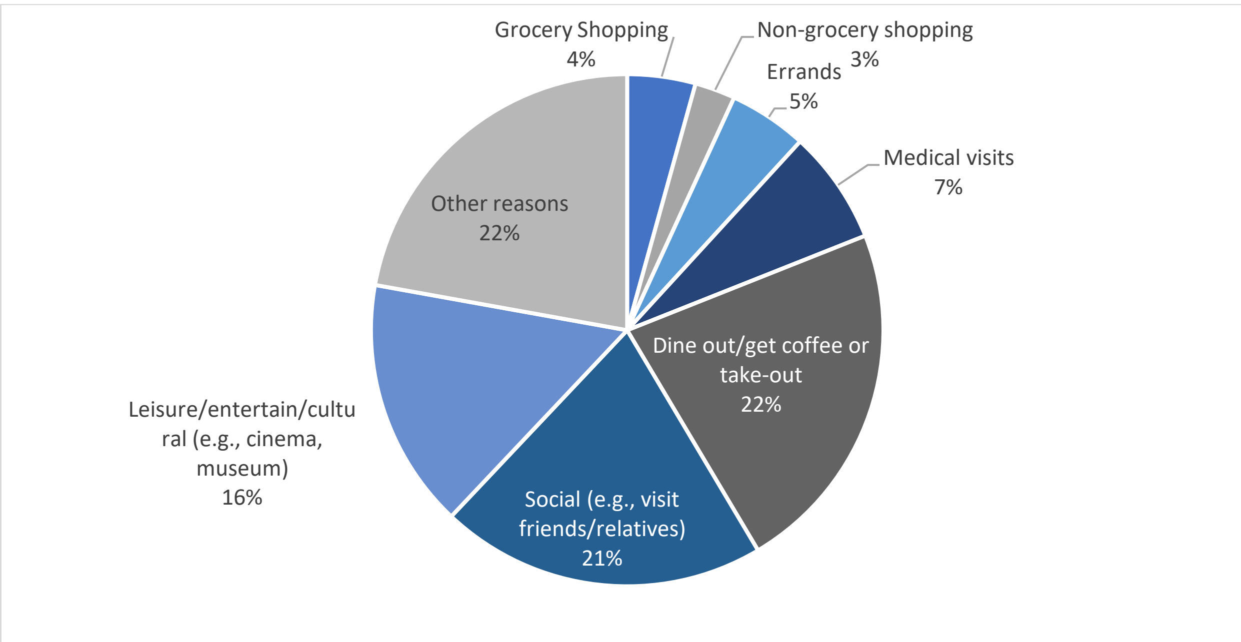

Figure 3-1 Detailed trip purposes for discretionary trips using ridehailing (n=628 trips made by 302 individuals)

Source: SACOG HHTS

Socio-Demographics and Attitudes

The survey asked respondents to report their key socio-demographics – gender, age, gross household income, race and highest education degree. We also asked them to report their employment status, if they are currently a student, and if they have any household members below the age of 18 living with them. At the beginning of the survey respondents were presented with 30 attitudinal statements and asked to indicate their agreement with the statement on a five-point Likert scale from *Strongly Disagree* (1) to *Strongly Agree* (5). The intention here was to measure underlying constructs about choice of home location, attitudes about modes of transportation, technology and internet connectivity, and the built environment. In the next subsection we explain how we use these variables to explain our dependent variables.

Table 3-3 Description of the variables used in the model

	Urban (n=624)	Non-urban (n=2,445)
Dependent Variable		
Odds of ridehailing	0.27 (2.30)	0.09 (0.19)
Log odds of ridehailing	-2.71 (1.28)	-3.03 (1.05)
Total number of non-work trips	26.92 (22.60)	19.72 (15.94)
Log of total number of non-work trips	2.97 (0.89)	2.64 (0.94)
Socio-Demographics		
Age		
Millennials (18 – 34 yrs.)	39.6%	30.2%
GenX (35 – 54 yrs.)	37.8%	33.3%
Baby boomers (55 yrs. or older)	22.6%	36.5%
Gross Annual Household Income		
Less than $50,000	29.3%	32.4%
$50,000 to $100,000	30.3%	32.4%
More than $100,000	40.4%	35.1%
Gender		
Male	48.2%	44.2%
Female	51.8%	55.8%
Race		
White	71.5%	81.6%
Other	28.5%	18.4%
Employed		
Yes	80.3%	69.6%
No	19.7%	30.4%
Student		
Yes	14.7%	12.1%
No	85.3%	87.9%
Education		
More than Bachelors	69.2%	52.9%
Bachelors' or less	30.8%	47.1%
Children in the Household		
At least one	20.7%	21.7%
None	79.3%	78.3%
Built Environment		
Inverse sum restaurant in 1miles		27.58 (69.53)
Restaurants within 0.5 miles		
Yes	97.6%	
No	2.4%	
Walkscore	82.07 (14.33)	42.09 (26.33)
Movie theater within 0.5 miles		
Yes	9.5%	
No	90.5%	
Distance to the nearest movie theater		
Less than 0.65 miles		6.1%
Between 0.65 miles to 8 miles		75.5%
More than 8 miles		18.4%
Distance to the nearest department store		
Less than 0.65 miles	38.9%	21.1%

Between 0.65 miles to 8 miles	61.1%	68.1%
More than 8 miles		10.8%
Type of house		
Stand Alone	44.1%	
Apartments/others	55.9%	
Jobs available via 30 min transit ride		7543.95 (10496.62)
Vehicle Ownership		
Zero Vehicle Households	8.8%	7.3%
Households with Vehicles	91.0%	92.6%

*For continuous variables, this table shows means and (in parentheses) standard deviations.

3.4.3. Model Structure and Estimation

We now describe our modeling approach, and how it addresses issues raised in section 2.2. Recall that there are six main dependent variables, where not all six are simultaneously observable due to a respondent's residential choice ($i = 1$ [Urban], or $i = 0$ [Nonurban]): Residential Choice (*RC*), Vehicle Ownership (*VO*), Total Trips (TT_i , $i = 1, 0$), and Log Odds for Share of Ridehailing (LO_i , $i = 1, 0$). For vehicle ownership, $VO = 1$ if the respondent belongs to a household that owns a vehicle, and 0 otherwise.

All dependent variables are potentially influenced by respondent *n's* demographic variables (x_n), and, additionally, travel-related choices (*TT* and *LO*) are potentially impacted by characteristics of the built environment in place-type *i* where respondent *n* lives. One important modeling consideration is our decision to distinguish between shorter-term decisions (e.g., *TT* and *LO*) versus longer-term decisions (*RC* and *VO*). In our current approach, we assume that longer-term decisions are a function of personal characteristics only (x_n), and shorter-term decisions as a function of both demographics and the built environment (denoted x_{ni}). In what follows we first define a modeling framework for implementing these effects, and then discuss additional assumptions that yield the particular specifications employed here.

Recall that two dependent variables are binary and the other four are continuous, leading to the following modeling framework:

$$RC_n^* = \beta^{RC} x_n + \epsilon_n^{RC*},\ \ RC_n = 1\ (Urban) if\ RC_n^* \geq 0, and\ 0\ otherwise;$$

$$VO_n^* = \beta^{VO} x_n + \epsilon_n^{VO*},\ \ VO_n = 1\ (Owns\ a\ vehicle)\ if\ VO_n^* \geq 0, and\ 0\ otherwise;$$

$$\begin{aligned} TT_n &= TT_{n1} = \beta_1^{TT} x_{n1} + \epsilon_{n1}^{TT*}, \qquad when\ RC_n = 1, \\ &= TT_{n0} = \beta_0^{TT} x_{n0} + \epsilon_{n0}^{TT*}, \qquad when\ RC_n = 0; \end{aligned}$$

$$\begin{aligned} LO_n = LO_{n1} &= \beta_1^{LO} x_{n1} + \epsilon_{n1}^{LO*}, \qquad when\ RC_n = 1, \\ = LO_{n0} &= \beta_0^{LO} x_{n0} + \epsilon_{n0}^{LO*}, \qquad when\ RC_n = 0; \end{aligned}$$

where the ϵ^*'s are disturbance terms. This framework specifically incorporates the residential choice and vehicle choice decisions (which are discrete), and models travel choice (continuous) variables using linear models that are conditional on residential choice. This allows us to address the methodological concerns discussed in section 2.2. First, effects due to the difference in wait times for ridehailing vehicles between urban and non-urban areas, which may have a very direct impact on the use of ridehailing services, is readily captured by estimating different models for urban and nonurban, respectively.

Second, we also hypothesized that (unobserved) attitudes that drive individuals to live in urban locations might also have an effect on their number of trips and/or their likelihood of choosing ridehailing over other modes. Such effects, if not taken into account, can lead to, e.g., residential self-selection bias in model estimation. In the above framework these effects are assumed to be included in the disturbance terms, which we now represent as unobserved latent variables for respondent *n* (x_n^*). Because x_n^* can be included as an error component in multiple disturbance terms simultaneously, this produces correlation among the ϵ^* disturbance terms that is now automatically taken into account. Specifically, the ϵ^*'s can be modeled as follows:

$$\epsilon_n^{RC*} = \gamma^{RC} x_n^* + \epsilon_n^{RC};$$

$$\epsilon_n^{VO*} = \gamma^{VO} x_n^* + \epsilon_n^{VO};$$

$$\epsilon_{ni}^{TT*} = \gamma_i^{TT} x_{ni}^* + \epsilon_n^{TT}, i = 0,1;$$

$$\epsilon_{ni}^{LO*} = \gamma_i^{LO} x_{ni}^* + \epsilon_n^{LO}, i = 0,1;$$

where the (newly introduced) ϵ disturbance terms are assumed to be statistically independent (discussed in more detail below).

As described above, the survey data includes additional information in the form of attitudinal questions that can aid in identifying these effects. Specifically, respondents provided responses to 5-level Likert scale questions indicating their level of agreement/disagreement with a wide range of statements.

These observed indicators (i_n) are assumed to arise from the unobserved latent variables as specified in this *measurement equation*:

$$i_n = \delta x_n^* + \eta_n,$$

as in a factor analysis model. Finally, socio-demographics could potentially explain some variation in the values of the unobserved latent variables via the following *structural equation*:

$$x_n^* = \alpha x_n + \nu_n.$$

Both η_n and ν_n are assumed to be statistically independent and are modeled as normally distributed. Taken together, this system of equations has the form of an Integrated Choice and Latent Variable (ICLV) model (see, e.g., Vij & Walker, 2016).

In this framework, the binary choice models are treated as logit models (conditional on x_n^*), i.e., the $\epsilon's$ are assumed *iid* Gumbel, and RC_n^* is interpreted as a random utility. Although this includes a direct demographic effect, in our models we assume that $\beta^{RC} = 0$ so that the utility is affected by the latent variables only. Under these assumptions, the probability that respondent *n* chooses to live in an urban location is given by:

$$P(RC = 1|x_n, x_n^*) = \frac{e^{(\beta^{RC}x_n + \gamma^{RC}x_n^*)}}{1 + e^{(\beta^{RC}x_n + \gamma^{RC}x_n^*)}} = \frac{e^{\gamma^{RC}(\alpha x_n + \nu_n)}}{1 + e^{\gamma^{RC}(\alpha x_n + \nu_n)}}$$

with a similar expression for owning a vehicle (*VO = 1*). The first part of the equation shows that the probabilities are conditional on x_n^* for which $\alpha x_n + \nu_n$ is substituted. This means that these probabilities are still dependent on demographics, although now the dependence is indirect through the structural equation. Moreover, the logit probability is conditional on the unobserved disturbance term ν_n, so the total probability must be determined by integrating over ν_n, i.e., the model is a mixed logit.

As noted, the remaining dependent variables are modeled using the linear equations specified above, which also include error components due to x_n^*. For maximum likelihood estimation of the parameters ($\beta_1^{TT}, \beta_0^{TT}, \beta_1^{LO}, \beta_0^{LO}, \gamma_i^{TT}, \gamma_i^{LO}, \ \delta, \ \alpha$), computing the likelihood expression for respondent *n*'s full vector of observed dependent variables and indicators requires integration over the disturbance terms

ϵ_n^{TT}, ϵ_n^{LO}, η_n and ν_n. As noted, these are statistically independent and treated here as normally distributed.[4] For details on likelihood expressions for the ICLV model, see Vij and Walker (2016). As will be discussed later, we also add an error component to the system that captures unobserved factors that (1) impact both total number of trips and share of ridehailing, but (2) are for some reason not otherwise being captured by the latent variables (attitudes) we are explicitly modeling.[5] We use the *Apollo* library in R for performing maximum simulated likelihood estimation. As noted, the likelihood function requires integration over multiple error components, which is performed via simulation using random draws from the normal distributions identified previously. The likelihood for a respondent jointly incorporates all dependent variables and components for the entire modeling system (Hess & Palma, 2020).

To provide more specifics about the methodology, we now discuss attitudes and latent variables in a bit more detail. The survey included 26 Likert scale questions using statements that provide insight into personal attitudes that are relevant to the decisions we are modeling. We conducted an exploratory factor analysis (EFA) using the *Psych* package in *R* with *promax* rotation (Revelle, 2020). The eigenvalue > 1 (EGO) rule suggested seven factors, but we chose nine based on improved interpretability (explaining 46% of the total variance). For factor loadings and our names for the factors, see Malik, Alemi, & Circella (2020) . These results were used as a guide for formulating ICLV model specifications. Based on these interpretations, we postulated the existence of a *Pro-Urban* attitude dimension that could be used to explain choice of residential location (urban versus non-urban) but that also could simultaneously help explain propensity to allocate trips to ridehailing. Past evidence of such a relationship to residential choice is suggested by the discussion in Mokhtarian & Herick (2016). Similarly, the attitude dimension *Car Lover* would clearly be expected to explain vehicle ownership but perhaps other decisions as well.

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[4] Depending on the assumptions adopted, estimation of additional parameters for normal standard deviations (σ's) might also be required. In our models, the σ's for the measurement equations are assumed to be unity (consistent with the typical assumption of factor analysis), whereas the σ's for the linear models are estimated (as is typical in standard regression).

[5] Specifically, the expressions for ϵ_{ni}^{TT*} and ϵ_{ni}^{LO*} would have yet one more error component on the right-hand side.

Ultimately, we settled on these two attitudes, plus a third (*Tech-Averse*). Specifically, we used the eleven Likert scale responses as indicators in a measurement equation and assumed three latent attitudes for implementing the ICLV model.

Limitations

Even though our choice of variables and modeling approach address the issues raised above, this chapter does not completely resolve all of the gaps in the literature on ridehailing and the built environment. First, we can only observe how the built environment features associated with the home-location might affect respondents' use of ridehailing and their total number of trips. This is a limitation because people also make non-home-based trips that would be included in the dependent variable measures. Given the flexibility and the on-demand availability of ridehailing services it is possible that it is also used at locations other than homes, e.g., work location.

Second, our analysis is limited to understanding the effects of the built environment on trip frequency and mode share of ridehailing. The built environment also has an effect on trip length, which is not accounted for in this chapter. Moreover, the combination of the built environment and use of ridehailing services can influence activities in which people engage. In this chapter we analyze cross-sectional survey datasets, which prevents us from conducting an in-depth analysis and restricts our analysis to trips rather than tours and activities. In future, we plan to analyze the travel diary dataset from SACOG for a more exhaustive analysis.

Finally, by simultaneously estimating the effect of a variable on log-odds of ridehailing and total number of trips, we can discern the underlying reasons for, e.g., an observed change in ridehailing *frequency* (the dependent variable in many previous studies on ridehailing) due to a change in that variable. Recall, trips made by ridehailing by an individual depends on odds of using ridehailing (over other modes) and total number of trips made by the individual. For instance, if a variable has a positive coefficient for log-odds of ridehailing but negative or no effect on total number of trips made by an individual, then that variable is associated with ridehailing replacing other modes of transportation. However, if ridehailing frequency were to increase due to an increase in ridehailing mode share, we cannot comment with surety which mode (active/public transit/private) is being replaced by ridehailing. This is a limitation of our current modelling approach. In future studies models can be extended to estimate the trade-off between other modes and ridehailing.

3.5. Results and Discussion

In Table 3-4, we present model estimation results for the ICLV model which includes (sub-) models for both log-odds of ridehailing services and total number of trips for non-work purposes. In the following subsections we first discuss the implications of the estimated signs and significance of coefficient estimates for latent attitudinal constructs and socio-demographics. We then explain the implications of the unbiased estimated effects for the built environment variables.

3.5.1. Latent Variables and Random Effects

Table 3-5 shows the values and the significance of the coefficients associated with the latent variables – *Pro-Urban*, *Car Lover*, and *Technology Averse* - in explaining the eleven indicator variables in the measurement model. As a reminder to the readers, in order to account for the possibility of residential self-selection bias, we use the *Pro-Urban* latent variable to simultaneously explain log odds of ridehailing in urban and non-urban areas, and residential choice of urban/non-urban neighborhood[6]. The significance of this latent variable, and the direction of the effect in all three sub-models shows that, indeed, underlying attitudes drive the decision to choose an urban home-location and to choose ridehailing services over other modes of transportation. We observe that younger individuals and individuals with lower household incomes have higher *Pro-Urban* attitudes, possibly because of better access to jobs and other activities in urban locations. Students and respondents with more than bachelors' degrees also have a higher *Pro-Urban* attitude.

An increase in the *Car Lover* latent variable decreases the log odds of ridehailing services in non-urban areas. This makes sense because this attitude captures an individual's desire to own or drive a personal vehicle. We simultaneously estimate the effect of *Car Lover* on vehicle ownership, and the

[6] The robustness of this technique is discussed in Mokhtarian & Herick (2016).

coefficient estimate is positive and significant (as would be expected). Thus, we believe that the *Car Lover* attitude captures a source of (otherwise) unobservable correlated effects on both vehicle ownership and this travel behavior choice. At the same time, we find that some variation in this attitude is explained by demographics: younger individuals and those with low household incomes have a lower than average *Car Lover* attitude. It is possible that their stage in life and economic constraints influence this attitude. Moreover, having a high level of education is also associated with lower than average *Car Lover* attitude.

Finally, we also find that a *Technology Averse* attitude is associated with less travel in general in both urban and non-urban areas. However, we found no evidence that this attitude also influences log odds of ridehailing. Previously, Alemi et al. (2019) found that a *Techsavvy* attitude positively influences the *frequency* with which individuals use ridehailing services. However, since frequency of ridehailing is a function of both mode share (log odds) and total number of trips, it is possible that the observed relationship is primarily due to the effect of this variable on total number of trips, and not a preference for ridehailing. The *Technology Averse* attitude is observed to be higher in older individuals, with low household income and low levels of education; women and respondents with children (below the age of 18 yrs.) are also more technology averse.

These results illustrate one of the known advantages of ICLV models: we have been able to incorporate additional information on attitudes to specify and estimate structural models that capture what would otherwise be unobservable, correlated effects on multiple travel-related choices. However, there could also be unobserved effects that are not related to any of the attitudes for which we have measures, but that also are correlated across travel choices. When developing our models, we discovered evidence of an unobserved random effect that negatively affects log odds of ridehailing while also causing the total number of trips to increase, and that this effect exists for individuals in both urban and non-urban locations. Because none of the variables in our dataset could explain this variable, it was necessary to represent it as an additional underlying error component. From a modelling standpoint, it was important to include this variable because excluding it essentially caused the measurement model for the three latent variables to be miss-specified. Without it, the estimated measurement coefficients (essentially 'factor loadings') diverged from what we knew to be true from the factor analysis, and magnitudes and significance of coefficients on the latent variables in the behavioral models were both diminished. There could of course be a variety of other unobservable effects that remain unaccounted in our model.

3.5.2. Socio-Demographic Variables

The models show the impact of socio-demographics on log odds of ridehailing and total number of trips through two pathways. The first pathway is indirect, where the impact of socio-demographics on travel behavior is mediated through attitudes, as discussed in the previous subsection. In the second, we study the direct effects of socio-demographics after controlling for the indirect effects.

Our estimates indicate that younger individuals are more inclined to use ridehailing, as has been found in almost every study on ridehailing services. In our approach, age is an important variable in predicting log odds of ridehailing (in both urban and non-urban areas) and total number of trips (in non-urban areas), showing both direct and indirect impacts on travel choices. The ICLV approach adopted here provides a more detailed behavioral interpretation for these effects than in other types of models that ignore the effect of attitudes. This is demonstrated by the model in Table 7-3: the effect of age on log odds of ridehailing and number of trips (for non-urban individuals) appears to be a direct effect of age in this model. However, these direct effects lose significance in Table 3-4, because the effect of age becomes an indirect effect through its influence on attitudes.

With regard to other demographic effects, we observe that individuals with high household income make more trips for non-work purposes. However, in urban areas, individuals with low-household incomes have a higher mode share for ridehailing services. In our model, we find that employed respondents have a higher mode share for ridehailing services but made fewer trips than unemployed respondents. The signs of these two coefficients imply that employed individuals replace other modes with ridehailing services for non-work travel (possibly originating at their work locations due to time constraints).

3.5.3. Built Environment

After controlling for the socio-demographic variables, and the effect of home-location and vehicle ownership with the help of latent variables, we observe the unbiased estimated effects of the built environment on ridehailing mode share and number of non-work trips in Table 3-4.

Notably, the signs and significance of the estimated coefficients of the built environment variables change between the urban and non-urban models. This suggests that there is a difference in the way the built environment influences the log odds of ridehailing and total number of trips in the two kinds of areas. Yu & Peng (2019) had a similar observation when they analyzed aggregated data using geographically weighted regression.

We hypothesized that individuals who live in vibrant neighborhoods with plenty of restaurants in close proximity (walking distance) would have a lower mode share for ridehailing. However, the urban model showed that if individuals have at least one restaurant within a half mile of their residence, they will have a *higher* mode share for ridehailing services. Moreover, they make fewer trips for non-work purposes than those who do not live in such neighborhoods (the opposite of our original hypothesis). Even in non-urban neighborhoods, having more restaurants within a one-mile radius is associated with higher ridehailing mode share and lower total number of trips. The increase in the mode share of ridehailing and decrease in total number of trips could be an indication that ridehailing replaces other modes (possibly walking) for individuals who live in areas with close proximity to restaurants. It seems counter-intuitive that lower non-work trip-frequencies are associated with the presence of restaurants within a walkable distance. As mentioned in the above section, it may be that a more detailed model that also takes into account the role of individuals' underlying activity patterns may be required when examining the effect of the built environment on ridehailing and trips.

We also examine the effect of the *Walkscore* for the home locations of respondents on their ridehailing mode share and total number of non-work trips. In urban areas, a higher *Walkscore* is associated with a higher ridehailing mode share; in non-urban areas the mode share for ridehailing *decreases* with *Walkscore*. In urban areas, where ridehailing service is available at much shorter waiting times (as compared to non-urban areas) it is possible that ridehailing replaces walking trips. The fact that the increase in mode share for ridehailing with *Walkscore* is not accompanied by an increase in total number of trips for non-work purposes is also consistent with this interpretation. The differential effect of *Walkscore* on mode share and number of trips may help to explain why previous studies, which have examined the effect of land-use mix on the number of ridehailing trips, have found both positive effects (Sabouri et al. 2020; Yu & Peng. 2019) and negative effects (Alemi et al. 2019).

The ease of reaching destinations that are not necessarily available in all neighborhoods, but that people still visit occasionally, can have an impact on travel behavior. We found that individuals living in non-urban areas have a higher mode share of ridehailing if the nearest movie theatre is in the range of 0.65 miles to 8 miles from their home locations, as opposed to those who either live closer (less than 0.65 miles) or further away (more than 8 miles). This finding is consistent with our hypothesis that this range of distances is close enough for movie theatres to attract trips even though they are not close enough to reach by walking. In urban areas, living in a home which has a nearest movie theater in a distance between 0.5 miles to 8 miles is associated with higher mode share of ridehailing as compared to living in a home which has a movie theater within 0.5 miles.

The presence of a department store in a medium range distance (0.65 miles to 8 miles) from the home location induces more trips but the effect on the mode share of ridehailing is not significant. This makes sense because as observed in Figure 3-1, only 7% of the ridehailing trips were made to department stores.

To understand if our ICLV approach mitigates potential issues with, e.g., the effect of RSS bias on estimated effects of the built environment variables, we formulated a model without latent variables and random effects (Table 7-3). This model indicates a significant effect of living in a stand-alone house (in urban areas), and also high neighborhood transit accessibility (in non-urban areas) on mode share of ridehailing services. Previously, Yu & Peng (2019), who did not control for RSS, also found a positive relationship between job access by transit and use of ridehailing services. They speculated that this could be an indication of ridehailing serving as a first- and last-mile connection with transit. However, the significance of both these effects goes away in the ICLV model, indicating that RSS bias could indeed be a problem when attempting to ascertain the effect of the built environment.

Table 3-4 Main models and structural models from the ICLV model

	Main Models												**Structural Models**					
	Urban				Non-urban				Residential choice		Vehicle Ownership		Pro-Urban		Car Lover		Tech averse	
	Log Odds		Total Trips		Log Odds		Total Trips											
	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.
(Intercept)	-3.83	-10.06	2.92	27.07	-2.83	-29.79	2.39	25.87										
Asc. Non-urban									1.83	20.00								
Asc. Zero Vehicle HH											3.20	20.42						
Age (ref=Millennials)																		
GenX	-0.36	-3.29			-0.09	-1.31	-0.07	-1.19					-0.13	-2.05	0.03	0.34	0.51	7.70
Baby boomers	-0.56	-4.51			-0.10	-1.50	0.04	0.54					-0.40	-5.65	0.43	5.08	1.13	14.26
Gross Annual Household Income (ref=Less than $50,000)																		
$50,000 to $100,000	-0.27	-1.87	0.31	3.02			0.13	3.45					-0.23	-3.59	0.17	2.13	-0.10	-1.31
More than $100,000	-0.01	-0.10	0.19	1.92			0.18	4.53					-0.29	-3.89	0.35	4.04	-0.28	-3.32
Gender (ref=male)																		
Female			-0.19	-2.92			-0.07	-2.39									0.14	2.61
Race(ref = other)															-0.18	-2.44		
White			0.24	3.16			0.15	4.00										
Employed (ref=no)																		
Yes	0.57	4.21	-0.45	-4.59	0.15	2.44	-0.17	-3.12							0.12	1.70	-0.40	-6.21
Student(ref = no)																		
Yes			0.14	1.30	0.11	1.76							0.27	3.47			-0.45	-5.73
Education (Ref = Bachelors' or less)																		
More than Bachelors					-0.18	-3.40	0.14	3.02					0.54	8.76	-0.27	-3.94	-0.15	-2.33
Children in the HH (ref=none)																		
At least one			0.20	2.12													-0.28	-4.10
Built Environment																		
Inverse sum restaurant in 1miles					5.14E-04	1.89	-5.31E-04	-2.06										
Restaurant within 0.5 miles (ref = Yes)																		
No	-0.49	-2.38	0.36	3.43														
Walkscore	0.01	2.41			-2.59E-03	-2.25	3.75E-03	3.82										
Movie theater within 0.5 miles (ref = Yes)																		
No	0.27	1.62																
Distance to the nearest movie theater (ref = between 0.65 miles to 8 miles)																		
Less than 0.65 miles					0.02	0.28												
More than 8 miles					-0.13	-3.36												
Distance to the nearest department store (ref = between 0.65 miles to 8 miles)																		
Less than 0.65 miles	-0.17	-1.60	0.15	2.16	0.05	0.86	-0.11	-1.90										
More than 8 miles					0.16	1.68	-0.19	-2.29										
Type of house (ref = Apartments/others)																		
Stand Alone	-0.15	-1.60																

Jobs available via 30 min transit ride					3.16E-06	1.57												
Attitudes																		
Pro Urban	0.23	2.18			0.13	4.99			1.35	11.43								
Car Lover					-0.14	-5.83					1.47	8.24						
Tech Averse			-0.19	-4.80			-0.15	-6.57										
Error Component	-0.59	-7.47	0.45	8.37	-0.90	-31.68	0.78	27.78										
Model Fit																		
LL(start)	-90820.24																	
LL(final, whole model)	-60753.95																	
AIC	121703.9																	
BIC	122294.7																	
Number of estimated parameters	98																	
N	3,066																	

Table 3-5 Estimates from measurement model

Pro Urban	Estimate	T-ratio
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.	-0.37	-15.91
I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.	0.51	32.15
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	0.41	21.50
Car Lover		
I definitely want to own a car.	0.42	13.75
I prefer to be a driver rather than a passenger.	0.37	16.83
I am fine with not owning a car, as long as I can use/rent one any time I need it.	-0.43	-19.25
Tech Averse		
I like to be among the first people to have the latest technology.	-0.43	-25.42
Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.	-0.41	-24.95
I like trying things that are new and different.	-0.38	-18.55
Learning how to use new technologies is often frustrating for me.	0.30	15.56
I try to make good use of the time I spend commuting.	-0.34	-17.28
My commute is a useful transition between home and work (or school).	-0.28	-14.67

3.6. Conclusion

Ridehailing services have become a mainstream mobility option in many cities across the world. Planners and policymakers want to ensure that ridehailing is a net positive in the transportation system, that it increases mobility options for travelers but does not replace sustainable modes of transportation such as active modes and public transit. Ridehailing and its impacts has been much studied by the academic community, but research on the effect of the built environment on the use of ridehailing services has notable gaps.

In this chapter, we take the view that accessibility measures based on behavioral considerations are potentially a more effective way to measure the effect of the built environment than, e.g., the more common "D-measures' (density, diversity, design, etc.). We employ measures from existing sources (Walkscore and jobs accessibility) as well as measures we developed ourselves for this chapter. We also employ a modeling framework that allows us to test whether the effect of the built environment is different in urban and non-urban neighborhoods, a difference that could be driven by a better supply of ridehailing services in urban areas. Because it is well known that residential self-selection (RSS) can bias estimates of built environment effects on travel behavior, we explicitly incorporate the effect of attitudes and other unobserved variables using an ICLV modeling framework to address this issue. Estimation of a simpler model indicates that RSS bias is indeed a problem.

Two notable policy implications emerge from our analysis. The first implication is that, if the goal is to discourage ridehailing from replacing active modes, pricing should be employed to discourage short distance ridehailing trips. We found that the mode share of ridehailing services is higher when destinations are within walkable distance of the home location. Since the total number of trips made by individuals in not positively associated with an increase in the accessibility (by walking) of the neighborhood they live in, we speculate that ridehailing replaces active modes in such neighborhoods. More studies examining trip lengths and trip chains using travel diary datasets are required to confirm this speculation. It is undesirable from a policy perspective if this increase in mode share of ridehailing comes at the expense of walking, which is a more sustainable and cleaner mode of travel than ridehailing, in addition to its direct benefits. In order to prevent replacement of walking trips by ridehailing services it is important to appropriately price short distance trips made by ridehailing services in urban areas.

Second, the relationship between ridehailing and public transit has been central to many studies in the past few years. Some suggest that ridehailing services act as a first- and last-mile connection to mass transit services (Yan, Levine, & Zhao, 2019; Yu & Peng, 2019) while others find that ridehailing may be replacing public transit (Schaller, 2018). Our model indicates that after controlling for individual attitudes about where they choose to live and their perceptions about public transit, this relationship becomes insignificant. Interestingly, a recent study by Malalgoda & Lim (2019), which instead of relying on the total number of trips made using ridehailing (like most other studies) focused on transit ridership and availability of ridehailing service in cities around the U.S. over the past decade, found no evidence of a linkage between the two. It is possible that other studies may have overestimated the linkage between transit ridership and ridehailing due to lack of control for residential self-selection.

This chapter provided new insights into the relationship between the built environment (at the home-location) and use of ridehailing services for non-work purposes. As the research on this topic evolves, future studies can explore how the built environment affects decision to use ridehailing for non-home-based trips. The use of ridehailing for commute purposes has also not been examined closely. Finally, analyzing data collected through travel diary surveys focusing on tours and activities rather than trips can reveal new insights into the link between ridehailing services and the built environment.

4. Adoption of Ridehailing in Four Megacities in Developing Countries

4.1. Abstract

Shared mobility, and ridehailing (Uber, DiDi) in particular, is quickly changing travelers' patterns around the world. Still, the adoption and impact of these services has been mainly studied, to date, in more mature markets in developed countries, while there is much to learn about the changes brought by these services in the developing world. In this study, we conducted a data collection in four large cities in Asia and Latin America – Mumbai, Beijing, Mexico City and Sao Paulo – with the objective of understanding the factors affecting the adoption of ridehailing services in these markets. In this chapter, we estimate a binary logit model, including the geographic regions as interaction terms, to explore the factors that affect the likelihood of using ridehailing. Our analysis shows that women and younger respondents are more likely to adopt these services in all locations. A number of other factors are found to have significant effects only in selected regions. Among the most relevant findings, in Mumbai, all else equal, respondents who live in zero-vehicle households are more likely to use ridehailing, while this is not true in the other regions. The chapter provides useful information to help understand how these services are changing mobility in these quickly growing urban regions, and the way they interact with other traditional transportation options.

4.2. Introduction

Travel behavior, particularly car use, is changing across the world. In the United States, the per-capita vehicle miles travelled (VMT) and vehicle ownership in the US also increased until 2009. But for a period of approximately four years (2009-2013), per-capita VMT and vehicle ownership declined. Starting in 2015, total VMT, per-capita VMT and car ownership have been on a rise in the US (Circella et al., 2016). In other developed countries, car ownership also increased considerably in the past decades, e.g. changing from 400 cars per 1,000 individuals in 1993 to 520 in 2015 in Germany, though mode share in the country has remained rather constant (with almost half of the trips made by private cars)(Kuhnimhof, 2017).

Transportation patterns are also changing in developing countries. The automobile modal share in China increased from approximately 5% in 1986 to 34% in 2010. However, since 2010, this trend has started to slow down. For example, the per-capita passenger kilometer travelled on Chinese highways peaked in 2012 and has steadily declined since then (National Bureau of Statistics, 2018). The total number of registered vehicles in India has increased from 55 million in 2001 to 210 million in 2015 (Ministry of Statistics and Programme Implementation, 2017). At the same time, the number of registered vehicles per 1000 residents increased from 53 to 167 (Government of India, 2017). This change is accompanied by a shrinking mode share of public transit and walking in the country (Tiwari et al., 2016). In Mexico City, the local car fleet doubled from 1990 to 2014. In the same time, the total vehicle miles kilometers travelled in the city (on an average weekday) increased from 24 million to 32 million from 1990 to 2010 (Guerra, 2014).

There are a lot of factors contributing to these changes in travel behavior. Some of them include changes in economic activity, gas prices, changes in urban form, socio-demographic traits, generational effects, and changes in vehicle technology – including increased fuel efficiency, electric vehicles, government restrictions and technological innovation (Circella et al., 2016; Gao & Peter, 2018). Information and communication technology, by providing real time locational information and internet on smartphones, has enabled deployment of new transportation services. These modern technology-enabled services are increasing the available options for a trip and offering the opportunity to dynamically make travel decisions without planning in advance.

New shared-mobility services include a variety of new options, such as carsharing (e.g. Zipcars) to ridesharing (e.g. Carma), ridehailing (e.g. Uber, DiDi), as well as bikesharing and e-scooter services (Shaheen, Cohen, Zohdy, & Kock, 2016). Ridehailing (also known as ridesourcing, or Transportation Network Companies, or TNCs) is rapidly gaining attention in many markets. The largest ridehailing providers include Uber and Lyft in the United States, Ola in India and DiDi in China. These services allow passengers to instantly book their rides using their smartphone app. The app connects the riders to a network of available drivers in proximity. The matched drivers then drive the passengers from the trip origin to the desired destination for a monetary compensation.

In 2017, nearly 10% of the US population used ridehailing at least once a month, showing how quickly these services are being adopted, in particular in large urban areas (M. Conway, Salon, & King, 2018). Uber completed 1 billion rides in December 2017, and in 18 months that number grew to 5 billion serving almost 500 cities across the world (Uber, 2019b). DiDi announced completion of 1.43 billion rides in 2015 and serves about 10 million trips on a daily basis (DiDi, 2019). This service has potential to substantially alter people's travel behaviors if it keeps growing at this pace. Thus, it is important to understand the factors which affect the adoption of these services, as well as the modifications in the use of the transportation system brought by their adoption.

The adoption of ridehailing in developed countries and the factors affecting the use of these services have been already discussed in a number of previous studies; however, much more limited knowledge in this regard is available for developing countries. This chapter explores the factors affecting the use of ridehailing services through the estimation of a (binary) adoption model using data from four large cities in developing countries: Mumbai (India), Beijing (China), Mexico City (Mexico) and Sao Paulo (Brazil). The remainder of this chapter is organized has follows: the following section summarizes related research in both developing and developed countries. Section 4.4 summarizes the research method, data collection and conceptual model for this chapter. In section 4.5, we report the results from the model estimation. Finally, in section 4.6, we summarize the main findings of the chapter and potential for future work.

4.3. Literature Review

Over the past few years, researchers have used a number of methods and datasets to understand the factors affecting the adoption of ridehailing services especially in Northern America, China and some European countries. These include the analysis of the U.S. National Household Travel Survey (NHTS) data (M. Conway, Salon, King, et al., 2018), online surveys, and intercept surveys (Rayle et al., 2016). In the U.S., young individuals with relatively high household income, and who live in urban areas have been found to be more likely to adopt ridehailing (Alemi, Circella, Handy, et al., 2018; M. Conway, Salon, King, et al., 2018; Rayle et al., 2016). On the other hand, there is also evidence that households with low income, under certain conditions, are ridehailing users (M. Conway, Salon, King, et al., 2018; Gehrke et al., 2018). Alemi et al. showed how dependent millennials (18-34 yrs.) and older members of Gen X (42-50 yrs.) who live with their families are also likely to adopt ridehailing: their likelihood of using these services increases if they make frequent long-distance trips and need to travel to/from airports. Low availability of vehicles in the household also increases the propensity to adopt ridehailing services (M. Conway, Salon, & King, 2018). Individuals with strong pro-environmental attitudes, variety-seeking individuals and those who easily embrace technology are more likely to adopt these services (Alemi, Circella, Handy, et al., 2018; Dias et al., 2017; Patricia S Lavieri & Bhat, 2019). Outside the U.S., a study conducted in Toronto, Canada, analyzed household travel survey data finding that younger individuals with higher income are more likely to use ridehailing services (Young & Farber, 2019).

The impact of ridehailing on travel patterns has also been the object of several studies. Some of these have reported that ridehailing increases VMT (Anderson, 2014; Henao & Marshall, 2018; Schaller Consulting, 2017). This is caused not only by the deadheading miles of TNC drivers but also by the mode substitution for trips made by ridehailing – which often replace travel that would have been otherwise made by walking and/or using public transit (Henao & Marshall, 2018). In another analysis, Circella and Alemi classified ridehailing users into three groups, based on the self-reported impacts on the use of other travel modes of their last Uber/Lyft trip. Members of the first group reduce walking, bicycling, and public transportation in urban areas, while members of a second group replace car/taxi trips with ridehailing. Finally, only a smaller group of users complements (increasing) the use of transit through first/last mile access and safe rides to return back home late at night using ridehailing. As a general trend, research seems to suggest that ridehailing often replaces low-quality transit trips like in the case of city buses, but they complement fast transit services like commuter rail and subway (Babar & Burtch, 2017).

In the Asian sub-continent, the study conducted by Lim et al. in Malaysia showed a positive association of ridehailing with the perceived usefulness of technology, societal pressure to adopt new technologies, and propensity of the respondents to use technology for leisure. In a study from Beijing, 37-day trip data of 9,000 taxis operating through two Chinese ridehailing apps – Didi and Kuaidadi were analyzed (Leng, Du, Wang, Li, & Xiong, 2016). The study found that competition between the two companies led a decrease in wait time for customers and an increase in short trips within the central core of the city.

In Latin America, Tirachini & Lobo conducted an online survey in Chile to understand the impact of ridehailing on VMT. They found that ridehailing generally increases VMT, mostly by attracting public transit riders. Also in Chile, Lagos et al. Lagos, Muñoz, & Zulehner (2019) analyzed fatalities and accident data in Santiago. They reached the conclusion that Uber's entry in Santiago is associated with reduction in drunk-driving fatalities. In Sao Paulo, Brazil, about 83% of the ridehailing trips were found to replace private modes, with the remaining trips replacing the use of public transit (Haddad et al., 2019).

4.4. Study Area

The focus of this study is to understand the factors affecting the adoption of ridehailing services in four megacities in developing countries from Asia and Latin America, including Mumbai, Mexico City, Beijing and Sao Paulo. Mumbai is the financial capital of India with a population of 12.4 million spread in an area of 603 sq. km. making it the most densely populated city among the four cities in our study (Directorate of

Census Operations, 2011). Beijing, on the other hand, has a high population – close to 21 million (Henrik Beckera, , Felix Beckera, Ryosuke Abeb, Shlomo Bekhorc et al., 2019). The car ownership is the lowest in Mumbai with only 54 cars per thousand residents in the city (Directorate of Census Operations, 2011); instead, both Latin American cities included in the study have more than 500 cars per 1,000 residents. At least half of the commuting trips in all these cities are made using public transit as a mode of transportation. Nearly one-third of commuters in Mexico City and Mumbai use active modes such as bicycling and walking as primary modes of transportation. Mexico City and Sao Paulo have relatively higher median household income (11,680 and 6,180 US Dollars at Purchasing Power Parity (PPP), respectively) compared to the other two cities in the study. Mumbai has the highest household size with approximately 4.1 household members, on average (Henrik Beckera, , Felix Beckera, Ryosuke Abeb, Shlomo Bekhorc et al., 2019).

Table 4-1 Summary details of the regions included in the study

		Mumbai, India	**Mexico City, Mexico**	**Beijing, China**	**Sao Paulo, Brazil**
	Population size *(millions)*	12.4	8.8	21.7	12.2
	Population density *(residents/km2 of metro area)*	20,634	6,671	1,291	7,994
	Numbers of cars per 1,000 residents	54	507	260	516
Mode Share	Private Modes	15%	15%	36%	32%
	Public Transit	52%	58%	50%	58%
	Active modes	33%	27%	12%	7%
	Median [7]Annual HH income *(US-$ at PPP)*	3,168	11,680	6,180	7,522
	HH size	4.1	3.9	2.6	3.1

Source: (City Population, n.d., 2019; Directorate of Census Operations, 2011; Gallup, 2019; Government of Mahrashtra, 2009; Henrik Beckera, , Felix Beckera, Ryosuke Abeb, Shlomo Bekhorc et al., 2019; OECD, 2019; Pai, n.d.; USDA Foreign Agricultural Service, 2013)

[7] We report median incomes for the countries, as information for each city was not available

4.5. Methods

4.5.1. Data Collection

The data for this chapter were collected by the World Resources Institute (WRI) in collaboration with the research team at the University of California, Davis. A specifically-designed survey was administered to a sample of residents in the four cities in fall 2018. The survey collected information on individual attitudes towards the use of technology, the environment, and various transportation modes; the respondent's use of technology; current travel patterns; use of ridehailing services; and sociodemographic information about their households.

A mix of sampling methods were used to collect data in the four cities. Respondents were recruited using local online opinion panels in Mumbai and Beijing. In order to reduce sampling bias, the service providers employed quota sampling approaches and recruited respondents among the members of the online opinion panel mirroring the distribution age and gender of the population in the two cities. To ensure high quality of the responses, during the survey design, we included a *trap question* in the survey, which prompted the respondents to select a certain answer "for quality assurance purposes". We disregarded cases from respondents who did not pay attention to the survey and failed to answer this question correctly. A total of 2,700 and 3,551 complete responses were collected from Mumbai and Beijing, respectively. After data cleaning, the sample size reduced to 1,895 for Mumbai and 3,503 for Beijing.

Intercept surveys were conducted in Sao Paulo and Mexico City due the assessed unreliability of online opinion panels in these countries. In Mexico City, 20 city hubs were chosen across the city to conduct the data collection and ensure some geographic representation. These locations are distributed along nine municipalities from Mexico City and four in the neighboring regions in other states, which are part of the metropolitan area. Figure 4-1 shows these locations on these locations in Mexico City. These locations represent hubs of various interest including workplaces, recreational spots, shopping centers and medical centers. The surveys were conducted each day starting at 8 am in the morning until 6 pm in the evening. A screener question was asked at the beginning of the survey to ensure they were adults and residents of Mexico City. Some of the survey responses were screened out to meet the desired characteristics to mirror the city census. Every 5th person crossing the surveyor was approached and invited to participate in the survey. This was modified on one location where every 3rd person was surveyed due to low influx of people. As this technique was mainly targeted at pedestrians, we do not have much representation of car travelers. In all, 2,521 complete surveys were collected from Mexico City, which became 2,201 valid cases after data cleaning.

The city of Sao Paulo was divided into five zones for the survey: the City Center, and the South Zone, North Zone, East Zone and West Zone, as shown in Figure 4-2. The City Center has many workplaces and transit terminals; the South Zone has shopping centers and a good representation of high-income people; the East and North Zones mainly include middle- and low-income households; and the West Zone has high representation of students and high-income residents. Depending upon the flow of people in each location, the surveyors approached every third, fourth or fifth pedestrian. The surveys were conducted during daytime (9AM to 8PM). Just like in Mexico City, the team in Sao Paulo also filtered out responses to match the age and gender in the sample distribution with the respective distributions in the city. After data cleaning, 2,456 valid cases are available for this region.

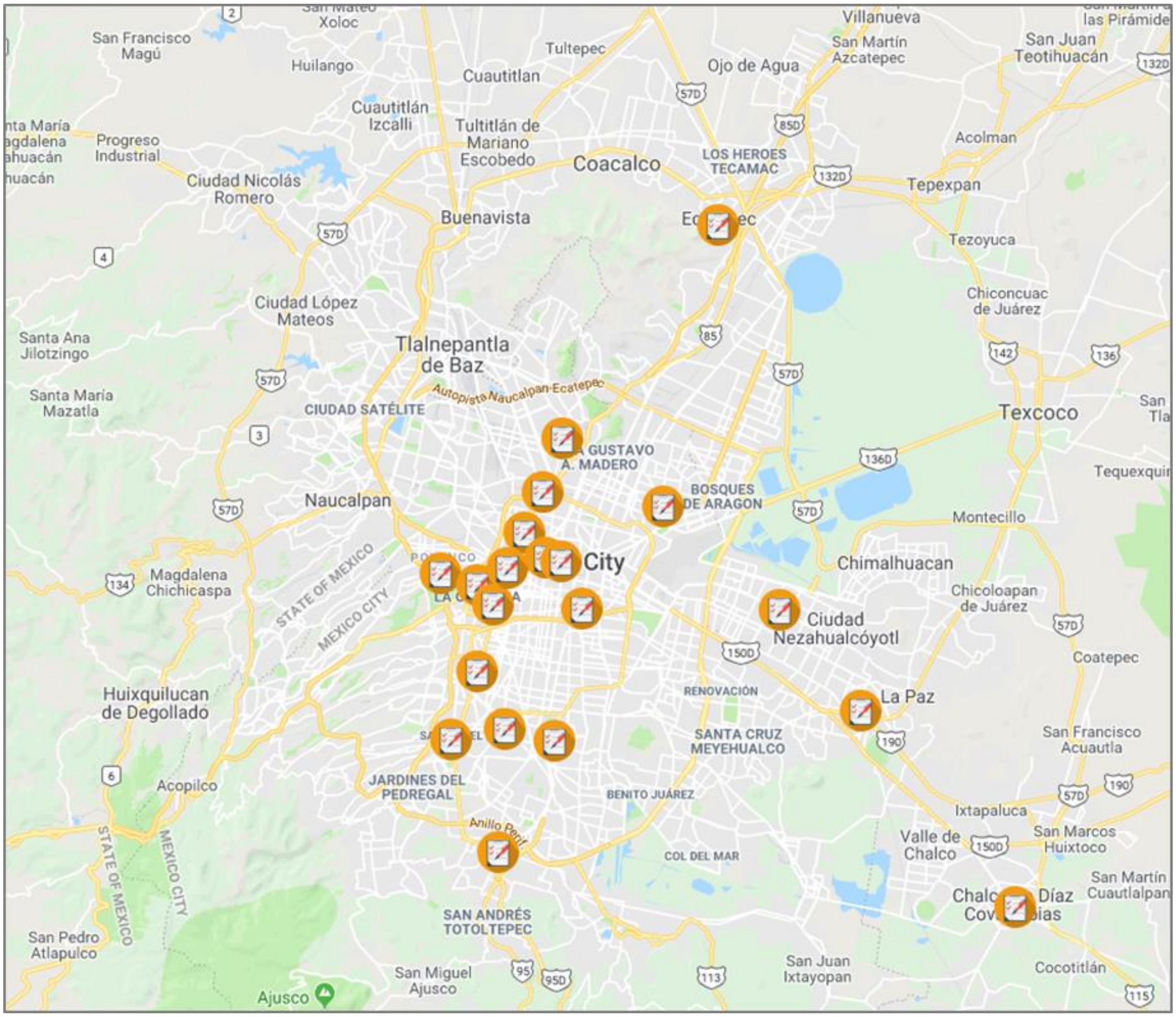

Figure 4-1 Locations of intercept surveys in Mexico City, Mexico

The difference in the sampling strategy is one of the limitations of our chapter, especially for the research question that focuses on the importance of various factors affecting the adoption of ridehailing services in these four locations. Further, the survey was developed within an infrastructure that helped us ask questions in a manner that was locally meaningful. Local staff employed by our research partners were part of the survey design process. They provided contextual input and managed the survey testing and data collection. This helped us to clarify questions across languages or alter questions to adjust to local contexts (For example, Chinese norms mean that few individuals know household income though they know their personal income). Despite this considerable effort, the nature of a cross-cultural survey means that some questions asked in geographically-separated contexts using different languages may introduce some levels of ambiguity or bias which can be difficult to account for.

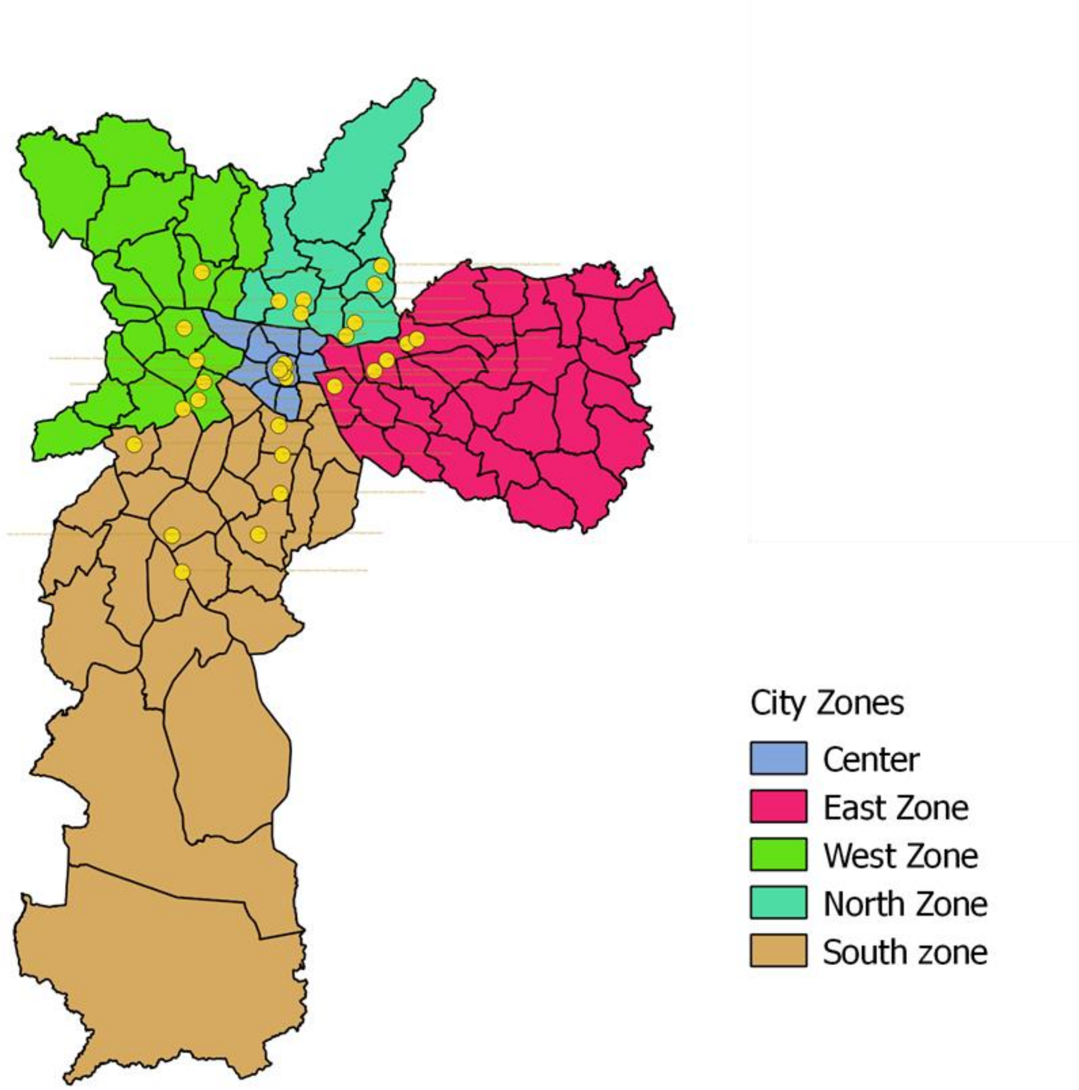

Figure 4-2 Survey locations in Sao Paulo

After merging the four different datasets, we conducted an extensive data cleaning process. The final sample size from the four cities is 10,068 after data cleaning. Table 4-2 summarizes the distribution of all relevant variables in each region. Table 4-3 compares the distribution of all independent variables among ridehailing users and non-users in each region.

4.5.2. Conceptual model and data description

Some studies (Ozaki & Sevastyanova, 2011; Peters, Gutscher, & Scholz, 2011) have applied the Theory of Planned Behavior TPB with some variation in modeling the adoption of hybrid vehicles and fuel-efficient vehicles in the European context. Perhaps, more important to the topic of discussion in this – the adoption of ridehailing services – a previous study (Boon Lim et al., 2018) applied the Theory of Reasoned Action (TRA) to understand the factors affecting the adoption of ridehailing services in Malaysia. TRA is a variation of the TPB with an emphasis on the role that a person's intention to engage in a behavior plays in adopting new technologies. These frameworks lay the foundation for the models that we develop in this chapter to understand the adoption of ridehailing services in the selected four cities. We reviewed relevant literature to understand which variables have been most effective in predicting travel choices. We conducted one-way ANOVA and chi-square tests to understand which variables are significantly different among users and non-users.

Dependent variable: Our dependent variable (ridehailing adoption) has two levels – to identify ridehailing users and non-users. Anyone who has ever used ridehailing service at least once is defined as a user. The highest adoption rate was observed in Sao Paulo, where 70% of the respondents reported using ridehailing at least once. In the other three cities the adoption rate varied between 50% and 60%.

The following categories summarize the main groups of independent (explanatory) variables that were introduced in the adoption model.

Socio-demographic: For the purpose of this analysis, the age group 18-29 was classified as 'young'; individuals in the 30-49 age range are considered of 'middle age'; and those who are 50+ years are considered "older". In India, Mexico and Brazil the survey asked respondents to report the household income by selecting one of six income categories. The six income brackets were modified to fit the income distribution in each city in local currency. In China, the respondents were asked to report their personal income in a similar fashion. We obtained the median household income for Mexico City, Mumbai and Sao Paulo (Gallup, 2019; Statista, 2015) and personal income in Beijing from the literature ("Beijing Basic Database of Macroeconomic and Social Development," n.d.; Bösch, Becker, Becker, & Axhausen, 2018;

National Bureau of Statistics, 2018). Any income categories below these thresholds were labelled as *low*, rest were labelled as *high*. We controlled for sex in our model by adding a binary variable with two levels – male and female.

Lifestyle: The importance of lifestyle in explaining travel behavior of individuals has been demonstrated in several studies. Salomon & Ben-Akiva (1983) explained how lifestyle can be understood through three dimensions – individuals' participation in labor force, household formation and leisure activities. Thus, in our model, we included employment status (dummy variable) and student status (dummy variable). We also tested if having children in the household had any impact on the decision to adopt ridehailing, but the estimated coefficients for this variable were not found to be statistically significant.

Travel Choices Vij, Carrel, & Walker (2013) demonstrated the complexity of mode choice by introducing the concept of modality style - recognizing the repetitive nature of mode choice. The habitual drivers display a strong positive preference towards using automobiles whereas multimodal individuals are more open to alternative modes of travel. There is a strong correlation between medium- and long-term decisions including vehicle ownership and modality style. The variables included in the model allowed us to test a number of hypotheses on the expected impacts of various factors on the likelihood of an individual to use ridehailing. For example, all else equal (e.g., after controlling for the impacts of income, and household composition), we expect that people who live in lower vehicle-owning household are more likely to adopt and use ridehailing to fulfill their mobility needs. To test this hypothesis, we created another variable called vehicle availability in the household. This variable has three categories – zero-vehicle households, vehicle-deficit households and vehicle-sufficient households. If there are no vehicles in the household then this is defined as a zero-vehicle household. Households with at least one vehicle in the household but fewer vehicles than household members with a driving license are considered vehicle-deficit households. Vehicle-sufficient households have more vehicles than household members with a driving license.

Table 4-2 Distribution of all variables used in the model, by region

	Sao Paulo (N=2,456)	Beijing (N=3,503)	Mumbai (N=1,895)	Mexico City (N=2,201)
Dependent Variable				
Ridehailing Usage				
User	69.7%	57.5%	56.5%	50.3%
Non-user	30.3%	42.5%	43.5%	49.7%
Socio-demographics				
Sex				
Male	46.70%	52.40%	54.20%	50.80%
Female	53.20%	47.60%	45.80%	49.20%
Age				
Young (18 to 29 yrs.)	32.9%	35.5%	30.7%	28.7%
Middle age (30 to 49 yrs.)	42.1%	38.9%	46.5%	39.0%
Older (50 yrs. or more)	25.0%	25.6%	22.8%	32.3%
Household Income				
Low	22.5%	34.9%	11.9%	75.3%
High	77.4%	65.0%	88.0%	24.6%
Lifestyle				
Employed				
Yes	62.4%	68.4%	87.4%	67.2%
No	37.6%	31.6%	12.6%	32.8%
Student				
Yes	11.4%	22.6%	36.4%	16.4%
No	88.6%	77.4%	63.6%	83.6%
Members in Household with Driving License[1]	1.3 (0.9)	1.8 (0.9)	1.9 (1.0)	1.0 (1.0)
Travel Choices				
Vehicle Availability				
Zero vehicle	32.6%	37.6%	3.6%	39.9%
Vehicle deficient	21.5%	38.0%	20.2%	13.6%
Vehicle sufficient	46.0%	24.4%	76.2%	46.5%
Driving License				
Yes	62.1%	64.5%	90.9%	43.0%
No	37.9%	35.5%	9.1%	57.0%
Cars in Household[1]	0.9 (0.8)	0.7 (0.7)	1.1 (0.7)	0.7 (0.7)
Two Wheelers in Household[1]	0.1 (0.4)	0.1 (0.4)	1.3 (0.7)	0.2 (0.5)
Built Environment				
Accessibility Score of Neighborhood[1]	3.6 (5.5)	0.3 (0.8)	2.9 (2.1)	2.6 (3.2)
Personal Attitudes				
Tech Savviness				
Agree	81.2%	84.0%	82.0%	75.3%
Do not agree	18.8%	16.0%	18.0%	24.7%
Increase in Gas Tax to Fund Public Transit				
Agree	8.5%	42.4%	49.2%	86.9%
Do not agree	91.5%	57.5%	50.7%	13.1%

Note: [1]for continuous variables, the mean and standard deviation (in parentheses) are reported

Table 4-3 Distribution of independent variables among users and non-users

		Sao Paulo		Beijing		Mumbai		Mexico City	
		User (N=1712)	**Non-User (N=744)**	**User (N=2013)**	**Non-User (N=1490)**	**User (N=1071)**	**Non-User (N=824)**	**User (N=1107)**	**Non-User (N=1094)**
Socio-demographics									
Sex									
	Female	72.2%	27.8%	56.6%	43.4%	63.3%	36.7%	49.0%	51.0%
	Male	66.8%	33.2%	58.3%	41.7%	50.7%	49.3%	51.6%	48.4%
Age									
	Young	78.3%	21.7%	66.2%	33.8%	76.8%	23.2%	65.8%	34.2%
	Middle age	69.9%	30.1%	65.2%	34.8%	47.3%	52.7%	51.6%	48.4%
	Older	57.9%	42.1%	33.7%	66.3%	48.1%	51.9%	34.9%	65.1%
Lifestyle									
Student									
	Yes	79.9%	20.1%	60.4%	39.6%	75.1%	24.9%	46.3%	53.7%
	No	68.4%	31.6%	56.6%	43.4%	45.9%	54.1%	16.7%	83.3%
Employed									
	Yes	75.1%	24.9%	66.9%	33.1%	52.8%	47.2%	51.2%	48.8%
	No	61.6%	38.4%	37.1%	62.9%	33.3%	66.7%	48.4%	51.6%
Household Income									
	Low	63.1%	36.8%	43.8%	56.2%	77.5%	22.5%	47.7%	52.3%
	High	71.6%	28.4%	64.8%	35.2%	53.6%	46.3%	60.6%	39.4%
Members of Household with Driving License[1]		1.4 (0.9)	1.2 (0.9)	1.9 (0.9)	1.7 (1.0)	2.0 (0.9)	1.9 (1.0)	1.2 (1.0)	0.9 (0.9)
Travel Choices									
Vehicle Availability									
	Zero Vehicle HH	67.1%	32.9%	52.7%	47.3%	70.6%	29.4%	42.8%	57.2%
	Deficit	81.6%	18.4%	61.8%	38.2%	49.6%	50.4%	61.9%	38.1%
	Sufficient	66.0%	34.0%	58.1%	41.9%	57.7%	42.3%	53.4%	46.6%
License									
	No	69.2%	30.8%	41.6%	58.4%	52.3%	47.7%	45.0%	55.0%
	Yes	70.0%	30.0%	66.2%	33.8%	56.9%	43.1%	57.2%	42.8%
Two wheelers in household[1]		0.1 (0.4)	0.1 (0.4)	0.1 (0.4)	0.1 (0.4)	1.3 (0.7)	1.2 (0.5)	0.2 (0.5)	0.1 (0.4)
Cars in household[1]		0.8 (0.7)	0.9 (0.9)	0.8 (0.7)	0.6 (0.7)	1.2 (0.8)	0.9 (0.5)	0.8 (0.8)	0.7 (0.8)
Built Environment									
Accessibility score of neighborhood[1]		3.6 (5.5)	3.5 (5.5)	0.2 (0.6)	0.3 (1.0)	2.7 (2.2)	3.3 (2.0)	2.7 (3.3)	2.6 (3.1)
Personal Attitudes									
Tech Savviness									
	Agree	71.0%	29.0%	59.8%	40.2%	59.8%	40.2%	54.2%	45.8%
	Do not agree	64.1%	35.9%	45.5%	54.5%	41.8%	58.2%	38.3%	61.7%
Increase in Gas Tax to Fund Public Transit									
	Agree	79.4%	20.6%	56.9%	43.1%	46.8%	53.2%	49.9%	50.1%
	Do not agree	68.8%	30.3%	57.9%	42.1%	65.9%	34.1%	52.4%	47.6%

Note: [1]for continuous variables, the mean and standard deviation (in parentheses) are reported

Built environment: Acker et al. found that even after controlling for attitudes and lifestyle, land use might still influence car availability. Handy & Niemeier (1997) suggest that accessibility can be defined as the diversity in the destinations which can be reached within a given distance or travel time by a particular travel mode. Controlling for land-use characteristics in our model was challenging due to lack of unified open-source information for these very different regions. We collected information on the landmark or bus stop nearest to the home location of the respondents. These addresses were geocoded using the Google API geocoding service. The Google Places API (Google Developers, 2019) provides the information on the number of places (departmental stores, in this chapter) available within a given distance (2 km in this chapter) of a given location. This number ranges from 0 to 20. Although not ideal, we treated the number of departmental stores accessible with a two-kilometer radius of a given location as a proxy measure of accessibility.

Personal attitudes: the survey had a set of statements about use of technology, opinions about cars, environment and government actions. The respondents were asked to indicate their agreement with those statements on a five-point Likert-type scale from "strongly disagree" to "strongly agree". In our models, we included two attitudinal statements as explanatory variables. The first, measuring *tech savviness*, indicates if the respondent is likely to embrace new technologies. The second statement asked if the respondents agreed to increase gasoline tax to provide better funding for public transportation.

4.5.3. Model Estimation

Our objective is to improve the understanding of the factors affecting the adoption of ridehailing services in each geographic context. We tried two different modelling approaches to understand the effect of the factors that were discussed in the previous section on the adoption of ridehailing. In the first approach, we separated the data from each country and estimated four binary logit models on the segmented datasets. Although we did observe some interesting results, it was difficult to compare the coefficients estimated from four different models because they were estimated on separate datasets.

In the second approach, we included all the variables mentioned in the Table 4-2 using dummy variables for each of the four countries, as well as interaction terms for all variables reported Table 4-2 with the dummy variables for each country. This approach has advantages over the previous approach as it uses the complete dataset to estimate the coefficients. The results of the segmented and pooled models were similar. That is, for both models, and in each specific country, the same variables were found to have statistically significant coefficients that explain the adoption of ridehailing services. Moreover, the sign of the significant coefficients was also the same in both modelling approaches. However, in the pooled model, all coefficients are estimated simultaneously with the same dataset, and they can be compared across segments. Accordingly, in the remainder of the chapter we will follow on this approach. Table 4-4 reports to the estimated coefficient with the robust standard errors, which were estimated relaxing the condition of normal distribution of error terms and heteroscedasticity in the model.

4.6. Results and Discussion

Table 4-4 reports the results of the ridehailing adoption binary logit model with attitudinal variables that we estimated on the pooled dataset. It is important to note that, given the model specification that was used with the use of interaction terms to account for different adoption patterns in the four regions, the results for the base model should be interpreted as the impact of those explanatory variables in Sao Paulo. The coefficient for Beijing, Mumbai and Mexico City should be interpreted as *modifiers* (due to the interaction terms) of the coefficient for each variable from the base model in each of these three regions.

Table 4-4 Binary logit model with interaction terms estimated on the pooled dataset

	Base (Sao Paulo)		**Beijing**		**Mumbai**		**Mexico City**	
	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval
(Intercept)	0.227	0.197	-1.108***	0.000	-0.575	0.383	-0.299	0.312
Socio Demographics								
Gender (Ref: Male)								
Female	0.361***	0.000	-0.150	0.229	0.899***	0.000	-0.348**	0.013
Age (Ref: Young)								
Middle Aged	-0.497***	0.000	-0.157	0.331	-0.686***	0.003	0.010	0.955
Older	-0.848***	0.000	-0.531***	0.004	-0.386	0.152	-0.198	0.314
Household Income (Ref: Low)								
High	0.367***	0.002	0.318**	0.048	-0.631*	0.065	-0.059	0.725
Lifestyle								
Student (Ref: No)								
Yes	0.233	0.160	0.111	0.599	1.458***	0.000	0.341	0.150
Employed (Ref: No)								
Yes	0.647***	0.000	0.069	0.638	0.557	0.017	-0.581***	0.000
Travel Choices								
License (Ref: No)								
Yes	-0.182	0.145	0.705***	0.000	1.024***	0.000	0.531***	0.003
Vehicle Availability in the Household (Ref : Zero)								
Deficit	0.814***	0.000	-0.654***	0.001	-2.526***	0.000	-0.389	0.103
Sufficient	-0.101	0.437	0.322*	0.053	-0.795	0.151	0.303*	0.090
Built Environment								
Accessibility Score of the Neighborhood	3.29E-03	0.703	-0.15***	0.002	-0.143***	0.000	-3.02E-04	0.986
Techsavvy (Ref : Do Not Agree)								
Agree	0.186	0.114	0.057	0.721	1.215***	0.000	0.049	0.767
Increase in Gas Tax to Fund Public Transit (Ref: Do Not Agree)								

Agree	0.545***	0.004	-0.375*	0.068	-1.857***	0.000	-0.636***	0.008
Log Likelihood (Model)	-5471.32							
Log Likelihood (Market Share)	-6816.35							
Log Likelihood (Equally Likely)	-6969.59							
ρ^2 (EL)	0.21							

*** pvalue < 0.00, ** pvalue < 0.05, * pvalue < 0.1

As shown in the table, the results of the model estimation indicate that even after controlling for other important variables, the likelihood of adoption of ridehailing services is higher in Sao Paulo compared to Beijing and Mexico City. Women are more likely to use ridehailing than men in Sao Paulo, and this effect is significantly stronger in Mumbai but not in Mexico City. Younger individuals are more likely to use ridehailing services in all regions. Respondents from high-income households are more likely to use ridehailing in Sao Paulo, Beijing and Mexico City, but the reverse is true for Mumbai. Among the lifestyle variables, students are more likely to use ridehailing services in Mumbai. Employed individuals are more likely to use ridehailing services in Sao Paulo, Beijing and Mumbai but not in Mexico City.

In Sao Paulo, Mexico City and Beijing, households with fewer vehicles than adult members with a driver's license are more likely to use ridehailing services as compared to households with zero vehicles. However, in Mumbai, individuals who live in households with zero vehicles are more likely to use ridehailing, all else equal. This suggests a speculation about the replacement that ridehailing causes on the use of other modes of transportation (including active travel and public transportation) for individuals with zero vehicles and high household income.

In Mumbai, respondents who indicated that they rely heavily on modern technology (such as smartphones) are more likely to use ridehailing. In Sao Paulo, respondents who felt that government should tax gasoline to fund public transit are more likely to use ridehailing services. The reverse is true for Mumbai and (to some extent) Mexico City.

4.7. Conclusion

Ridehailing services are becoming a prominent component of the transportation system. In the past few years, a number of studies have investigated how these services are used, the factors affecting their adoption, and the impact of these services on transportation patterns in the US and other developed countries. However, only a few studies have studied the use of these services in developing countries. We conducted this chapter with an objective to fill this knowledge gap. We chose four cities in developing countries – Mumbai, Beijing, Sao Paulo and Mexico City – and administered surveys in these four locations across more than 10,000 individuals in total, to improve the understanding of the factors affecting the adoption of ridehailing services in these important rapidly growing megacities of developing countries.

This chapter presents the first early results from the analyses of this dataset. We estimated a binary logit model with interaction terms using the full dataset while controlling for differences in the variable impacts in the four locations. Due to limitations in the data (and the low number of users that use these services frequently), this first analysis mainly focused on the binary choice of whether to use or not use ridehailing (while future extensions of the project will focus on analyzing the factors affecting the frequency of use of these services). Our adoption model revealed important differences in these markets. On average, the adoption rate was found to be highest among respondents in Sao Paulo even after controlling for other variables in the model. In Sao Paulo, Beijing and Mumbai women were found to be more likely to use ridehailing, while being younger is associated with a higher likelihood of being a user in all markets.

Our findings help understand the differences among adopters of ridehailing services and help lay the groundwork for future studies. For example, in Mumbai, we found that respondents with zero vehicles in the household were more likely to use ridehailing. This seems to suggest that a higher proportion of trips in Mumbai replaces traditional modes of transportation such as active modes and public transportation (as well as autorickshaws), with potential negative impacts on environmental externalities from transportation. At the same time, an alternative interpretation is also that, in the medium/long term, ridehailing might allow some travelers that are in the position to buy a personal vehicle to avoid (or postpone) that purchase. This in turn can result in lower car dependence and vehicle trips, thus resulting in positive, or at least neutral impacts of ridehailing on traffic congestion or pollutant emissions. To further explore this topic, future stages of this project will focus on the analysis of the impact that the adoption of ridehailing has on the use of other travel modes in the four regions, as well as its relationship with the propensity to change household vehicle ownership, among other directions for future research.

Like all other studies, even this study suffers from certain limitations. There is a difference in the way participants were recruited for the survey in this project. In Mexico City and Sao Paulo, participants were recruited using intercept surveys, but online opinion panels were used in Beijing and Mumbai. Even though it was ensured that the final samples from each country had respondents from all age, gender and income categories the recruitment method can bias the type of respondents with respect to some other unobserved variables. For instance, it can be expected that respondents from online opinion panels are more tech-savvy than those recruited from intercept surveys. Unfortunately, the final model in the study does not account for these unobserved effects, which could lead to biases in the estimated coefficients for the independent variables. I corrected for this limitation when I conducted another comparative analysis in the following study.

5. Telecommuting and Commute Patterns during the COVID-19 Pandemic in Canada, Chile, Germany, and the United States.

5.1. Abstract

Telecommuting has been promoted as an effective tool for travel demand management. However, its adoption has remained relatively low due to various barriers including cultural and institutional resistance. Consequently, its impacts on travel demand (and potential traffic reduction) have been below expectations – until now. The COVID-19 pandemic that began in 2020 led governments and private companies world-wide to embrace telecommuting as a way to contain the spread of the virus, leading to much higher levels of telecommuting adoption at least for some. Understanding new trends in telecommuting adoption during the disruptive pandemic could be beneficial for transportation planners. We analyze the data collected in Canada, Chile, Germany, and the US during the early phase of the pandemic. We jointly model two behaviors: 1) whether to telecommute exclusively (binary variable) and 2) how often to commute physically if the individual does not telecommute exclusively (ordinal variable). The model accounts for confounding effects, including those associated with different recruiting and sampling methods for each country and unobserved country-specific attribute (e.g., COVID-19 response). In all countries, affluent workers (i.e., high-income, high-educated, or non-essential-workers) had a higher propensity to exclusively telecommute and report to work at a lower frequency if commuting physically. We also show that the effects of a few selected sociodemographic characteristics differed greatly by country, including household size, full/part-time worker status, gender, and vehicle ownership. This chapter contributes to the academic literature by comparing how the response to the global COVID-19 pandemic in terms of telecommuting behavior depended on the local context.

5.2. Introduction

For decades, telecommuting has been explored as a strategy for transportation demand management (P. L. Mokhtarian, Koenig, & Henderson, 1995; Shabanpour, Golshani, Tayarani, Auld, & Mohammadian, 2018; Walls & Safirova, 2004), even if telecommuting adoption has usually remained below expectations, and its overall impacts on travel demand unclear. Studies have claimed both decrease (Koenig, Henderson, & Mokhtarian, 1996; Ory & Mokhtarian, 2006) and increase (Ravalet & Rérat, 2019) in individual travel on account of telecommuting. The increase in travel is often because of an enhanced engagement in non-work activities for those who telecommute, which often reduces – or sometimes completely offsets – any travel reduction from the elimination of the commute. Even so, telecommuting (as well as of flexible work schedules) can reduce the peak hour commute traffic, itself a significant benefit. A recent Chicago based study (Shabanpour et al., 2018), which incorporated a surge in the engagement in non-work activities due to flexible work schedules, found that an increase in flexible work time hours from the baseline of 12% to 50% could result in up to 2% reduction in system-level vehicle miles traveled (VMT), resulting in about 0.71% and 1.14% reduction in greenhouse gases emissions and particulate matter emissions, respectively. The impacts can be as high as about 77% decrease in the VMT as observed in an older before-after study of a small telecommuting pilot program in California where a group of participants exclusively telecommuted for one third of the observation period (Koenig et al., 1996).

Despite its known benefits, widespread adoption of telecommuting faces many barriers. In the jobs which can accommodate telecommuting, lack of encouragement by employers and inflexible firm policies are some of the major barriers to telecommuting, among other factors (Bailey & Kurland, 2002). Besides, acceptance of telecommuting and its type (home-based-telecommute or satellite offices) also depends on country-level policies and work culture (Higa, Sivakumar, Yen, & Bui, 1998). In 2020, the COVID-19 pandemic presented a unique situation in which there was a powerful signal from governments and workplaces in most countries worldwide for their employees to telecommute. In a recent survey of 133 executives from offices across the U.S., more than 80% of them reported that post-pandemic their offices would have more telecommuting than pre-pandemic (Pwc, 2021). This merits an investigation into the new changes in the patterns of adoption of telecommuting due to the broader changes in workplace policies, government restrictions and outreach brought by the pandemic.

The impacts of the COVID-19 pandemic on the transportation sector have received extensive coverage in the academic literature. The topics typically covered by the studies so far include the impacts on changing preferences for travel modes (Eisenmann et al., 2021; Shamshiripour et al., 2020), perceptions about modes of transportation (Barbieri et al., 2021; Shamshiripour et al., 2020), operation and ridership in public transportation, aviation (Abu-Rayash & Dincer, 2020) and congestion (Selod & Soumahoro, 2020). However, the pandemic has also had a pronounced impact on individuals' activity patterns and thus trip generation patterns. One of the most effective strategies to control the spread of the virus (until mass vaccination) is to reduce the contact between individuals. Accordingly, many governments worldwide issued shelter-in-place orders and encouraged individuals to telecommute whenever possible (Cheng et al., 2020). As a result, many workplaces changed their work policies and encouraged their employees to telecommute (Belzunegui-Eraso & Erro-Garcés, 2020) or were forced by new regulations to stop on-site non-essential work activities, especially if they involved a large amount of interpersonal contacts. But not all workers had that option, and not all workers who had the option took advantage of it.

From a post-pandemic transportation planning perspective, it is important to identify who are the new adopters of full- or partial-telecommuting. It is also worthwhile to explore if these behaviors will persist after the pandemic is over, and what effects on transportation this might cause. This question can have implications for several transportation-related and other lifestyle issues, such as changes in travel demand, which eventually might affect investment in transportation infrastructure and downstream impacts of the transportation sector, and housing patterns (e.g., urban sprawl). This research inquiry can also shed the light on social inequity among the employed population, especially in emergencies in which public health risks are abnormal.

In this chapter, we analyze survey data collected independently by three research teams in Chile, Germany, and the United States of America (US) and Canada, during the initial stages of pandemic, to identify the population segments which were more likely to telecommute than others. In addition, we also investigate who reduced their commuting frequency among the population segments that did not exclusively telecommute during the initial phases of the pandemic. The main contribution of this research is to explore the factors that affect the adoption of telecommute and physical commute frequency, as well as investigate the heterogeneity in the behavior of the respondents from each country after controlling for other confounding effects attributed to differences between these countries (e.g., COVID related policies or cultural differences) and the difference in the sampling and recruiting strategies deployed by the three research teams.

The remainder of the chapter is organized as follows. Section 5.3 discusses selected relevant recent research on COVID-19 and travel behavior. Section 5.4 summarizes the data collection, construction of the variables for the models, and model estimation. The results from the model are presented and discussed in section 5.5. In the final section we conclude the chapter by presenting the major implications from the analysis.

5.3. Literature Review

There is a wealth of research informing the understanding of the adoption of telecommuting and its impacts on the transportation system (P. L. Mokhtarian, 1991; Ory & Mokhtarian, 2006; Sener & Bhat, 2011; Shabanpour et al., 2018; Yen & Mahmassani, 1997). Some of the survey-based studies conducted before the pandemic have shown that women are less likely than men to have a telecommuting option but are more likely to telecommute when they have the choice. Individuals working in manufacturing, transportation, and retail are less likely to telecommute than those working in other industries. Highly educated individuals are more likely to have the option of telecommuting and have a higher propensity to telecommute (Sener & Bhat, 2011; Singh, Paleti, Jenkins, & Bhat, 2013). The adoption of telecommuting also varies spatially. Given the option, individuals living in rural areas are more likely to telecommute but with a lower frequency than those in urban areas (Singh et al., 2013). However, the COVID-19 pandemic is a shock to the transportation system; people's travel behavior and activity patterns have changed drastically, and some of these behaviors may persist in the future. This crisis has set the agenda for many transportation researchers around the world.

Several studies have investigated these changes. These studies use a variety of data and methods, including aggregated transportation trends from Google and Apple Mobility dataset (e.g., Agarwal et al. 2020; Hadjidemetriou et al. 2020; Selod and Soumahoro 2020), stated preference surveys (e.g., Shamshiripour et al. 2020), revealed preference surveys (e.g., Circella 2021; Conway et al. 2020; Eisenmann et al. 2021), travel diary data collected through mobile phone application (e.g., Molloy et al. 2021), and public transportation ridership and supply dataset (e.g., Brough, Freedman, and Phillips 2020; Hu and Chen 2021). Almost all these studies have reported a drastic decline in the overall mobility immediately after the spread of the disease in the respective study regions. Furthermore, some studies reported a sharper drop in activity patterns, trip generations, and overall travel even before the enforcement of lockdown policies (or similar policies like curfews and shut down of restaurants, bars, cafes, or businesses in general) by the respective government in the study regions. This effect indicates that the change in travel behavior was also driven by a sense of fear of contracting the virus and not just a response to government policies (Hadjidemetriou et al., 2020; Jain, Currie, & Aston, 2021; Molloy et al., 2021). People reduced travel by engaging in in-home activities like telecommuting and e-shopping. A survey in Chicago showed that people working from home all five days a week increased from 15% (before the pandemic) to 48% (during the pandemic). The survey also reported that 13% of the respondents tried online shopping and online food delivery for the first time during the pandemic (Shamshiripour et al., 2020). Conway et al. (2020), who collected online survey responses from the entire US, also reported a significant uptake in telecommuting. Among the employed respondents, the percentage of respondents telecommuting almost doubled (40% to 80% in their sample, which seems to overrepresent telecommuters, as it is often common for online surveys) during the pandemic, as compared to before. Studies from Australia (Beck, Hensher, & Wei, 2020), Vietnam (Nguyen, 2021), and Switzerland (Molloy et al., 2021) show similar findings.

While there was an immediate sharp decline in the aggregate travel, the decrease in the amount of travel varied with the mode and socio-demographic characteristics of the population. Among the socio-demographic variables, (Molloy et al., 2021) observed that larger households showed a more significant drop in travel than those living alone; the authors suggested that those living with other people are more cautious about the virus is why there may be a more considerable drop. Another survey-based study from Chile reported that 80% of the respondents from high-income households worked from home during the first week of lockdown in Chile, but only 23% of the respondents from low-income households could do the same (Astroza et al., 2020). The reduction in travel also varied by the mode of transportation. A cross-sectional survey in Germany (Eisenmann et al., 2021), where the respondents reported their mode-use before and during the lockdown period, found a magnified mono-modal behavior during the pandemic. About 83% of the respondents restricted their behavior to just one mode of transportation instead of 68% before the pandemic. Furthermore, the mono-modal use of cars and bicycles increased, but that of public transit dropped. Studies report disproportionately steeper declines in public transit ridership also in Seattle (Brough et al., 2020), Chicago (Hu & Chen, 2021), and New York City (Wang et al., 2021).

It is important to track which modes were used by the population segments which were still traveling during the pandemic to assess the equity impacts of the pandemic, which is a central theme of this chapter. A study investigating public transportation ridership data in Kings County, Washington, found low-income and less-educated residents showed a milder change in trips during the stay-at-home restrictions due to limited ability to work remotely. Furthermore, low-income residents working for essential businesses[8] used transit for commute (Brough et al., 2020). A similar study from Chicago reported that the transit ridership decreased the most in neighborhoods with a higher proportion of more educated, high income, and white race population. Neighborhoods with a higher proportion of African American population reported a lower decline in public transit ridership (Hu & Chen, 2021). The analysis in the study suggests that residents of marginal communities (low-income, less educated and/or racial minorities) showed a lower decline in the use of public transit due to the nature of their jobs, which required commute, and lack of alternative transportation options. Similar findings from other studies

[8] https://coronavirus.wa.gov/what-you-need-know/safe-start/whats-open

indicate that the relatively disadvantaged population did not get an opportunity to reduce their trips during the pandemic and were probably captive public transportation users (Tirachini & Cats, 2020).

Many studies have also investigated how much the behavioral changes induced during the pandemic will persist once it is over (e.g., Conway et al. 2020; Molloy et al. 2021; Nguyen 2021). Most studies observed a gradual increase in travel. However, as expected, these effects varied with the mode of transportation, trip purposes, and socioeconomic characteristics of the population. In Switzerland, highly educated individuals showed the highest decrease in physical travel, but when lockdown restrictions finished, the less educated returned to previous trip levels and the educated individuals stayed at home. The behavior of educated participants during pandemic restrictions remained similar even after those restrictions were lifted (Molloy et al., 2021). In Vietnam, Nguyen (2021) also observed that educated respondents and women in their survey sample are more likely to continue telecommute after the pandemic. Finally, some studies recorded skepticism about specific modes of transportation, leading to speculations that the changes in behavior during the pandemic may persist after the pandemic is over, based on current risk perceptions. For instance, Shamshiripour et al. (2020) observed that more than 70% of the respondents reported public transit and ridehailing services as high-risk modes for travel during the pandemic.

In summary, there is an increasing number of recent studies which analyze the impact of the COVID-19 spread on travel behavior around the world. However, most of the above-mentioned studies investigate the impact of the pandemic in a specific city or a country. Given the global aspect of the pandemic it might be useful to determine whether certain behavioral changes are universal or specific to certain regions. Some studies have tried to fill this knowledge gap (Barbieri et al., 2021; Morita, Kato, & Hayashi, 2020; Selod & Soumahoro, 2020). However, the main goal of these studies is to relate the macro-level indicators at the country level (e.g., GDP) with the changes in the general traffic movement data, obtained from Google or Apple mobility datasets, due to the pandemic. Even in the survey-based studies (Barbieri et al., 2021) the focus has been on how the perception about the transportation modes is linked with macro-level country specific indicators after controlling for socio-demographics. The focus is less on how context of each country (among other factors) may introduce biases in the analyses.

We contribute to this burgeoning literature by focusing on the telecommuting behavior (instead of general travel trends) by using individual-level data collected using surveys in Chile, Canada, the US, and Germany. We pay close attention to the biases which could be introduced in our analysis due to methodological and context-specific reasons. It is worth noting that these biases are also relevant to other studies on the topic which have attempted to compare datasets from different countries. The following section presents the data collection efforts that made this research possible.

5.4. Methods

5.4.1. Data Collection

The data used in our analysis comes from three research projects from four different countries – Canada, Chile, Germany, and the US - to understand the changing travel patterns during the *first wave* of the pandemic in each of these countries. Here the first wave refers to the first time when the infection became large enough to lead to restrictions issued by the government. Figure 7-1. shows the number of new COVID-19 cases per million population, in each of the four countries, during the study period. Hale et al. (2021) created publicly available 20 indicators of government responses during the crisis in countries all over the world. They created a composite stringency index for each country. The index varied between 0 and 100, where 100 being the highest level of stringency. As shown in table 5-1, along with a summary of the data collection processes, all the four countries had an average stringency level of around 70 during the data collection process.

The team from the University of California, Davis, led the data collection in Canada and the US using online opinion panels. The research team selected 15 major cities in the US and two in Canada and carefully picked counties adjacent to the cities to understand the changing travel patterns in all kinds of neighborhoods (urban, suburban, and rural). The beginning of the survey included screener questions for key demographic information – age, gender, employment, race, ethnicity, and household income – to ensure that the distribution of these variables in the final sample mimics the distribution in the population of the study region. In all, 8,285 and 1,036 complete responses were collected in the US and Canada, respectively. The 1,000 completed responses in Germany were also collected using online opinion panels as part of a German Aerospace Center (DLR) research project. The sampling scheme ensured that the distribution of age, gender and spatial distribution in the sample reflects the actual distribution of the three variables in the country's population. Finally, researchers at U. de Chile, U. Católica, and U. de Concepción designed the Chilean survey, disseminated through online forums, social media, and a public transportation app (Transapp) thereby collecting data from a convenience sample that is not representative of the country. For instance, 48% of the sample belongs to households with a monthly income lower than 1,180 USD, while the median household income in Chile was 931 USD in 2017 (INE, 2018), suggesting that low-income households are underrepresented in the sample. However, given the relatively large sample size reached (n=4,395), all income, age, and gender strata are well covered, which allows us to analyze the effects of those variables on relevant outcomes, such as the option to telecommute. Convenience samples, which have the advantage of being a fast and affordable way to obtain results, have often been used in transportation research to analyze quickly emerging issues and new topics, particularly when a probability sampling strategy is costly for the research team (for a discussion about types of convenience sampling, see (Jager, Putnick, & Bornstein, 2017)). Table 5-2 presents the distribution of the key demographic variables in the sample from each country.

Table 5-1 Data collection strategy in each country

	Canada	Chile	Germany	US
Sample size	1,036	4,395	1,000	8,285
Region of study	Metro regions of Toronto and Vancouver	Entire Chile	Entire Germany	Metro regions of Seattle, Sacramento, San Francisco, Los Angeles, San Diego, Denver, Kansas City, Salt Lake City, Chicago, Atlanta, New York City,

				Boston, Washington DC, Tampa
Timeline	May - July 2020	March 23-29, 2020	April 6-10 2020	May - July 2020
Recruitment	Online opinion panel	Online forums, social media, email, messaging apps, and one public transportation app (Transapp)	Online opinion panel	Online opinion panel
Sampling	Quota sampling	Convenience sampling	Quota sampling	Quota sampling
Socio-demographic targets for the data collection	Age, gender, household income, employment, race	N/A	Age, gender, spatial distribution	Age, gender, household income, employment, race, and ethnicity
Average stringency index in the study period	76.8	68.0	69.4	68.9

Table 5-2 Distribution of key socio-demographic variables in each dataset

	Canada (n=1,036)	**Chile (n=4,395)**	**Germany (n=1,000)**	**U.S.A (n=8,284)**
Age				
18 to 35 years old	40.7%	55.4%	32.6%	35.8%
36 to 60 years old	41.2%	39.5%	41.1%	42.2%
61 years old or more	18.1%	5.1%	26.2%	22.0%
Education				
Lower than bachelors	41.7%	75.1%	71.1%	44.9%
Bachelors or higher	58.3%	24.9%	28.9%	55.1%
Number of Household members				
One	18.9%	8.0%	28.5%	17.5%
Two	30.1%	20.5%	37.1%	32.2%
Three or more	51.0%	71.5%	34.4%	50.2%
Number of Vehicles in Household				
None	16.1%	31.6%	19.2%	10.1%
One	46.8%	44.3%	51.7%	33.7%
Two or more	37.0%	24.0%	29.1%	56.2%
Female				
Yes	57.7%	59.1%	50.2%	59.0%
No	42.3%	40.9%	49.8%	41.0%
Essential Worker[9]				
Yes	28.6%	30.3%	17.1%	30.3%

[9] The definition of 'Essential Workers' in this table and the rest of the analysis is explained in section 3.2

No	71.4%	69.7%	82.8%	69.7%
Household Income*				
Low	29.5%	25.7%	38.3%	32.9%
Medium	34.2%	32.8%	53.5%	31.1%
High	36.3%	41.4%	8.2%	36.0%

**Income categories*:
Low: US & Canada – Less than $50,000 per year; Chile - Less than CLP600, 000 per month; Germany - less than 2,000 Euros per month
Medium: US & Canada – $50,000 to $100,000 per year; Chile - CLP 600,000 to $1,500,000 per month; Germany - 2,000 to 5,000 Euros per month
High: US & Canada – More than $100,000 per year; Chile - More than $1,500,000 per month; Germany - More than 5,000 Euros per month
Currency:
$: US Dollar, CLP: Chilean Peso. $ 1 = CLP 700, Euro 1 = CLP 850

5.4.2. Variable Selection and Construction

To analyze which individuals from the working-population were more likely to telecommute or reduce their physical commute, we estimated two regression models. The study, for all datasets, has two dependent variables: the behavior of exclusively telecommuting or not (binary) and the frequency of travel to work if not exclusively telecommuting (ordinal). Figure 5-1 shows the distribution of these variables in the samples from the four countries. Table 5-3 shows the cross tab between telecommute and key demographic variables in each country's sample.

The survey conducted in the U.S.A., Canada, and Germany requested respondents to report the number of days per week they physically traveled to their work locations during the pandemic. This value became an ordinal variable – '*Low*' (Less than 5 days per week)," *Regular*' (5 days per week), and '*High*' (more than 5 days per week). The survey in Chile asked respondents to report the number of work trips performed per week using eight travel modes (car, motorcycle, bus, subway, bicycle, walk, and ride-hailing). We added trips from each mode to everyone from Chile to get the total number of trips made per week during the first week of the COVID-19 pandemic. Assuming each person makes two commute trips per day, we divided the total number of trips by two to estimate the number of days per week traveled to work by everyone during the pandemic. This approximate number of days traveled was then defined into three ordinal variables – '*Low'* (number of days <= 4), '*Regular*' (4<number of days <= 6), and '*High'* (number of days >6), to match the categories considered in the other countries. Figure 5-1 shows the distribution of the dependent variable.

Table 5-3 Crosstab between the behavior of exclusively telecommuting or not and key demographic variables of the working population each country

	Canada		Chile		Germany		US	
	Yes (n=257)	No (n=320)	Yes (n=509)	No (n=2,688)	Yes (n=181)	No (n=319)	Yes (n=2,111)	No (n=2,447)
Age								
18 - 35 yrs.	35.80%	46.30%	45.60%	48.70%	34.30%	30.40%	33.60%	42.00%
35-60 yrs.	54.90%	45.30%	49.10%	47.50%	53.00%	60.80%	53.80%	48.00%
60 yrs. or older	9.30%	8.40%	5.30%	3.70%	12.70%	8.80%	12.60%	10.00%
Gender								
Male or others	37.00%	55.30%	37.50%	43.90%	48.60%	52.00%	41.70%	52.30%
Female	63.00%	44.70%	62.50%	56.10%	51.40%	48.00%	58.30%	47.70%
Education								
Lower than Bachelors	20.60%	33.80%	61.70%	70.90%	43.30%	26.80%	22.50%	43.70%
Bachelors or higher	79.40%	66.30%	38.30%	29.10%	56.70%	73.20%	77.50%	56.30%
Household Income								
Low	16.00%	23.10%	15.30%	27.70%	19.00%	37.30%	16.80%	31.50%
Medium	31.50%	36.60%	27.60%	33.80%	34.80%	39.30%	30.70%	35.90%
High	52.50%	40.30%	57.00%	38.50%	46.10%	25.30%	52.50%	32.60%
Number of household members								
One	18.10%	19.80%	9.20%	9.67%	30.30%	25.10%	17.40%	16.40%
Two	32.60%	25.80%	25.10%	22.00%	40.00%	33.60%	32.80%	28.70%
Three or more	49.20%	54.30%	65.60%	68.30%	29.70%	41.30%	49.80%	54.80%
Number of Vehicles in the Household								
No vehicle	12.10%	12.50%	25.50%	34.00%	11.00%	12.80%	7.00%	6.30%
One	52.90%	46.40%	44.90%	44.90%	59.10%	52.90%	35.10%	33.70%
Two or more	35.10%	41.10%	29.40%	21.10%	29.80%	34.10%	57.80%	59.80%
Essential Worker								
No	87.20%	36.60%	88.20%	66.20%	93.40%	76.30%	85.50%	25.80%
Yes	12.80%	63.40%	11.80%	33.80%	6.50%	23.70%	14.50%	74.20%

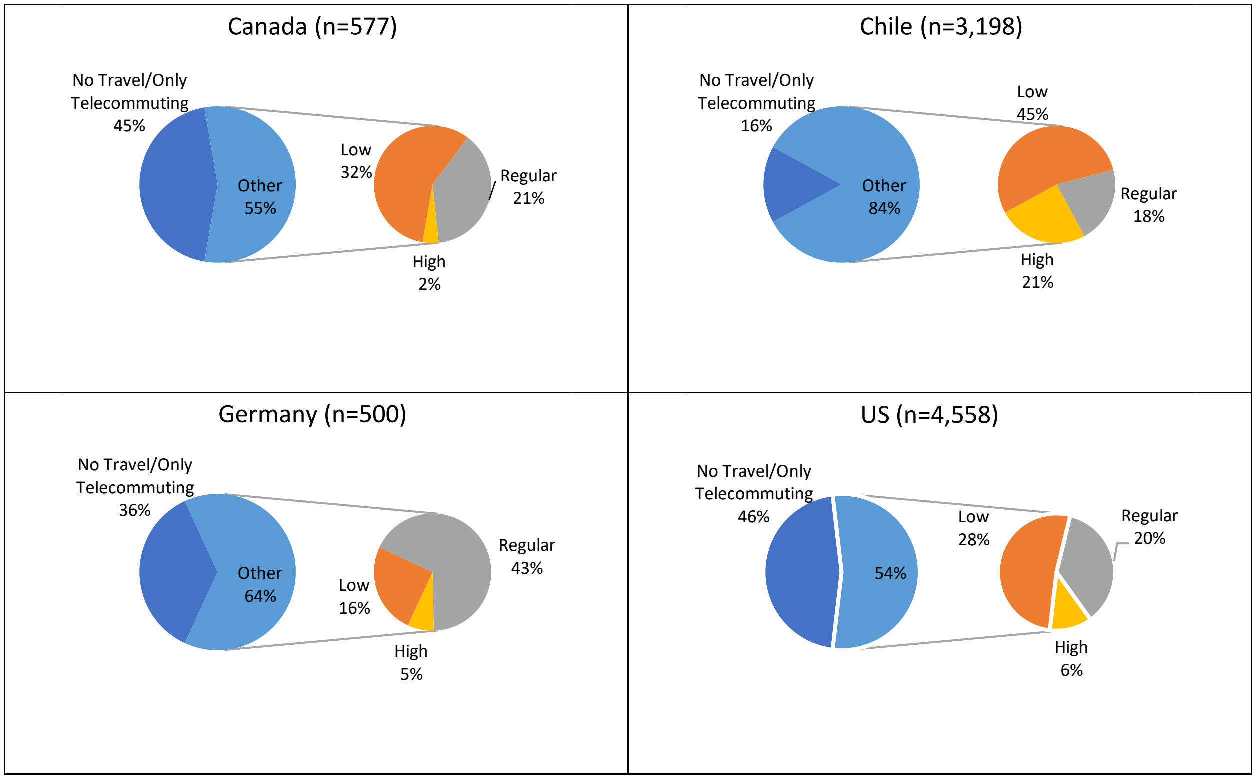

Figure 5-1 Telecommuting and physical commute in the sample from the four countries

In our modeling approach, explanatory variables only include the socio-demographic characteristics of the respondents. While most of the questions asking respondents about their socio-demographic characteristics were straightforward and consistent in the three questionnaires, the question about job type (*essential workers*) was asked differently and required some processing before its inclusion. In the US and Canada, respondents reported their level of agreement with the statement – "*The nature of my job requires me to physically go to work*" – on a five-point Likert scale. All those who agreed with the statement were labeled as essential workers. The respondents from Chile indicated they were essential workers by responding to categorical questions asking if they worked in healthcare, pharmacy, police jobs, which expected them to report to work during the pandemic. Finally, in Germany, the respondents were asked, "*What is your current profession?*" in an open-ended question. We created a dummy variable in the dataset that takes the value '1' if the respondents' profession overlapped with occupations including healthcare workers, police, emergency respondents, firefighters, etc. Please note that being an essential worker does not necessarily imply that the respondent cannot telecommute in the unusual circumstances presented by the pandemic. For instance, a respondent could be a doctor (identified as essential worker in this study) who could 'telecommute' by seeing their patients over a video call, depending on context (e.g., availability of internet, acceptance of medical advising over video calls etc.). Relatedly, Blau, Koebe, and Meyerhofer (2020) used the guidelines issued by the Department of Homeland Security (DHL) in the US to identify the group of essential workers in the US and found that some of the jobs could be performed by working from home.

5.4.3. Model Estimation

We jointly estimate a binary logit model (behavior of exclusively telecommuting or not) and an ordinal logit model (frequency of physical travel) where the frequency of travel is only observed if the individual is not exclusively telecommuting. We consider different specifications for both, instead of estimating a single ordered logit model, to allow for possible differences between the factors affecting the behavior of commuting physically and the frequency of physical commute. We follow this approach because, in general, the marginal effect of independent variables on the behavior of travelling is expected to be very different from their effect on the quantity of travel (Cameron & Trivedi, 2005; Sener & Bhat, 2011; Singh et al., 2013). Our results confirm this hypothesis, as later verified by the signs, magnitude, and significance of the coefficients in the models.

The binary model can be represented in the following equations, where y_i^* is a latent variable that can be interpreted as the propensity to commute, which is explained by observed characteristics of $\boldsymbol{X_i}$, estimated coefficients $\boldsymbol{\beta_c}$ (which can vary by the country), and ε_i^* being the error term with iid Gumbel assumption. Instead of the latent variable y_i^*, the researcher observes the binary variable y_i that records the participation for each individual i, and which is defined by the cut-off τ_c^0 that can be estimated for each country c.

$$y_i^* = \boldsymbol{\beta_c} * \boldsymbol{X_i} + \varepsilon_i^*$$

$$y_i = \begin{cases} 1\ (i\ physically\ travells\ at\ least\ once\ a\ week), if\ y_i^* \geq \tau_c^0 \\ 0\ (i\ exclusively\ teleworks), if\ y_i^* < \tau_c^0 \end{cases}$$

The following equations explain the ordinal model for the frequency f_i of physical commute, an ordinal variable that is observed only if the individual *i* has made the decision not to exclusively telecommute (i.e.,$y_i^* \geq \tau_c^0$). In this model, f_i^* is a latent variable explained by observed characteristics of $\boldsymbol{X'_i}$, estimated coefficients $\boldsymbol{\alpha_c}$ (which can vary by country), and ϵ_i^* being the error term with iid Gumbel assumption. ζ_c^n is the *n* cut-off estimated for each country *c*.

$$f_i^* = \boldsymbol{\alpha_c} * \boldsymbol{X'_i} + \epsilon_i^*$$

$$f_i = \begin{cases} 3\ (high\ frequency\ of\ physical\ commute), if\ f_i^* > \zeta_c^2 \\ 2\ (regular\ frequency\ of\ physical\ commute), if\ \zeta_c^1 < f_i^* \leq \zeta_c^2 \\ 1\ (low\ frequency\ of\ physical\ commute), if\ \zeta_c^0 < f_i^* \leq \zeta_c^1 \end{cases}$$

The iid assumption of ε_i^* and ϵ_i^* in the above equations is a strong (and most likely inaccurate) assumption. These disturbance terms account for the differences in each research team's recruitment and sampling strategies in the four countries. Moreover, among other unobserved effects, there could be country-specific effects (e.g., culture and differences in COVID-19 policies) which could have affected individual's behavior of telecommuting and their frequency of physical commute. In other words, the estimated coefficients can have heterogeneity across countries. While the observed independent variables may play a more prominent role in explaining the behavior than the unobserved effects for respondents from one country, the reverse may be true for the respondents from another country. Besides, a scale difference between the binary and the ordered models can be expected because of their different nature. However, this second scale difference cannot be identified because there is no reason to a priori maintain that some coefficients may be shared among the binary and the ordered models. Identification is thus achieved by fixing, for both models, the scales of Canada and the US to 1 and estimating country-specific scale parameter μ_c and μ'_c. Nevertheless, given that the difference in scale between the binary and the ordered model exists, we note that the size of the coefficients is not necessarily comparable among them. Following, e.g., Train (2009; 2.5.2), the equations are given as follows:

$$y_i^* = \mu_c \boldsymbol{\beta_c} * \boldsymbol{X_i} + \varepsilon_i$$

$$y_i = \begin{cases} 1\ (i\ physically\ travells\ at\ least\ once\ a\ week), if\ y_i^* \geq \tau_c^0 \\ 0\ (i\ exclusively\ teleworks), if\ y_i^* < \tau_c^0 \end{cases}$$

$$f_i^* = \mu_c' \boldsymbol{\alpha_c} * \boldsymbol{X'_i} + \epsilon_i$$

$$f_i = \begin{cases} 3\ (high\ frequency\ of\ physical\ commute), if\ f_i^* > \zeta_c^2 \\ 2\ (regular\ frequency\ of\ physical\ commute), if\ \zeta_c^1 < f_i^* \leq \zeta_c^2 \\ 1\ (low\ frequency\ of\ physical\ commute), if\ \zeta_c^0 < f_i^* \leq \zeta_c^1 \end{cases}$$

For comparison purposes, we also estimated a *base model* (not shown in this chapter) where the scale terms for all countries in both binary and ordered logit models were constrained to 1.

As mentioned above, we combined the survey data collected from four different countries to identify the common and diverging patterns about the personal characteristics of people telecommuting and physically commuting during the first wave of the pandemic. The sampling and recruitment methodologies of the surveys in the US and Canada are different from those in Chile and Germany. This difference is not ideal because the four countries also vary in context, culture, transportation supply (e.g., frequency of public transit), and COVID response policies. The observed patterns in the analysis could be attributed to both sampling/recruitment vs. context-specific effects. It is difficult to isolate the contribution of one effect from the other in the observed patterns. However, combining all the datasets and analyzing them in one model is still a better approach than analyzing the dataset from each country in isolation and then comparing the effects. This method diminishes the potential bias due to the non-response of specific segments of the population (attributable to the sampling strategies), which could correlate with observable (e.g., gender, income, and age) and unobservable (e.g., being tech-savvy enough to answer surveys online) respondent characteristics. Estimating a model which controls for key socio-demographic variables, and estimating constants for each country, allows us to see the effect of each variable, keeping all else equal. In addition, we use scale parameters in the model, which account for the variance differences between countries as they would be confounded and may have been misinterpreted without a joint interpretation.

5.5. Results and Discussions

Table 5-4 shows the results from the model with discrete scale parameters for each country. At first, the scale parameter for the US was set to 1, and the scale parameters for all the other countries were estimated relative to it. Upon a closer look, the scale parameter for Canada was not significantly different from 1. This result makes sense conceptually because the recruitment method and sampling in the US and Canada were the same. Also, the transportation trends in the US and Canada are very similar to each other, when compared with Germany and Chile. Thus, in the final model, the scale parameter is constrained to be 1 for both Canada and the US, and different scale parameters are only estimated for the responses from Germany and Chile. The values of their scale parameters are less than 1 in the model predicting the behavior of travelling but larger than 1 in the model predicting the frequency of physical commute. Recall, the value of the scale parameter indicates whether the model is more deterministic (> 1) or probabilistic (< 1). Thus, for those cases from Chile and Germany, factors not controlled for in the model (e.g., differences across countries in recruitment and sampling methods, confirmed COVID-19 cases and deaths at the moment, non-pharmaceutical interventions, and mobility culture) play a *bigger* role than the socio-demographics (i.e., more probabilistic) in explaining the behavior of commuting physically than these factors do for their counterparts in North America. In contrast, those socio-demographic variables controlled for in the model account for the frequency of physical commutes better than unobserved variables do (i.e., more deterministic) for cases from Chile and Germany, in comparison to cases from North America. These nuances would be lost, and biased coefficients would have been estimated in the model, had there been no scale parameters.

We initially also estimated a base model where the scale parameters for all countries was set to 1 (not shown in this chapter). Two broader observations about the comparison between the base model and the model with scale parameters (shown in Table 5-4) are worth pointing out. First, the model with scale parameters has lower AIC and BIC than the base model, indicating a better fit, suggesting that the scale differences among countries exist. Second, the estimates of most of the significant parameters in the ‘behavior of travelling at least once a week’ model are systematically larger than in the base model, and the reverse is true for the "frequency of physical commute' model. A systematic difference in the values of the estimates between the base model and model with scale parameters is expected because the base model shows the general estimates of all four countries. In contrast, the estimates of the coefficients of the explanatory variables in the discrete scale model are true only for the US and Canada (where the scale is set to 1). And by looking at the scale parameter values, the estimates of the coefficients of the explanatory variables are larger for Germany and Chile (in comparison with the US and Canada) in the behavior of travelling at least once a week model but smaller in the "frequency of physical commute” model. Again, this difference shows how, for respondents from Chile and Germany (relative to the US and Canada), the observed variables are playing a bigger role than the unobserved variables in explaining the behaviors of exclusively telecommuting but not the frequency of commute.

Age, job nature, education, and income (common patterns across four countries): In all four countries, age does not affect the telecommute behavior, but being in the age group *36-59 years old* is associated with a lower frequency of physical commute than in the age group *18-24 years old.* This result is expected given that the health risks associated with the Sars-Cov-2 virus increase with age. Moreover, respondents in the age group 36-59 years old are more likely to be in a stage of life where they have to take care of minors who maybe at home due to closing of schools and daycares. However, being 60+ years old has no significant effect, though the lack of significance of this variable might be explained, at least in part, by the relatively small sample size of this age group across all four sample groups. As expected, essential workers have a higher likelihood of commuting to work during the pandemic and do so at a higher frequency than non-essential workers. This result makes sense as the nature of the job requires individuals to work on site, on the frontlines. All surveys conducted in this chapter did not capture the details about the nature of the respondents' jobs (e.g., white-collar jobs), other than being essential workers. Education of the employed respondents, to an extent, captures this information.

Individuals with more than a bachelor's degree tend to have a lower likelihood of commuting to their regular workplace. Not surprisingly, having a bachelor's degree is also associated with a lower frequency of physical commute even if college graduates report to work on site. As expected, household income is negatively associated with having physical commute in all four countries; however, this association is statistically significant only for the cases from Chile and the US. In the remainder of this section, we discuss the differences in the coefficients' signs of socioeconomic variables across the four countries in the model for two dependent variables.

Household Structure: Only in Chile, living with three or more people in the household is associated with a higher frequency of physical commute than those living alone. The variable is not significant in explaining the behavior of travelling at least once a week in any country. We investigated other demographic and attitudinal characteristics of the individuals living with three or more people in the household to further explain this observation in the sample from Chile. As shown in Figure 5-2, those living with three or more people in the household reported a higher proportion of essential workers (35%) than those living alone (27%). A smaller proportion of the respondents with three or more people in the household have a bachelors' degree or higher (25%) when compared with those living alone (44%). The survey from Chile also asked respondents to indicate their agreement with the statement - "I am afraid that my household income decreases due to the Coronavirus Pandemic" - on a Likert scale (1-5). Those living with three or more people in the household have statistically (t-test) higher levels of agreement with this statement than those living alone. In summary, respondents from Chile with three or more people living in the household have lower levels of education and a higher proportion of essential workers were more likely to face economic hardships during the pandemic. These factors could explain why people living in households with three or more individuals reported working at a higher frequency. This result is the opposite of what Molloy et al. (2021) found in their study conducted in Switzerland. They observed that individuals living in larger households reduced their travel during the pandemic as they were more concerned about catching and spreading the disease in their household. Even though the sample from Chile is not representative of the country, the observed differences in the behavior of the respondents from large families in Chile vs. Switzerland could be stemming from differences in the society in the two countries.

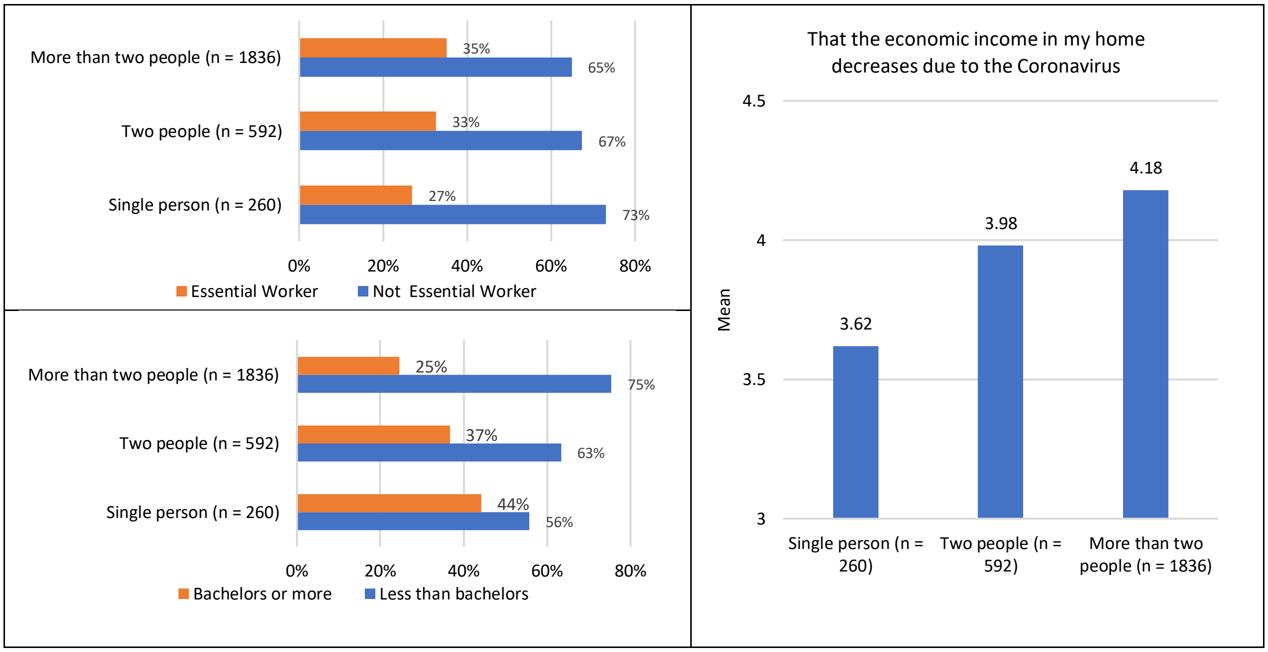

Figure 5-2 Socioeconomic situations of large households in the sample Chile

Note: In the sample from Chile, respondents who live in households with three or more members face the economic impacts of the pandemic more than other groups, have a higher proportion of essential workers, and have a lower level of education.

Gender: In all countries, except Germany, women are significantly less likely than men to travel outside of their homes for work during the pandemic. This finding aligns with another study (Ding et al., 2020), suggesting that women have a higher risk perception of COVID-19 than men. Alternatively, women may telecommute more than men to care for household members staying home during to the pandemic (e.g., home-schooling children during school closer). In comparison, gender is not significant among the German cases, and we speculate that this pattern is related to their occupations. In fact, only in Germany, the share of women at essential jobs was larger than that of men (see Figure 5-3). Note that given the small sample size (and limitations in recruitment and sampling), patterns present among German cases in Figure 5-3 might not represent the overall patterns in Germany.

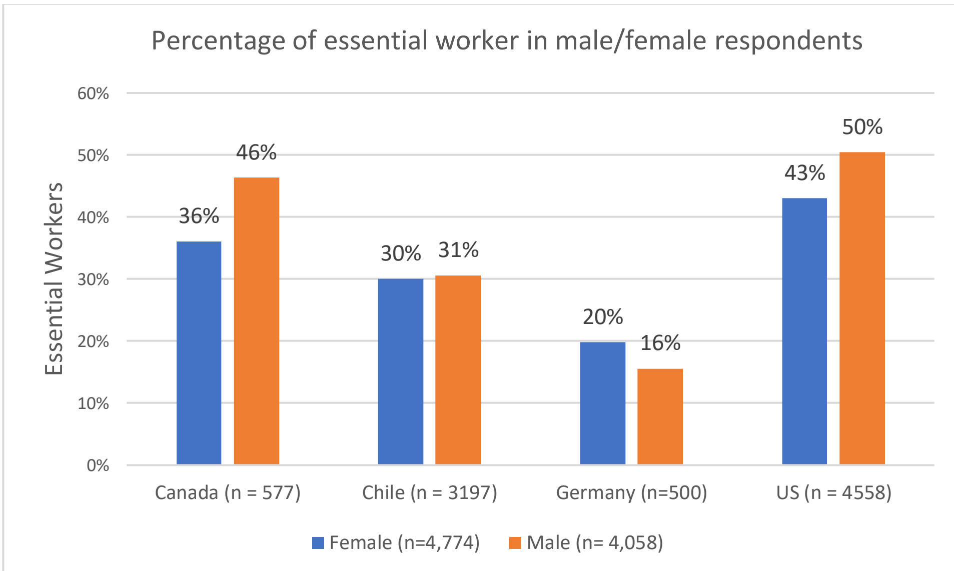

Figure 5-3 Percentage of essential workers by gender in the sample from the four countries

Note: In Germany, more women respondents reported being essential workers as opposed to other countries (y-axis: percentage of essential workers)

Full-time workers: In the US, being a full-time worker has opposite effects on the two dependent variables. Full-time workers were significantly less likely (than part-time workers) to physically commute to workplaces during the pandemic. However, once full-time workers decided to travel outside the household, they presented more frequent physical commutes than those by part-time workers. In the other countries, full-time workers had a higher frequency of commute and either a positive or no significant effect in traveling out of the home. Further investigation found that there are two different demographics of full-time workers in the US. About three-quarters of full-time workers who traveled outside of their homes during the pandemic are essential workers, and 62% of these physically commuting full-time workers have a bachelor's degree (see Figure 5-4). In comparison, only 13% of the full-time workers who telecommuted exclusively during the pandemic are essential workers. Also, 81% of the full-time telecommuters have a bachelor's" or a higher degree. Furthermore, the survey in the US also asked the respondents to report if paying the bills was a struggle or not. A higher proportion of full-time workers who physically commuted reported having troubles paying their bills when compared with the full-time workers who telecommuted exclusively. These insights explain the different signs of coefficient observed for the variable of full-time workers in predicting behavior of travelling at least once a week and frequency of commute.

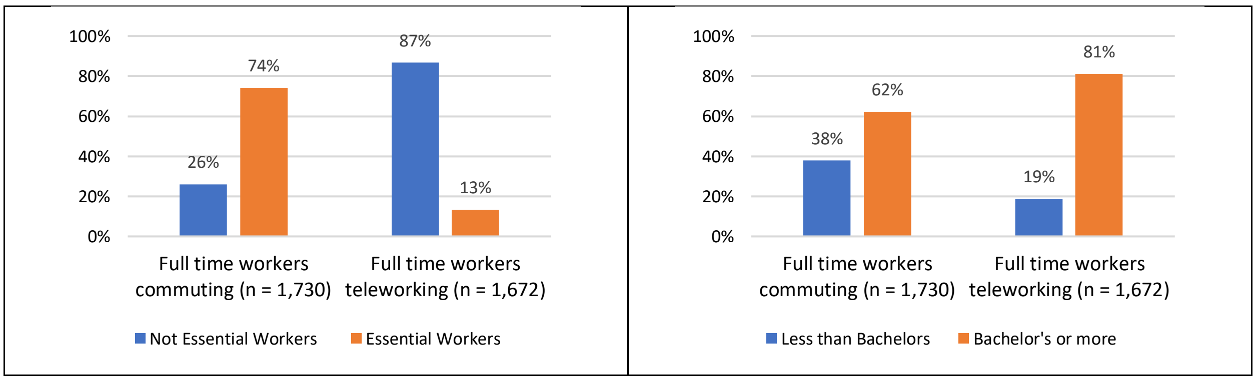

Figure 5-4 Heterogeneity in the demographics of full-time workers in the sample from the US

Note: Two different groups of telecommuters in the US (telecommuting and physically commuting). The telecommuting full-time workers tended to be non-essential workers and more educated.

Vehicle Ownership: The number of vehicles owned by the household is significant in explaining the commuting behavior only for the sample from Chile and the US. In Chile, the respondents who own one vehicle or more reported a lower frequency of physical commute than respondents who do not own a vehicle. This finding suggests that in Chile, the segment that had to travel regularly for work did so using modes other than private cars. In the US, the respondents who own vehicles were more likely to telecommute during the pandemic exclusively. Figure 5-5 shows the characteristics of zero vehicle households in the sample from each country. In the samples from Germany and Chile, respondents who do not own a vehicle are low- and medium-income, and 80% of them don't have a bachelor's degree. These patterns do not hold true for those cases from Canada and the US, among which a quarter of carless respondents are high income and the majority have a bachelor's degree or higher. It is worth reminding the readers that high education and high income characteristics of the carless respondents from the US and Canada is an artefact of the sampling method. We recruited respondents from commercial online opinion panels, which tend to more educated than the true population. This correlation of zero vehicle households in our sample with high income and education could explain a significant and negative association of vehicle ownership with the behavior of travelling at least once a week.

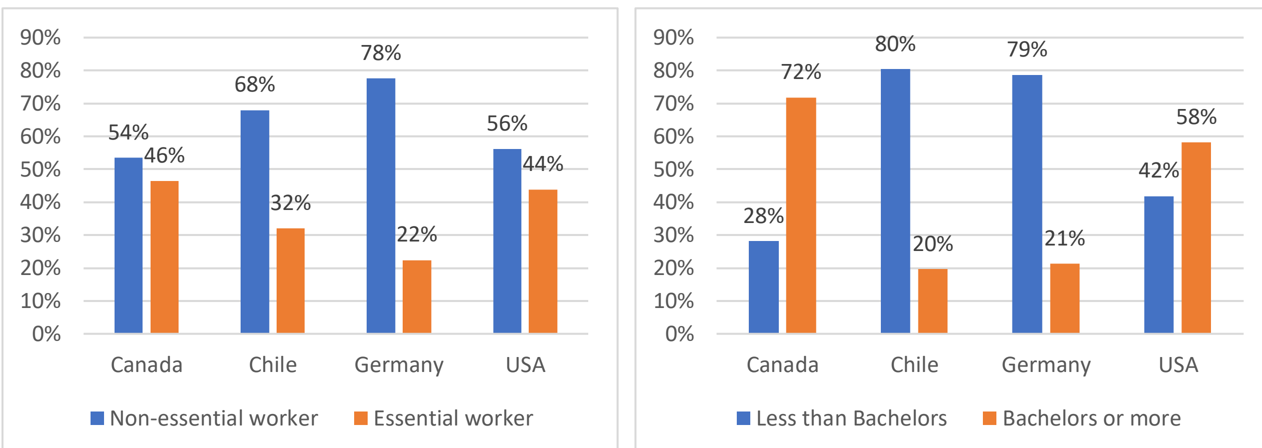

Figure 5-5 Characteristics of the respondents with zero vehicles in the household in the sample from each country

To briefly summarize the discussion above, we would like to introduce the term *affluence* into the discussion. Broadly defined, respondents with higher household income, education level of a bachelor's degree or higher, and non-essential jobs can be described as *affluent*. In all four countries, affluent respondents were more likely to work exclusively from home during the pandemic than the less affluent ones. Those affluent workers who did travel for work also reported a lower frequency. In this context, the one of the contributions of this chapter is in identifying how other demographic characteristics of the affluent respondents varied across the sample from four countries. Table 5-5 summarizes the demographic characteristics (other than those used for the definition of affluence) of the respondents from each country who exclusively telecommuted or traveled to work at a lower frequency if not exclusively telecommuting.

Table 5-4 Final estimated model

	Behavior of travelling at least once a week (binary)		Frequency of Physical Commute (ordered)	
	Estimate	Rob.t-ratio (0)	Estimate	Rob.t-ratio (0)
Age (Base = 18 -35 yrs.)				
36 - 59 yrs.			-0.0983	-1.96
60 yrs. and older			0.0252	0.24
Number of HH members (Base = Living alone)				
2 Members - Canada			-0.0937	-0.32
2 Members - Chile			0.0782	0.68
2 Members - Germany			-0.319	-1.43
2 Members - US			0.0649	0.50
3 Members or more - Canada			0.0772	0.28
3 Members or more - Chile			0.219	1.95
3 Members or more- Germany			-0.237	-1.13
3 Members or more - US			0.0569	0.44
Number of cars in HH (Base = No cars)				
One - Canada			0.0982	0.35
One - Chile			-0.154	-1.95
One - Germany			-0.0386	-0.17
One - US			0.183	1.03
Two or more - Canada			-0.0011	0.00
Two or more - Chile			-0.348	-2.99
Two or more- Germany			-0.0756	-0.29
Two or more - US	0.238	2.93	0.134	0.74
Education level (Less than Bachelors')				
Bachelors or more	-0.598	-7.79	-0.280	-4.66
Sex (base = not female)				
Female - Canada	-0.798	-3.71	0.0697	0.34
Female - Chile	-0.605	-2.24	-0.317	-4.40
Female - Germany	-0.347	-1.16	-0.0645	-0.39
Female - US	-0.478	-6.26	-0.203	-2.51
Household Income (Base = Low)				
Medium-Canada	0.007	0.02	-0.169	-2.76
Medium-Chile	-0.858	-2.14		
Medium-Germany	0.018	0.05		
Medium-US	-0.158	-1.48		
High-Canada	-0.307	-1.06	-0.516	-7.10
High-Chile	-2.04	-4.39		
High-Germany	-0.285	-0.49		
High-US	-0.651	-5.99		
Essential Worker (Base = No)				
Yes	2.72	36.15	0.559	7.41
Full-time worker (Base = No)				
Yes - Canada			0.803	3.40
Yes - Chile	1.09	3.64	0.267	3.42
Yes - Germany			1.37	3.37
Yes - US	-0.172	-1.86	1.10	10.75
Constants				
Cut off 1 - US & Canada			0.954	4.93
Cut off 2 - US & Canada			3.08	14.94
Cut off 1 - Chile			-0.0396	-0.23
Cut off 2 - Chile			0.983	5.70
Cut off 1 - Germany			-0.134	-0.27
Cut off 2 - Germany			4.12	6.90
Canada	0.323	1.16		
Chile	4.57	6.17		
Germany	0.947	2.40		

U.S.A.	-0.027	-0.23		
Scale				
Canada	1.00		1.00	
Chile	0.42**	7.70	1.32*	7.72
Germany	0.69**	4.69	1.82*	3.69
US	1.00		1.00	
Model Fit				
Number of observations	8459			
LL (start)	-9181.38			
LL (final, whole model)	-8910.09			
AIC	17942.18			
BIC	18371.81			
Estimated parameters	61			

*Significantly different from 1 at p value <0.1
**Significantly different from 1 at p value <0.05

Table 5-5 Country-specific characteristics of affluent respondents who telecommuted or reported a lower frequency of physical commute during the pandemic.

	Gender	Job Type (full-time vs. part-time)	Household Structure	Vehicle Ownership
Canada	Women are more likely to telecommute; no effect on the frequency of commute	Full-time workers have a higher frequency of physical commute	No effect	No effect
Chile	Women are more likely to telecommute and travel less frequently to work	Full-time workers have a lower likelihood of telecommuting and a higher frequency of physical commute	Individuals living alone travel at a lower frequency for work	Vehicle owners travel at a lower frequency for physical commute
Germany	No effect	Full-time workers have a higher frequency of physical commute	No effect	No effect
US.	Women are more likely to telecommute and travel less frequently to work	Full-time workers have a higher likelihood of telecommuting and a higher frequency of physical commute	No effect	Individuals with a car more likely to telecommute

What would be the pandemic's impact on the transportation system? To answer this question, we compare pre-pandemic practice and post-pandemic expectation of telecommuting. Figure 5-6 shows the degree of exclusive telecommuting before and during the pandemic among the *affluent respondents* in the sample from all four countries. Please note that figure 5-6 is not a result of the model shown in table 5-4, but is based on the descriptive statistics of the survey data. The affluent respondents in the sample from Chile had the lowest levels of telecommuting (~2%) before the pandemic. The affluent respondents from all the other countries were roughly on the same level (11%-14%). Among the affluent respondents, the highest uptakes of exclusive telecommuting are the US (79%) and Canada (68%), followed by Germany (52%) and Chile (42%). However, when looking at the expectation to continue telecommuting among the affluent respondents from all four countries, the order reverses. The majority of the affluent telecommuting respondents from Germany (81%) and Chile (78%) reported that this telecommuting behavior would continue or increase in the future. The corresponding figures were slightly lower in the US (65%) and Canada (69%).

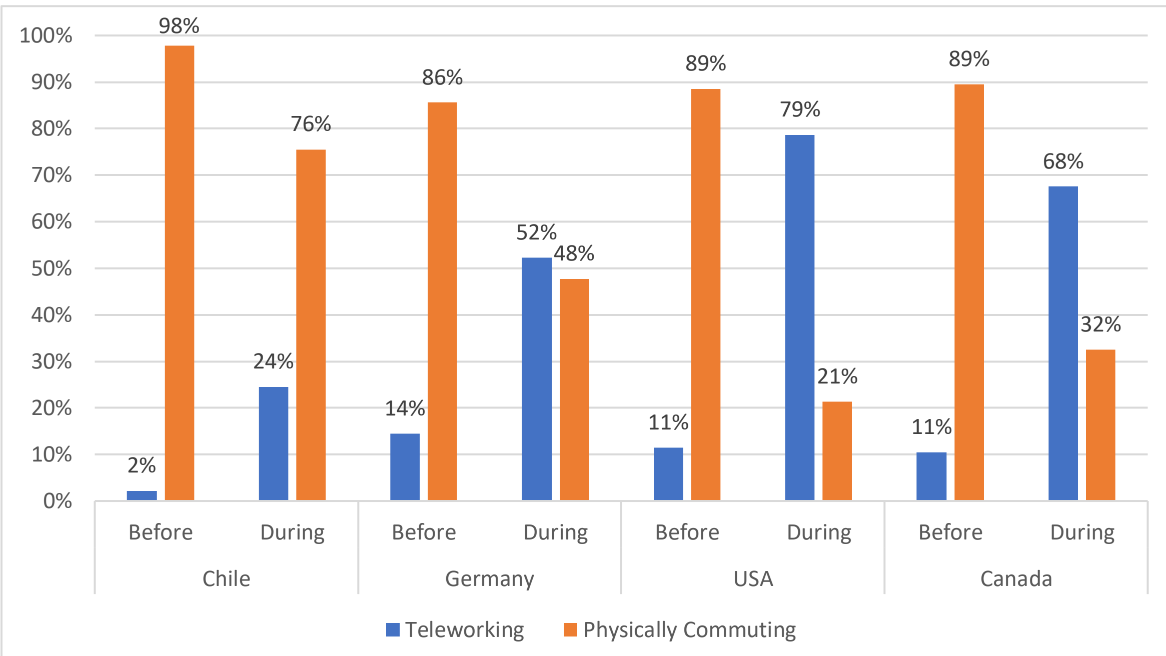

Figure 5-6 The telecommuting behavior of 'affluent' respondents in the sample from each country before and during the pandemic

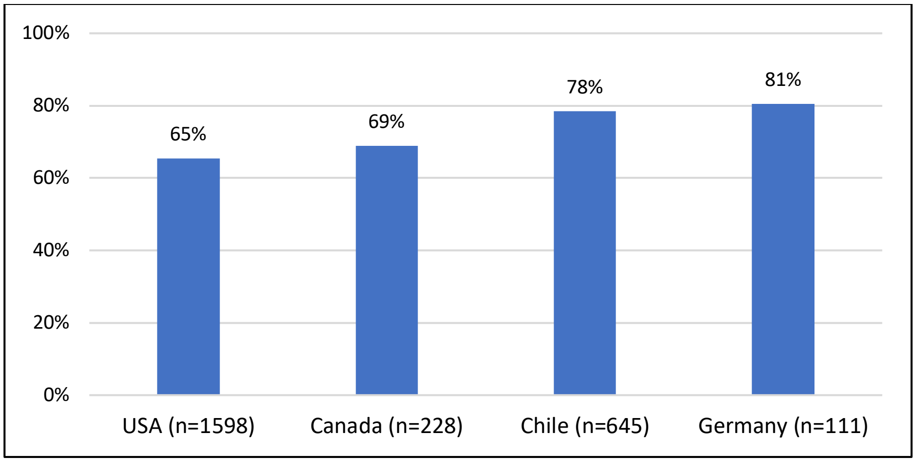

Figure 5-7 Percentage of affluent respondents in the sample from each country who expect a long-term continuity or increase in telecommuting

5.6. Conclusion

In this chapter, we merged survey datasets collected from the U.S.A., Canada, Germany, and Chile, and examined the socioeconomic characteristics of those who exclusively worked from home or commuted to the workplace during the early phase of the pandemic. Our modeling results revealed common patterns in all these countries: non-essential, college-educated, or relatively wealthy (i.e., affluent) workers had a higher chance of working exclusively from home *and* low frequencies of physical commutes, if they commuted to work. Despite these similarities, substantial discrepancies in telecommuting practice by key factors were present across countries (see Figure 7-2). Overall, the US and Canada presented larger shares of those who worked entirely from home than Germany and Chile: e.g., Chile reported the smallest shares of exclusive telecommuters among four countries. The gap in the exclusive-telecommuter shares between essential and non-essential workers is the largest in the US, and the smallest in Chile. In other words, essential workers are under greater health risks (than their non-essential counterparts) in the US than in the other countries. Interestingly, a larger share of German essential workers commutes to work at a medium frequency than their counterparts in the other countries; a larger share of Chilean essential workers reports to work at a high frequency than those in the other countries. Although it is universal that essential workers are under greater health risks, not all essential workers in these countries underwent the same level of health risks. Thus, each country may want to prioritize their limited resources to help the group with the greatest health risk, even among essential workers.

By analyzing data from multiple countries, we could uncover unique, country-specific characteristics of exclusive telecommuters and physical commuters during the pandemic. The meaning or context of a few sociodemographic factors differed greatly by country: e.g., household size, full/part-time worker status, gender, and vehicle ownership. We found two important implications. First, the ways that these factors are associated with working from home and physical commutes differed by country. Thus, we cannot simply borrow an approach, proven effective in one country in terms of targeting sociodemographic subgroups with more needs, and apply it to another country. Context matters, and this chapter presents one effective way to understanding various contexts. Second, our comparative study helped identify those areas for which each country does better than others, and those areas for which they need to (further) improve. For instance, in Chile, household size is *positively* associated with physical commutes in Chile, which is the opposite to a pattern reported in Switzerland (as reported in Molloy et al. (2021)). That is, the Chilean government needs to respond to unique travel needs of larger households during the pandemic, more so than their counterpart in Switzerland.

Not surprisingly, we found universal patterns across developed and developing countries in our study in particular regarding the fact that affluent workers could avoid potential exposure to viral infection and contraction during the pandemic by exclusively working from home or commuting less frequently to a much greater extent than other groups. These patterns highlight an important challenge related to social equity during the pandemic. How can/should policymakers and transportation professionals help those who report to work and maintain basic functions in society during a health crisis? First, we better identify their travel needs and make their daily travel safe and smooth. Prioritizing them for personal protective equipment, testing, medical treatment, and vaccination could be effective ways to handle their concerns while protecting them. Also, we advise policymakers to invest in the safety of alternative transportation systems to facilitate the safe movement of carless individuals during such events (Tirachini & Cats, 2020).

We are aware of a few limitations of this chapter, and we suggest directions for future research. Survey methods including sampling frames and recruitment methods differ by country, which does not allow us to separate out effects of survey methods from those of unique context in individual countries. Thus, consistent survey methods are required to identify the latter on behavioral changes during a disruptive event at the international scale. Also, survey questionnaires vary across countries, which greatly limited an available set of common explanatory variables for modeling. For future studies, we recommend including similar questions, and especially attitudinal statements that help in understanding the reasons behind individuals' behaviors. Last but most importantly, the pandemic has been constantly evolving in terms of the spread of the virus, preventive measures by the government, businesses, and individuals, inoculation, and recovery. Thus, follow-up surveys and analyses are critical to determine the ways that temporarily adopted behaviors last long after the pandemic across various segments in the population, and their social implications.

6. Conclusion

The goal of this dissertation is to provide new insights about the impacts of major disruptions in the transportation sector, and to explore the different factors affecting their impacts and the effects that these disruptions have in different geographic contexts. While there are a number of relevant disruptions in the sector, I focus on two: first, the disruptions brought by ridehailing services; and second, by the global COVID-19 pandemic. Some of the other disruptions being the popularity of shared e-scooters in North America and Europe; an exponential increase in the use *supersapps* in southeast Asia (e.g., Grab, Gojek) which combine all kinds of mobility, delivery and other non-mobility services in one smartphone app; feasibility of electric vehicles for commercial and personal use. This dissertation provides new insights about the use of ridehailing services, filling the gaps that I noticed in the literature when I started my PhD journey. I answer three main research questions about the use of ridehailing services - 1) how the factors influencing the use of solo-ridehailing services are different from (and in some cases similar to) the use of shared ridehailing services; 2) how the built environment influences the use of ridehailing services after accounting for some of the confounding effects which have been ignored in the studies so far; and 3) how the effect of the factors influencing the use of ridehailing services varies with the context in which they are used. I then investigate how the unprecedented COVID-19 pandemic has disrupted the transportation sector at a very fundamental level and explore its impacts on telecommuting and commuting patterns. This dissertation adds to scientific research and informs planning and policy processes, in particular at a time in which regulatory agencies want to leverage these new mobility services to reduce the environmental impacts of the transportation sector and use it to increase accessibility, equity, and resilience of the transportation system, especially in events such as the recent global pandemic.

By focusing just on one relatively homogenous region - California, I answer in-depth questions about the use of ridehailing services. I use the data collected using individual travel surveys in California in 2018. More than 4,000 participants were recruited for this survey using two different recruitment channels – online opinion panels and stratified random mailing-in of surveys to almost 30,000 households in the entire state. Using this data, I estimate a semi-ordered bivariate probit model which jointly estimates the decision to adopt shared ridehailing services and the frequency of use of ridehailing services to understand the differences between the use of two services. This model offers interesting insights in the differences between the users of the two services, but it suffers from two main methodological limitations. First, I primarily rely on more easily available D's variables (density, diversity, design etc.) to quantify the built environment of the location in which the respondents live. Such measures make it difficult to identify the specific aspects of these areas that influence travel behavior (Handy, 1996). Second, to include the effect of attitudes on the dependent variables, I resort to a two-step modelling approach. In the first stage, I estimate factor scores from the detailed measures from the survey using exploratory factor analysis. Then I use the point estimates of these factor scores in the main choice models. This approach ignores the measurement error in estimating the factor scores (or latent variables) and would give smaller standard errors when used in the choice models. However, despite these limitations, this model provided me with enough insights to frame a more robust model in the next chapter of my dissertation.

I correct for these limitations when I conduct a deeper investigation into effect of the built environment on the use of ridehailing services, where I simultaneously estimate six dependent variables (where only four are observed conditional on residential location) in an ICLV model – residential location type, vehicle ownership status, ridehailing mode share and total number of non-work trips. Here I construct and use special person-level accessibility measures in the main choice models. These measures offer a way to more meaningfully evaluate the destination options offered to an individual and the 'cost' of reaching them as a function of the built environment. In other words, accessibility (potential for travel) is a more appropriate type of measure for modeling the impact of the built environment on travel behavior. Next, I estimate the latent variables using the attitudinal measures simultaneously with main dependent variables of the model using an ICLV modelling approach, hence ensuring that standard errors of the estimated coefficients of the latent variables account for the measurement errors.

Despite the methodological differences, the two studies converge on one conclusion – failure to account for individuals' attitudes about home locations leads to residential self-selection bias in the models, i.e., an overestimation of the impact of the built environment on ridehailing use. This is an important contribution to the literature of ridehailing as this effect has been largely ignored in previous studies.

Several other inferences can be drawn from these two analyses which may be relevant for policymakers and transportation planners. First, if the goal is to discourage ridehailing from replacing active modes, pricing should be employed to discourage short distance ridehailing trips. I find that the mode share of ridehailing services is higher when destinations are within walkable distance of the home location. Since the total number of trips made by individuals is not positively associated with an increase in the accessibility (by walking) of the neighborhood they live in, I speculate that ridehailing replaces active modes in such neighborhoods. More studies examining trip lengths and trip chains using travel diary datasets are required to confirm this speculation. It is undesirable from a policy perspective if this higher mode share of ridehailing comes at the expense of walking, which is a more sustainable and cleaner mode of travel than ridehailing, in addition to its direct benefits. In order to prevent replacement of walking trips by ridehailing services it is important to appropriately price short-distance trips made by ridehailing services in urban areas.

Second, the relationship between ridehailing and public transit has been central to many studies in the past few years. Some suggest that ridehailing services act as a first- and last-mile connection to mass transit services (Yan, Levine, & Zhao, 2019; Yu & Peng, 2019) while others find that ridehailing may be replacing public transit (Schaller, 2018). My models indicate that after controlling for individual attitudes about where they choose to live and their perceptions about public transit, this relationship becomes insignificant. Interestingly, a recent study by Malalgoda & Lim (2019), which instead of relying on the total number of trips made using ridehailing (like most other studies) focused on transit ridership and availability of ridehailing service in cities around the U.S. over the past decade, found no evidence of a linkage between the two. It is possible that other previous studies may have misestimated the linkage between transit ridership and ridehailing due to lack of control for residential self-selection.

Third, among other demographics, younger and employed individuals are found to be more likely to adopt shared ridehailing and use ridehailing frequently. However, in the current market conditions, barriers to the adoption of shared ridehailing include concerns about privacy and the increased travel times. Planning agencies and service providers can use this information to implement targeted promotional strategies to overcome these barriers. For instance, modifying the internal structure of shared ridehailing vehicles can help mitigate some of the privacy concerns. At the same time, this research shows how individuals with *pro-urban* and *tech-savvy* attitudes are more likely to use shared ridehailing services. Promotional campaigns and advertisements designed around these sentiments may further increase the uptake of these services among market segments which currently use these services.

In the following two chapters of my dissertation, I explore the importance of the local context while conducting travel behavior research, i.e., studying the use of ridehailing services and the adoption of telecommuting behavior during the COVID-19 pandemic. In chapter four, I compile the survey data collected among more than 10,000 respondents in Mexico City, Sao Paulo, Beijing and Mumbai. I estimate a binary logit model with discrete segmentation for each country to investigate the country-specific effect of each independent variable on the decision to use ridehailing services. The model reveals important differences in these markets. In Sao Paulo, Beijing and Mumbai women are found to be more likely to use ridehailing, while being younger is associated with a higher likelihood of being a user in all markets.

My findings help us understand the differences among adopters of ridehailing services and help lay the groundwork for future studies. For example, in Mumbai, I find that the respondents with zero vehicles in the household are more likely to use ridehailing. This seems to suggest that a higher proportion of trips in Mumbai replaces traditional modes of transportation such as active modes and public transportation (as well as autorickshaws), with potential negative impacts on environmental externalities from transportation. At the same time, an alternative interpretation is also that, in the medium/long term, ridehailing might allow some travelers who are in the position to buy a personal vehicle to avoid (or postpone) that purchase. This in turn can result in lower car dependence and fewer vehicle trips, thus resulting in positive, or at least neutral, impacts of ridehailing on traffic congestion or pollutant emissions. To further explore this topic, future studies can focus on the analysis of the impact that the adoption of ridehailing has on the use of other travel modes in the four regions, as well as its relationship with the propensity to change household vehicle ownership.

Like all other studies, even this study suffers from certain limitations. Participants for the survey were recruited differently across countries in this project. In Mexico City and Sao Paulo, participants were recruited using intercept surveys, but online opinion panels were used in Beijing and Mumbai. The research design ensured that the final samples from each country had respondents from all age, gender and income categories but the recruitment method can still bias the type of respondents with respect to some other unobserved variables. For instance, it can be expected that respondents from online opinion panels are more tech-savvy than those recruited from intercept surveys. Unfortunately, the final model in the study does not account for these unobserved effects, which could lead to biases in the estimated coefficients for the independent variables. I correct for this limitation when I conduct another comparative analysis in the following study.

In Chapter 5, I compare the factors affecting the decision to exclusively telecommute and the frequency of physical commute (if not exclusively telecommuting) during the initial wave of the pandemic in Canada, Chile, Germany and the U.S. The data was collected independently by teams in Chile, Germany, and the U.S. and Canada. Just like in previous chapter, the method of recruitment and sampling is not consistent across the countries. While convenience sampling was adopted in Chile, in all the other countries the respondents were recruited using online opinion panels. In this chapter I try to overcome this limitation in the analysis by simultaneously estimating a binary logit (decision to telecommute) and an ordered logit model (frequency of commute) and introduce country-specific scale parameters in the model. This model diminishes the potential bias due to the non-response of specific segments of the population (attributable to the sampling strategies), which could correlate with observable (e.g., gender, income, and age) and unobservable (e.g., being tech-savvy enough to answer surveys online) respondent characteristics.

My modeling results reveal common patterns in all these countries: non-essential, college-educated, or relatively wealthy (i.e., affluent) workers have a higher chance of working exclusively from home and having low frequencies of physical commutes if they commuted to work. Despite these similarities, substantial discrepancies in telecommuting patterns by key factors were present across countries. Overall, the US and Canada display larger shares of those who work entirely from home than Germany and Chile: e.g., Chile reported the smallest shares of exclusive telecommuters among four countries. The gap in the exclusive-telecommuter shares between essential and non-essential workers is the largest in the US, and the smallest in Chile. In other words, essential workers are under greater health risks (than their non-essential counterparts) in the US than in the other countries. Interestingly, a larger share of German essential workers commutes to work at a medium frequency than their counterparts in the other countries; a larger share of Chilean essential workers reports to work at a high frequency than those in the other countries. Although it is universal that essential workers are under greater health risks, not all essential workers in these countries underwent the same level of health risks.

By analyzing data from multiple countries in this portion of my dissertation, I could uncover unique, country-specific characteristics of exclusive telecommuters and physical commuters during the pandemic. The meaning or context of a few of the sociodemographic factors differed greatly by country, specifically in the case of household size, full/part-time worker status, gender, and vehicle ownership. I find two important implications. First, the ways that these factors are associated with working from home and physical commutes differed by country. Thus, we cannot simply borrow an approach, proven effective in one country in terms of targeting sociodemographic subgroups with more needs, and apply it to another country. Context matters, and my study presents one effective path to understanding various contexts. Second, my comparative study helped identify those areas for which each country does better than others, and those areas for which they need to (further) improve. For instance, in Chile, household size is positively associated with physical commutes in Chile, which is the opposite of a pattern reported in Switzerland (by Molloy et al. (2021)) and Germany (this analysis). That is, the Chilean government needs to respond to unique travel needs of larger households during the pandemic, more so than their counterparts in Europe.

Not surprisingly, I find universal patterns across developed and developing countries in my study in particular regarding the fact that affluent workers could avoid potential exposure to viral infection and contraction during the pandemic by exclusively working from home or commuting less frequently to a much greater extent than other groups. These patterns highlight an important challenge related to social equity during the pandemic. How can/should policymakers and transportation professionals help those who report to work and maintain basic functions in society during a health crisis? First, we can better identify their travel needs and make their daily travel safe and smooth. Prioritizing them for personal protective equipment, testing, medical treatment, and vaccination could be effective ways to handle their concerns while protecting them. Also, I advise governments to invest in the safety of alternative transportation systems to facilitate the safe movement of carless individuals during such events (Tirachini and Cats 2020).

6.1. Next Steps and Future Work

During the course of my dissertation I have explored the impacts of the disruptions caused by the new transportation technologies and the COVID-19 pandemic. My work improved our understanding of how these disruptions are changing the transportation sector and created evidence for transportation policy. Still, it only scratches the surface of a full understanding of all the impacts of the disruptions occurring in the transport sector right now. More importantly, what remains unanswered are these questions: what are the implications of these disruptions towards achieving a sustainable, greener, and more equitable transportation system globally? How can the new technologies be improved to meet these broader goals? And, what is the role of these technologies in ensuring the resilience of society in the face of global pandemics and similar crises expected due to climate change?

As I noted in Chapter 2 and Chapter 3 of my dissertation, the use of ridehailing services with public transportation is largely done by individuals who are already oriented towards leading a multimodal lifestyle. They choose to live in places where they can use these alternative modes of transportation. Hence, in future research I plan to focus on what could be done to ensure that a wider segment of the population uses ridehailing services in combination with active modes and public transportation so that they offer fierce competition to private vehicles. The answer could likely lie in two parallel strategies.

To begin with, ridehailing services are merely one of the many 'products' of the technological advancement in the information and communication technologies. While many studies, including this dissertation, have focused on four-wheeled ridehailing, there is a need to evaluate the importance of other technologies. In western countries, shared e-scooters and electric bicycles are causing similar disruptions (Mitra & Hess, 2021; Reck, Haitao, Guidon, & Axhausen, 2021). Mobility as a Services (MaaS) which integrates all shared passenger transportation technologies and public transportation to provide end-to-end transportation solutions for customers has been explored as a pilot in many European countries (Kamargianni, Li, Matyas, & Schäfer, 2016; Smith, Sarasini, Karlsson, Mukhtar-Landgren, & Sochor, 2019; Sochor, Strömberg, & Karlsson, 2015). The overall acceptance of these services was positive in northern European countries. This could serve as a starting point for transportation innovation in other contexts, such as the US, which is somewhat different than northern Europe. Future applied research could focus on developing such context-specific transportation solutions which can meaningfully compete with private vehicles on all fronts, and eventually lead to a lower levels of car ownership and reliance on private cars for mobility needs.

While innovation is needed on the technological front, there is also a need to revolutionize the governance, regulatory, and financial institutions relevant to ridehailing services and public transportation. For instance, the state of California is in the process of developing the 'Clean Miles Standards' for regulating ridehailing services. The regulations establish statewide targets regarding the electrification of the ridehailing fleet, increasing the vehicle occupancies of the rides, decreasing deadheading, and promoting the integration of ridehailing with public transportation and active mods of travel at the state level (CARB, 2020). However, Pike & Pilatwosky Gruner (2020) recently uncovered how local regulatory bodies in California, who are responsible for implementing these targets are still largely unsure about the most effective policies. With the exception of a handful of larger local governments, most local governments are still in a 'wait-and-see' mode, i.e., waiting for another city/county to implement the right policy and learn from their experiences. There is a dire need for policy and governance research in this area to chart out a path which local governments can follow to bring about changes in their regulatory framework which will eventually drive these technologies towards sustainability, integrate them with other technologies and public transportation, and offer a viable alternative to private vehicles.

Chapter 4 in my dissertation sheds light on how the market segments adopting four-wheeled ridehailing services highly depend on the local context. For instance, as opposed to western countries, women are more likely to use these services in the developing countries possibly because of safety concerns in other non-private modes of transportation. The scope of the discussion of my dissertation only includes four wheeled ridehailing services. However, the biggest innovation in the developing countries has been in digitalization of informal modes of transportation. For instance, both in Sub-Saharan African region and Southeast Asian region motorcycle taxis have been a predominant mode of informal transportation. These are now being digitalized by ridehailing service providers such Grab and GoJek (ITF, 2019). However, a more interesting aspect of these services is that they provide a suite of passenger mobility options (e.g., e-scooters, carsharing in addition motorcycle and car ridehailing), delivery services (e.g., food and grocery delivery, and delivery of parcels) and many non-mobility services (e.g., electricity bill payment, house cleaning services, purchase of insurance). This is a big innovation in the field of digital services in the mobility sector. The impact of these services became even more predominant during the COVID-19 pandemic when public transportation service stopped and people in the countries had to rely on the apps for travelling and delivery of goods. Grab reported a five-fold increase in the number of users who used two or more services on their app in the last two years of pandemic (Grab, 2021). It can be speculated that, at least in the developing countries where incumbent transportation services (e.g., informal and public transportation) are popular, these emerging services are adding to the resilience of the transportation system in the face of crises like the global pandemic. More studies are needed to confirm these hypotheses. In addition, there is very little information about the impact of these new technologies on congestion, greenhouse gases emissions and air quality.

In summary, digital transportation technologies are evolving very rapidly and differently in both developing and developed countries. There is a need for more studies to track these technological developments, improve our understanding about how they are transforming the transport sector, and create evidence to support policies to leverage these technologies in making the transport sector more sustainable, greener, and equitable.

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7. Appendix

Table 7-1 Relationship between Land Use and Demand for Ridehailing

	Sabouri et al. 2020	Yu & Peng. 2019	Gerte et al. 2019	Lavieri et al. 2018	(Alemi, Circella, Mokhtarian, et al., 2018)	Alemi et al. 2019	(Alemi, Circella, Handy, et al., 2018)
Activity density (Population and Employed Population per sq. mile)	(+) Conventional gravity models say - more people mean more trip generation and more employment means more trip attraction in a TAZ. This explains why Uber demand is positively associated with total population and employment of the neighborhood.	(+) more people mean more ridehailing demand		(+)		(+) for frequency of ridehailing usage	
Percent retail by floor area/ Retail density			(+) Uber attracts shopping trips, possibly by tourists	(+) Retail employment density acts as a proxy for shopping destinations, which attract a lot of trips.			
Total built area			(+) more activity (people) leads to more travel demand. This is also a basis of gravity-based travel models.				

Percent residential by floor area			(+) local residents are also users of Uber NYC, in addition to tourists				
Land-Use Mix (Mix of land-use)	(+) More diversity in land-use means more trip attraction, hence more travel demand by Uber.	(+) High land-use mix induces more TNC travel as there is a variety of destinations which can be accessed				(-) for ridehailing frequency. High usage of non-motorized modes is popular in diverse neighborhoods as greater number of destinations are accessible via walking and bicycling	(+) for adoption of ridehailing
Employment and Population Balance		(-) A neighborhood with well-balanced employment opportunities does not require motorized vehicles to meet travel needs.			(-) for Class 2. Class 2 comprises students and working parents; largely rely more on their own vehicles or public transit to meet their travel needs. However, in diverse neighborhoods, alternative modes (such as Uber) become more attractive, and members of class 2 have a higher likelihood of using these modes. (Note: authors refer to this variable as land-use mix)		
Sidewalk Density		(+) This shows a complementary relationship with active modes.					
Road Intersection Density	(-) High intersection density is positively related with high usage of non-motorized modes which explains its negative	(+) Higher road density is related with higher exposure to ridesourcing vehicles and less response time.					

	relationship with ridehailing						
Destination Accessibility (Regional Centrality)							(+) for ridehailing adoption
Destination Accessibility by Automobiles	(-) Ridehailing is less of a competition to private modes of travel, especially when it is more convenient and accessible						
Destination Accessibility by Transit	(-) Ridehailing becomes a popular option in suburban areas which are less accessible via transit	(+) 1. Indication of a successful first- and last-mile connection. 2. This variable might as well be masking the effects such as regional centrality index etc.					
Transit Stop Density	(+) Ridehailing acts as an option for first- and last-mile connection to public transit						

Frequency of buses				(-) for ridehailing trip generation on weekdays; no effect on weekends. Ridesourcing is more popular in regions of poor transit supply.			
Transit Performance Index					(+) for class 1 and class 3; (-) for class 2. Due to low auto-availability and low household income, respondents from Class 1 and Class 3 are more multi-modal. Thus, if the live in areas with high accessibility via transit, they are more likely to rely on other modes.		
Count of Citi Bike stations			(+) same kinds of users using shared-bike services also use shared bikes ;maybe Uber is used to complement trips made on Citi Bikes				
Neighborhood type - urban/urban core						(+) adoption of ridehailing; no effect on frequency of usage.	

Table 7-2 Details of studies in table 7-1

	Study Area	Main research question	Data	Methodology	Dependent Variable

Sabouri et al. 2020	71,789 CBGs in 24 metro areas in the U.S.	How is demand for ridesourcing affected by built environment? How is ridesourcing affected by D's?	Ride volumes between 71,789 CBGs; provided by Uber.	Multi-level modelling	natural log of number of trips between each two CBGs
Yu & Peng. 2019	Austin, Texas	Examine the relationship between built environment and the demand for ridesourcing with a focus on spatial variation in these relationships	Examine the relationship between built environment and the demand for ridesourcing with a focus on spatial variation in these relationships	Geographically weighted Poisson regressions	Average daily ridesourcing demand for weekdays and weekends at CBG in sept 15 2016 to March 14, 2017 (only pick-up locations)
Gerte et al. 2019	New York City	Investigate if the demand for Uber is unbounded or if it stagnates after some point in time.	Aggregated data made available by Uber in the period of April - September 2014 and January to June 2015. The data is available at "taxi zone" level. A typical taxi zone consists of 4 census tracts.	Linear panel-based model with random effects	Weekly pick up demands in a taxi zone

Lavieri et al. 2018	Austin, Texas	Investigate the patterns leading to ridesourcing trip generation and trip distribution across different TAZs in Austin, Texas. How are these patterns linked with socio-demographics, and land-use of TAZs. More, importantly, the authors focus how these trip patterns are different for weekdays and weekends	6 months of trip data offered by RideAustin in Austin, Texas. The data includes origin/destinatio n and time-stamps.	The following two models were used by authors to analyze data: 1. Spatial bivariate count model which simultaneously models trip generations in each TAZ in a) weekdays and b) weekends. This model controls for spatial dependence between TAZs and between two types of days. 2. Fractional split distribution model - understand what fraction of trips generated from one TAZ are distributed in all of the other TAZs	1. Count of trips generated by a TAZ in a weekday 2. Count of trips generated by TAZ in weekends 3. Trips attracted by TAZ in a weekday 4. Trips attracted by TAZ in a weekend
Alemi, Circella, Mokhtarian, et al., (2018)	California	Investigation of factors affecting the adoption of ridehailing while focusing on heterogeneity in individual taste and preference.	Cross-sectional household travel survey of millennials and GenX in California	latent class choice models	1. Adoption of ridesharing - users/non-users

Alemi et al. 2019	California	1. How does frequency of ridehailing use vary across different segments of the population 2. Which built environment characteristics have highest impact on ridehailing use	Cross-sectional household travel survey of millennials and GenX in California	1. Ordered Probit model with Sample Selection 2. Zero inflated ordered probit model with correlated error terms	1. Frequency of use of ridehailing 2. Adoption of ridehailing
Alemi, Circella, Handy, et al., (2018b)	California	Understand the influence of the factors affecting the adoption of ridehailing services	Cross-sectional household travel survey of millennials and GenX in California	1. Binary logit model without attitudes 2. Same model with attitudes	Adoption of ridehailing (binary)

Table 7-3 Model without latent variables and random effects

	Urban				Non-urban			
	LO ridehailing		Total Trips		LO ridehailing		Total Trips	
	Est.	T-rt	Est.	T-rt	Est.	T-rt	Est.	T-rt
(Intercept)	-3.59	-9.36	2.82	25.95	-2.95	-39.47	2.49	30.30
Age (ref=Millennials)								
GenX	-0.36	-3.20			-0.11	-2.04	-0.16	-3.36
Baby boomers	-0.60	-4.66			-0.19	-3.32	-0.16	-3.23
Annual Household Income (ref=Less than $50,000)								
$50,000 to $100,000	-0.25	-1.77	0.28	2.86			0.13	2.61
More than $100,000	0.02	0.17	0.21	2.17			0.18	3.51
Gender (ref=male)								
Female			-0.22	-3.15			-0.10	-2.53
Race (ref = other)								
White			0.25	3.18			0.16	3.18
Employed (ref=no)								
Yes	0.57	4.33	-0.31	-3.38	0.13	2.76	-0.14	-3.19
Student (ref = no)								
Yes			0.23	2.20	0.21	2.85		
Education (Ref = Bachelors or less)								
More than Bachelors					-0.10	-2.39	0.15	3.83
Kids in the HH (ref=none)								
At least one			0.32	3.53				
Built Environment								
Inverse sum of restaurant in 1mile	-0.22	-2.17			6.03E-04	1.86	-6.09E-04	-1.97
Distance to the nearest restaurant (ref = less that 0.5 miles)								
More than 0.5 miles	-0.57	-2.94	0.33	2.60				
Walkscore	0.01	2.29			-2.00E-03	-2.01	3.65E-03	4.45
Distance to the nearest Movie theater (less than 0.5 miles)								
More than 0.5 miles	0.28	1.65						
Distance to the nearest movie theater (ref = between 0.65 miles to 8 miles)								
Less than 0.65 miles					-0.01	-0.16		
More than 8 miles					-0.17	-2.67		
Distance to the nearest department theater (ref = between 0.65 miles to 8 miles)								
Less than 0.65 miles	-0.17	-1.66	0.14	1.95	0.03	0.51	-0.09	-1.72
More than 8 miles					0.15	1.78	-0.19	-2.95
Type of house (ref = Apartments/others)								
Stand Alone	-0.22	-2.17						
Jobs available via 30 min transit ride					5.23E-06	2.23		

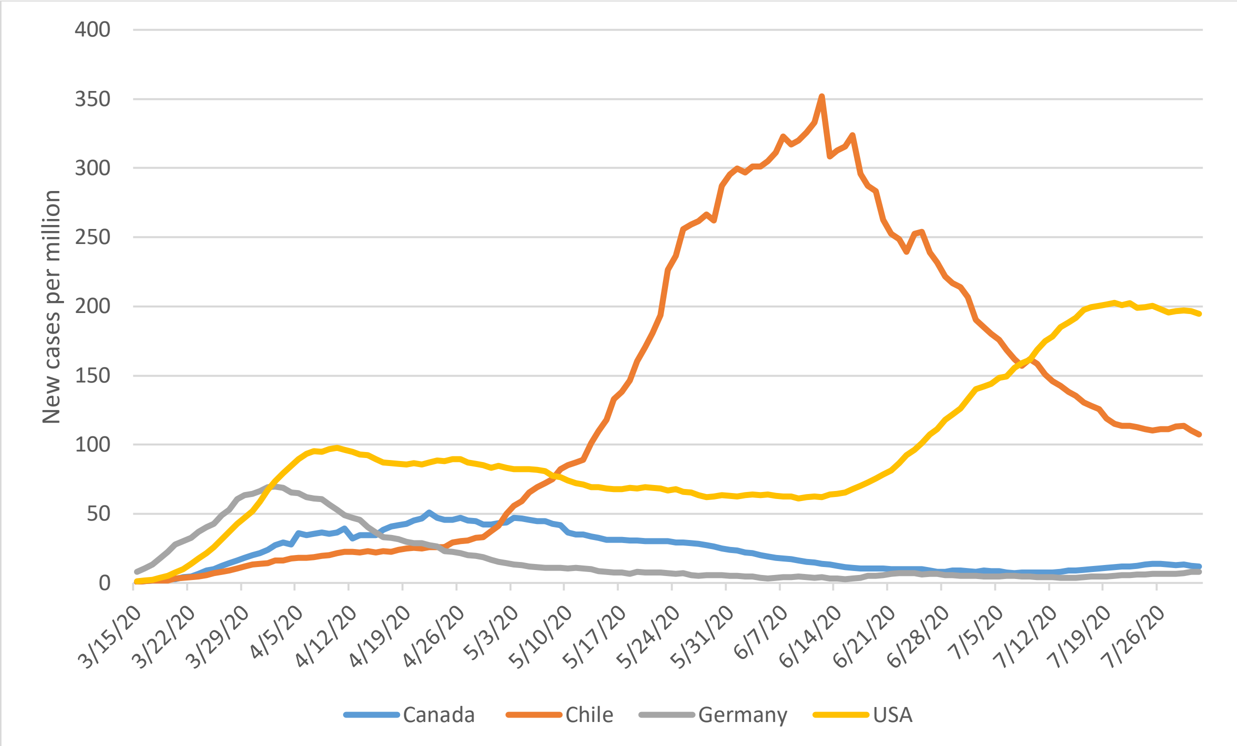

Figure 7-1 Number of new COVID cases in each of the countries during the study period.

Figure 7-2 Probability of exclusively telecommuting and commute frequency as predicted by the final model