USING SURVEY DATA TO UNDERSTAND RIDESOURCING IN TENNESSEE: WHO, WHERE, WHEN, AND WHY?

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ABSTRACT

With companies like Uber and Lyft leading the way, ridesourcing has grown and continues to grow in popularity in the United States since its introduction just over ten years ago. While research on this new transportation mode has largely focused on national level trends and studies of large metropolitan areas, little has been written about its impacts in smaller and mid-sized cities and states. This paper aims to understand the socioeconomic characteristics and travel behavior trends of those using ridesourcing in less studied regions, using Tennessee as a case study. This thesis has three parts: a literature review of past research; a comparison of the demographics of ridesourcing users at the national, census division, and state levels based on the 2017 National Household Travel Survey (NHTS); and a comparison of different user groups within the state of Tennessee using survey data collected in three metropolitan regions in Tennessee: Knoxville, Nashville and Memphis. The results of the NHTS survey data analysis reveal some key differences in national/large city characteristics as compared to those found in the state level analysis, including the importance of gender and race. The subsequent survey data analysis revealed four distinct market segments: those who use ridesourcing in their own city, those who use ridesourcing only when traveling, those who use ridesourcing only with friends or family, and those who do not use ridesourcing. By understanding the differences between user locations and user types, better policies and regulations can be created to more efficiently and effectively harness the potential of this growing transportation mode.

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CHAPTER I
INTRODUCTION

Ridesourcing, ridesharing, ridehailing, and transportation network companies (TNC) are the terms used to describe companies that provide "prearranged (services) and on-demand transportation services for compensation in which drivers and passengers connect via digital applications" (SAE 2018). Per guidance from Society of Automotive Engineers International (SAE), the term ridesourcing will be used throughout this thesis, except when describing results from a study or describing responses to survey questions that use one of the other terms previously listed.

The two most common ridesourcing companies in the United States are Uber and Lyft, which launched in 2009 and 2012, respectively (Blystone 2019; Greiner et al. 2019). Ridesourcing is rapidly growing in popularity across not only the United States, but the entire world, with both Uber and Lyft completing one billion rides within their first six years of service (Lyft 2018; Uber 2018). Since this mode of transportation is continuing to grow and be used in innovative ways, ridesourcing research must as well.

The majority of research to date has focused on large metropolitan areas where ridesourcing has been in service the longest; therefore, research to understand users in and the impacts of ridesourcing on smaller cities is not as extensive. The purpose of this thesis is to determine whether there are differences between users in these large cities and cities in Tennessee that are mid-sized.

This thesis will incorporate several data sources to seek to determine if there are differences in ridesourcing user groups. As seen in Table 1, there are three main data sources in the chapters of this thesis. First, previous studies are reviewed to determine the common trends among ridesourcing users. Next, the 2017 National Household Travel Survey (NHTS) had two questions that asked about ridesharing use; this data are analyzed at the national, census division, and state levels. The third chapter uses data collected by the company Populus during a 2019 survey of people in Knoxville, Memphis, and Nashville which asked about their ridehailing use. All of the data used in this thesis was collected prior to the COVID-19 pandemic.

While these are the main data sources used in the thesis, there were additional data sources found that are included in the appendices. First, a local survey in Nashville asked whether anyone from the respondent's household had used rideshare, bikeshare, or a similar service within the last year. Since the survey question included other modes of transportation and was only asked for one city in Tennessee, the results of this survey are provided in Appendix 1 rather than included in an analysis (Metro 2019). This survey is conducted on a quarterly basis in Nashville; the analysis period in Appendix 1 is Quarter 1 of 2018 to Quarter 1 of 2019. Second, results using weighted data from the 2017 NHTS are provided in Appendix 2. Appendix 3 provides additional summary statistics from the dataset from the Populus survey. These results include additional ridehailing questions that were not used in the chapter as well as summary statistics for several questions asked to the few drivers in the sample.

The thesis is organized as follows. Chapter 2 provides an extensive literature review on Ridesourcing in North America. Chapter 3 provides the insights from the 2017 National Household Travel Survey. Chapter 4 describes research analysis results of Populus Technologies, Inc. survey data. This is followed by the conclusions, implications, and future research areas in Chapter 5 and then the appendices.

Table 1: Comparison of Data and Methods Used in Thesis.

	Data source	Collection Date	Ridesourcing term used	Location of data	Method Used
Chapter 2	Previous Literature	Studies were published between 2015 and 2020	Ridesourcing *(when talking about results of a specific study, whichever term used in that study is used)*	Varied from study to study. Studies focused on national, state, and large metropolitan areas	Literature Review
Chapter 3	NHTS	2016-2017	Ridesharing	National *(unweighted and weighted)* Census Division *(unweighted and weighted)* State *(unweighted)*	Summary Statistics Binary Logit Model
Chapter 4	Survey from Populus Technologies, Inc.	2019	Ridehailing	Knoxville, Memphis, and Nashville, Tennessee	Summary Statistics Multinomial Logit Model

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CHAPTER II
LITERATURE REVIEW ON RIDESOURCING USERS' TRAVEL BEHAVIOR IN NORTH AMERICA

This paper is currently under review at the Journal of Advanced Transportation: Crossland, C. and Brakewood, C. "Literature Review on Ridesourcing Users' Travel Behavior in North America".

Cassidy Crossland was the principle author of "Literature Review on Ridesourcing Users' Travel Behavior in North America". Cassidy's contribution was collecting the sources, conducting the literature review, and writing the text contained in the manuscript. Dr. Candace Brakewood created the concept and design of the project and provided guidance and ideas throughout the research process as well as editorial assistance.

ABSTRACT

The rapid growth of ridesourcing services in North America over the past ten years has introduced a new area of research. Since this area of research is constantly changing, the objective of this paper is to provide a comprehensive literature review of the latest research and summarize findings relating to ridesourcing users' traveler behavior. In total, 44 studies were reviewed, and six main traveler-focused categories were identified: demographics; frequency and time of use; trip purpose; reason for using ridesourcing services; relationship between ridesourcing and other modes; and transportation system impacts. The results pertaining to demographics revealed that ridesourcing users are likely younger with higher incomes and education levels, are full-time students or employed, and live in urban areas. Most ridesourcing trips occur on weekends and at night, with the most common trip purpose being for social events. Common reasons for using ridesourcing were to avoid driving under the influence, parking difficulties, and faster travel and wait times. Ridesourcing was found to substitute for taxis and personal vehicles; however, the results were mixed for public transit. Some studies suggest that ridesourcing can increase both vehicle miles travelled and the number of vehicles on the road; however more research is needed in this area to have conclusive findings. As both the use of ridesourcing services and research involving ridesourcing continue to grow, it is important to understand the trends of who is using these services and how travel behavior might be changing during this period of expansion.

INTRODUCTION

Ridesharing, ridehailing, transportation network companies (TNC), and ridesourcing are the terms used frequently over the past ten years to describe companies that provide "prearranged (services) and on-demand transportation services for compensation in which drivers and passengers connect via digital applications" (SAE 2018). Per guidance from Society of Automotive Engineers International (SAE), the term ridesourcing will be used through the remainder of this paper (SAE 2018).

Ridesourcing in the United States first launched in 2009 with UberCab (now known as Uber Technologies) (Blystone 2019). Over the past ten years, several other companies have entered the market, including Lyft in 2012 (Greiner et al. 2019); however, Uber and Lyft have the largest market share in the United States (Mazareanu 2019). Uber completed its first one billion rides in December 2015 which grew to 10 billion rides in July 2018 (Uber 2018). Lyft completed its first billion rides in September of 2018 (Lyft 2018). With the rapid growth of ridesourcing services around the world, many researchers and transportation system managers are interested in understanding this ever-changing mode of transportation. This paper provides a systematic review of the studies and reports written during this period of rapid growth regarding the travel behavior of ridesourcing users.

The paper is organized as follows: first, the review methodology is laid out, then an overview of the results of the comprehensive review are described followed by an in-depth description of the six main categories relating to ridesourcing users. These include demographics; frequency and time of use; trip purpose; reason for choosing ridesourcing; relationship between ridesourcing and other transportation modes; and transportation system impacts. This paper concludes with areas for future research and a summary.

METHODS

The primary search engine for this literature review was Google Scholar. The key words searched to find articles included ridehailing, ridesourcing, ridesharing, transportation network companies, Uber, and Lyft. This resulted in roughly 250 papers.

The selection was narrowed further by only including papers published after 2009 when ridesourcing companies entered the American market. Only sources with a study area in the United States or Canada were then selected. The studies also had to pertain to the users of the ridesourcing services or the transportation system usage impacts. Studies that focused on regulation, environmental impacts, and business models were not selected because this paper is focused on traveler demographics and behaviors.

After the research team identified these six main categories, a peer-reviewed article entitled *Ride-Hailing, Travel Behaviour, and Sustainable Mobility: An International Review* was published in the journal Transportation; this study included an in-depth literature review on previously published studies from the United States, China, Chile, Brazil, Canada, India, and Lebanon (Tirachini 2019). This study separated the literature into the following categories: ridehailing and travel behavior; ridehailing as a substitution for and/or complement to other modes; ridehailing and traffic externalities; encouraging pooling; automated vehicles; and policy implications. For those categories which coincided with those previously determined for this literature review, prior work was adapted and expanded to reflect all of the studies, including more recent publications from the United States and Canada.

RESULTS

Overview

A total of 44 journal articles and reports from 2015 to 2020 fit the criteria previously stated (Table 1). One article was published in 2015, 3 were published in 2016, 4 were published in 2017, 15 were published in 2018, 14 were published in 2019, and 8 were published in 2020 (through May 2020). The increasing frequency of publications reflects the growing interest of researchers in this important and expanding field. The location of each study is provided in Table 2. Of the 44 articles and reports, 16 had a study area of the United States or multiple major cities across the United States. Nine studies used state-level data, with four of these being in California. The remaining 19 studies focused on specific cities. Seven studies investigated cities in California; specifically, five in San Francisco and two in Los Angeles. New York City was the focus of five studies while Toronto was used for two additional studies. Denver, Chicago, Philadelphia, and Dallas were each the subject for one study. The final report looked at many cities around the world; however, for the purpose of this literature review, only the cities in the United States and Canada were used in the findings.

Finally, the studies were categorized based on key topics pertaining to the travel behavior of ridesourcing users. The categories that were identified included demographics; frequency and time of use; trip purpose; reason for using ridesourcing; relationship between ridesourcing and other modes; and transportation system impacts. Each category is discussed in further detail below. The most frequently studied category within the literature was demographics, and results relating to ridesourcing user demographics were reported in 23 studies, as seen in Table 2. Frequency and time of use results were reported in 14 studies. Nine studies included trip purpose. Reasons for using ridesourcing was analyzed in six studies. The relationship between ridesourcing and other modes of transportation was investigated in 16 studies. Transportation system impacts were discussed in 18 studies.

Demographics of Ridesourcing Users

The demographics of ridesourcing users was one of the six topics identified in numerous prior studies. Of the 44 studies, 23 (52%) contained results pertaining to the demographics of ridesourcing users

Table 2: Distribution of Papers and Reports by Year and Topic.

Yr	Author	Location	Demographics	Frequency and Use	Trip Purpose	Reasons	Other Modes	System Impacts	Total Studied
2015	(MADD 2015)	United States		■	■	■			3
2016	(Circella et al. 2016)	California	■					■	2
	(Rayle et al. 2016)	San Francisco		■	■	■		■	4
	(Smith 2016)	United States	■	■					2
2017	(Clewlow and Mishra 2017)	United States	■			■	■		3
	(Henao 2017)	Denver			■			■	2
	(Mahmoudifard et al. 2017)	Chicago	■		■	■	■		4
	(Schaller 2017)	New York		■				■	2
2018	(Alemi et al. 2018)	California	■					■	2
	(Brodeur and Nield 2018)	New York						■	1
	(Castiglione et al. 2018)	San Francisco						■	1
	(Chu et al. 2018)	United States	■				■		2
	(Circella et al. 2018)	California	■	■		■			3
	(Cooper et al. 2018)	San Francisco		■				■	2
	(Feigon and Murphy 2018)	United States	■	■		■	■		4
	(Gehrke and Reardon 2018)	Massachusetts						■	1
	(Gehrke et al. 2018)	Massachusetts	■	■	■		■		4
	(Gerte et al. 2018)	New York	■	■			■		3
	(Hall et al. 2018)	United States					■	■	2
	(Lahkar 2018)	Virginia	■						1
	(Lee et al. 2018)	United States					■	■	2
	(Schaller 2018)	United States	■				■	■	3
2019	(Bischak 2019)	Texas		■	■				2
	(Brown 2019)	Los Angeles	■	■					2
	(Deka and Fei 2019)	United States	■	■					2
	(Erhardt et al. 2019)	San Francisco			■			■	2
	(Felix and Pollack 2019)	Massachusetts	■						1
	(Grahn et al. 2019)	United States	■						1
	(Habib 2019)	Toronto			■		■		2
	(Joshi et al. 2019)	Major Cities Worldwide						■	1
	(Lavieri and Bhat 2019)	Dallas		■	■		■		3
	(Mitra et al. 2019)	United States	■						1
	(Sikder 2019)	United States					■		1
	(Sturgeon 2019)	San Francisco					■		1
	(Young and Farber 2019)	Toronto	■						1
	(Zheng 2019)	New York					■	■	2
2020*	(Bansal et al. 2020)	United States	■						1
	(Brown 2020)	Los Angeles	■	■					2
	(Dong 2020)	Philadelphia	■				■		2
	(Fulton et al. 2020)	California					■		1
	(Jiao et al. 2020)	United States	■					■	2
	(Qian et al. 2020)	Manhattan						■	1
	(Sabouri et al. 2020a)	United States						■	1
	(Sabouri et al. 2020b)	United States	■						1
Total Number of Studies per Topic			23	14	9	6	16	18	86

(Alemi et al. 2018; Bansal et al. 2020; Brown 2019, 2020; Chu et al. 2018; Circella et al. 2016; Circella et al. 2018; Clewlow and Mishra 2017; Deka and Fei 2019; Dong 2020; Feigon and Murphy 2018; Felix and Pollack 2019; Gehrke et al. 2018; Gerte et al. 2018; Grahn et al. 2019; Jiao et al. 2020; Lahkar 2018; Mahmoudifard et al. 2017; Mitra et al. 2019; Sabouri et al. 2020b; Schaller 2018; Smith 2016; Young and Farber 2019). As seen in Table 3, commonly considered demographic characteristics include age, household income, education level, location of home, employment status, race, and gender. Age was evaluated in 18 of the 23 studies (78%), and the results revealed that the most common generation using ridesourcing was millennials. People born between 1981 and 1996 are considered millennials; currently this generation is between the ages of 24 and 39 (Dimock 2019). Household income was addressed in 14 studies; the results indicated that ridesourcing users generally had higher income levels. Nine studies considered education level among ridesourcing users, and eight of those concluded that ridesourcing users were likely to have a higher level of education. The eight studies relating to location found ridesourcing usage occurred more frequently in dense, urban areas. Six studies evaluated the employment status of ridesourcing users, and the findings generally indicated that users were employed (either full- or part-time) or were students. Six studies presented findings related to race, with several of the studies concluding that many ridesourcing users were white. Gender was a focus in just four studies; these concluded that males were more likely to use ridesourcing services than females.

Frequency and Time of Use of Ridesourcing

Frequency and time of use of ridesourcing was evaluated in 14 studies (32%) as seen in Table 2 (Bischak 2019; Brown 2019, 2020; Circella et al. 2018; Cooper et al. 2018; Deka and Fei 2019; Feigon and Murphy 2018; Gehrke et al. 2018; Gerte et al. 2018; Lavieri and Bhat 2019; MADD 2015; Rayle et al. 2016; Schaller 2017; Smith 2016). Table 4 provides information on the commonly considered frequency and time of use characteristics, which included time of day, day of week, how often ridesourcing was used, trip length, and time of year. Eight of these studies contained findings related to the time of day that ridesourcing was used; the two most common times were during commute hours and late at night. Six studies considered which day of the week ridesourcing was used most frequently; five of those studies found that the weekends were the days with the highest demand for ridesourcing services. Five studies looked at how frequently ridesourcing services were used; these studies found different percentages, which makes it difficult to draw consistent conclusions. While one study found that 66% of respondents used ridesourcing at least once a week, another found that 84% of respondents used it a few times a month or even less frequently. These disparities may be due to the studies being completed in different areas of the country or for different geographic areas, such as a city versus a state. Two studies considered trip length. One found the average ridesourcing trip length to be between 2.2 and 3.1 miles while the other found that shared ridesourcing trips were one mile shorter on average than regular ridesourcing trips. Finally, one study reported on seasonal changes in ridesourcing use and found ridesourcing to be used more in the winter and less in the summer, as compared to spring and autumn.

Ridesourcing Trip Purpose

The next category identified in the literature review pertained to the trip purpose of ridesourcing. Table 5 provides the five typical trip purposes found in the literature: going out or social events, to from the home, work trips and commuting, other, and to and from the airport. Table 2 reveals that nine studies (20%) contain conclusions broadly related to ridesourcing trip purpose (Bischak 2019; Erhardt et al. 2019; Gehrke et al. 2018; Habib 2019; Henao 2017; Lavieri and Bhat 2019; MADD 2015; Mahmoudifard et al. 2017; Rayle et al. 2016). Five of the studies found that ridesourcing was commonly used for non-work or social events. Three studies focused on trips to and from the home; two of these studies reported that ridesourcing was more likely to be used to return home while the third study found that more ridesourcing trips were used to leave rather than return home. Two studies considered ridesourcing for travel to/from the workplace

Table 3: Demographics Key Findings.

	Age	Household Income	Education	Employment	Race	Gender	Location
(Circella et al. 2016)	Millennials had higher adoption rates						
(Smith 2016)	Median age of adult ride-hailing users was 33 years						
(Clewlow and Mishra 2017)	Average age of ride-hailing users was 37						Ride-hailing users were likely to be urban dwellers
(Mahmoudifard et al. 2017)	Age influenced mode choice decision	23% of high-, 6% average-, and 9% low-income used regularly			Race influenced mode choice decision	Gender influenced mode choice decision	
(Alemi et al. 2018)	31.8% of millennials have adopted on-demand ride services	Users had a higher income	Users had a bachelor's degree or higher	Users were students or workers			Users were urban dwellers
(Chu et al. 2018)	Ride-hailing adopters were younger in age	Ride-hailing adopters had a higher income					
(Circella et al. 2018)	Ridehailing users were more likely to be millennials		Ridehailing users tended to have a higher education				Ridehailing users tended to live in an urban setting
(Feigon and Murphy 2018)		TNC usage took place in communities of all income levels					
(Gehrke et al. 2018)	64% of ride-hailing users were 22-34 years old	Ride-hailing users' yearly income: 26% <$38,000; 22% $38,000-$60,000; 52% >60,000	70% of users had a college degree; 25% had an advanced degree	74% of ride-hailing users had at least part time employment	67% of ride-hailing users were white; 10% Hispanic; 13% Asian; 7% black		
(Gerte et al. 2018)	Pickup demand increased with people under 19 and decreased with people over 65		Pickup demand increased with people having some college education		Pickup demand decreased with more African Americans in the population	Pickup demand increases with more males in the population	
(Lahkar 2018)	Older ages decreased familiarity by 2.6% and use frequency by 4.9%	Higher income level increased familiarity and frequency of use by 0.7%	Just a bachelor's degree decreased odds of use frequency by 24.27%	Students had a 93.9% increase in odds of familiarity with TNCs	Identifying as white increased odds of frequency of use by 47.25%		

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

Table 3 continued

	Age	Household Income	Education	Employment	Race	Gender	Location
(Schaller 2018)	Users were likely to be between 25 and 34	Users' income was likely over $50,000	TNC users were likely to have a bachelor's degree				Concentrated in large, densely populated areas
(Felix and Pollack 2019)	Generational differences in ride-hailing adoption						
(Deka and Fei 2019)	Young people used ridesourcing more than others	People with higher incomes used more than others	People with a higher education used more often	Workers used more than those without a job		Women had a lower frequency of use	Areas with larger population used more frequently
(Mitra et al. 2019)	Of users 65+, those 65-74 were more likely to use	More likely to use if they had a higher income	Those with higher education were more likely to use			Males were more likely to use	
(Brown 2019)		Lower income neighborhoods used Lyft more per month			Asians/Hispanics used pooled more than Whites/Blacks		
(Grahn et al. 2019)	Younger people were more willing to adopt	Users had a higher income than non-users	Users had a higher education than non-users				TNC use was higher in urban areas
(Young and Farber 2019)	74.44% of users were 20 to 39	42.18% of users' household income was >$125,000		73.41% of ride-hailing respondents worked full-time			
(Jiao et al. 2020)		Income was not significant on weekend				Females created more trips	
(Sabouri et al. 2020b)				Uber demand was positively correlated with employment			Demand was correlated with population and land use mix
(Bansal et al. 2020)	Younger people were more likely to use TNCs	People from affluent families were more likely to use TNCs	Those with higher education were more likely to use				Metropolitan areas had more use
(Dong 2020)	People over 30 were more likely to use ridehail over transit	As income increased, willingness to use ridehail also increased				Females were likely to use ridehail over transit	
(Brown 2020)	People 15-34 were more likely to share rides	Lower income neighborhoods were more likely to share rides			Racial/ethnically diverse areas were less likely to have shared rides		Most shared trips were in the urban core

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

Table 4: Frequency and Time of Use Key Findings

	Day of Week	Time of Day	Trip Length	Season	How Often Used
(MADD 2015)		Large spike in Uber requests during bar closing time in Pittsburgh			
(Rayle et al. 2016)	48% of ridesourcing trips were taken on Friday or Saturday				
(Smith 2016)					26% used ridesourcing on a monthly basis; 56% used ridesourcing less than once a month
(Schaller 2017)	TNC trip growth was concentrated during the weekends	TNC trip growth was concentrated during the morning and evening peak periods and late evenings			
(Circella et al. 2018)		Majority of ridesourcing trips were taken between 10pm and 4 am			
(Cooper et al. 2018)	TNC trips increased throughout the week (130,000 on Monday to 220,000 on Friday and Saturday) with the lowest usage being on Sunday	Evening peak was higher and longer than the morning peak; TNCs had a second peak around 11 pm on Thursdays and Fridays			
(Feigon and Murphy 2018)	Highest TNC usage volume hour was on Saturday; Lowest TNC usage volume hours occurred uniformly on weekdays	Highest TNC usage volume hour occurred on Saturday night (9 or 10 pm); Lowest TNC usage volume hours occurred uniformly on early weekday mornings	Median TNC trip lengths (2.2 to 3.1 miles) and maximum trip length (20 to 30 miles) varied		
(Gehrke et al. 2018)		42% of weekend ride-hailing rides happened between 7pm and midnight; 40% of weekday ride-hailing rides occurred during morning/evening commute			66% used ride-hailing at least once a week; 29% used at least 4 times per week
(Gerte et al. 2018)				Demand increased during winter and decreased during summer	

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

Table 4 continued

	Day of Week	Time of Day	Trip Length	Season	How Often Used
(Deka and Fei 2019)					People in higher population and employment density areas had a higher frequency of use; Women and non-Hispanic whites had a lower frequency of use
(Bischak 2019)	TNCs were used most often on weekends	TNCs were used most often in the evenings			84% used TNCs a few times a month or less frequently
(Brown 2019)					Most users rode infrequently (40% rode less than once a month)
(Lavieri and Bhat 2019)		Highest activity was during afternoon commute peak period; Millennials made the majority of nighttime ride-hailing trips			
(Brown 2020)	Shared trips were more likely to occurs on weekdays	Shared trips were more likely to occur during peak periods	Shared rides were a mile shorter on average than regular trips		

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

Table 5: Trip Purpose Key Findings.

	Going Out/Social	Work/Commuting	To/From Airport	To/From Home	Other
(MADD 2015)	Most late-night origins were near establishments that serve alcohol				
(Rayle et al. 2016)	67% of ridesourcing trips were for social/leisure	16% of ridesourcing trips were for work			
(Henao 2017)	Social outings accounted for 16% of trip origins and 18% of trip destinations	Work accounted for 13% trip origins and 17% of trip destinations	12% of trips ended at an airport	Homes accounted for 41% of trip origins and 29% of trip destinations	
(Mahmoudifard et al. 2017)	53.84% of Uber trips were for a social/leisure activity				
(Gehrke et al. 2018)				58% of trips that began somewhere other than home ended at home	
(Bischak 2019)	TNCs were used for bars, restaurants, or other entertainment purposes				
(Erhardt et al. 2019)					TNCs were concentrated in the downtown area of San Francisco
(Habib 2019)				Uber was more likely to be chosen for the return home rather than going to an activity	
(Lavieri and Bhat 2019)					Women were less likely to use for running errands

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

and found that between 13 and 17 percent of ridesourcing trips were associated with this type of travel. Two studies had findings related to trip purpose that were categorized as other. The first found that ridesourcing trips were concentrated in the downtown area while the other found that women were less likely to use ridesourcing to run errands than males. One study revealed that 12% of trips ended at an airport.

Reasons for Using Ridesourcing

As seen in Table 2, six studies (14% of the 44 total studies) considered the motivations that led a traveler to choose ridesourcing (Circella et al. 2018; Clewlow and Mishra 2017; Feigon and Murphy 2018; MADD 2015; Mahmoudifard et al. 2017; Rayle et al. 2016). Table 6 identifies commonly considered reasons for choosing ridesourcing: not having to pay or search for parking, faster travel times, not driving while under the influence, ease of payment, wait time, and other. Difficulty finding parking or the expense of parking was the primary reason for selecting ridesourcing in three studies. Three additional studies found the important reason for selecting ridesourcing was shorter travel times since users were picked up and dropped off directly at their destinations. Three studies concluded that not driving while under the influence of alcohol or drugs was the main motivation when travelers opted for ridesourcing. Shorter wait times were an important aspect of choosing to use ridesourcing services in two other studies. Ease of payment on ridesourcing applications was a top consideration when choosing this mode of transportation for travelers in one study.

Ridesourcing Relationship with Other Transportation Modes

Table 2 shows that 16 studies (36%) compared ridesourcing services to other modes of transportation to identify complementary or substitutionary relationships (Chu et al. 2018; Clewlow and Mishra 2017; Dong 2020; Feigon and Murphy 2018; Fulton et al. 2020; Gehrke et al. 2018; Gerte et al. 2018; Habib 2019; Hall et al. 2018; Lavieri and Bhat 2019; Lee et al. 2018; Mahmoudifard et al. 2017; Schaller 2018; Sikder 2019; Sturgeon 2019; Zheng 2019). As seen in Table 7, the other modes of transportation compared to ridesourcing were taxi, public transit, personal car, and other. Eleven studies examined the relationship between ridesourcing and public transit. Of the 11 studies, 5 found a complementary relationship, 5 found a substitutionary relationship, and the final study found no clear relationship. Five studies investigated the relationship to personal vehicles, and three of them found the relationship to be substitutionary. One study found that ridesourcing was a substitute for taxis.

Transportation System Impacts of Ridesourcing

Table 2 indicates that 18 studies (41% of the 44 total studies) had findings related to transportation system impacts (Alemi et al. 2018; Brodeur and Nield 2018; Castiglione et al. 2018; Circella et al. 2016; Cooper et al. 2018; Erhardt et al. 2019; Gehrke and Reardon 2018; Hall et al. 2018; Henao 2017; Jiao et al. 2020; Joshi et al. 2019; Lee et al. 2018; Qian et al. 2020; Rayle et al. 2016; Sabouri et al. 2020a; Schaller 2017, 2018; Zheng 2019). As ridesourcing continues to grow in popularity and presence around the United States, it is important to understand how it is impacting the current conditions of roadways. Table 8 delineates the most commonly considered impacts, including vehicle miles traveled (VMT) or additional miles, additional trips or total trips, additional vehicles on the roadway or congestion, vehicles hours of delay or changes in speed, and other. Eight of the studies contained findings broadly related to vehicle miles traveled. Two of these VMT-related studies analyzed additional miles added by ridesourcing; these two studies found that ridesourcing could account for an additional 600 million to 5.7 billion miles every year across the United States. Five studies examined additional or total trips taken by ridesourcing users; one noteworthy study from New York City-based Schaller Consulting found that there was a net 31 million trip increase after accounting for decreases in other cab and car services over a 3-year period in New York City (Schaller 2017). Six studies looked at additional vehicles on the road and/or the congestion impacts of ridesourcing. In general, most of these studies found that ridesourcing vehicles increased the number of vehicles on the

Table 6: Reasons for Using Ridesourcing Key Findings.

Author	Not having to search or pay for parking	Travel time	No need to drive after drinking alcohol	Ease of payment	Wait time	Other
(MADD 2015)			88% of respondents agreed Uber has made it easier to avoid driving home after drinking too much; 78% of respondents said their friends are less likely to drive after drinking since Uber launched; 57% of respondents agreed they would drive more after drinking at a bar or restaurant without Uber			
(Rayle et al. 2016)		30% of respondents chose faster travel time as a reason		35% of respondents chose ease of payment as a reason	30% of respondents chose shorter wait times as a reason	
(Clewlow and Mishra 2017)	Difficulty/expense of parking (37%)		Avoid driving under the influence (33%)			
(Mahmoudifard et al. 2017)	Parking was a reason to choose ridesourcing	Uber riders experienced shorter travel times		Cost and affordability were reasons to choose ridesourcing		Convenience, safety, fast service, friendliness of driver, availability, user friendly application, reliability, and weather conditions were reasons to choose ridesourcing
(Circella et al. 2018)	Parking, including difficulty finding and cost of (80%)		To avoid drinking and driving (60%)			
(Feigon and Murphy 2018)		Faster travel times			Less wait time	

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

Table 7: Ridesourcing Relationship with Other Modes Key Findings.

Author	Taxi	Public Transportation	Personal Car	Other
(Clewlow and Mishra 2017)		Ride-hailing was a substitute for bus but complement for some rail		
(Mahmoudifard et al. 2017)	Higher income riders would drive or use taxi	44-55% would use transit if Uber was not available	Higher income riders would drive or use taxi	
(Chu et al. 2018)				Primary commute mode did not have a significant influence on ride-hailing adoption
(Feigon and Murphy 2018)		No clear relationship between the level of peak-hour TNC use and longer-term changes in public transit usage	TNC use was associated with decreases in respondents' vehicle ownership	
(Gehrke et al. 2018)	41% of ride-hailing users would have used their own vehicle or a taxi	42% of ride-hailing users would have used public transit	41% of ride-hailing users would have used their own vehicle or a taxi	
(Gerte et al. 2018)				Bikeshare infrastructure increased demand for rideshare
(Hall et al. 2018)		Complement for lower ridership systems; Substitute for higher ridership systems		
(Lee et al. 2018)		Complementary effect of Uber was stronger than its substitution effect for public transit	Uber and public transit were a substitute for personal vehicles	Uber allowed walkers as well as non-commuters to travel more conveniently
(Schaller 2018)		TNCs compete with public transportation		TNCs compete with biking and walking
(Habib 2019)		Complement for public transit	Complement for private automobiles	
(Lavieri and Bhat 2019)		Women substitute transit for ride-hailing more than men		
(Sikder 2019)		People that used transit had a positive association with ridehail use		People who also used bikeshare and carshare were more likely to adopt ride-hailing
(Sturgeon 2019)		TNCs were a substitute for rail		
(Zheng 2019)		Transit trips increased by 3.28% from 2013 to 2018		
(Dong 2020)		Females and those over the age of 30 were willing to use ridehail over transit		
(Fulton et al. 2020)			Personal vehicles were cheaper than ridesourcing overall	

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

Table 8: Transportation System Impacts Key Findings.

	VMT or Additional Miles	Additional or Total Trips	Additional Vehicles or Congestion	Vehicle Hours of Delay or Speed	Other
(Circella et al. 2016)	Millennials had lower vehicle miles traveled				
(Rayle et al. 2016)	Impact on vehicle miles traveled was unclear				
(Henao 2017)	If Denver results were true for the entire country, 1 billion rides per year could create an additional 5.5 billion miles in the US				Approximately 69 miles of deadheading per 100 passenger miles
(Schaller 2017)	TNCs accounted for the addition of 600 million miles of vehicular travel over the past three years	TNCs generated net increases of 31 million trips over the past three years	TNC growth added nearly 50,000 vehicles		
(Alemi et al. 2018)	Net vehicle miles traveled impacts still uncertain				
(Brodeur and Nield 2018)		10% increase in Uber rides on rainy days			
(Castiglione et al. 2018)	47% of the increase for daily vehicle miles traveled between 2010 and 2016 was due to TNCs			TNCs caused 51% of the increase in vehicle hours of delay and 55% of the decrease in average speed	
(Cooper et al. 2018)	Vehicle miles traveled per trip is lowest during typical rush hours				
(Gehrke and Reardon 2018)		Ride-hailing trips comprised 1.3% of all trips taken in the region and 2.4% of all trips downtown			
(Hall et al. 2018)			Increased congestion		
(Lee et al. 2018)			May lead to increased traffic congestion		
(Schaller 2018)	TNCs added 5.7 billion of miles of driving annually in the nation's largest metro areas				

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

Table 8 continued

	VMT or Additional Miles	Additional or Total Trips	Additional Vehicles or Congestion	Vehicle Hours of Delay or Speed	Other
(Erhardt et al. 2019)			1 TNC vehicle is the reduction of 0.31 non-TNC vehicles	Vehicle hours of delay increased and speed decreased	Vehicle hours traveled increased as a result of TNCs
(Joshi et al. 2019)		Total trips on a monthly (8.8 million trips in Chicago) or daily basis (6 cities, Max: 700,000 trips in New York City, Min: 170,000 trips in San Francisco)	New York City and Toronto number of vehicles per day was 60,000 and 90,453, respectively		
(Zheng 2019)			Had trivial effects on number of vehicles	Average travel speed decreased by 0.122 mph	
(Jiao et al. 2020)		Ridehailing may be inducing people to make more trips			
(Qian et al. 2020)				Weekday speeds decreased by 22.5%	
(Sabouri et al. 2020a)					Ride-sourcing can help reduce the number of cars in a household and open up parking

Ridesourcing is referred to in the tables using same terminology as the prior study (e.g. TNC, ride-hailing)

road and had the potential to increase congestion. Similarly, four studies examined vehicle hours of delay (VHD) and the speed impacts of ridesourcing; notably, all four studies found that ridesourcing resulted in congestion and a decrease in speeds in their respective study areas. Three studies considered "other" transportation system impacts of ridesourcing including deadheading, vehicle hours traveled, and parking availability.

DISCUSSION, CONCLUSION, AND FUTURE RESEARCH

The rapid growth of ridesourcing services in North America over the past ten years has led to a large research focus on the services provided as well as the travelers using them. Since this area of research is constantly changing, the objective of this paper was to provide a comprehensive literature review of the latest research and summarize findings relating to ridesourcing users and their travel behavior. Forty-four studies on ridesourcing were reviewed for this paper. After reviewing the papers, six common categories of research were identified: demographics; frequency and time of use; trip purpose; reason for using ridesourcing services; ridesourcing versus other modes of transportation; and transportation system impacts. While there were some differing results in these studies, general trends can be summarized and are shown in Figure 1.

In terms of demographics, numerous studies found that ridesourcing users were often those who were younger (17 of 19), had higher incomes (12 of 16), and had obtained some higher education (10 of 10). In terms of frequency and time use, ridesourcing trips were commonly taken on the weekends (7 of 9), especially at night (6 of 6). Social activities were the most common trip purpose for ridesourcing users. The most common reasons for using ridesourcing were to avoid driving under the influence, to avoid expensive or difficult parking situations, and to have shorter travel times. The most common modes to be compared to ridesourcing usage were public transit, personal vehicles, and taxi; however, there were mixed results on whether these were substitutes or complements, especially for public transit. Lastly, some transportation system related studies found ridesourcing increased VMT and number of vehicles on the roadways; however, there were too few studies to have conclusive finding in regards to the impacts.

These six main categories related to ridesourcing user travel behavior are interrelated. For example, this can be seen with the frequency and time of use, trip purpose, and reasons categories. Most trips were taken on weekends and at night, which is a common time for social events and going out to restaurants and bars. It is common for alcohol to be consumed during these types of social events, which could result in ridesourcing travelers wanting to avoid driving under the influence. There is also a relationship between transportation system impacts and the relationship between ridesourcing and other modes. VMT could increase when examining the substitutive relationship between ridesourcing and personal vehicles, especially when considering deadheading.

It is important for transportation system planners and policy-makers to understand who is using ridesourcing and how they are using it. For example, if planners and policy-makers are looking at trip purpose and find that most people are using ridesourcing to travel downtown to go to bars and restaurants, they may want to implement curb space management strategies. Further understanding of when these trips are being made (e.g., primarily on weekends) could potentially change curb space management decisions, since ridesourcing loading zones may only be needed on weekends rather than all week. Similarly, if planning and policy-makers are in an area with an airport and find that many of the ridesourcing trips are to and from the airport, they may want to work with airport authorities to create better curb space manage pick up and drop off locations for ridesourcing, as well as allocate space for ridesourcing vehicles waiting to pick up users (Mandle and Box 2017).

Based on this research, general trends are emerging about the travel behavior of ridesourcing users. These trends help form a clearer image of who is using ridesourcing and how their behaviors are impacting transportation systems. This review finds substantial evidence for both demographics and the frequency and use of ridesourcing. However, some of the six categories are not as commonly researched and,

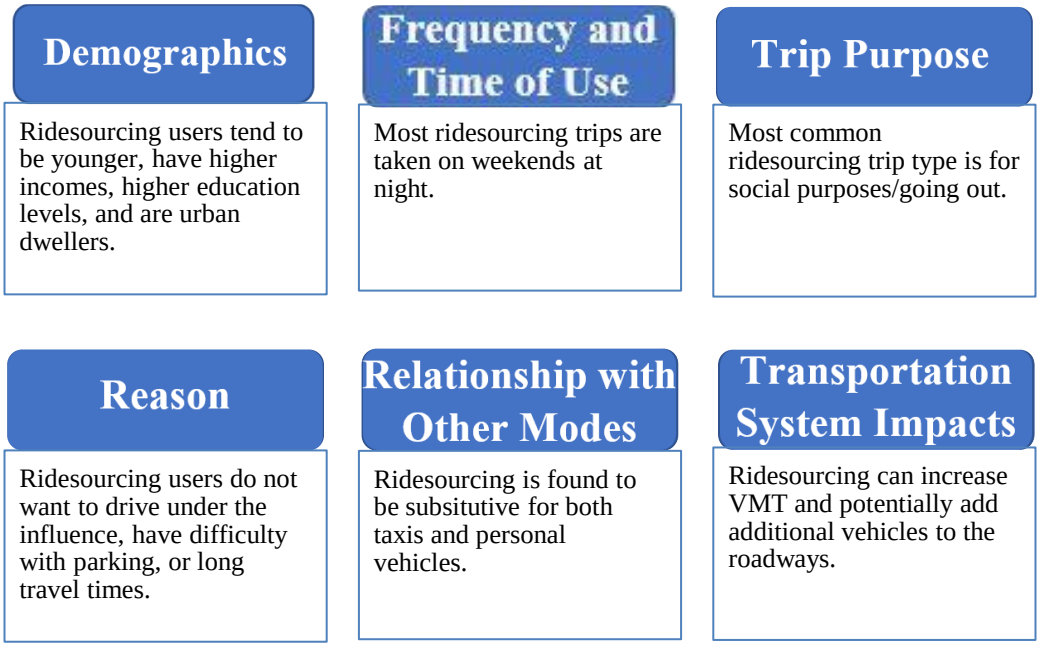

Figure 1: **Summary of Main Findings by Category.**

therefore, present areas for future research. The two categories with the fewest number of studies are the reason behind selecting ridesourcing and the trip purpose when using ridesourcing. Although the relationship between ridesourcing and other modes is more commonly studied, the results do not show a clear trend, especially for public transit. Future research should be conducted in this area to clarify the relationship between ridesourcing and public transit. Another area for future research should be an increase in studies regarding transportation system impacts so that results may be comparable. Additionally, the majority of the studies focused on the United States as a whole or individual large American cities, most of which are on the coasts (Table 2). Focusing research on smaller cities as well as more rural areas may render different results than those for national studies and major cities. For planners and policy-makers, it is important to understand who is likely to use ridesourcing services in their region, which can be accomplished by looking at trends from comparable areas. Other areas of research not included in this literature review include ridesourcing demand modeling and studies using ridesourcing movement data from service providers (Roy et al. 2020). As ridesourcing continues to expand and adapt over time, additional research areas are likely to emerge.

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CHAPTER III
USING NATIONAL HOUSEHOLD TRAVEL SURVEY DATA ON RIDESHARING TO ASSESS DIFFERENCES BETWEEN STATES AND NATIONAL TRENDS: A CASE STUDY OF TENNESSEE

This paper is in preparation for submission to the journal Case Studies on Transport Policy: Crossland, C., West, J., and Brakewood, C. "Using National Household Travel Survey Data on Ridesharing to Assess Differences between States and National Trends: A Case Study of Tennessee".

Cassidy Crossland was the principle author of "Using National Household Travel Survey Data on Ridesharing to Assess Differences between States and National Trends: A Case Study of Tennessee". Cassidy's contribution included data collection, analysis and interpretation of results, and draft manuscript preparation. Jonathan West assisted in the data collection and analysis. Dr. Candace Brakewood created the concept and design of the project and assisted in both the interpretation of results and draft manuscript preparation.

ABSTRACT

Over the past ten years, ridesharing has grown significantly in the United States with companies such as Uber and Lyft at the forefront of this growth. While research on this new transportation mode has largely focused on national level trends and studies of large metropolitan areas, little has been written about its impacts in smaller and mid-sized cities and states. This paper aims to provide a way for these less commonly researched areas to understand the demographics of who might be using ridesharing in their area using Tennessee as a case study. This study uses the 2017 National Household Travel Survey (NHTS) to determine if there are any significant socioeconomics differences between national, regional, and state levels of ridesharing users. In the 2017 NHTS, there were two questions that asked about ridesharing. Binary logit models were estimated to compare these two questions at the state, regional, and national levels. While the results of the models align with the many findings in previous literature, there are fewer significant differences in characteristics at the state level, including both gender and race being insignificant. By understanding the characteristics of local ridesharing users, policy makers and transportation professionals in can make more informed decisions when creating new policies and practices to best manage ridesharing in their states and cities.

INTRODUCTION

The terms ridesharing, ridehailing, ridesourcing, and transportation network companies (TNCs) have been used to describe "prearranged and on-demand transportation services for compensation in which drivers and passengers connect via digital applications" (SAE 2018). Ridesharing was first introduced in the United States in 2009 by the company UberCab, known today as Uber Technologies (Blystone 2019). Many companies began to appear after the launch of Uber including Lyft, the most common competitor for Uber in the United Sates, in 2012 (Greiner et al. 2019). Both Uber and Lyft completed its first billion rides within six years of launching their services (Lyft 2018; Uber 2018). As ridesharing continues to grow in popularity both in the United States and around the world, many transportation planners and policy-makers want to understand who is using this service in their localities.

In the most recent National Household Travel Survey (NHTS), administered in 2017, there were two questions asked pertaining to ridesharing that were asked for the first time. The aim of this study is to use the 2017 NHTS to evaluate if there are significant differences between a mid-size state and national ridesharing socioeconomic characteristics. Tennessee is used as a case study, but the methodology could be replicated for any state or region within the United States.

The paper is organized as follows. First, a literature review is presented in two parts, one about ridesharing users and another about the 2017 National Household Travel Survey. This is followed by a description of the research question. A description of the data and method of analysis is provided next, after which the results are presented. This is followed by the discussion, areas for future research, and conclusions.

LITERATURE REVIEW

Ridesharing Users

Various characteristics of ridesharing user socioeconomics were explored in prior literature, including age, income, educational attainment, employment status, number of household vehicles, and whether users are in an urban or rural setting. Numerous prior studies found that ridesharing users tend to be younger, typically in the millennial generation (Alemi et al. 2018; Bansal et al. 2020; Brown 2020; Chu et al. 2018; Circella et al. 2016; Circella et al. 2018; Clewlow and Mishra 2017; Deka and Fei 2019; Gehrke et al. 2018; Grahn et al. 2019; Schaller 2018; Smith 2016; Young and Farber 2019). Several prior studies that looked at income levels of ridesharing users determined that higher incomes typically resulted in greater use of ridesharing (Alemi et al. 2018; Baker 2020; Bansal et al. 2020; Chu et al. 2018; Deka and Fei 2019; Dong 2020; Gehrke et al. 2018; Grahn et al. 2019; Lahkar 2018; Mahmoudifard et al. 2017; Mitra et al. 2019; Schaller 2018; Young and Farber 2019). Many studies found that having a higher education increased use of ridesharing (Alemi et al. 2018; Bansal et al. 2020; Circella et al. 2018; Deka and Fei 2019; Gehrke et al. 2018; Gerte et al. 2018; Grahn et al. 2019; Mitra et al. 2019; Schaller 2018). Several studies found that people who were employed were more likely to use ridesharing (Alemi et al. 2018; Deka and Fei 2019; Gehrke et al. 2018; Sabouri et al. 2020; Young and Farber 2019). A handful of studies found that people from households with fewer vehicles were more likely to use ridesharing (Bansal et al. 2020; Deka and Fei 2019; Gerte et al. 2018; Young and Farber 2019). Several studies that looked at the residential area the user is from determined that ridesharing was more often used in urban areas (Alemi et al. 2018; Bansal et al. 2020; Brown 2020; Circella et al. 2018; Clewlow and Mishra 2017; Grahn et al. 2019). Other socioeconomics studied include gender, which had inconclusive findings (Deka and Fei 2019; Dong 2020; Gerte et al. 2018; Jiao et al. 2020; Mitra et al. 2019), and race which found white people are more likely to use ridesharing (Gehrke et al. 2018; Lahkar 2018).

2017 NHTS and Ridesharing

At least four prior studies examined the 2017 NHTS ridesharing data. Two studies found that people used ridesharing more frequently in highly populated/urban areas (Deka and Fei 2019; Sikder 2019). Mitra et al. focused on ridesharing use among the elderly population and found that the younger group of the elderly population was most likely to adopt, even if they did not use the services frequently (Mitra et al. 2019). Jiao et al. looked at the difference between weekday and weekend trip generation and found that ridesharing increased number of trips made any time during the week (Jiao et al. 2020). Each of these studies used the entire nationwide dataset, except for Mitra et al., which used nationwide data for only those above the age of 65.

RESEARCH QUESTION

To the best of the authors' knowledge, there have been no studies using the 2017 NHTS that look at ridesharing for individual states. This leads to the question, do ridesharing user characteristics change in different parts of the country? This study seeks to answer this question by using a mid-size state, Tennessee, as a case study.

DATA AND METHODOLOGY

Assemble 2017 NHTS Data

The 2017 National Household Travel Survey data consists of four datasets: household, person, vehicle, and trip. These datasets, along with the NHTS codebook, were downloaded from the NHTS website (ORNL n.d.). The questions used in the two-phase survey were downloaded from the Recruitment Survey and the Retrieval Questionnaire files. The NHTS took 14 months to collect all responses beginning March 31, 2016

and ending May 8, 2017 (Westat 2019). The survey was given in two parts, the first being the household recruitment survey and the second being the retrieval questionnaire. The household recruitment survey was filled out by a single member of the household while the retrieval questionnaire required responses from all members of the household.

There were two questions related to ridesharing in the 2017 NHTS. The first question was found in the recruitment survey: "How often do you use taxi service or rideshare such as Uber/Lyft to get from place to place?" with potential responses being daily, a few times a week, a few times a month, a few times a year, or never (USDOT 2018). Since this question was asked in the household recruitment survey, this question was only answered by one person in the household resulting in 129,696 responses nationwide. The second question was found in the retrieval questionnaire: "In the past 30 days, how many times have you purchased a ride with a smartphone rideshare app (e.g. Uber, Lyft, Sidecar)?" with potential responses of I don't know, I prefer not to answer, or a number (Westat 2018). This question was asked for each member of the household resulting in 264,234 responses nationwide.

Using the NHTS 2017 codebook, several demographic variables were selected in the person datasets. These variables included: household size, number of household vehicles, imputed age, educational attainment, employment status, household income, Hispanic origin, medical condition making it difficult to travel outside of the home, race, imputed gender, and residential area type. Imputed age and gender are provided by the NHTS when certain answers were left blank, including age and gender, and put into the NHTS dataset as separate variables. Cross Tabulations were run to compare the responses for both age and gender compared to the imputed age and gender and there was little change between the two. The imputed age and gender were selected for the following analysis because these were the variables used in the weighting process (Roth et al. 2017).

The NHTS data were compiled for both ridesharing questions and the selected demographic variables. For the question relating to the frequency of use of taxi and/or ridesharing, the person dataset and the household dataset were combined since this question was only provided in the household dataset and the remaining demographic information was found in the person dataset. For the ridesharing app question, all variables were in the person dataset. After compilation, the data were further cleaned. First, the three samples of interested were determined to be Tennessee, Census Division 6 (Alabama, Kentucky, Mississippi, and Tennessee), and National. The 2017 NHTS weights are significant to the census division level and the national level (Roth et al. 2017). The 2017 NHTS did not provide state level weights for Tennessee; therefore, the data at the state level may not statistically representative of the entire state. The remainder of this paper uses the unweighted data since the focus is on the state of Tennessee; however, the weighted summary statistics and cross tabulations for the census division and national levels can be found in the appendix.

Calculate Statistics

First, summary statistics were calculated for Tennessee, the census division, and the nation using both the frequency of taxi/ridesharing use and the ridesharing app questions. The unweighted summary statistics excluded non-response entries for each question, resulting in a sample size of 401 for Tennessee, 1,311 for Census Division 6, and 116,089 for the nation for the taxi/ridesharing question and 827 for Tennessee, 2,331 for Census Division 6, and 236,089 for the US for the ridesharing app question.

Second, cross tabulations were then generated using SPSS (Corp 2019) with the selected demographic variables for both the frequency of taxi/ridesharing use and the ridesharing app questions. The unweighted cross tabulations excluded non-response entries for all variables, resulting in a sample size of 385 for Tennessee, 1,100 for Census Division 6, and 111,809 for the nation for the taxi/ridesharing question and 769 for Tennessee, 2,210 for Census Division 6, and 222,095 for the nation for the ridesharing app usage question.

Finally, weighted cross tabulations were calculated for Census Division 6 and the nation, since the weights are statistically representative for both the division and national levels. These results are shown in

the Appendix for both the frequency of taxi/ridesharing use and the ridesharing app questions. When using the weights, the data included non-response entries to keep the results statistically representative. This resulted in a sample size of 7,683,303 for Census Division 6 and 126,322,007 at the national level for the taxi/ridesharing question and 17,730,127 for Census Division 6 and 301,599,169 at the national level for the ridesharing app usage question.

Binary Logit Model Analysis

Six binary logit models were created using STATA16 (StataCorp 2019). Two models were run for Tennessee (one for the taxi/ridesharing question and one for the rideshare app usage question), two models for Census Region 6 (again, one for the taxi/ridesharing question and one for the rideshare app usage question), and two models for the nation. First, a binary variable was created for the frequency of use of taxi and ridesharing question. This variable had values of zero for those who never used taxi or ridesharing services and one for anyone who used taxi or ridesharing services, regardless of frequency of use. Similarly, for the ridesharing app question, a ridesharing variable was created. This variable has values of zero for those who reported not buying a ride from a ridesharing app in the past 30 days and one for those who had.

In these models, household size and number of household vehicles were the only continuous independent variables, ranging from one to thirteen and zero to twelve, respectively. All remaining independent variables were binary; when the respondent fell into a given category, the value was set equal to one. For all categories that used binary variables, a reference variable was defined and used as the reference when interpreting the coefficients. The data used in the models excludes the non-response entries, is not weighted, and has the same sample sizes as the unweighted cross tabulations.

RESULTS

2017 NHTS Unweighted Summary Statistics

Taxi or Ridesharing Frequency of Use Summary Statistics

In Tennessee, a total of 24.9% of respondents use taxi or rideshare with 20.2% using a few times a year, 4.0% using a few times a month, 0.7% using a few times a week, and 0.0% using daily, as seen in Figure 2. Tennessee has a greater use of taxi and rideshare than its neighboring states in Census Division 6 but is below the national figures. At the national level, a total of 32.9% of respondents use taxi or ridesharing services with 25.6% using a few times a year, 5.6% using a few times a month, 1.4% using a few times a week, and 0.3% using daily.

Ridesharing App Usage Summary Statistics

As seen in Figure 3, 5.1% of Tennessee respondents purchased a ride using a smartphone rideshare app in the past 30 days. More respondents in Tennessee purchased rideshare rides compared to neighboring states in Census Division 6 (3.9%). Fewer people in Tennessee purchased rideshare rides than the United States as a whole; at the national level, 7.4% of respondents purchased a ride in the past 30 days.

2017 NHTS Unweighted Cross Tabulations

Before completing the cross tabulations for the taxi/ridesharing frequency of use and ridesharing app usage, the data was further cleaned and manipulated. All respondents under the age of 18 were removed from the dataset because Uber does not allow those under the age of 18 to create an account (Uber 2020). Ages were then grouped into five categories: 18 to 24, 25 to 34, 35 to 44, 45 to 54, and 55 and older. Once the respondents under the age of 18 were removed, the number of responses for the educational attachment question (specifically, less than high school and high school graduate) decreased. These two educational attainment categories were then combined. The NHTS has 11 income brackets that were further combined into six brackets: less than $25,000; $25,000-$49,999; $50,000 to $74,999; $75,000 to $99,999; $100,000 to $149,999; and $150,000 or greater. Due to the small number of responses in some race categories,

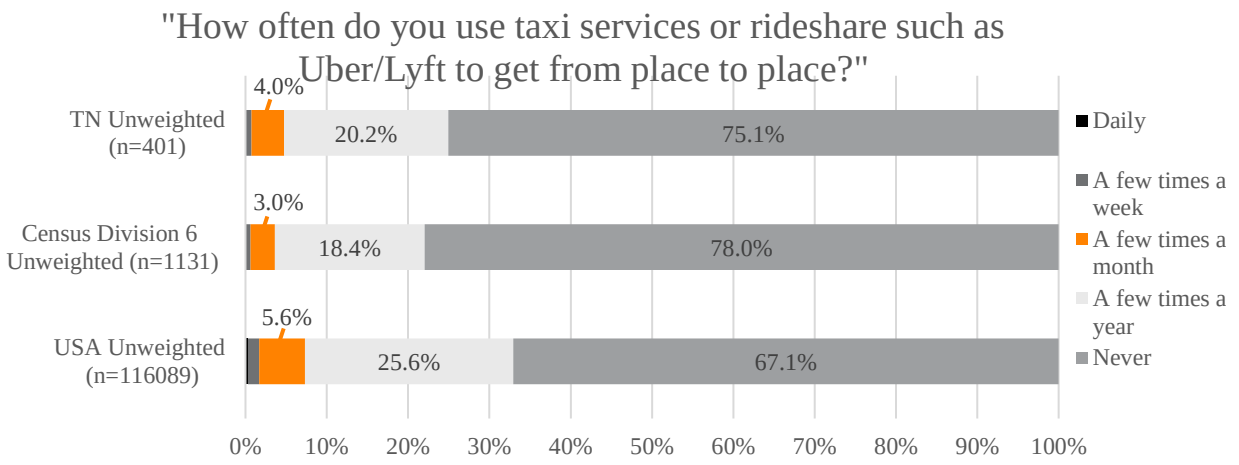

Figure 2: Taxi and Ridesharing Frequency of Use, Unweighted Responses.

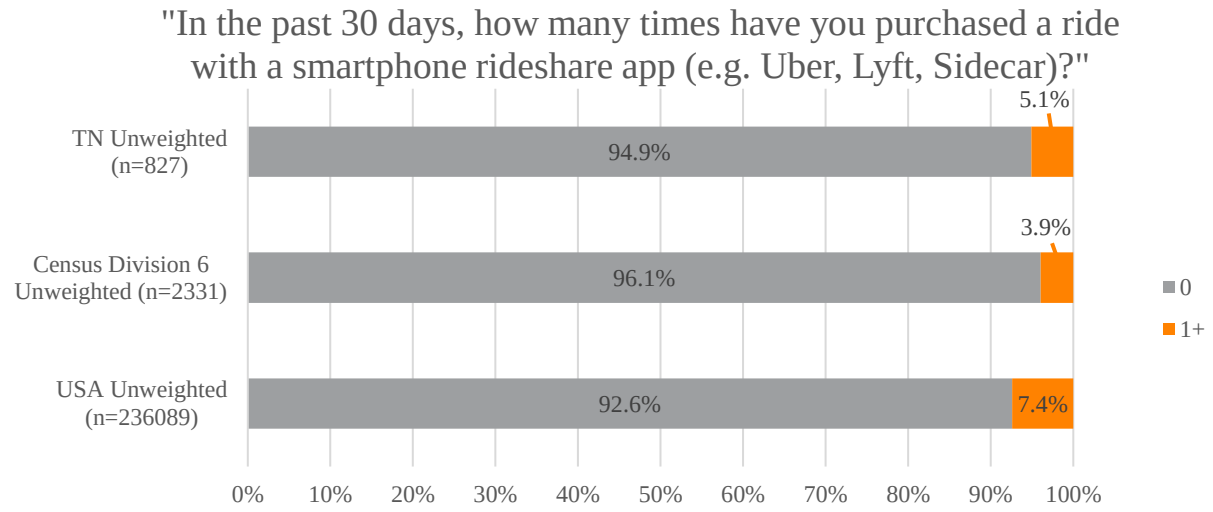

Figure 3: Rideshare App Usage Over the Past 30 Days, Unweighted Responses.

American Indian or Alaska Native, Native Hawaiian or other Pacific Islander, and multiple responses were combined with the Other race category. Last, the sample was cleaned to remove non-response entries in the dataset. The non-response entries included: appropriate skip; I don't know; I prefer not to answer; and not ascertained.

Taxi or Ridesharing Frequency of Use Cross Tabulation

As seen in Table 9, the unweighted cross tabulations for the question "How often do you use Taxi service or ridesharing to get from place to place?" were calculated for Tennessee, Census Division 6, and National.

Of those who reported using taxi or ridesharing services, one- or two-person households were most frequent. In Tennessee, 35.4% of those who use these services were from one-person households while only 30.4% of those who never use these services were from one-person households. Households with one or two vehicles were found to have the highest percentages amongst those who use taxi or ridesharing.

The data suggest that people under the age of 55 were more likely to use taxi or ridesharing services. In Tennessee, 25.3% of those who use these services were 45 to 54 years old whereas this group represents just 15.4% of non-users. This trend continues in Tennessee for the younger age groups as well: 35 to 44 years old (17.2% use and 11.2% do not use); 25 to 34 years old (13.1% use and 8.7% do not use); and 18 to 24 years old (4.0% use and 1.7% do not use). Similar trends appear in both the census division and national cross tabulations.

Of those who reported using taxi services or ridesharing, the majority had some form of higher education. In Tennessee, the most common education level among users of taxi or ridesharing was a bachelor's degree, while a graduate degree or professional degree was most common for users at the census division and national level. In Tennessee, Census Division 6, and the nation, the most common education level for those who never use these services was some college or an associate degree.

The taxi and rideshare users were more frequently employed, with Tennessee having the largest portion of employed users at 74.7% and the lowest portion of employed non-users at 48.3%.

High incomes were common for those using taxi or ridesharing. In Tennessee, 46.5% (sum of $100,000 to $149,999 and $150,000 or more) of those who use taxi or rideshare have an annual household income of at least $100,000 compared to 16.1% of non-users in Tennessee in these income brackets.

Within the Hispanic category, the data show a greater percentage of users than non-users at the Tennessee and National levels (2.0% users compared to 1.7% non-users and 7.4% users compared to 6.5% non-users, respectively).

Similarly, almost 93% of all respondents using taxis or ridesharing do not have a medical condition that makes it difficult to travel. Those who do not have a medical condition account for 85 to 90% of all non-users.

Results showed that the majority of taxi or rideshare users were white. In Tennessee, 89.9% of people using these services were white and 89.5% of non-users were white.

Gender was almost evenly split between taxi and ridesharing users. When comparing users versus non-users in Tennessee, males tend to use these services more than females (48.5% of males use compared to 46.5% do not use, while 51.5% of females use these services compared to 53.5% who do not).

People living in an urban setting were more likely to use taxi or ridesharing than those in a rural setting. In Tennessee, 81.8% of people who reported using these services were in an urban setting while 60.1% of people who reported not using taxi or rideshare services were in an urban setting.

Ridesharing App Usage Cross Tabulation

Table 10 presents the results of the unweighted cross tabulations for the question "In the past 30 days, how many times have you purchased a ride with a smartphone rideshare app?" for Tennessee, Census Division 6, and National.

Of those who reported buying a rideshare ride, one- or two-person households were most frequent. In Tennessee, 31.0% of those who purchased a ride were from one-person households while 17.5% of all those who have not purchased a ride were from one-person households.

Table 9: How Often Do You Use Taxi Services or Rideshare to Get from Place to Place? Unweighted Cross Tabulation.

		Tennessee						Census Division 6						National					
		Never Uses		Uses		Total		Never Uses		Uses		Total		Never Uses		Uses		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		286	100%	99	100%	385	100%	853	100%	247	100%	1100	100%	74792	100%	37017	100%	111809	100%
Count of Household Members	1	87	30.4%	35	35.4%	122	31.7%	260	30.5%	83	33.6%	343	31.2%	22935	30.7%	11705	31.6%	34640	31.0%
	2	120	42.0%	34	34.3%	154	40.0%	344	40.3%	96	38.9%	440	40.0%	32831	43.9%	14942	40.4%	47773	42.7%
	3	35	12.2%	18	18.2%	53	13.8%	114	13.4%	40	16.2%	154	14.0%	8738	11.7%	4916	13.3%	13654	12.2%
	4	31	10.8%	6	6.1%	37	9.6%	95	11.1%	19	7.7%	114	10.4%	6542	8.7%	3850	10.4%	10392	9.3%
	5	5	1.7%	5	5.1%	10	2.6%	26	3.0%	8	3.2%	34	3.1%	2503	3.3%	1177	3.2%	3680	3.3%
	6	6	2.1%	1	1.0%	7	1.8%	8	0.9%	1	0.4%	9	0.8%	810	1.1%	297	0.8%	1107	1.0%
	7	1	0.3%	0	0.0%	1	0.3%	4	0.5%	0	0.0%	4	0.4%	272	0.4%	84	0.2%	356	0.3%
	8`	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	96	0.1%	25	0.1%	121	0.1%
	9	1	0.3%	0	0.0%	1	0.3%	2	0.2%	0	0.0%	2	0.2%	34	0.0%	11	0.0%	45	0.0%
	10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	26	0.0%	8	0.0%	34	0.0%
	11	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	3	0.0%	1	0.0%	4	0.0%
	12	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	1	0.0%	1	0.0%	2	0.0%
	13	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	1	0.0%	0	0.0%	1	0.0%
Count of Household Vehicles	0	5	1.7%	5	5.1%	10	2.6%	24	2.8%	18	7.3%	42	3.8%	1972	2.6%	2878	7.8%	4850	4.3%
	1	88	30.8%	29	29.3%	117	30.4%	256	30.0%	73	29.6%	329	29.9%	23717	31.7%	11390	30.8%	35107	31.4%
	2	114	39.9%	33	33.3%	147	38.2%	323	37.9%	95	38.5%	418	38.0%	29242	39.1%	14613	39.5%	43855	39.2%
	3	45	15.7%	20	20.2%	65	16.9%	158	18.5%	42	17.0%	200	18.2%	12421	16.6%	5269	14.2%	17690	15.8%
	4	14	4.9%	10	10.1%	24	6.2%	48	5.6%	15	6.1%	63	5.7%	4790	6.4%	1873	5.1%	6663	6.0%
	5	17	5.9%	2	2.0%	19	4.9%	31	3.6%	3	1.2%	34	3.1%	1617	2.2%	612	1.7%	2229	2.0%
	6	3	1.0%	0	0.0%	3	0.8%	9	1.1%	1	0.4%	10	0.9%	605	0.8%	224	0.6%	829	0.7%
	7	0	0.0%	0	0.0%	0	0.0%	4	0.5%	0	0.0%	4	0.4%	227	0.3%	88	0.2%	315	0.3%
	8	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	102	0.1%	28	0.1%	130	0.1%
	9	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	42	0.1%	24	0.1%	66	0.1%
	10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	27	0.0%	6	0.0%	33	0.0%
	11	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	12	0.0%	3	0.0%	15	0.0%
	12	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	18	0.0%	9	0.0%	27	0.0%
Imputed Age	18-24	5	1.7%	4	4.0%	9	2.3%	22	2.6%	10	4.0%	32	2.9%	1114	1.5%	1073	2.9%	2187	2.0%
	25-34	25	8.7%	13	13.1%	38	9.9%	86	10.1%	41	16.6%	127	11.5%	5959	8.0%	6905	18.7%	12864	11.5%
	35-44	32	11.2%	17	17.2%	49	12.7%	105	12.3%	43	17.4%	148	13.5%	7739	10.3%	6723	18.2%	14462	12.9%
	45-54	44	15.4%	25	25.3%	69	17.9%	125	14.7%	56	22.7%	181	16.5%	11502	15.4%	6990	18.9%	18492	16.5%
	55+	180	62.9%	40	40.4%	220	57.1%	515	60.4%	97	39.3%	612	55.6%	48478	64.8%	15326	41.4%	63804	57.1%

Table 9 continued

		Tennessee						Census Division 6						National					
		Never Uses		Uses		Total		Never Uses		Uses		Total		Never Uses		Uses		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		286	100%	99	100%	385	100%	853	100%	247	100%	1100	100%	74792	100%	37017	100%	111809	100%
Educational Attainment	High School Graduate or Less	76	26.6%	10	10.1%	86	22.3%	249	29.2%	26	10.5%	275	25.0%	16095	21.5%	3109	8.4%	19204	17.2%
	Some College or Associate's Degree	88	30.8%	20	20.2%	108	28.1%	270	31.7%	47	19.0%	317	28.8%	25359	33.9%	8017	21.7%	33376	29.9%
	Bachelor's Degree	66	23.1%	38	38.4%	104	27.0%	169	19.8%	86	34.8%	255	23.2%	17907	23.9%	12263	33.1%	30170	27.0%
	Graduate or Professional Degree	56	19.6%	31	31.3%	87	22.6%	165	19.3%	88	35.6%	253	23.0%	15431	20.6%	13628	36.8%	29059	26.0%
Worker Status	Is Employed	138	48.3%	74	74.7%	212	55.1%	419	49.1%	176	71.3%	595	54.1%	37483	50.1%	25936	70.1%	63419	56.7%
	Is Not Employed	148	51.7%	25	25.3%	173	44.9%	434	50.9%	71	28.7%	505	45.9%	37309	49.9%	11081	29.9%	48390	43.3%
Household Income	Less than $25,000	66	23.1%	11	11.1%	77	20.0%	226	26.5%	32	13.0%	258	23.5%	15144	20.2%	4956	13.4%	20100	18.0%
	$25,000 to $49,999	80	28.0%	21	21.2%	101	26.2%	231	27.1%	46	18.6%	277	25.2%	19105	25.5%	5222	14.1%	24327	21.8%
	$50,000 to $74,999	61	21.3%	9	9.1%	70	18.2%	167	19.6%	40	16.2%	207	18.8%	14839	19.8%	5402	14.6%	20241	18.1%
	$75,000 to $99,999	33	11.5%	12	12.1%	45	11.7%	105	12.3%	29	11.7%	134	12.2%	10223	13.7%	5108	13.8%	15331	13.7%
	$100,000 to $149,999	34	11.9%	25	25.3%	59	15.3%	91	10.7%	59	23.9%	150	13.6%	10473	14.0%	7863	21.2%	18336	16.4%
	$150,000 or more	12	4.2%	21	21.2%	33	8.6%	33	3.9%	41	16.6%	74	6.7%	5008	6.7%	8466	22.9%	13474	12.1%
Hispanic	Is Hispanic or Latino	5	1.7%	2	2.0%	7	1.8%	15	1.8%	4	1.6%	19	1.7%	4868	6.5%	2750	7.4%	7618	6.8%
	Is Not Hispanic or Latino	281	98.3%	97	98.0%	378	98.2%	838	98.2%	243	98.4%	1081	98.3%	69924	93.5%	34267	92.6%	104191	93.2%
Presence of Medical Condition	Has a Medical Condition	44	15.4%	6	6.1%	50	13.0%	111	13.0%	18	7.3%	129	11.7%	8306	11.1%	2749	7.4%	11055	9.9%
	No Medical Condition	242	84.6%	93	93.9%	335	87.0%	742	87.0%	229	92.7%	971	88.3%	66486	88.9%	34268	92.6%	100754	90.1%
Race	White	256	89.5%	89	89.9%	345	89.6%	706	82.8%	207	83.8%	913	83.0%	63860	85.4%	30014	81.1%	93874	84.0%
	Black or African American	21	7.3%	7	7.1%	28	7.3%	126	14.8%	27	10.9%	153	13.9%	5469	7.3%	2558	6.9%	8027	7.2%
	Asian	3	1.0%	1	1.0%	4	1.0%	5	0.6%	2	0.8%	7	0.6%	1838	2.5%	2271	6.1%	4109	3.7%
	Other	6	2.1%	2	2.0%	8	2.1%	16	1.9%	11	4.5%	27	2.5%	3625	4.8%	2174	5.9%	5799	5.2%
Imputed Gender	Male	133	46.5%	48	48.5%	181	47.0%	364	42.7%	122	49.4%	486	44.2%	34971	46.8%	18019	48.7%	52990	47.4%
	Female	153	53.5%	51	51.5%	204	53.0%	489	57.3%	125	50.6%	614	55.8%	39821	53.2%	18998	51.3%	58819	52.6%
Residential Area Type	Urban	172	60.1%	81	81.8%	253	65.7%	484	56.7%	204	82.6%	688	62.5%	54477	72.8%	32758	88.5%	87235	78.0%
	Rural	114	39.9%	18	18.2%	132	34.3%	369	43.3%	43	17.4%	412	37.5%	20315	27.2%	4259	11.5%	24574	22.0%

Table 10: In the Past 30 Days, How Many Times Have You Purchased a Ride With a Smartphone Rideshare App? Unweighted Cross Tabulation.

		Tennessee						Census Division 6						National					
		0 Trips		1+ Trips		Total		0 Trips		1+ Trips		Total		0 Trips		1+ Trips		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		727	100%	42	100%	769	100%	2116	100%	94	100%	2210	100%	205201	100%	16894	100%	222095	100%
Count of Household Members	1	127	17.5%	13	31.0%	140	18.2%	376	17.8%	25	26.6%	401	18.1%	36241	17.7%	3573	21.1%	39814	17.9%
	2	323	44.4%	17	40.5%	340	44.2%	939	44.4%	36	38.3%	975	44.1%	96812	47.2%	7418	43.9%	104230	46.9%
	3	130	17.9%	8	19.0%	138	17.9%	370	17.5%	21	22.3%	391	17.7%	32522	15.8%	2767	16.4%	35289	15.9%
	4	89	12.2%	2	4.8%	91	11.8%	282	13.3%	9	9.6%	291	13.2%	24623	12.0%	2277	13.5%	26900	12.1%
	5	31	4.3%	2	4.8%	33	4.3%	99	4.7%	3	3.2%	102	4.6%	9689	4.7%	625	3.7%	10314	4.6%
	6	23	3.2%	0	0.0%	23	3.0%	35	1.7%	0	0.0%	35	1.6%	3290	1.6%	160	0.9%	3450	1.6%
	7	2	0.3%	0	0.0%	2	0.3%	10	0.5%	0	0.0%	10	0.5%	1212	0.6%	45	0.3%	1257	0.6%
	8	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	472	0.2%	15	0.1%	487	0.2%
	9	2	0.3%	0	0.0%	2	0.3%	5	0.2%	0	0.0%	5	0.2%	160	0.1%	13	0.1%	173	0.1%
	10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	145	0.1%	1	0.0%	146	0.1%
	11	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	19	0.0%	0	0.0%	19	0.0%
	12	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	11	0.0%	0	0.0%	11	0.0%
	13	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	5	0.0%	0	0.0%	5	0.0%
Count of Household Vehicles	0	20	2.8%	2	4.8%	22	2.9%	68	3.2%	8	8.5%	76	3.4%	6417	3.1%	998	5.9%	7415	3.3%
	1	148	20.4%	10	23.8%	158	20.5%	451	21.3%	22	23.4%	473	21.4%	46674	22.7%	4509	26.7%	51183	23.0%
	2	293	40.3%	18	42.9%	311	40.4%	855	40.4%	39	41.5%	894	40.5%	85341	41.6%	7248	42.9%	92589	41.7%
	3	147	20.2%	9	21.4%	156	20.3%	442	20.9%	17	18.1%	459	20.8%	40161	19.6%	2583	15.3%	42744	19.2%
	4	56	7.7%	2	4.8%	58	7.5%	153	7.2%	7	7.4%	160	7.2%	16846	8.2%	1049	6.2%	17895	8.1%
	5	57	7.8%	1	2.4%	58	7.5%	99	4.7%	1	1.1%	100	4.5%	5962	2.9%	323	1.9%	6285	2.8%
	6	6	0.8%	0	0.0%	6	0.8%	31	1.5%	0	0.0%	31	1.4%	2272	1.1%	108	0.6%	2380	1.1%
	7	0	0.0%	0	0.0%	0	0.0%	17	0.8%	0	0.0%	17	0.8%	843	0.4%	43	0.3%	886	0.4%
	8	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	341	0.2%	11	0.1%	352	0.2%
	9	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	158	0.1%	8	0.0%	166	0.1%
	10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	80	0.0%	7	0.0%	87	0.0%
	11	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	42	0.0%	0	0.0%	42	0.0%
	12	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	64	0.0%	7	0.0%	71	0.0%
Imputed Age	18-24	41	5.6%	3	7.1%	44	5.7%	135	6.4%	9	9.6%	144	6.5%	11298	5.5%	1663	9.8%	12961	5.8%
	25-34	72	9.9%	9	21.4%	81	10.5%	230	10.9%	27	28.7%	257	11.6%	22073	10.8%	5204	30.8%	27277	12.3%
	35-44	83	11.4%	8	19.0%	91	11.8%	254	12.0%	20	21.3%	274	12.4%	24532	12.0%	3585	21.2%	28117	12.7%
	45-54	124	17.1%	10	23.8%	134	17.4%	364	17.2%	17	18.1%	381	17.2%	32316	15.7%	2781	16.5%	35097	15.8%
	55+	407	56.0%	12	28.6%	419	54.5%	1133	53.5%	21	22.3%	1154	52.2%	114982	56.0%	3661	21.7%	118643	53.4%

Table 10 continued

		Tennessee						Census Division 6						National					
		0 Trips		1+ Trips		Total		0 Trips		1+ Trips		Total		0 Trips		1+ Trips		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		727	100%	42	100%	769	100%	2116	100%	94	100%	2210	100%	205201	100%	16894	100%	222095	100%
Educational Attainment	High School Graduate or Less	254	34.9%	3	7.1%	257	33.4%	744	35.2%	9	9.6%	753	34.1%	53148	25.9%	1146	6.8%	54294	24.4%
	Some College or Associate's Degree	207	28.5%	5	11.9%	212	27.6%	609	28.8%	13	13.8%	622	28.1%	63543	31.0%	3205	19.0%	66748	30.1%
	Bachelor's Degree	149	20.5%	17	40.5%	166	21.6%	393	18.6%	33	35.1%	426	19.3%	47367	23.1%	6445	38.1%	53812	24.2%
	Graduate or Professional Degree	117	16.1%	17	40.5%	134	17.4%	370	17.5%	39	41.5%	409	18.5%	41143	20.1%	6098	36.1%	47241	21.3%
Worker Status	Is Employed	370	50.9%	36	85.7%	406	52.8%	1077	50.9%	77	81.9%	1154	52.2%	109899	53.6%	13625	80.6%	123524	55.6%
	Is Not Employed	357	49.1%	6	14.3%	363	47.2%	1039	49.1%	17	18.1%	1056	47.8%	95302	46.4%	3269	19.4%	98571	44.4%
Household Income	Less than $25,000	132	18.2%	4	9.5%	136	17.7%	452	21.4%	12	12.8%	464	21.0%	33567	16.4%	1355	8.0%	34922	15.7%
	$25,000 to $49,999	181	24.9%	5	11.9%	186	24.2%	502	23.7%	10	10.6%	512	23.2%	43757	21.3%	1756	10.4%	45513	20.5%
	$50,000 to $74,999	151	20.8%	7	16.7%	158	20.5%	410	19.4%	22	23.4%	432	19.5%	37971	18.5%	2064	12.2%	40035	18.0%
	$75,000 to $99,999	87	12.0%	2	4.8%	89	11.6%	292	13.8%	2	2.1%	294	13.3%	29778	14.5%	2194	13.0%	31972	14.4%
	$100,000 to $149,999	120	16.5%	11	26.2%	131	17.0%	310	14.7%	28	29.8%	338	15.3%	35971	17.5%	3870	22.9%	39841	17.9%
	$150,000 or more	56	7.7%	13	31.0%	69	9.0%	150	7.1%	20	21.3%	170	7.7%	24157	11.8%	5655	33.5%	29812	13.4%
Hispanic	Is Hispanic or Latino	10	1.4%	0	0.0%	10	1.3%	40	1.9%	0	0.0%	40	1.8%	16212	7.9%	1623	9.6%	17835	8.0%
	Is Not Hispanic or Latino	717	98.6%	42	100%	759	98.7%	2076	98.1%	94	100%	2170	98.2%	188989	92.1%	15271	90.4%	204260	92.0%
Presence of Medical Condition	Has a Medical Condition	103	14.2%	2	4.8%	105	13.7%	290	13.7%	5	5.3%	295	13.3%	23022	11.2%	518	3.1%	23540	10.6%
	No Medical Condition	624	85.8%	40	95.2%	664	86.3%	1826	86.3%	89	94.7%	1915	86.7%	182179	88.8%	16376	96.9%	198555	89.4%
Race	White	647	89.0%	38	90.5%	685	89.1%	1777	84.0%	78	83.0%	1855	83.9%	170257	83.0%	13378	79.2%	183635	82.7%
	Black or African American	56	7.7%	2	4.8%	58	7.5%	270	12.8%	10	10.6%	280	12.7%	14780	7.2%	1044	6.2%	15824	7.1%
	Asian	8	1.1%	2	4.8%	10	1.3%	17	0.8%	3	3.2%	20	0.9%	8648	4.2%	1321	7.8%	9969	4.5%
	Other	16	2.2%	0	0.0%	16	2.1%	52	2.5%	3	3.2%	55	2.5%	11516	5.6%	1151	6.8%	12667	5.7%
Imputed Gender	Male	323	44.4%	21	50.0%	344	44.7%	951	44.9%	50	53.2%	1001	45.3%	95265	46.4%	8601	50.9%	103866	46.8%
	Female	404	55.6%	21	50.0%	425	55.3%	1165	55.1%	44	46.8%	1209	54.7%	109936	53.6%	8293	49.1%	118229	53.2%
Residential Area Type	Urban	448	61.6%	38	90.5%	486	63.2%	1223	57.8%	86	91.5%	1309	59.2%	154178	75.1%	15803	93.5%	169981	76.5%
	Rural	279	38.4%	4	9.5%	283	36.8%	893	42.2%	8	8.5%	901	40.8%	51023	24.9%	1091	6.5%	52114	23.5%

Similarly, households with fewer vehicles (i.e., zero, one, or two vehicles per household) had higher percentages who had reported buying a rideshare ride compared to those households that had not purchased a rideshare ride. For example, in Tennessee, 42.9% of all respondents who have purchased a ride had two vehicles in their household while 40.3% of those who did not purchase a ride had two vehicles.

The data suggest that people under the age of 55 were more likely to purchase a ride using a smartphone ridesharing app. In Tennessee, 23.8% of those who purchased a ride were 45 to 54 years old whereas this group represents 17.1% of non-users. This trend continues in Tennessee for the younger age groups as well: 35 to 44 years old (19.0% have and 11.4% have not purchased a ride); 25 to 34 years old (21.4% have and 9.9% have not purchased a ride); and 18 to 24 years old (7.1% have and 5.6% have not purchased a ride). Similar trends appear in both the census division and national cross tabulations.

Of those who reported purchasing a ride through a smartphone application, the majority had some form of higher education. In Tennessee, the most common education levels for those who had purchased a rideshare ride were bachelor's degree and graduate or professional degree (both 40.5%), while a graduate degree or professional degree was most common for the census division and bachelor's degree was the most common for the National level. For both Tennessee and Census Division 6, the most common education level for those who did not purchase a ride was high school graduate or less, and for the National level, the most common was some college or associate degree.

Between 80 and 86% of those who reported purchasing a ride were employed. Tennessee had the highest percentage of employed with 85.7% and had the lowest percentage of employed workers who did not purchase a ride with 50.9%.

High incomes were common for those purchasing rides through smartphones. In Tennessee, 57.2% (sum of $100,000 to $149,999 and $150,000 or more) of those who purchased a ride have an annual household income of at least $100,000 compared to 24.2% of those who did not purchase a ride in Tennessee in these income brackets.

For both Tennessee and Census Division 6, 0.0% Hispanic or Latino respondents reported purchasing a ridesharing ride. For the National level, 9.6% of those who reported purchasing a ride were Hispanic while 7.9% of those who did not purchase a ride were Hispanic.

Almost all respondents who purchased a ride with a smartphone did not have a medical condition that makes it difficult to travel. In Tennessee, 95.2% of those who purchased a ride reported not having a medical condition while 85.8% of those who did not purchase a ride did not have a medical condition.

In Tennessee, the majority of those purchasing a ride were white: 90.5% of people purchasing a ride were white and 89.0% of people who did not purchase a ride were white.

Gender was almost evenly split for those whose who purchased a ride with a smartphone app. When comparing those who have and have not purchased a ride in Tennessee, males purchase rides more than females (44.4% of males have not purchased a ride while 55.6% have not purchased a ride).

People living in an urban setting were more likely to purchase a ride than those in a rural setting. In Tennessee, 90.5% of people who reported purchasing a ride were from an urban setting while 61.6% of people who reported purchasing a ride were from an urban setting.

2017 NHTS Logit Model Results

Binary logit models for both the taxi/ridesharing use and ridesharing app usage questions were estimated. The following discussion summarizes the results of these models.

Taxi or Ridesharing Use Logit Model

Three models were run for the use of taxi and ridesharing services NHTS question. The responses to this question were formulated as a binary variable (1 = use taxi/ridesharing services and 0 = does not use taxi/ridesharing services). Model 1 used Tennessee respondents, Model 2 used respondents from Census Division 6, and Model 3 used all respondents (National). Results are delineated in Table 11.

For all three models, household size has a negative, significant coefficient, suggesting that as household size increases, the probability that the person will use taxi or ridesharing services decreases.

Table 11: Taxi or Ridesharing Use Binary Logit Models.

Variable	Model 1 Tennessee	Model 2 Census Division 6	Model 3 National
Household Size	-0.2675*	-0.2655***	-0.2030***
Number of Household Vehicles	-0.2654	-0.4448***	-0.2320***
Age^ (Reference: 18-24 years old)	-	-	-
25-34	-0.5875	-0.0431	-0.1380***
35-44	-0.4054	-0.4307	-0.5081***
45-54	-0.5109	-0.1542	-0.8635***
55+	-1.1639	-0.9545**	-1.3775***
Educational Attainment (Reference: High School Graduate or Less)	-	-	-
Some College or Associate's Degree	0.1981	0.1986	0.3128***
Bachelor's Degree	0.6015	0.8607***	0.6986***
Graduate Degree or Professional Degree	0.3916	0.7355**	0.8530***
Employed (Reference: Not Employed)	0.6159*	0.3915*	0.2923***
Household Income (Reference: Less than $25,000)	-	-	-
$25,000 to $49,999	0.4516	0.3308	-0.1891***
$50,000 to $74,999	-0.3465	0.3372	0.0654**
$75,000 to $99,999	0.6410	0.6360*	0.4081***
$100,000 to $149,999	1.4314**	1.5256***	0.8439***
$150,000 or more	2.3986***	2.3558***	1.7033***
Hispanic or Latino (Reference: Not Hispanic)	-0.0119	-0.1182	0.0692**
Has Medical Condition (Reference: No Medical Condition)	-0.1374	0.0444	0.2372***
Race (Reference: Other^{+})	-	-	-
White	-0.0861	-0.6626	-0.3000***
Black or African American	-0.5321	-1.0272**	-0.2011***
Female^ (Reference: Male)	-0.0189	-0.2690	-0.0560***
Urban (Reference: Rural)	0.8483**	0.9855***	0.7220***
Constant	-0.9708	-0.5023	-0.2818***
Number of Observations	385	1,100	111,809
LR chi^2	85.44	233.45	22035.20
Prob > chi^2	0.0000	0.0000	0.0000
Pseudo R^2	0.1947	0.1992	0.1552
Log likelihood	-176.74828	-469.13416	-59973.99

*legend: * p<0.1; ** p<0.05; *** p<0.01; ^ imputed values; $^{+}$ includes Asian*
Data Source: Unweighted 2017 NHTS

For number of household vehicles, the coefficient is negative for all three models (Tennessee, Census Division 6, and National) but is only significant at the census division and national level.

The imputed age variable was evaluated with a reference group of 18 to 24 years old. The preliminary results show that all other age groups are less likely to use taxi or ridesharing services. However, all age variables are significant for Model 3 (National) while the only significant age group for Model 2 (Census Division) is 55 and older.

The coefficients for the educational attainment variables were all positive when a reference group of high school graduate or less was used. This suggests that higher education results in a higher probability of using taxi or ridesharing services. The coefficients for all education levels were found to be significant in Model 3 (National) and the coefficients for a bachelor's degree and a graduate/professional degree were found to be significant in Model 2 (Census Division).

The employment variable was found to be positive and significant in all three models. This suggests that being employed will increase the probability that someone will use a taxi or ridesharing.

For household income, a reference of less than $25,000 annual income was used. In Tennessee (Model 1), incomes of $100,000 to $149,999 and $150,000 or more were found to be positive (1.4314 and 2.3986, respectively) and significant. Similarly, these income groups and $75,000 to $99,999 were found to be positive and significant in Model 2 (Census Division). In Model 3 (National), all income groups greater than $50,000 were positive and significant. These results suggest that as income level increases, the probability that someone will use a taxi or ridesharing service increases.

Being of Hispanic or Latino origin was found to be significant and slightly positive with a value of 0.0692 in Model 3 (National).

Likewise, the coefficient for those who have a medical condition which makes travelling difficult was found to be positive and significant for Model 3.

Using "other" as a reference for the race category, the models suggest that being white or black will decrease the probability of using taxi or ridesharing services. This is significant for white in Model 3 and for black in Models 2 and 3.

The imputed gender variable suggests that females are slightly less likely to use taxi or ridesharing than males but is only significant for Model 3.

For all three levels, an urban setting was positive (ranging from 0.7220 to 0.9855) and significant. This suggests that people living in an urban area are more likely to use taxi or ridesharing compared to those living in a rural setting.

The constant (ranging from -0.9708 to -0.2818) suggests that, all else being equal in this model, that people will not use taxi or ridesharing services, but is only statistically significant at the national level. The goodness of fit in these models is moderate; the pseudo rho-squared values range from 0.1552 to 0.1992.

Ridesharing App Usage Logit Model

Table 12 contains the analysis of data for the NHTS data question pertaining to the use of smartphone applications to purchase a rideshare ride. Again, three models were run: Model 4 used Tennessee respondents, Model 5 used respondents from Census Division 6, and Model 6 used all respondents (National).

For all three models, household size has a negative, significant coefficient, suggesting that as the household size increases, the probability that the person will purchase a ride using a ridesourcing app will decrease.

Likewise, the number of household vehicles has a negative, significant coefficient for all three models (Tennessee, Census Division 6, and National).

The 55 and older age group is the only significant coefficient in all three models. The age group 45 to 54 years old is significant in Models 5 and 6 and the remaining age groups being significant in Model 6. These preliminary results suggest that, compared to 18 to 24 years old, all other age groups are less likely to purchase a ride through a smartphone application.

Table 12: Ridesharing App Usage Binary Logit Models.

Variable	Model 4 Tennessee	Model 5 Census Division 6	Model 6 National
Household Size	-0.5398**	-0.3437***	-0.3292***
Number of Household Vehicles	-0.4116*	-0.3960**	-0.2601***
Age^ (Reference: 18-24 years old)			
25-34	-0.3775	-0.2144	-0.3174***
35-44	-0.6461	-0.7024	-0.8824***
45-54	-1.1155	-1.3117***	-1.4195***
55+	-1.6618**	-2.0085***	-2.2402***
Educational Attainment (Reference: High School Graduate or Less)			
Some College or Associate's Degree	0.2352	0.2174	0.5933***
Bachelor's Degree	1.1843*	1.1170**	1.1291***
Graduate Degree or Professional Degree	1.3347*	1.3882***	1.1671***
Employed (Reference: Not Employed)	0.9911*	0.6107*	0.4089***
Household Income (Reference: Less than $25,000)			
$25,000 to $49,999	-0.2197	-0.7338	-0.0689*
$50,000 to $74,999	0.3680	0.2664	0.1838***
$75,000 to $99,999	-0.6203	-1.8728**	0.4771***
$100,000 to $149,999	1.1221	0.6829	0.8750***
$150,000 or more	1.8892**	1.2169**	1.7259***
Hispanic or Latino (Reference: Not Hispanic)	(omitted)	(omitted)	0.2448***
Has Medical Condition (Reference: No Medical Condition)	0.1893	0.0257	-0.2948***
Race (Reference: Other)			
White	-0.8240	-0.2715	-0.0677***
Black or African American	-1.4348	-0.5087	0.0284
Female^ (Reference: Male)	-0.2267	-0.3472	-0.1676***
Urban (Reference: Rural)	1.4141**	1.5096***	1.0393***
Constant	-1.8848	-2.3158***	-2.3586***
Number of Observations	759	2,170	222,095
LR chi^2	87.68	202.88	24550.27
Prob > chi^2	0.0000	0.0000	0.0000
Pseudo R^2	0.2700	0.2621	0.2054
Log likelihood	-118.5398	-285.57928	-47480.813

*legend: * p<0.1; ** p<0.05; *** p<0.01; ^ imputed values; + includes Asian*
Data Source: Unweighted 2017 NHTS

The coefficients for the educational attainment variable were all positive when a reference group of high school graduate or less was used. This suggests that higher education results in a higher probability of purchasing a ride using a ridesharing app. The coefficients for all education levels were found to be significant for Model 6 (National) and the coefficients for a bachelor's degree and graduate degree were found to be significant in Models 4 and 5 as well.

The employment variable was found to be positive and significant in all three models. This suggests that being employed will increase the probability that someone will purchase a ride using a ridesharing app.

For household income, a reference of less than $25,000 was used. A household income of $150,000 or more was found to be positive and significant in all three models. This suggests that as income level increases, the probability that someone will purchase a ride using a ridesharing app increases.

The coefficient for Hispanic or Latino origin was omitted for both the Tennessee and census division level. This occurred because all Hispanic/Latino responses were responded the same way for those two questions. In Model 6 (National), the coefficient for being of Hispanic or Latino origin was found to be positive (0.2448) and significant.

The coefficient for those who have a medical condition which makes travelling difficult was found to be negative and significant in Model 6. This is the opposite result from what was found in the taxi/ridesharing use question models. For the taxi/rideshare question, the value is 0.2372 in Model 3 while the value for the rideshare app usage question is -0.2948 in Model 6. This may be explained by people with medical conditions choosing to use a taxi instead of rideshare.

Using "other" as a reference for the race category, Model 6 (National) suggests that being white will decrease the probability purchasing a ride.

The imputed gender variable in Model 6 (National) suggests that females are slightly less likely to purchase a rideshare than males.

For all three models, an urban setting was positive (ranging from 1.0393 to 1.5096) and significant. This suggests that people living in an urban area are more likely to purchase a ride from a ridesharing app compared to those living in a rural setting.

The constant (ranging from -1.8848 to -2.3586) suggests that, all else being equal in this model, that people will not purchase a ride using a ridesharing app and is statistically significant at the census division and national level. The goodness of fit in these models is moderate; the pseudo rho-squared values range from 0.2054 to 0.2700.

CONCLUSIONS AND FUTURE RESEARCH

Table 13 compares the findings of the literature review with the significant socioeconomic variables of the taxi and ridesharing frequency of use question and the ridesharing app usage question from the 2017 NTHS data set. The results of the models align with the literature for six significant socioeconomic variables (age, income, educational attainment, employment status, number of household vehicles, and residential area type) at all three levels (state, division and national). However, there are some variables that are only significant at the national level. These include some other well studied demographics including race and gender, which generally align with the previous literature.

Understanding if there are differences between a specific state and national characteristics of ridesharing users is important because it would inform policy makers and transportation professionals that they may need to incorporate different policies and practices to better manage ridesharing in their state.

There are numerous areas for improvement and future research that emerged from this research. To improve this study, future versions of the National Household Travel Survey could ask more ridesharing questions and also separate taxi and ridesharing in the question wording. In order to improve summary statistic results for the state level, it would be necessary to create weights since the NHTS data only weighted to the Census Division level. The weighted summary statistics for Census Division 6 and National level data can be found in Appendix 2. For future research, this could be done for any state or division in the 2017 NHTS and could then compare differences between states and divisions. It would also be interesting to compare the responses

Table 13: Comparison of Results from Literature Review and Models.

Demographic Variable	Literature Review Results	Taxi/Ridesharing Frequency of Use Model Results	Ridesharing App Usage Model Results
Age	Ridesourcing users tend to be younger	55 and older is negative and significant in Models 2 and 3.	55 and older is negative and significant for all models.
Income	Ridesourcing users tend to have a higher income	Positive and significant coefficients for $100,000 to $149,999 and $150,000 or more for all models.	Positive and significant coefficient for $150,000 or more for all models.
Educational Attainment	Ridesourcing users tend to have a higher education	Bachelor's and Graduate Degrees are positive and significant for Model 2. All are significant for Model 3.	Bachelor's and Graduate Degrees are positive and significant for all models.
Employment Status	Ridesourcing users tend to be employed	Employed coefficient is positive and significant for all models.	Employed coefficient is positive and significant for all models.
Household Vehicles	Ridesourcing users tend to have fewer vehicles	Number of household vehicles coefficient is negative and significant for Models 2 and 3.	Number of household vehicles coefficient is negative and significant for all models.
Residential Area Type	Ridesourcing users tend to be urban dwellers	Urban area coefficient is positive and significant for all models.	Urban area coefficient is positive and significant for all models.

Models 1 and 4 represent Tennessee, Models 2 and 5 represent Census Division 6, and Models 3 and 6 represent the US.

of the 2017 NHTS to future NHTS data to see if there is change in who is using ridesharing or if there is an increase in frequency of use of ridesharing in which case this model would not have to be binary (use or not use).

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CHAPTER IV
ARE PEOPLE USING RIDEHAILING DIFFERENTLY? A MARKET SEGMENTATION ANALYSIS USING SURVEY DATA FROM TENNESSEE

This paper is in preparation for submission to the journal Transportation: Crossland, C., Brakewood, C., and Cherry, C. "Are people using ridehailing differently? A market segmentation analysis using survey data from Tennessee".

Cassidy Crossland was the principle author of "Are people using ridehailing differently? A market segmentation analysis using survey data from Tennessee". Cassidy's contribution included analysis and interpretation of results, and draft manuscript preparation. Dr. Candace Brakewood created the concept and design of the project and provided guidance and ideas throughout the research process as well as editorial assistance. Dr. Chris Cherry assisted in the draft manuscript preparation.

ABSTRACT

Ridehailing has grown rapidly in the United States in the last ten years since the introduction of services from Uber and Lyft in many American cities. The objective of this study is to differentiate between segments of users and non-users based on socioeconomic and ridehailing travel behavior characteristics. This study uses survey data collected by the company Populus for residents of Knoxville, Memphis, and Nashville, Tennessee in 2019, prior to the COVID-19 pandemic. Approximately 1,000 respondents answered questions about ridehailing adoption and familiarity and their socioeconomics, attitudes, and neighborhood preferences. Respondents who use ridehailing were asked about their last ridehailing trip, and non-users were asked their rationale for non-use. Statistical and multivariate analyses of these survey responses reveal the following four primary market segments: young urban local users, wealthy travelers, tagalong users, and non-users. The first market segment, which aligns with prior research, is comprised of those who use ridehailing in/around the city; they are younger people who generally have high incomes, no vehicles in their households, and use ridehailing for social purposes. These young urban local users made up approximately 20% of the survey sample. The second prominent market segment is those who use ridehailing when traveling; these users tend to be slightly older, have higher education and income levels, and use often ridehailing to get to/from the airport. This segment of wealthy travelers was approximately 14% of the survey sample. The third market segment, which has largely been excluded from prior research, includes those who ride with friends/family; they tend to be younger, female, and/or black. We coined the term "tagalong users" to refer to this group, which made up 13% of the survey sample. The fourth group is non-users; they do not use ridehailing and tend to be older, live in more rural areas, and/or have lower incomes. Non-users were the largest segment, making up approximately 53% of the survey sample. Their most common reasons for not using ridehailing were car ownership, safety concerns, and the cost of ridehailing. Understanding the differences between these four distinct market segments can help practitioners and policy makers better plan for ridehailing services and integrate it into the operations of the transportation system.

INTRODUCTION

Ridehailing refers to "prearranged and on-demand transportation services for compensation in which drivers and passengers connect via digital applications" (SAE 2018). Other terms used to describe these services include ridesourcing, ridesharing, and transportation network companies (TNCs). Ridehailing first launched in the United States in 2009 with UberCab (now known as Uber Technologies) (Blystone 2019). Over the past ten years, several other companies have entered the market, including Lyft in 2012 (Greiner et al. 2019); however, Uber and Lyft have the largest market share in the United States (Mazareanu 2019). Uber completed its first one billion rides in December 2015, which grew to 10 billion rides by July 2018 (Uber 2018). Lyft completed its first billion rides in September 2018 (Lyft 2018). With the rapid growth of ridehailing services around the world, many researchers and transportation system managers are interested in understanding who is using this ever-changing mode of transportation and for what purposes.

Other transportation industries use market segmentation research to understand who is using their services. Market segmentation is the process of "identifying segments of the market and dividing a broad

customer base into sub-groups of consumers by looking for shared characteristics" (Camilleri 2018). This paper provides a multivariate analysis using survey data to determine the key characteristics of distinct segments of ridehailing users. To the best of the authors' knowledge, this topic has not been analyzed before. Understanding the characteristics of different groups can facilitate better marketing and planning in the future.

The paper is organized as follows: first, a literature review is provided. Then, a discussion of the survey data and methodology is laid out, which is followed by the results of summary statistics for socioeconomic, attitudinal, and neighborhood survey questions. Next the results of multinomial logit models are presented. After this, statistical analysis of travel behavior characteristics is presented, which is based on additional survey questions about ridehailing users' last trip, and this is followed by a discussion of non-users' reasons for not using ridehailing. This paper concludes with areas for future research and a summary.

LITERATURE REVIEW

This section discusses previous literature related to this study. There are two subsections in the literature review: studies that are related to ridehailing users in the United States and studies that are related to market segmentation.

Ridehailing Users in the United States

Various characteristics of ridehailing user demographics were explored in prior literature, including age, income, employment status, race, gender, and whether users are in an urban or rural setting. Many prior studies found that ridehailing users tend to be younger, typically in the millennial generation (Alemi et al. 2018; Bansal et al. 2020; Brown 2020; Chu et al. 2018; Circella et al. 2016; Circella et al. 2018; Clewlow and Mishra 2017; Deka and Fei 2019; Gehrke et al. 2018; Grahn et al. 2019; Schaller 2018; Smith 2016; Young and Farber 2019). Numerous prior studies that looked at income levels of ridehailing users determined that higher incomes typically resulted in greater use of ridehailing (Alemi et al. 2018; Bansal et al. 2020; Chu et al. 2018; Deka and Fei 2019; Dong 2020; Gehrke et al. 2018; Grahn et al. 2019; Lahkar 2018; Mahmoudifard et al. 2017; Mitra et al. 2019; Schaller 2018; Young and Farber 2019). Many studies found that having a higher education increased use of ridehailing (Alemi et al. 2018; Bansal et al. 2020; Circella et al. 2018; Deka and Fei 2019; Gehrke et al. 2018; Gerte et al. 2018; Grahn et al. 2019; Mitra et al. 2019; Schaller 2018). Several studies that looked at the location of ridehailing trips determined that ridehailing was more often used in urban areas (Alemi et al. 2018; Bansal et al. 2020; Brown 2020; Circella et al. 2018; Clewlow and Mishra 2017; Grahn et al. 2019). Studies that looked at gender had mixed results; some found that men were more likely to use ridehailing (Deka and Fei 2019; Gerte et al. 2018; Mitra et al. 2019) while others found that women were more likely to use ridehailing (Dong 2020; Jiao et al. 2020). Several studies found that people who were employed were more likely to use ridehailing (Alemi et al. 2018; Deka and Fei 2019; Gehrke et al. 2018; Sabouri et al. 2020; Young and Farber 2019). A couple of studies that looked at race determined that white people were more likely to use ridehailing (Gehrke et al. 2018; Lahkar 2018).

Numerous prior studies considered trip purpose for ridehailing. Some of the most common trip purposes found in the literature are going out or social events, to and from home, work trips and commuting, and to and from the airport. A couple of studies found that social trips were over 50% of trips (Mahmoudifard et al. 2017; Rayle et al. 2016). Prior studies have found that between 29% and 58% of all trips end at home (Gehrke et al. 2018; Henao 2017). A couple of studies found that ridehailing was used for commuting purposes between 16 and 30% of the time (Henao 2017; Rayle et al. 2016). A study in Colorado found that 12% of all trips ended at the airport (Henao 2017).

Market Segmentation

As previously mentioned, market segmentation is common in the other transportation industries, such as the airline industry. A study based in Europe used a stated preference survey for frequent flyer passengers on both long- and short-haul flights (Teichert et al. 2008). The study found that using just price and flexibility needs as the segmentation divider was no longer sufficient. To best segment the airline passengers, the authors suggest other product specializations such as comfort, efficiency, and price-oriented offerings. Another study found that the rich data provided by the airline industry benefits the marketers when trying to segment passengers. Not only are airlines able to look at the demographics of their passengers, they can also look at the retained information based on how the passengers interact with airlines on social media, websites, and phone-based applications (Avram 2019). A final study in western Australia used a stated preference survey to determine the ideal number of segments for both airline users and non-users (Zhou et al. 2020). The study found that the ideal number of segments for airline users was three segments. The first segment was for businessmen who used airlines for regional travel, and the second segment was for people who used regional travel but specifically those who were middle-aged or older and did not have a specific trip purpose. The final segment was a group that did not have a strong preference for using air travel and tended to be of lower income or mid-income levels.

In addition to transportation applications, market segmentation has been used in the recent literature on the sharing economy, particularly for the home sharing service Airbnb. In one study, the authors used a linear regression model to determine the characteristics of consumers who preferred to stay in a shared room versus the characteristics of those who preferred to stay in an entire home and compared these to characteristics the provider is targeting (Lutz and Newlands 2018).

Last, it should be noted that there have been some prior market segmentation studies of ridehailing services. However, these have used big data information from the rides/trips with no demographic or trip purpose information and typically use machine learning. One study used Uber data from Chicago, and the authors identified six user clusters (Soria et al. 2020). These clusters included those highly affected by weather; those who use Uber late at night; those who go longer distances and cannot use transit; those who use Uber to get to the airport; those who could take their short trips using transit but choose Uber anyway; and those who used ridesharing or pooled ridehailing. Another study in New York City used Uber request data from a transit-focused smartphone application and identified eight user clusters (Guo et al. 2021).

The authors were unable to find any prior ridehailing papers that used survey data to identify distinct groups of both users and non-users based on demographics and preferences. Therefore, the authors aim to help fill this gap in the research by using survey data to identify ridehailing market segments.

STUDY OBJECTIVE AND HYPOTHESES

Prior studies focus on the differences between users and non-user; however, this study seeks to better understand whether there are characteristically different user types as well as non-users. This study sets forth the following five hypotheses (H-1 to H-5), as follows:

- ***H-1****: There is group of ridehailing users who is predominantly young people using ridehailing for social purposes.*
- ***H-2:*** *There is a group of ridehailing users who typically use these services when they are traveling outside of the city in which they reside.*
- ***H-3:*** *There is a group of people who use ridehailing if the trip is requested by someone else, so they are not alone in the vehicle and/or they do not pay for it themselves.*
- ***H-4:*** *There is a group of people who have heard of ridehailing but do not use it.*
- ***H-5****: There is a segment of people who do not know what ridehailing is.*

DATA AND METHODOLOGY

Dataset

The dataset for this project comes from a survey administered by the company Populus Technologies, Inc. between May and September of 2019, prior to the COVID-19 pandemic (Populus Technologies 2020). In total, 1,000 people from the three largest metropolitan areas in Tennessee (Knoxville, Memphis, and Nashville) were surveyed. The dataset was weighted based on age, income, gender, race, and Hispanic/Latino origin based on 2017 American Community Survey (ACS) 5-year counts to be representative at the metropolitan level. In total, 996 respondents were weighted; the remaining four did not answer all of these socioeconomic questions and were therefore excluded from the weighting process. The remainder of this paper focuses on these 996 weighted responses. The survey dataset included 494 different variables, with the majority relating to socioeconomic characteristics of the respondents, attitudes of the respondents, ridehailing travel behavior characteristics, reasons for not using ridehailing, and a few other topics not analyzed in this paper.

Methodology

First, the ridehailing familiarity and adoption question was analyzed. In the survey, the question was posed as "*Are you aware of app-based on-demand ride services such as Uber or Lyft? Please select the option that best applies to you.*" There were five potential answers that could be selected:

- *Yes, I use them while traveling in/around the city*
- *Yes, I use them only when traveling away for business or vacation*
- *Yes, have ridden in them with friends or family, but don't have the apps on my phone*
- *Yes, heard of them, but haven't used them*
- *No, never heard of them*

Next, summary statistics were calculated for the survey questions pertaining to three categories: socioeconomics, attitudinal questions, and neighborhood questions. Socioeconomic questions included things such as age, race, income, and household size. Attitudinal questions explored topics such as willingness to adopt new technologies, the desire to drive less, and opinions about transit service. Neighborhood preference questions considered topics such as the importance of having restaurants within walking distance of home, limited traffic on the streets near the home, and personal outdoor space. Summary statistics were calculated for the entire sample (N=996) as well as for the five ridehailing adoption and familiarity groups.

The survey data were then used in a multivariate analysis. Three multinomial logit models were estimated. The dependent variable for all three of these models was the familiarity and adoption of ridehailing question. While the original question had five groups for the ridehailing familiarity and adoption question, this was condensed into four groups for the analysis by combining those who have heard of but never used ridehailing and those who have never heard of ridehailing, since the latter group had a very small sample size (N=18). The first multinomial logit model analyzed the socioeconomic variables. The second model analyzed the same socioeconomic variables as well as additional variables pertaining to the respondent's attitudes. The third model analyzed both the socioeconomic and attitudinal variables and additional questions regarding neighborhood preferences. All models were estimated using STATA16 (StataCorp 2019).

Finally, two additional sets of survey questions were explored to provide additional insights into different market segments. The first of these was a series of travel behavior survey questions for the user groups about their most recent ridehailing trip. The second questions were asked of the non-user group to explore their reasons for not using ridehailing. The results are presented in the following section.

RESULTS

There are five parts in the results section. First, a summary of the ridehailing familiarity and adoption survey question is provided; this is followed by the results of socioeconomic, attitudinal, and neighborhood preferences survey questions. The third part presents the results of the multinomial logit models. The fourth part discusses the results of the last ridehailing trip questions, and this section concludes with the results of the reasons for not using ridehailing question.

Summary of the Ridehailing Familiarity and Adoption Survey Question

As seen in Figure 4, 20% (205 respondents) used ridehailing when traveling in/around the city, and 14% (141 respondents) used ridehailing only when traveling away for business or vacation. Another 13% (126 respondents) used ridehailing before, but only with friends or family. Additionally, 51%, or 505 respondents, had heard of ridehailing but never used it and 2%, or 17 respondents, had never heard of ridehailing. This question will be the basis of the subsequent analyses in this paper to explore the different demographic and travel behavior characteristics of these groups.

Results of Socioeconomic, Attitudinal, and Neighborhood Preferences Survey Questions

Results of the Socioeconomics Questions

As seen in the following three figures, the survey respondents were asked a series of socioeconomic questions. Each of the socioeconomic questions is shown for the entire sample (N=996), and then broken into smaller groups based on the responses to the ridehailing familiarity and adoption question discussed in the previous section. Figure 5 includes responses to socioeconomic questions relating to the respondent alone, and the questions in Figure 6 pertain to the household.

The first question in Figure 5 pertains to age. The results reveal that 45% of those who used ridehailing in/around the city were 34 years old or younger, 17% (34 of 205) were in the 18 to 24 years old age range, and another 28% (58 of 205) were 25 to 34 years old. At the other end of the spectrum, 45% (226 of 506) of those who had heard of but never used ridehailing were 55 years old or older.

The second question in Figure 5 asks about race. Sixty-nine percent (141 of 205) of those who used ridehailing in/around the city identified as white. Meanwhile 53% of those who have used ridehailing with friends or family identified as a minority; 36% (45 of 126) were black or African American and an additional 17% (21 of 126) identified as another minority.

In the overall sample, gender was fairly evenly split; 51% of respondents were female and the remaining 49% were male. Males were more likely to use ridehailing only when traveling (61% of this group, or 86 of 141). Sixty-two percent (77 of 126) of those who only used ridehailing with friends or family were female.

Respondents were asked to specify the highest education level they completed, and the results were relatively evenly distributed overall. The group with largest proportion of higher education was those who used ridehailing when traveling (58% overall); this included 35% (49 of 141) with a bachelor's degree and 23% (33 of 141) with a graduate or professional degree.

For the overall sample and many of the sub-groups, about two-thirds of the sample size was employed while the remaining third was not. However, for those who had heard of but never used ridehailing, 50% (253 of 506) of respondents were employed and the other 50% (253 of 256) were not employed.

The final question in Figure 5 pertains to the disability status of the respondent. For all groups, the majority of respondents claimed not to have a disability. The group with the largest amount of disabled people was those who have heard of but never used ridehailing with 22% (111 of 506). This may be a result of respondents feeling that a ridehailing vehicle would not be equipped to transport them properly.

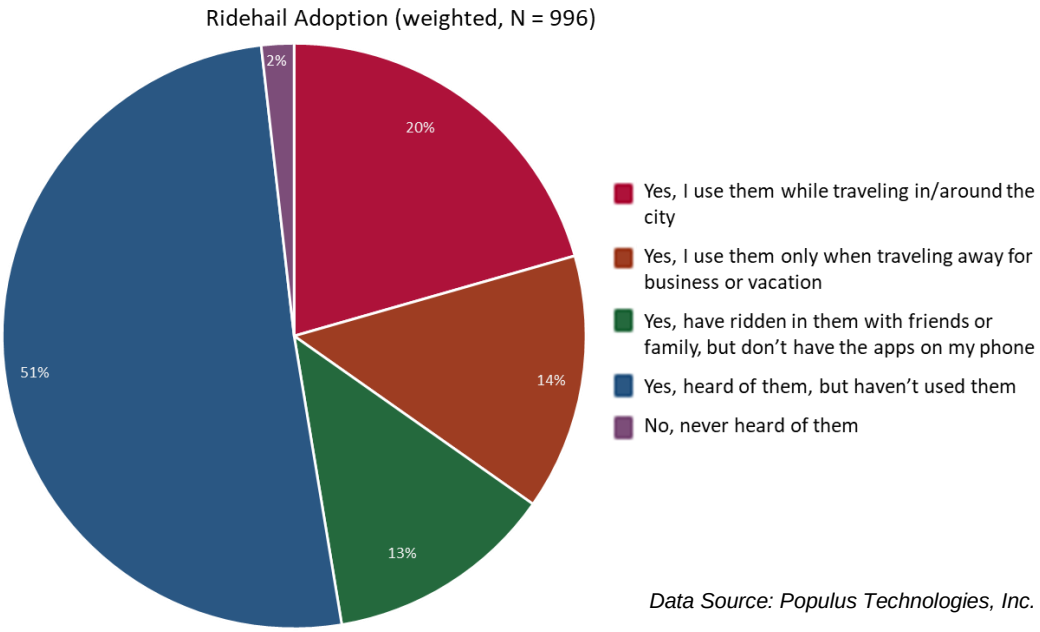
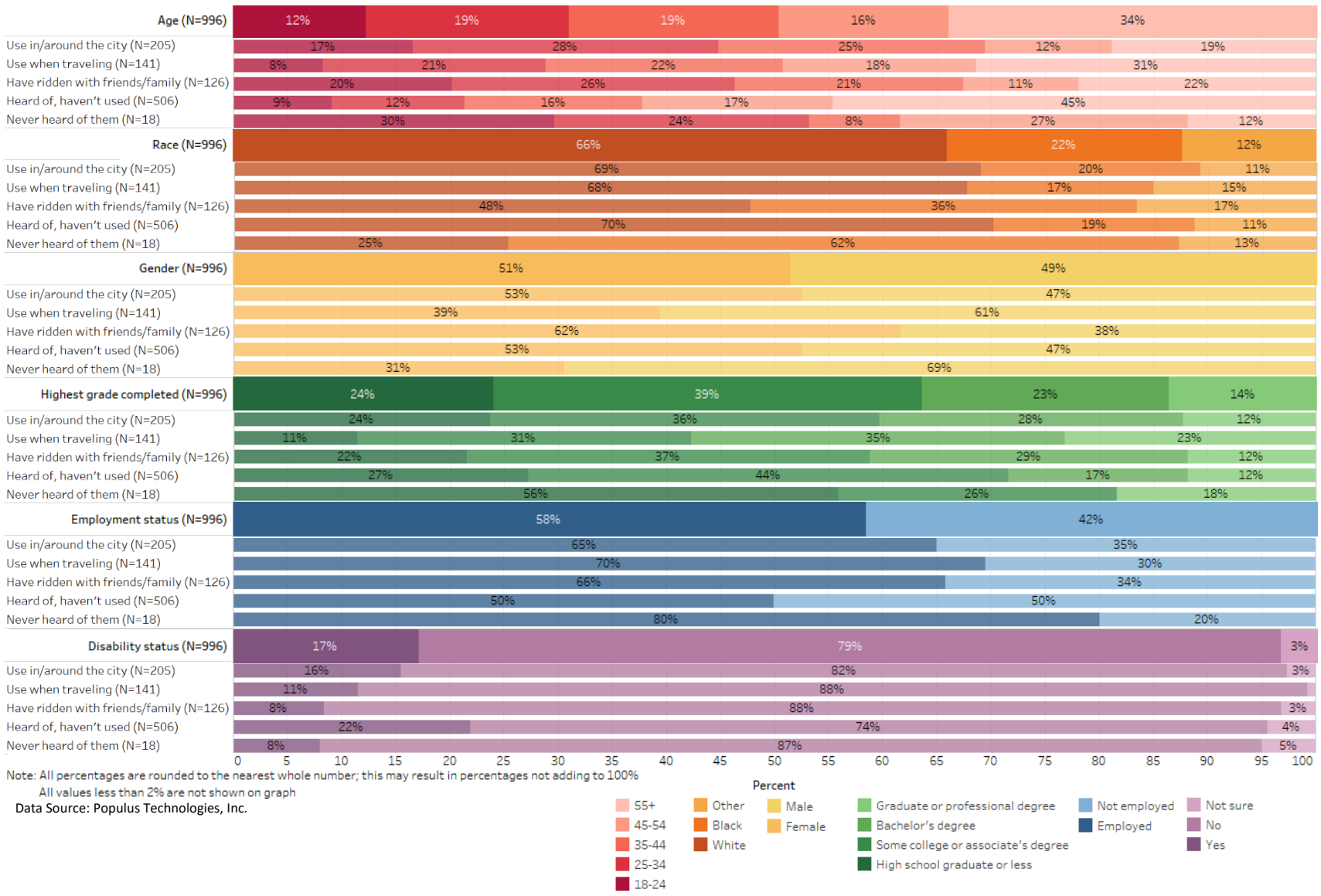
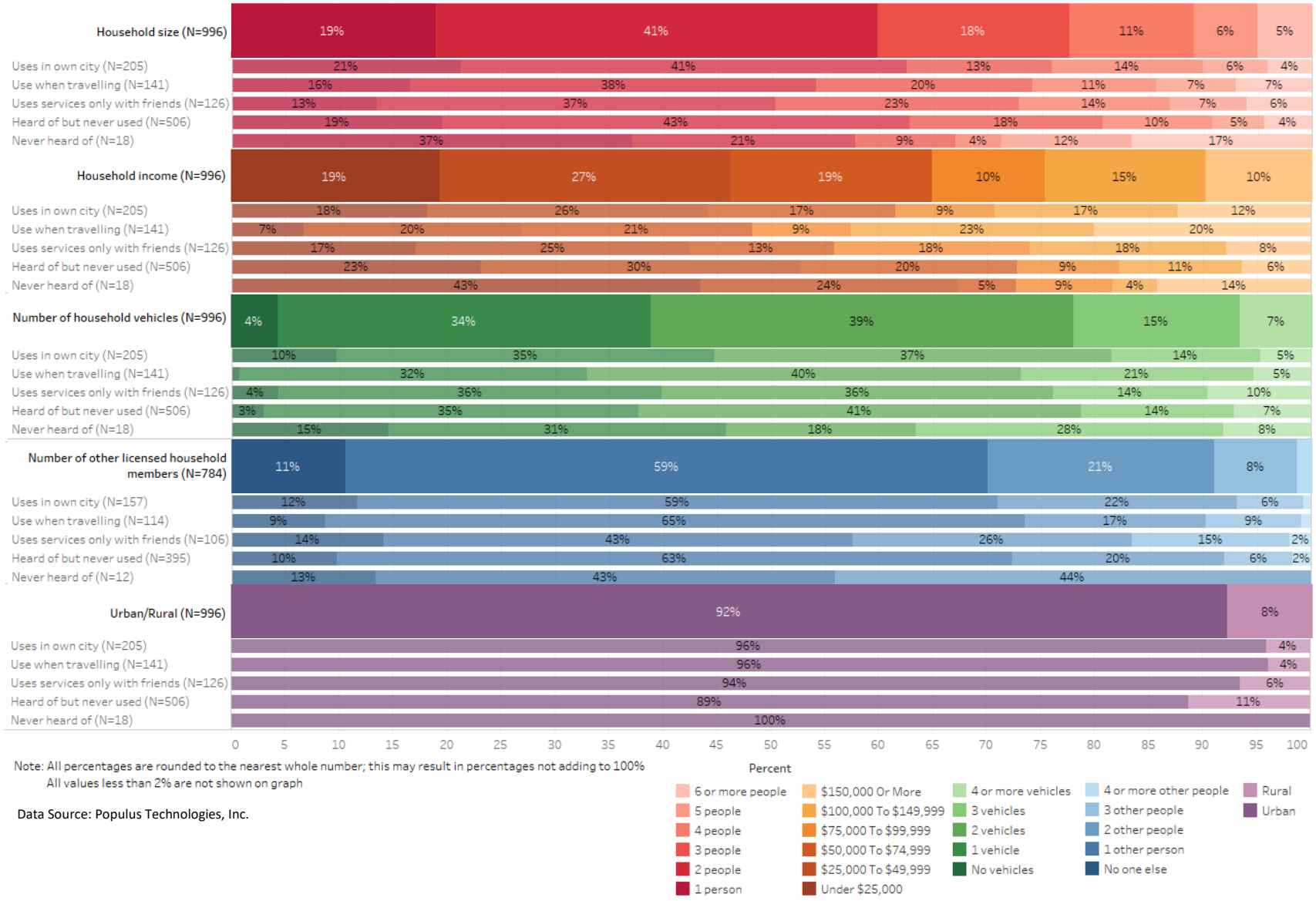


Figure 4: Ridehailing Familiarity and Adoption.



Note: All percentages are rounded to the nearest whole number; this may result in percentages not adding to 100%
All values less than 2% are not shown on graph
Data Source: Populus Technologies, Inc.

Figure 5: Socioeconomic Questions About Respondent.



Note: All percentages are rounded to the nearest whole number; this may result in percentages not adding to 100%
All values less than 2% are not shown on graph

Data Source: Populus Technologies, Inc.

Figure 6: Socioeconomic Questions About Respondent's Household.

The first question pertaining to household characteristics in Figure 6 was about the size of the household. Sixty-two percent of those who used ridehailing in/around the city either lived alone (21%, 44 of 205) or with one other person (41%, 84 of 205).

Respondents were also asked about their annual household income. Twenty-nine percent of those who used ridehailing in/around the city had an annual household income of $100,000 or more, with 17% (35 of 205) having an income of $100,000 to $149,999 and 12% (25 of 205) having an income of $150,000 or more. Forty-three percent of those who used ridehailing when traveling have an annual household income of $100,000 or more, with 23% (32 of 141) having an income of $100,000 to $149,999 and 20% (28 of 141) having an income of $150,000 or more. Of those who had heard of but never used ridehailing, just 17% of respondents had an annual household income of $100,000 or more with 11% (58 of 506) having an income of $100,000 to $149,999, and 6% (32 of 506) having an income of $150,000 or more.

Ten percent (20 of 205) of those who used ridehailing in/around the city reported that they do not have a car, which is higher than the four percent of the overall sample size. Of those who used ridehailing when traveling, 66% had at least two vehicles with 40% (57 of 141) having two vehicles, 21% (30 of 141) having three cars, and the remaining 5% (8 of 141) having four or more vehicles in their household.

Respondents were also asked how many other members of their household had a license. The responses were fairly similar across the different groups.

The final question relating to household factors pertained to location. Respondents were asked for their zip code, and this was then used to group them by urban versus rural areas. The urban classification was created by the authors based on the zip code provided by the respondent and comparing it to the TIGER 2010 Shapefile (Westat 2020). If there was an urbanized area or urban cluster within the zip code, the entire zip code was considered urban. In all groups, the large majority of respondents live in an urban area. However, the highest number of rural respondents were in the group that had heard of but never used ridehailing with 11% (57 of 506).

Results of the Attitudinal Questions

Figure 7 provides the survey results for seven attitudinal questions. Again, the responses are shown for the entire sample and then broken down into five groups based on the response to the ridehailing familiarity and adoption question. A brief discussion of the results is provided below.

The first attitudinal question asked how strongly do you agree or disagree that, "*I am generally among the first to try a new technology*". Fifty-three percent of those who used ridehailing in/around the city agreed with this statement (15%, or 31 of 205, strongly agreeing and 38%, or 77 of 205, agreeing). Just 31% of those who had heard of but never used ridehailing agreed; there were 6% (32 of 506) strongly agreeing and 25% (128 of 506) agreeing.

The second statement in Figure 7 is, "*It takes too much time and effort to do things that are environmentally friendly*". Seventeen percent of those who used ridehailing in/around the city agreed with this statement, and this included 3% (7 of 205) strongly agreeing and 14% (28 of 205) agreeing. Twenty-eight percent of those who used ridehailing while traveling agreed; there were 7% (10 of 141) strongly agreeing and 21% (30 of 141) agreeing.

The responses to both of the following statements, "*If I had more money, I'd buy a nicer car*" and "*Owning and maintaining a car is a pain*" were fairly evenly distributed for the different groups.

Respondents were asked how strongly they agreed or disagreed with the following statement: "*If I could, I'd like to drive less*". Of those who used ridehailing in/around the city, 47% agreed with this statement, including 19% (38 of 205) strongly agreeing and 28% (57 of 205) agreeing. Thirty-seven percent of those who have heard of but never used ridehailing agreed; there were 12% (61 of 506) strongly agreeing and 25% (128 of 506) agreeing.

The final two statements concerned public transportation. Those who use ridehailing in/around the city were most likely to agree (46%) with the first statement, "*Public transit can get me to many of the place I go*". This included 18% (36 of 205) strongly agreeing and 28% (57 of 205) agreeing. Those who had heard of but never use ridehailing were least likely to agree (21%), including 7% (37 of 506) strongly

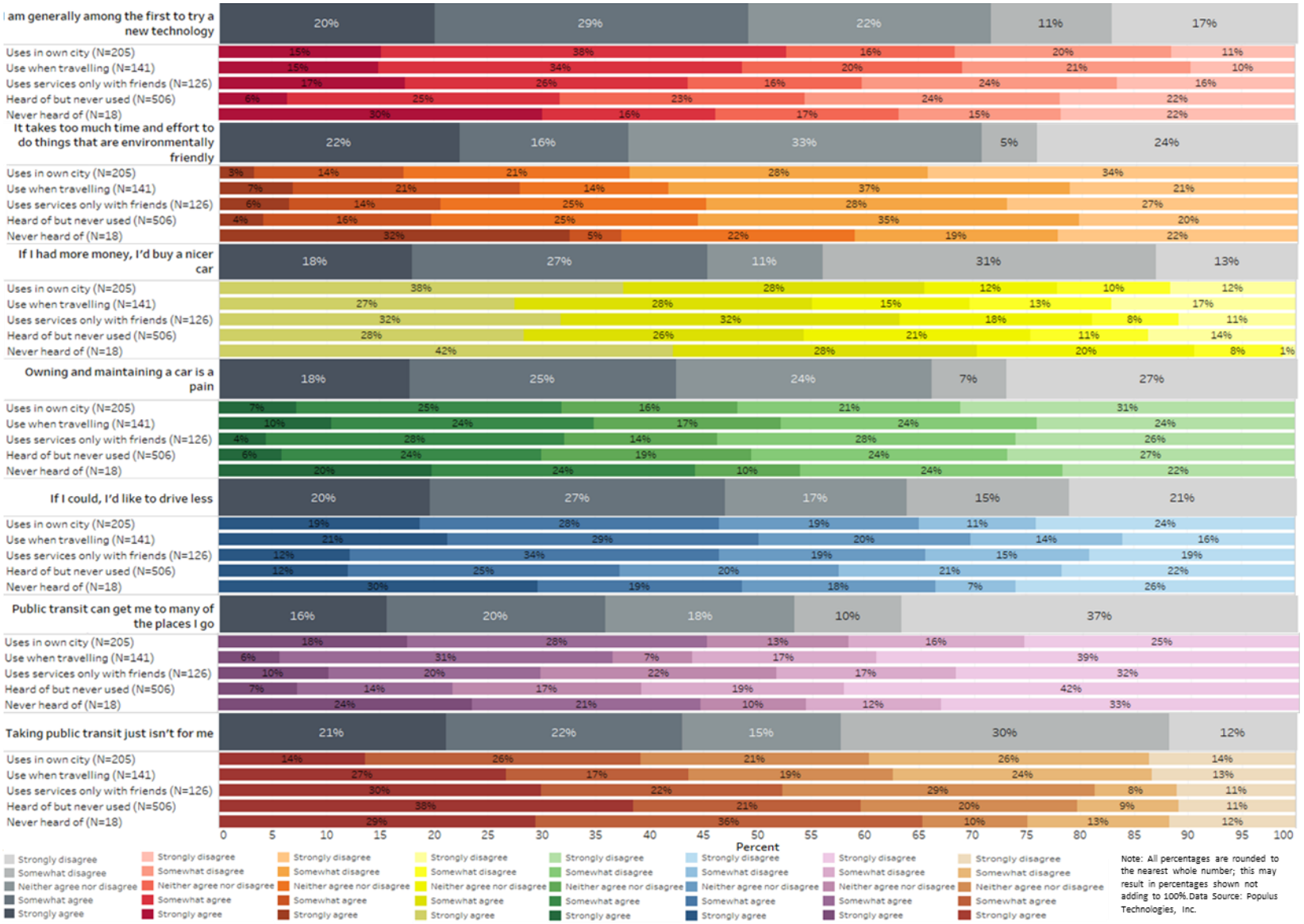


Figure 7: Attitudinal Questions.

agreeing and 14% (73 of 506) agreeing. For the second transit related attitudinal question, "*Taking public transit just isn't for me*", those who used ridehailing in/around the city were the least likely (40%) to agree; this was comprised of 14% (28 of 205) strongly agreeing and 26% (53 of 205) agreeing. Those who had heard of but never use ridehailing were most likely (59%) to agree with this statement, including 38% (194 of 506) strongly agreeing and 21% (107 of 506) agreeing.

Results of the Neighborhood Preference Questions

Six neighborhood preference questions were posed to survey respondents. Respondents were asked to indicate the relative importance of each of these statements on a five-point scale (Figure 8). Again, the responses are shown for the entire sample and then broken down into five groups based on the response to the ridehailing familiarity and adoption question, and a brief summary is provided in the following paragraphs.

The first neighborhood preference question asked the relative importance of the, "*Ability to commute to work or school by public transit*". Twenty-three percent of those who used ridehailing in/around the city found this to be essential (7%, 14 of 205) or very important (16%, 32 of 205). Fourteen percent of those who had heard of but never used ridehailing found commuting by public transit to be essential (4%, 22of 506) or very important (10%, 52 of 506).

The second question in Figure 8 asked the importance of having, "*Shops and restaurants are within walking distance of my home*". Thirty-two percent of those who used ridehailing in/around the city found this to be essential (5%, 10 of 205) or very important (27%, 56 of 205), while 15% of those who used ridehailing when traveling found this to be essential (3%, 5 of 141) or very important (12%, 17 of 141).

Thirty-one percent of those who used ridehailing in/around the city found that having "*Safe routes for biking*" was essential (10%, 20 of 205) or very important (21%, 44 of 205), whereas just 25% of those who had heard of but never used ridehailing found this to be essential (7%, 34 of 506) or very important (18%, 90 of 506).

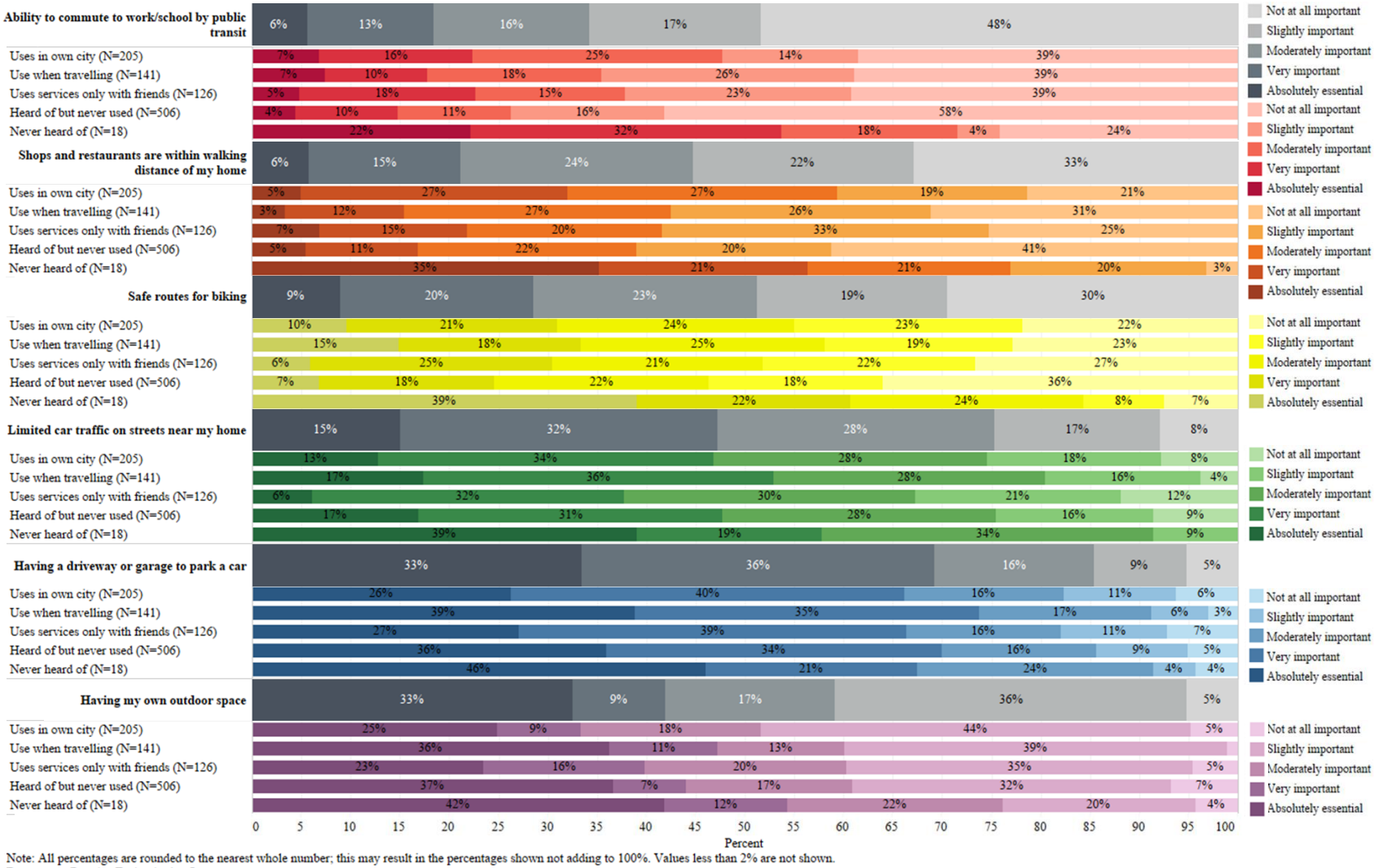
Responses for the statement "*Limited car traffic on streets near my home*" were fairly even amongst the groups. The statement "*Having a driveway or garage to park a car*" was found to be the most important to those who used ridehailing when traveling, including 39% (55 of 141) stating this was essential and another 35% (49 of 141) choosing very important.

The final neighborhood preference question asked how important is "*Having my own outdoor space*". Twenty-five percent (51 of 205) of those who used ridehailing in/around the city and 23% (30 of 126) of those who used ridehailing with friends and family found this to be essential, which is lower than the total survey sample of 33%.

Results of Multinomial Logit Models

Multinomial logit models were then estimated to identify significant differences between the different groups. To better understand the significant characteristics of each group, three sets of models were estimated. The first focused just on socioeconomic variables. The second used both socioeconomic variables and attitudinal questions. The third analyzed socioeconomic, attitudinal questions, and neighborhood preferences. Although only three models were selected for presentation in the following paragraphs, many additional models were estimated to assess which variables were significant and select these three preferred model specifications.

The dependent variables in the following models are the four groups from the ridehailing familiarity and adoption (those who use in/around the city, those who use only when traveling, those who use ridehailing with friends or family, and those who never use it). The reference group for the models is those who never use ridehailing, which is a combination of the two original groups: those who had heard of, but never used ridehailing and those who had never heard of ridehailing. These two categories were combined because the sample size for those who have never heard of ridehailing was 18 respondents, which would be too small to interpret accurately.



Note: All percentages are rounded to the nearest whole number; this may result in the percentages shown not adding to 100%. Values less than 2% are not shown.
Datasource: Populus Technologies, Inc.

Figure 8: Neighborhood Preference Questions.

Model 1: Socioeconomics

Table 14 provides the results of the first model concerning socioeconomics.

The age variable was evaluated with a reference group of 18 to 24 years old, and Table 14 shows that all other age groups were less likely to use ridehailing in some capacity. Being between the ages of 35 and 44 was only significant for those who use ridehailing with friends or family and the coefficient was negative. For ages 45 to 54, the values for all three groups were negative but was only significant for those who use ridehailing in/around the city and those who use ridehailing with their friends or family. Being 55 years or older was significant and negative for all three groups. This age group was most negative and significant for those who use ridehailing in/around the city while it was least negative and less significant for those who use ridehailing only when traveling.

Using White/Caucasian as the reference for race, there was significant differences between the three ridehailing user groups. Those who are black were less likely to use ridehailing in/around the city but were more likely to use ridehailing with friends or family. Both of these findings were significant. Being black was not significant for those who use ridehailing while traveling; however, being of another race (i.e., not white or black) was found to increase the likelihood that a person would use ridehailing when traveling. This is less significant than the findings for the other two groups.

While gender was not significant for those who use ridehailing in/around the city, being male was positive and significant for those who use ridehailing while traveling. Those who use ridehailing with friends or family were more likely to be female and was more significant than those who use ridehailing when traveling.

The education variable was evaluated with a reference group high school graduate or less, and Table 14 shows that all other education levels were more likely to use ridehailing in some capacity. Having completed some college or having an associate's degree was only significant for those who use ridehailing only when traveling and was positive. Having a bachelor's degree was significant and positive for all three groups. This was most positive and significant for those who use ridehailing when traveling. Having a graduate or professional degree was only significant for those who use ridehailing when traveling.

While living in a rural area had a negative value compared to living in an urban area for all three groups, this was only significant for those who use ridehailing in/around the city and those who use ridehailing when traveling.

For household income, a reference of less than $25,000 annual income was used. In all three groups, the coefficients for household incomes of $75,000 and above were positive and significant. These results suggest that as income level increases, the probability that someone will use ridehailing also increases. While the income levels of $25,000 to $74,999 were positive and significant for those who use ridehailing in/around the city and only when traveling, they were less significant.

Using zero household vehicles as a reference, all coefficients for one or more household vehicles were large, negative values and highly significant. Meanwhile, number of household vehicles was not significant for those who use ridehailing only when traveling. For those who use ridehailing with friends or family, having two household vehicles was negative and weakly significant.

The goodness of fit for this model is somewhat low; the pseudo rho-squared value is 0.1098.

Model 2: Socioeconomics and Attitudinal Questions

Table 15 provides the output of the second model, which examines both socioeconomic and attitudinal questions.

Comparing Model 1 and Model 2, the variables for age, education, living in an urban or rural area, and annual household income have similar results. Other socioeconomic variables had some minor differences, which are discussed briefly. For race, the results of Model 1 remained the same where a black person was less likely to use ridehailing in/around the city and was more likely to use ridehailing with friends or family. However, being of a race other than black or white was no longer significant for using ridehailing only when traveling. For gender, being female increased the likelihood of using ridehailing with friends or family and remains significant. However, gender was no longer significant for those who use ridehailing only

Table 14: Model 1—Socioeconomics.

		In/Around the City	Only When Traveling	With Friends/Family
Age	18-24 (Reference)	-	-	-
	25-34	-0.107 (0.288)	0.105 (0.408)	-0.398 (0.323)
	35-44	-0.444 (0.303)	-0.112 (0.421)	-0.773** (0.352)
	45-54	-1.623*** (0.352)	-0.606 (0.440)	-1.714*** (0.412)
	55+	-1.965*** (0.311)	-0.948** (0.406)	-1.761*** (0.349)
Race	White or Caucasian (Reference)	-	-	-
	Black or African American	-0.481** (0.237)	-0.0266 (0.302)	0.569** (0.261)
	Other	-0.264 (0.283)	0.558* (0.313)	0.393 (0.322)
Gender	Female (Reference)	-	-	-
	Male	-0.259 (0.188)	0.399* (0.224)	-0.476** (0.231)
Education	High School Graduate or Less (ref.)	-	-	-
	Some College or Associate's Degree	0.217 (0.225)	0.844** (0.343)	0.0175 (0.266)
	Bachelor's Degree	0.770*** (0.268)	1.415*** (0.371)	0.778** (0.306)
	Graduate or Professional Degree	0.218 (0.341)	1.139*** (0.413)	-0.103 (0.423)
Urban or Rural	Urban (reference)	-	-	-
	Rural	-1.026** (0.430)	-0.903* (0.548)	-0.328 (0.439)
Annual Household Income	Under $25,000 (reference)	-	-	-
	$25,000 to $49,999	0.437* (0.244)	0.763** (0.364)	0.370 (0.288)
	$50,000 to $74,999	0.637** (0.298)	1.170*** (0.398)	0.427 (0.367)
	$75,000 to $99,999	0.805** (0.386)	0.926* (0.507)	1.345*** (0.396)
	$100,000 to $149,999	1.256*** (0.356)	1.795*** (0.441)	1.481*** (0.408)
	$150,000 or more	1.656*** (0.423)	2.103*** (0.501)	1.333** (0.540)
Number of Household Vehicles	0 vehicles (reference)	-	-	-
	1 vehicle	-1.476*** (0.370)	0.854 (1.055)	-0.469 (0.500)
	2 vehicles	-2.043*** (0.393)	0.545 (1.064)	-0.936* (0.521)
	3 vehicles	-2.102*** (0.453)	0.759 (1.084)	-0.950 (0.585)
	4 or more vehicles	-2.557*** (0.560)	-0.155 (1.173)	-0.940 (0.655)
Constant		1.162*** (0.446)	-3.737*** (1.129)	-0.487 (0.575)
Observations	996			
Likelihood Ratio Chi^2	258.46			
Pseudo R^2	0.1098			
Log Likelihood	-1048.1872			

** p<0.1; ** p<0.05; *** p<0.01.*
Standard error is in the parentheses.
Model uses "Never Used" as reference group
Data Source: Populus Technologies, Inc.

Table 15: Model 2—Socioeconomics and Attitudinal Questions.

		In/Around the City	Only When Traveling	With Friends/Family
Age	18-24 (Reference)	-	-	-
	25-34	-0.0662 (0.292)	0.117 (0.411)	-0.369 (0.323)
	35-44	-0.377 (0.308)	-0.0725 (0.425)	-0.736** (0.353)
	45-54	-1.537*** (0.357)	-0.559 (0.443)	-1.689*** (0.415)
	55+	-1.753*** (0.320)	-0.817** (0.416)	-1.686*** (0.355)
Race	White or Caucasian (Reference)	-	-	-
	Black or African American	-0.629*** (0.243)	-0.0655 (0.308)	0.514* (0.267)
	Other	-0.476 (0.291)	0.512 (0.320)	0.296 (0.330)
Gender	Female (Reference)	-	-	-
	Male	-0.285 (0.193)	0.352 (0.227)	-0.486** (0.234)
Education	High School Graduate or Less (Ref.)	-	-	-
	Some College or Associate's Degree	0.243 (0.229)	0.840** (0.345)	0.0425 (0.268)
	Bachelor's Degree	0.764*** (0.272)	1.366*** (0.373)	0.787** (0.308)
	Graduate or Professional Degree	0.256 (0.349)	1.121*** (0.419)	-0.0641 (0.427)
Urban or Rural	Urban (Reference)	-	-	-
	Rural	-0.990** (0.437)	-0.917* ().553)	-0.328 (0.442)
Annual Household Income	Under $25,000 (Reference)	-	-	-
	$25,000 to $49,999	0.479* (0.248)	0.801** (0.367)	0.377 (0.291)
	$50,000 to $74,999	0.657** (0.305)	1.165*** (0.401)	0.436 (0.370)
	$75,000 to $99,999	0.831** (0.391)	0.902* (0.509)	1.380*** (0.400)
	$100,000 to $149,999	1.198*** (0.364)	1.741*** (0.449)	1.490*** (0.414)
	$150,000 or more	1.638*** (0.430)	2.097*** (0.507)	1.324** (0.546)
Number of Household Vehicles	0 vehicles (Reference)	-	-	-
	1 vehicle	-1.224*** (0.375)	1.071 (1.059)	-0.373 (0.503)
	2 vehicles	-1.780*** (0.397)	0.76 (1.068)	-0.840 (0.523)
	3 vehicles	-1.818*** (0.459)	0.961 (1.089)	-0.866 (0.588)
	4 or more vehicles	-2.084*** (0.573)	0.123 (1.182)	-0.765 (0.663)
I am generally among the first to try a new technology	Disagree (Reference)	-	-	-
	Neither agree nor disagree	0.00147 (0.252)	0.211 (0.295)	-0.229 (0.297)
	Agree	0.381* (0.211)	0.369 (0.255)	0.0744 (0.246)
Public transit can get me to many of the places I go	Disagree (Reference)	-	-	-
	Neither agree nor disagree	0.161 (0.265)	-0.640* (0.363)	0.360 (0.282)
	Agree	0.882*** (0.209)	0.322 (0.249)	0.351 (0.255)
Constant		0.353 (0.490)	-4.156*** (1.155)	-0.776 (0.609)
Observations	996			
Likelihood Ratio Chi^2	292.38			
Pseudo R^2	0.1242			
Log Likelihood	-1031.2255			

** p<0.1; ** p<0.05; *** p<0.01*
Standard error is in the parentheses
Model uses "Never Used" as reference group
Data Source: Populus Technologies, Inc.

when traveling. Last, having a household vehicle still negatively impacted the probability of using ridehailing in/around the city; however, vehicle ownership was not significant for those who use ridehailing with friends or family in Model 2.

For the attitudinal questions, people who agree with the statement that they are among the first to try a new technology were more likely to use ridehailing in/around the city, and this variable was significant. This statement was not significant for the other two groups.

When using disagree as a reference, the coefficient for people who agree with the statement "Public transit can get me to many of the places I go" was positive for all three groups. However, it was most positive and only significant for those who use ridehailing in/around the city.

The goodness of fit for this model is somewhat low; the pseudo rho-squared value is 0.1242.

Model 3: Socioeconomics, Attitudinal, and Neighborhood Preferences Questions

Table 16 describes the output of the third model, which investigates socioeconomics, attitudinal questions, and neighborhood preferences.

Comparing Model 1 and Model 2 to Model 3, the results of the variables age, education, living in an urban or rural area, and annual household income were generally similar.

For the neighborhood preference "limited car traffic on streets near my home", the reference category was "not at all important". Compared to those who think that it is not at all important to have limited car traffic on the streets near their home, those who find this to be absolutely essential were significantly less likely to use ridehailing with friends or family.

For the neighborhood preference "shops and restaurants are within walking distance of my home", the reference category was "not at all important". For those who use ridehailing in/around the city, the coefficients for moderately important and very important were positive and significant, with very important being more positive and significant. While all responses were positive for those who use ridehailing with friends or family, only the coefficient for slightly important was significant. For those who use ridehailing when traveling, the only significant coefficient was absolutely essential and this was negative.

The goodness of fit for this model is moderate; the pseudo rho-squared value is 0.1455.

Results of the Last Ridehailing Trip

As part of the survey, respondents who previously stated that they use ridehailing in/around the city or when traveling were then asked several questions about their last ridehailing trip. Table 17 compares the responses for those who use ridehailing in/around the city with those who use ridehailing only when traveling. Two hundred and fifty-five people (158 that use ridehailing in/around the city and 97 that use ridehailing only when traveling) responded to this series of questions.

The first question involved trip purpose. The most common trip purposes for those who use in/around the city were social events (45.6%, 72 of 158) and shopping or other personal errands (22.2%, 35 of 158) while the most common trip purposes for those who use ridehailing only when traveling were social events (34.0%, 33 of 97) and going to and from the airport (26.8%, 28 of 97). These results are highly significant (p=7.1E-5).

Respondents were also asked about the time of day of their latest trip. The most common time periods for those who use ridehailing in/around the city were 9 a.m. to 4 p.m. (43 of 158, or 27.2%) and 7 p.m. to midnight (42 of 158, or 26.6%) compared to the most common time periods for who use ridehailing only when traveling being 9 a.m. to 4 p.m. (27 of 97, or 27.8%) and 4 p.m. to 7 p.m. (23.7%). The largest difference between the groups occurs between midnight and 7 a.m. when 15.8% (25 of 158) those who use ridehailing in/around the city took their last ridehailing trip compared to only 8.2% (8 of 97) of those who use ridehailing when traveling. These results are somewhat significant (p-value =0.087).

Respondents were asked what day of the week their trip was made with the option to select weekday, Saturday, Sunday, or don't know. Fifty percent of trips made by those who use ridehailing in/around the city (79 of 158) occurred on a weekday and 31% (49 of 158) occurred on Saturday. For those who use

Table 16: Model 3—Socioeconomics, Attitudinal Questions, and Neighborhood Preferences.

		In/Around the City	Only When Traveling	With Friends/Family
Age	18-24 (Reference)	-	-	-
	25-34	-0.00838 (0.296)	0.103 (0.416)	-0.331 (0.328)
	35-44	-0.394 (0.313)	-0.129 (0.433)	-0.661* (0.356)
	45-54	-1.484*** (0.365)	-0.616 (0.450)	-1.548*** (0.418)
	55+	-1.727*** (0.325)	-0.839** (0.420)	-1.653*** (0.361)
Race	White or Caucasian (Reference)	-	-	-
	Black or African American	-0.574** (0.249)	-0.0447 (0.313)	0.598** (0.276)
	Other	-0.437 (0.295)	0.610* (0.328)	0.282 (0.238)
Gender	Female (Reference)	-	-	-
	Male	-0.339* (0.197)	0.355 (0.229)	-0.543** (0.238)
Education	High School Graduate or Less (Ref.)	-	-	-
	Some College or Associate's Degree	0.297 (0.235)	0.817** (0.350)	-0.00013 (0.273)
	Bachelor's Degree	0.801*** (0.279)	1.332*** (0.379)	0.726** (0.314)
	Graduate or Professional Degree	0.318 (0.355)	1.065** (0.425)	-0.0573 (0.433)
Urban or Rural	Urban (Reference)	-	-	-
	Rural	-0.888** (0.441)	-0.954* (0.558)	-0.289 (0.450)
Annual Household Income	Under $25,000 (Reference)	-	-	-
	$25,000 to $49,999	0.499** (0.253)	0.830** (0.373)	0.341 (0.297)
	$50,000 to $74,999	0.672** (0.312)	1.258*** (0.409)	0.438 (0.377)
	$75,000 to $99,999	0.954** (0.398)	1.014* (0.519)	1.441*** (0.409)
	$100,000 to $149,999	1.233*** (0.370)	1.804*** (0.456)	1.477*** (0.420)
	$150,000 or more	1.696*** (0.438)	2.244*** (0.518)	1.337** (0.551)
Number of Household Vehicles	0 vehicles (Reference)	-	-	-
	1 vehicle	-1.150*** (0.388)	1.026 (1.067)	-0.301 (0.512)
	2 vehicles	-1.699*** (0.410)	0.618 (1.076)	-0.736 (0.533)
	3 vehicles	-1.709*** (0.476)	0.787 (1.099)	-0.773 (0.603)
	4 or more vehicles	-1.972*** (0.585)	-0.0171 (1.193)	-0.577 (0.676)
I am generally among the first to try a new technology	Disagree (Reference)	-	-	-
	Neither agree nor disagree	-0.0722 (0.257)	0.217 (0.298)	-0.208 (0.303)
	Agree	0.318 (0.218)	0.424 (0.261)	0.167 (0.252)
Public transit can get me to many of the places I go	Disagree (Reference)	-	-	-
	Neither agree nor disagree	0.105 (0.270)	-0.691* (0.369)	0.302 (0.288)
	Agree	0.787*** (0.215)	0.391 (0.257)	0.303 (0.260)
Limited car traffic on streets near my home	Not at all important (Reference)	-	-	-
	Slightly important	0.115 (0.378)	0.915 (0.560)	-0.157 (0.419)
	Moderately important	-0.306 (0.360)	0.744 (0.538)	-0.352 (0.391)
	Very important	-0.344 (0.356)	0.843 (0.533)	-0.462 (0.389)
	Absolutely essential	-0.497 (0.405)	0.914 (0.567)	-1.355*** (0.505)
Shops and restaurants are within walking distance of my home	Not at all important (Reference)	-	-	-
	Slightly important	0.329 (0.274)	0.214 (0.290)	0.667** (0.294)
	Moderately important	0.576** (0.263)	0.265 (0.295)	0.169 (0.315)
	Very important	1.003*** (0.290)	-0.192 (0.380)	0.356 (0.369)
	Absolutely essential	-0.199 (0.444)	-1.455** (0.699)	0.271 (0.458)
Constant		0.119 (0.574)	-4.927*** (1.256)	-0.746 (0.691)
Observations	996			
Likelihood Ratio Chi^2	342.54			
Pseudo R^2	0.1455			
Log Likelihood	-1006.1456			

** p<0.1; ** p<0.05; *** p<0.01*
Standard error is in the parentheses
Model uses "Never Used" as reference group
Data Source: Populus Technologies, Inc.

Table 17: Last Ridehailing Trip for Those Using Ridehailing in/Around the City and Only When Traveling.

		In/Around the City		Only When Traveling		Total	
		#	%	#	%	#	%
	Total	158	100.0%	97	100.0%	255	100.0%
Trip Purpose	Commute	22	13.9%	8	8.2%	30	11.8%
	Going to/ from airport	12	7.6%	26	26.8%	38	14.9%
	Shopping/Personal Errands	35	22.2%	12	12.4%	47	18.4%
	Social events	72	45.6%	33	34.0%	105	41.2%
	Other	17	10.8%	18	18.8%	35	13.7%
	Pearson chi^2=24.2567, p=7.1E-5***						
Time of Day	Morning (7 a.m. to 9 a.m.)	16	10.1%	10	10.3%	26	10.2%
	Midday (9 a.m. to 4 p.m.)	43	27.2%	27	27.8%	70	27.5%
	Evening (4 p.m. to 7 p.m.)	26	16.5%	23	23.7%	49	19.2%
	Late evening (7 p.m. to midnight)	42	26.6%	19	19.6%	61	23.9%
	Overnight (midnight to 7 a.m.)	25	15.8%	8	8.2%	33	12.9%
	Don't know/ can't remember	6	3.8%	10	10.3%	16	6.3%
	Pearson chi^2=9.6131, p=0.087*						
Day of Week	Weekday	79	50.0%	47	48.5%	126	49.4%
	Saturday	49	31.0%	22	22.7%	71	27.8%
	Sunday	13	8.2%	7	7.2%	20	7.8%
	Don't know/can't remember	17	10.8%	21	21.6%	38	14.9%
	Pearson chi^2=6.3891, p=0.099*						
Cost of Trip	Less than $10	67	42.4%	27	27.8%	94	36.9%
	$11-$15	32	20.3%	25	25.8%	57	22.4%
	$16-$20	19	12.0%	20	20.6%	39	15.3%
	$21-$30	27	17.1%	14	14.4%	41	16.1%
	$30 or more	13	8.2%	11	11.3%	24	9.4%
	Pearson chi^2=8.0645, p=0.089*						
Vehicle Occupancy	Total	157	100.0%	97	100.0%	254	100.0%
	None, just me	84	53.5%	44	45.4%	128	50.4%
	1 other person who I know	48	30.6%	39	40.2%	87	34.3%
	2 or more people who I know	25	15.9%	14	14.4%	39	15.4%
	Pearson chi^2=3.9582, p=0.287						
Service Used	Total	157	100.0%	96	100.0%	253	100.0%
	Lyft	60	38.2%	25	26.0%	85	33.6%
	Uber	97	61.8%	71	74.0%	168	66.4%
	Pearson chi^2=3.9582, p=0.047**						
Alternative Mode	Total	157	100.0%	95	100.0%	252	100.0%
	Drive	74	47.1%	41	43.2%	115	45.6%
	Transit	15	9.6%	6	6.3%	21	8.3%
	Taxi	22	14.0%	34	35.8%	56	22.2%
	Walk	12	7.6%	6	6.3%	18	7.1%
	Wouldn't have made trip	34	21.7%	8	8.4%	42	16.7%
	Pearson chi^2=19.9468, p=0.001***						

** p<0.1; ** p<0.05; *** p<0.01.*

Note: some questions had minor differences in the response rate.

Data source: Populus Technologies, Inc.

ridehailing while traveling, 48.5% of trips (47 of 97) occurred on a weekday and 22.7% (22 of 97) occurred on Saturday. These results are weakly significant (p=0.099).

Total cost of the most recent trip taken was another point of inquiry. Forty-two percent of those who use ridehailing in/around the city (67 of 158) said that their last trip cost $10 or less compared to just 27.8% (27 of 97) of those who use ridehailing only when traveling paying that amount. The second most common price range for those who use ridehailing only when traveling to pay for their last trip was between $11 and $15 (25.8%, 25 of 97). These results are weakly significant (p=0.089).

Respondents were asked how many people were in their Uber or Lyft during their last trip. For both those who use ridehailing in/around the city and those who use ridehailing only when traveling, it was most common to ride alone. However, these results were not significant (p=0.287).

Respondents were also asked which service they used on their last trip. For both groups, Uber was the most used ridehailing service with 61.8% (97 of the 157) of those who use ridehailing in/around the city and 74.0% (71 of 96) of those who use ridehailing only when traveling. These results were significant (p=0.047).

The final question pertaining to the last trip was which mode the respondent would have used if Uber or Lyft had not been an option. The most common alternative modes for those who use ridehailing in/around the city were to drive (47.1%, 74 of 157) or to not make the trip (21.7%, 34 of 157). The most common alternative modes for those who use ridehailing only when traveling were to drive (43.2%, 41 of 95) or to use a taxi (35.8%, 34 of 95). These results were highly significant with a p-value of 0.001.

Results of Reasons for Not Using Ridehailing

While the previous three sections have mostly focused on respondents who use ridehailing, the largest portion of the sample (506 of 996) stated that they had heard of ridehailing but never used it. To better understand this large group of people, summary statistics were used to determine the major factors that deter people from using ridehailing. Figure 9 shows the different reasons respondents chose not to use ridehailing services. The sample size for this question consisted of 474 people who previously stated that they had heard of but never used ridehailing services. This question was not posed to people who had never heard of ridehailing because they do not know what it is. Respondents were able to select more than one reason for not using ridehailing.

Seventy-six percent (358 of 474) reported that they use a personal car instead of ridehailing as one of the reasons for not using Uber or Lyft. The second most common reason for not using ridehailing was they were uncomfortable with personal safety with 26% (124 of 474). Nineteen percent (90 of 474) of people who do not use Uber or Lyft claim it is because ridehailing is too expensive.

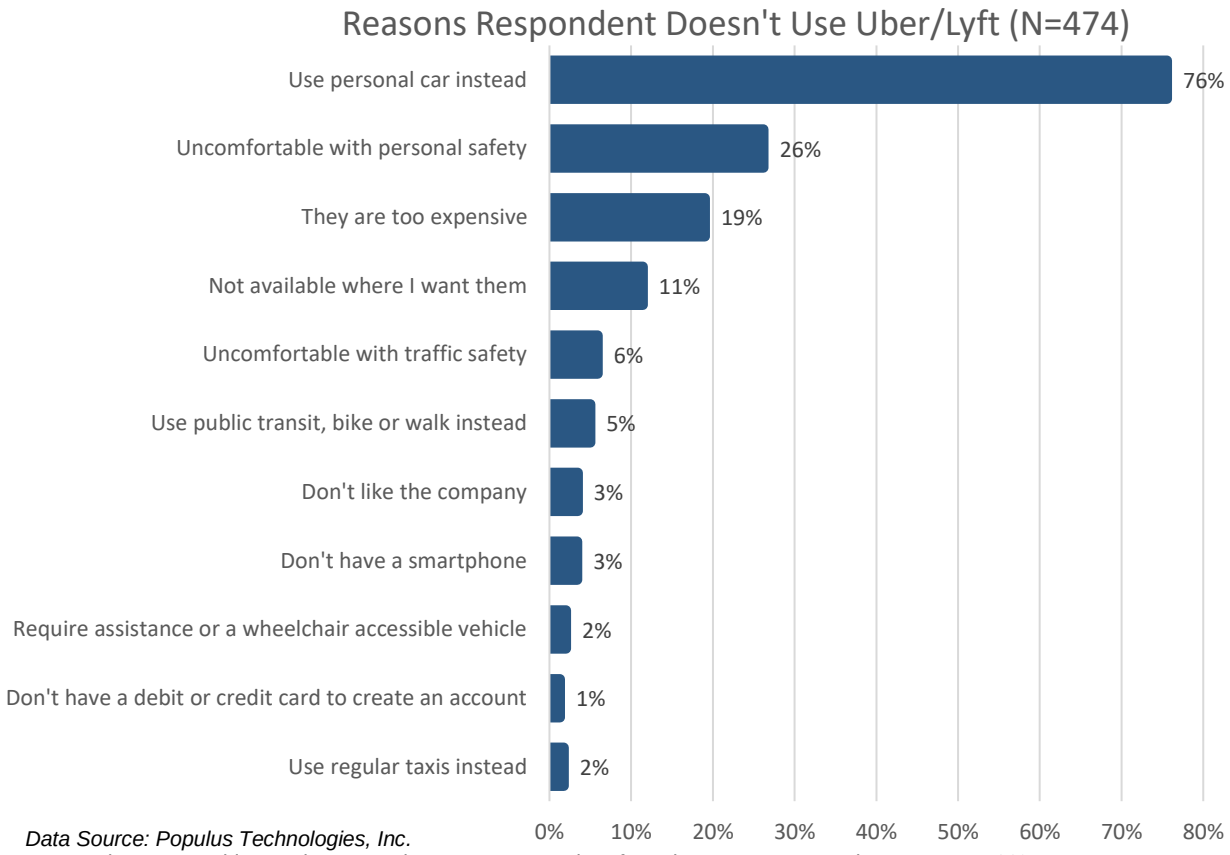
Market Segmentation Findings

The results of the previous analyses reveal that there appear to be four distinct market segments. The first market segment is comprised of those using ridehailing in/around the city; these respondents are likely to be *young urban local users*. The second segment is those using ridehailing primarily when traveling, and this group will be referred to as *wealthy travelers*. The third group only uses ridehailing with friends or family, and this segment will be called *tagalong users*. Finally, those who have never used or never heard of ridehailing are the *non-user group*. Each of these groups is described in more detail in the following subsections.

Young Urban Local Users

The young urban local user group is the largest user group with a sample size of 205 respondents (20%); it is second largest in overall sample size when compared to the non-user group.

These users are typically millennials who are living in the city and have higher incomes. Because these people are often living in the city, they tend not to own a vehicle. In terms of their attitudes, they generally agree that public transit is able to get them to where they need to go; since they are in urban areas, public transit is likely more frequent and available. This group tends to use ridehailing services to go out to



Data Source: Populus Technologies, Inc.
Respondents were able to select more than one reason. Therefore, these percentages do not sum to 100%.

Figure 9: Reasons for Not Using Ridehailing.

social events or to go shopping. Consequently, if these people were not able to use ridehailing, they would either drive or would not make the trip at all. In summary, the young urban local users are using ridehailing for non-essential trips meaning that ridehailing is a convenient mode that allows them to do extra things.

This group encompasses the majority of the socioeconomics stated in the previous literature, likely because this is the largest group of ridehailing users. The young urban local users align with Hypothesis 1: there are young people who use ridehailing mainly for social purposes.

Wealthy Travelers

The wealthy travelers market segment makes up about 14% (141 of 996) of all survey respondents, making it the third largest group overall and the second largest user group.

The wealthy travelers group tends to be slightly older than young urban local users but still younger than 55 years old. These users are highly educated and have high incomes. These users make most of their trips to and from airports or for social purposes, such as restaurants. From the survey questions, it is unclear whether the trips to and from the airport were for business or leisure travel. Due to the nature of when the wealthy travelers are using ridehailing (when they are not in their home city), these users will either drive, most likely a rental car, or take a taxi if ridehailing services are not available.

This group has not been well studied in the past. This is likely due to the nature of most travel surveys being household based and focus on travel around the respondent's home city. This group aligns with Hypothesis 2: there are people who use ridehailing when they are not in their own city.

Tagalong Users

The tagalong users are the smallest group of people using ridehailing, with 126 respondents (13%) in this group.

Like young urban local users, tagalong users tend to be millennials or younger. It is also more likely that these users are female and/or black/African American. The reasons for only using ridehailing when with friends or family could be a result of safety concerns. While this group is overall similar to the young urban local users, the significance of race and gender are key differentiating factors.

Similar to the wealthy travelers, this group has not been frequently studied in previous literature. Since this group had not been studied before, we coined the term *tagalong users* for this group since they only use ridehailing with other people. However, this group suggests that Hypothesis 3 is true: there are people who use ridehailing but never alone and /or never pay for it themselves.

Non-Users

This group is the largest group of survey respondents, making up 53% of the entire sample (524 of 996).

Compared to the three other groups, non-users tend to be older, live in rural areas, and/or have lower income. When non-users were asked why they choose to not use ridehailing services, the most common reasons, in descending order, were they could use their own car, they felt their personal safety would be at risk, and they found ridehailing to be too expensive.

Non-users have often been studied in previous literature, which has come to similar conclusions. This non-user groups aligns with Hypothesis 4, which is that there are people who are aware of ridehailing services but do not use it. However, the survey results do not support Hypothesis 5: there are people who do not know what ridehailing is. Only 1.8% of survey respondents stated that they had never heard of ridehailing before, which is a very small portion of the sample. This suggests that ridehailing companies such as Uber and Lyft have become household names and are widely known.

Figure 10 provides a summary of the key attributes of the four distinct market segments.

DISCUSSION, CONCLUSIONS, AND AREAS FOR FUTURE RESEARCH

The rapid growth of ridehailing in North America has led to a large research focus on the services provided as well as the travelers using them. However, the majority of the literature considers ridehailing users as a single group. This study aims to identify distinct market segments for both users and non-users of ridehailing services. While the majority of prior studies on ridehailing in the United States have focused on

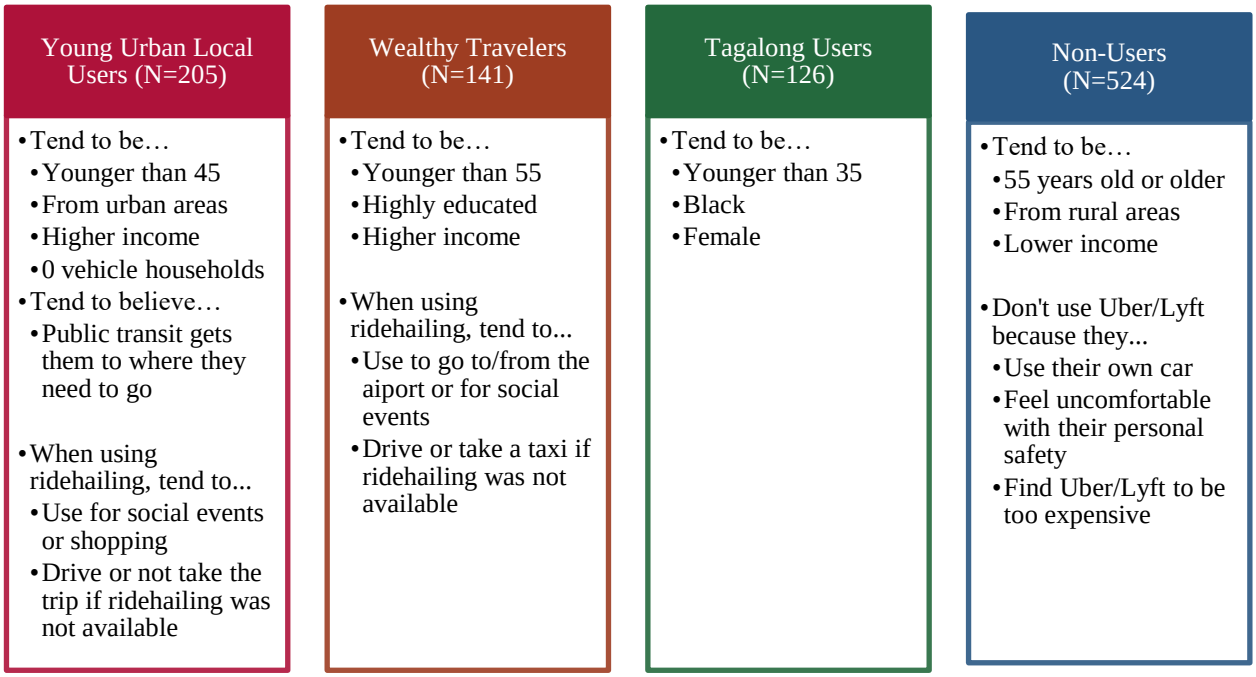


Figure 10: Summary of the Four Ridehailing Market Segments.

major metropolitan areas, this study focuses on three mid-size cities in Tennessee: Knoxville, Memphis, and Nashville.

It was first hypothesized that there would be five distinct segments: a group of young people using ridehailing for social purposes; a group that uses ridehailing when they are traveling; a group of people who use ridehailing when someone else requests the service for them; a group of people who have heard of ridehailing but do not use it; and a group of people who have never heard of ridehailing. However, statistical and multivariate analyses of the survey responses revealed that there were only four main market segments: *young urban local users, wealthy travelers, tagalong users,* and *non-users*. The first market segment, which aligns with prior research, is comprised of those users who use ridehailing in/around their own city; they are younger people who generally have high incomes, no vehicles in their households, and use ridehailing for social purposes. These young urban local users made up approximately 20% of the survey sample. The second prominent market segment is those who use ridehailing when traveling. These users tend to be slightly older, have higher education and income levels, and use ridehailing to get to/from the airport. This segment of wealthy travelers was approximately 14% of the survey sample. The third market segment, which has largely been excluded from prior research, includes those who ride with friends/family. These users are younger, female, and/or black, and we coined the term "tagalong users" to refer to this group. Of the three ridehailing user segments, the tagalong users were the smallest making up only 13% of the survey sample. The fourth segment contains non-users. They do not use ridehailing, tend to be older, live in rural areas, and/or have low incomes. The non-user group was the most common market segment comprising approximately 53% of the survey sample. Their most common reasons for not using ridehailing are car ownership, safety concerns, and cost. It is important to note that while the original hypotheses contained a fifth group that had never heard of ridehailing, it was so small it was combined with the other non-user group, demonstrating that companies such as Uber and/or Lyft have become commonplace and are widely known.

Understanding the demographics of each of these market segments may enable more targeted marketing of ridehailing services in the future. In past studies, the results have typically combined the three user groups (young urban local users, wealthy travelers, and tagalong users) into one group and tried to find the trends. However, these groups have different needs and wants when it comes to ridehailing services. Understanding how different people are using ridehailing could also have policy implications. For example, if people in the "wealthy travelers" group are not able to easily access ridehailing vehicles at the airport, they might be more inclined to either rent a car or use a taxi if, for example, those services are closer in proximity to the baggage claim. Improving loading zone signage and operations at airports and other high interest locations, such as hotels or convention centers, could improve congestion and safety for ridehailing users in this market segment.

There are numerous areas for improvement and future research that emerged from this research. To improve this study, future research could conduct a similar survey in which the respondent would be able to select multiple responses to the ridehailing familiarity and adoption question. The current form of the question only allows the respondent to select the answer they find is most applicable even if they use ridehailing in several ways. By changing the question, it could be possible to learn how people are using ridehailing when in their home city and if/how they also use it when traveling. A second way to improve this research would be to use different modeling frameworks when analyzing the survey data, such as latent class models. A further expansion of this research would be to investigate the two new market segments that were identified: the wealthy travelers who use ridehailing only when away from home and the tagalong users who only use ridehailing with friends or family. Many previous studies have used household-based surveys that ask about travel patterns around the respondent's own city. Creating surveys that specifically ask how one travels when they are not in their own city would be a way to capture more information about this user group. To best target travelers, intercept surveys could be administered at airports or hotels. If using an intercept survey at an airport, it could be of value to ask whether the person is flying for business or leisure purposes since this could further define the wealthy traveler group. Another question for intercept surveys at the airport could be about the duration of the trip; are they going for a one-day meeting where

renting a vehicle is not as essential or are they going to be on the trip for a week or two? This would start to look at how ridehailing is impacting the car rental industry. Questions to better understand the tagalong group could include ascertaining why respondents in this group will not use their own smartphone to request ridehailing service. Is it because someone else purchased the trip for the respondent and was willing to pay for it? Is the respondent part of a group traveling in a single ridehailing vehicle? What is the typical trip purpose for someone in this group? By better understanding the motives and trip patterns of these groups, policies can be put into place to better serve these groups and support expansion of the ridehailing markets.

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CHAPTER V
CONCLUSION

This chapter summarizes the findings of this thesis and is divided into four sections. First, the previous literature discussed in Chapter 2 is summarized. This is followed by a summary of the survey data and results found in Chapters 3 and 4. The third section discusses the implications of this thesis and is followed by areas for future research.

SUMMARY OF PREVIOUS LITERATURE

As ridesourcing continues to grow in popularity, the research surrounding this relatively new mode of transportation grows as well. Sixteen of the 44 reviewed studies from the literature review in Chapter 2 used national level data while only nine used state level data. The other 19 studies in this literature review used data from large metropolitan cities.

Six main areas were common themes throughout the literature: demographics, frequency of time and use, trip purpose, reasons for using, relationship between ridesourcing and other modes of transportation, and transportation system impacts. The general consensus of the previous literature is that ridesourcing users tend to be younger, have higher incomes, higher education levels, and live in urban areas. Ridesourcing was most commonly stated to be used at night and on the weekends. Ridesourcing was most commonly used to get to social events. The most common explanations for using ridesourcing were because people do not want to drive while intoxicated, people believe they will have difficulty parking at their destinations, and they think alternative modes will have longer travel times. Many prior studies found ridesourcing to be a substitute for taxis as well as personal vehicles. The previous literature also found that ridesourcing could potentially increase vehicle miles traveled and may add vehicles to the roadways.

SUMMARY OF SURVEY DATA RESULTS

Chapters 3 and 4 focused on survey data to further understand who is using ridesourcing. All of the data was collected prior to the COVID-19 outbreak.

Data from the 2017 National Household Travel Survey (NHTS) were used to determine the significant demographic characteristics at a state, census level, and national level. Age, income, educational attainment, employment status, household vehicle ownership, and residential area type were significant for the three levels and aligned with the findings of the previous literature. While other important demographic variables, including gender and race, aligned with previous literature, they were only significant at the national level.

Using survey data collected by the company Populus Technologies, Inc. in three cities in Tennessee (Knoxville, Memphis, and Nashville), demographics, attitudes, and neighborhood preferences were analyzed to determine which characteristics were significant for ridehailing users and non-users. Four distinct market segments were identified from this analysis: young urban local users, wealthy travelers, tagalong users, and non-users. The young urban local user segment most closely aligns with the previous literature and is the largest ridehailing user group based on the survey data. While there are some commonalities among the three segments that use ridehailing, the wealthy traveler and tagalong user segments have had limited, if any, treatment in the previous literature. The wealthy travelers, or those who use ridehailing exclusively while traveling, tend to be slightly older, have higher education and income levels, and use ridehailing to get to/from the airport. The tagalong users, or those who use ridehailing only when with friends or family, tend to be younger, female, and/or black. The largest segment of the sample, making up over half of the respondents, were those who have never used ridehailing. While there was a fifth group originally, those who have never heard of ridehailing, this group was extremely small (N=18) and was therefore combined with those who have never used ridehailing to make one non-user group. This small sample size shows that, even in mid-sized cities, ridehailing companies, such as Uber and Lyft, have become household names in just over ten years. While ridehailing companies have become household names, the large non-user group represents potential future ridehailing users.

IMPLICATIONS

Recognizing ridesourcing user differences between those in large cities and those in smaller or even mid-sized cities or states is important for policy-makers and transportation planners in their own city or state. Policy makers and transportation planners in smaller or less densely populated areas should focus on understanding how people are using ridesourcing to determine how to manage ridesourcing locally, rather than looking to cities and/or states with vastly different users and travel patterns. It is also important for policy-makers and transportation planners to recognize there are different types of ridesourcing users. Depending on which of these user groups is most prevalent in their area, they could better customize policies and regulations to be more effective. For example, in a city where most ridesourcing users are predominantly in dense urban areas, prioritizing ridesourcing policies in these areas may see more immediate benefits than focusing on the less densely populated areas where ridesourcing is not as prominent. If most people are using ridesourcing at night, it might be best to create curb space management policies that are only in effect during the evening hours. Alternatively, if most people are using ridesourcing to get to the central business district during the day, having curb space management policies during the day would be more effective. If airports are a common pick up or drop off location for ridesourcing, policy changes could help to mitigate increased levels of congestion by moving ridesourcing to a separate location or change the current curb space.

AREAS FOR FUTURE RESEARCH

Based on the studies presented in this research, some areas for improvement and future research have been identified and are briefly discussed in the following paragraphs. While there are many ways to continue to expand ridesourcing research, one of the most notable areas for improvement is to standardize and create mode-specific survey questions. To easily compare national surveys, such as NHTS, with local surveys, there should be consistent questions, including the time periods of questions (such as use over the past month or past year, etc.). It would also be beneficial to ensure that questions are focusing on frequency of use for a single mode, whether that be ridesourcing, taxis, or bikeshare. This was an issue when interpreting results of one of the NHTS questions (ridesharing or taxi) and the Metro Survey Question (ridesharing and bikeshare). It is also important that questions are asked for people who may use ridesourcing in multiple ways, including those who use locally as well as when they travel. This could further help to differentiate the market segments discussed in Chapter 4. One way to incorporate these suggestions for future research would be to create a ridesourcing survey question database. The National Association of City Transportation Officials (NACTO) created an intercept survey toolkit as well as a question bank with over 100 different questions for bike share, which could be used as a model (NACTO 2016).

Future research should further investigate the two groups that have not been studied as often, those who use ridesourcing while traveling and those who only use ridesourcing when with friends or family. This can be accomplished through additional data collection, including through surveys, interviews, and/or focus groups for people in these two groups. Determining motivations and further understanding their habits will solidify the differences between the market segments.

To discern changes and emerging trends in ridesharing use and behaviors since data for the 2017 NHTS was obtained, the next NHTS data publication should be compared against the 2017 data. This comparison could help policy makers ensure they are keeping abreast of this evolving transportation mode.

Finally, there should be continued research in smaller and mid-sized cities/states. This research identified some differences between smaller cities and states and larger ones, but further research will help to assess and identify differences as this mode of transportation continues to evolve and expand.

REFERENCES

NACTO (2021), 'A How-to Guide for Learning More about Bike Share in Your Community', <https://nacto.org/interceptsurveytoolkit/>.

APPENDIX

APPENDIX 1: SUMMARY STATISTICS FROM METRO RESIDENT SURVEY

The Metropolitan Government of Nashville and Davidson County, also known as METRO, conducts quarterly surveys of their residents to better understand their views on both the local government and the community. The market research and survey company, ETC Institute is administering the survey via mail, internet, and phone and is available in eight languages. The results are available on the Nashville Open Data Portal for each quarter starting in Quarter 1 of 2018.

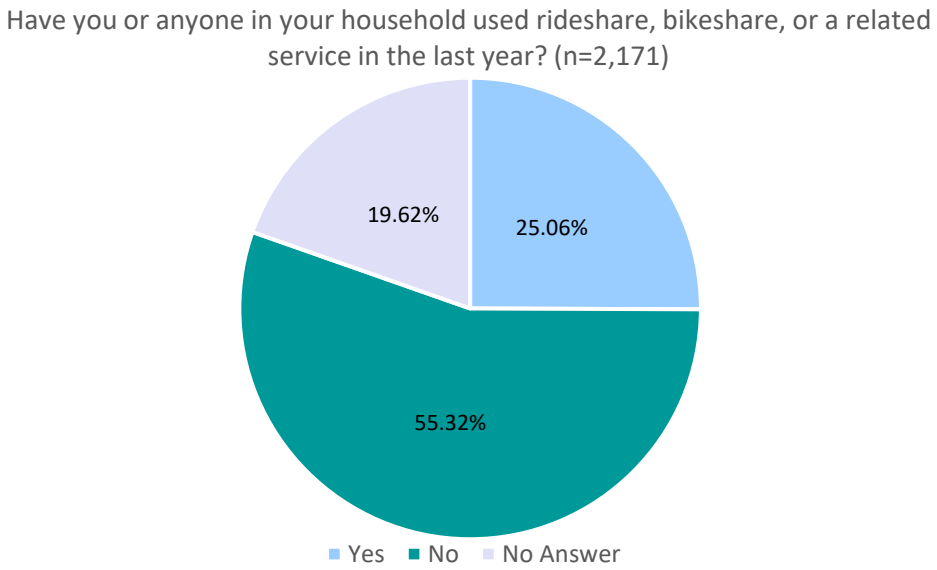
As of September 2019, there were five quarters available on the Nashville Open Data Portal (n = 2,171). Even though the surveys were conducted over a varying amount of days each quarter (ranging from 25 days to 41 days), each quarter has at least 400 survey results. Ten questions were used from the survey; they pertain to demographics, transit use, and ridesharing/bikesharing use. It is important to note that some of the answers to questions in the dataset were given as "9", which was not a viable answer. An example of this is for the question of gender. When the answer was given as 9, this was considered a blank or No Answer.

The answers from the question "Have you or anyone in your household used rideshare, bikeshare, or a related service in the last year?" were used to compare the remaining nine questions to see what the trends were among those who have used rideshare/bikeshare in the last year and those who have not. Figure A-1 looks at the usage of both rideshare/bikeshare and also transit usage. It is important to note that those entries that did not have an answer to the question about rideshare/bikeshare were then only considered as part of the total survey sample for the remaining analysis.

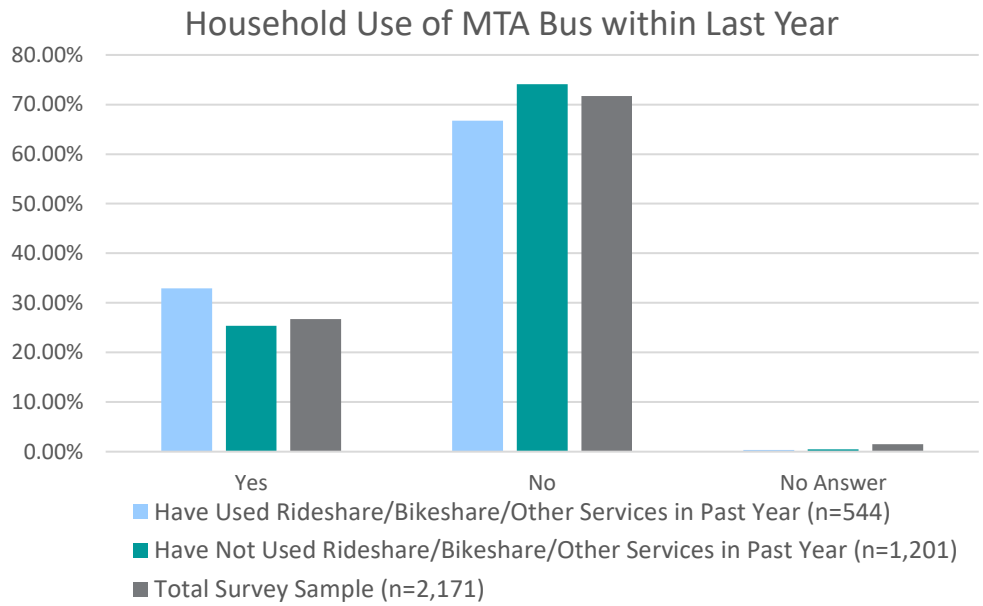
The demographics of the dataset followed national trends of rideshare users: well-educated, higher income, younger people are more likely to use rideshare than others, as seen in Figure A-2. It is important to note that users were able to indicate more than one race/ethnicity in the survey and also had an option to write in their own race/ethnicity after selecting other. Some of those who selected the "Other" category should have selected a different option. For example, one entry wrote in "white" and another wrote in "Black not African American". These were moved to their proper categories before analyzation was completed. A new category was created and called "Multiple Races" for those who selected more than 1 race/ethnicity or selected other and wrote in "2+ races" or "Multi-racial". The survey dataset had seven age groupings, some of which overlapped. There was an age range of 35 to 44 years old, 35-54 years old, and 45-54 years old. Because it cannot be determined how old the respondents are in the 35-54 years old category, these three groups have been combined. Another important note is that these demographics are about the person taking the survey, with the exception of annual household income. However, the rideshare/bikeshare questions is asking if anyone in the household has used these services within the past year.

Survey participants were asked about their satisfaction levels on many topics in the survey ranging from local government to school systems, from transportation to public health. As seen in Figure A-3, the data show that those who have used rideshare/bikeshare within the past year are more dissatisfied with public transportation access and quality than those who have not used it. This could be an explanation as to why they have been using these services. Satisfaction with curb space management is lower among those who have used rideshare/bikeshare within the past year. There are two varying examples in the question that explain curb space management: on-street parking and rideshare. If the respondent is very dissatisfied with on-street parking is terrible, they may be more inclined to use rideshare services. However, they may be very satisfied with rideshare services when it comes to curb space management in which case, the respondent would have to pick either very satisfied or very dissatisfied.

The current data seems to align with national trends when it comes to rideshare demographics. As more surveys are administered, there statistics will become more representative of Nashville. Moving forward, it may be suggested that the wording of the survey be clarified and more questions pertaining to rideshare are asked.

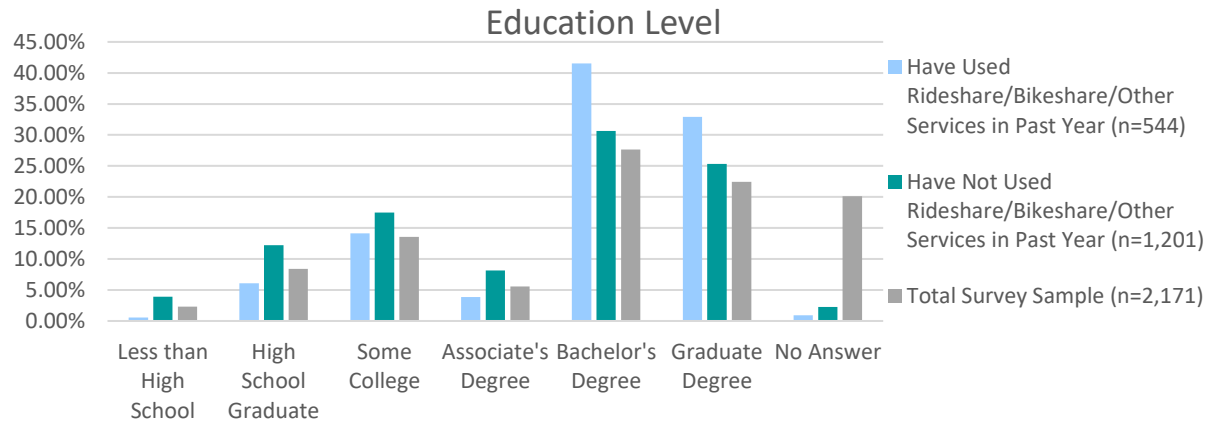


(a) Have You or Anyone in Your Household Used Rideshare, Bikeshare, or a Related Service in the Last Year?

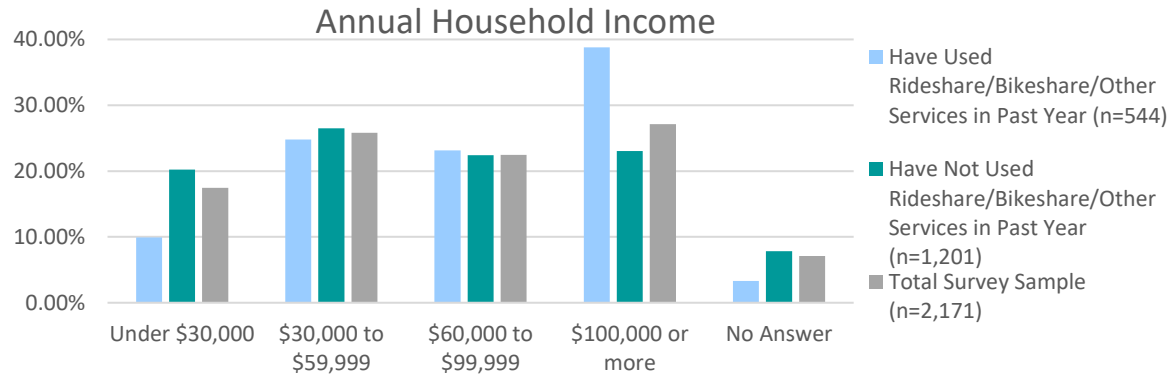


(b) Have You or Anyone in Your Household Used MTA Bus Service in the Last Year?

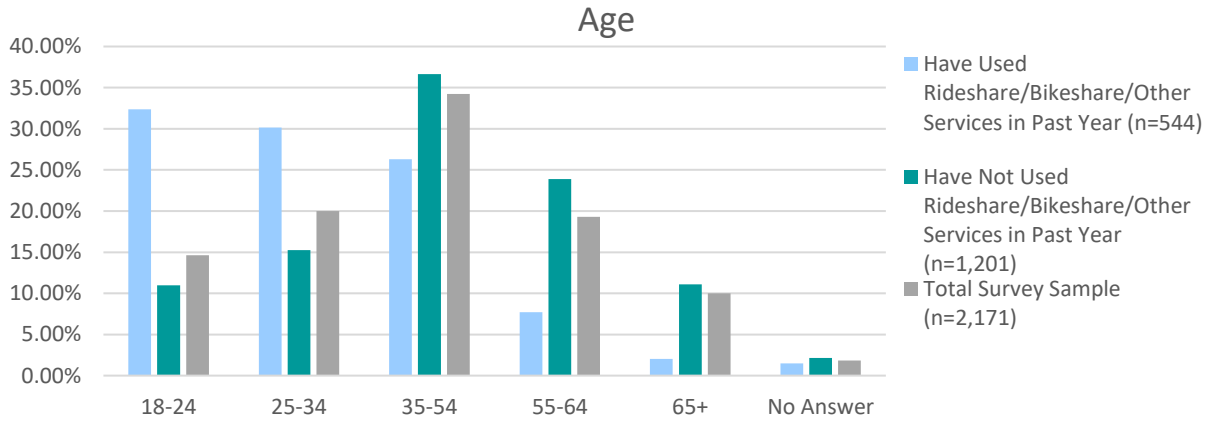
Figure A-1: Usage Data Based off of Use of Rideshare/Bikeshare Within the Past Year.



(a) What Is Your Educational Attainment?

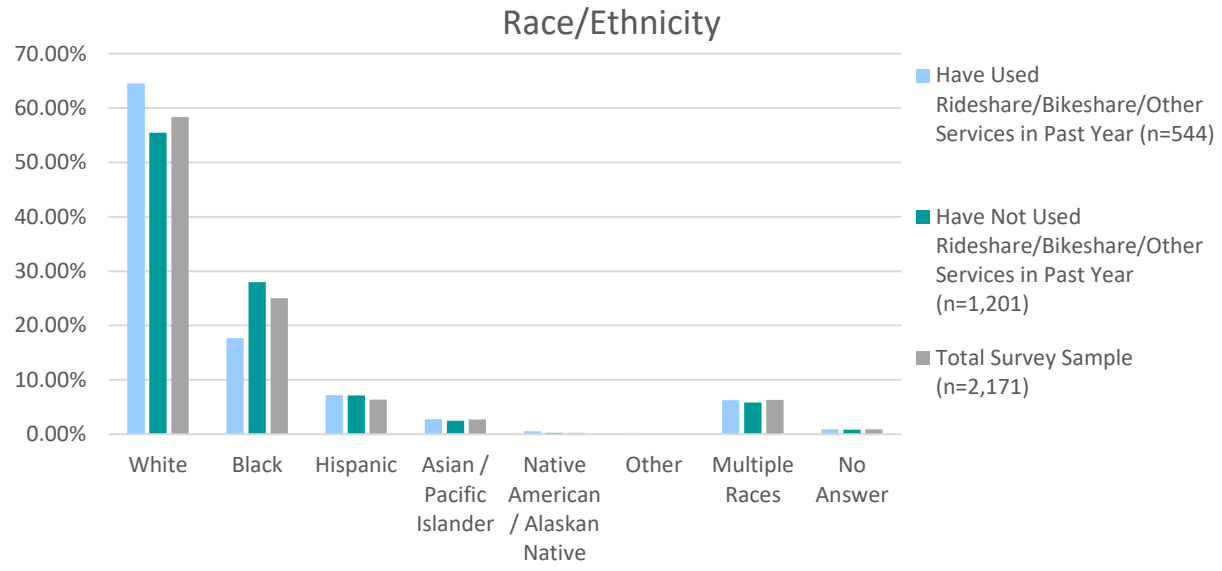


(b) What Would You Say Your Total Household Income Is?

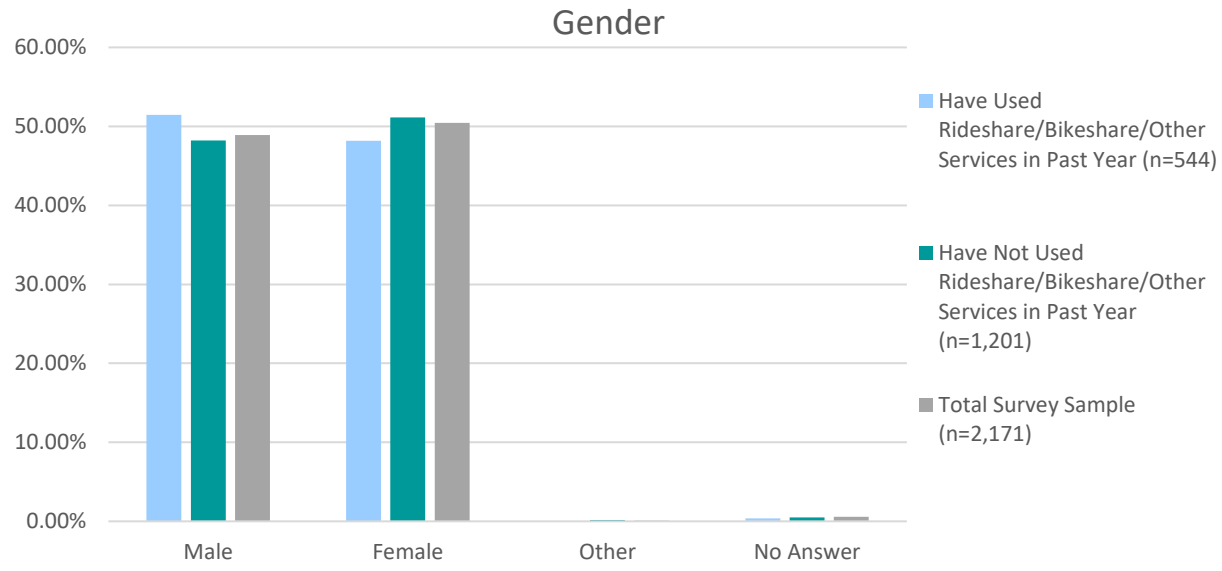


(c) What Is Your Age?

Figure A-2: Demographics Based off of Use of Rideshare/Bikeshare Within the Past Year.

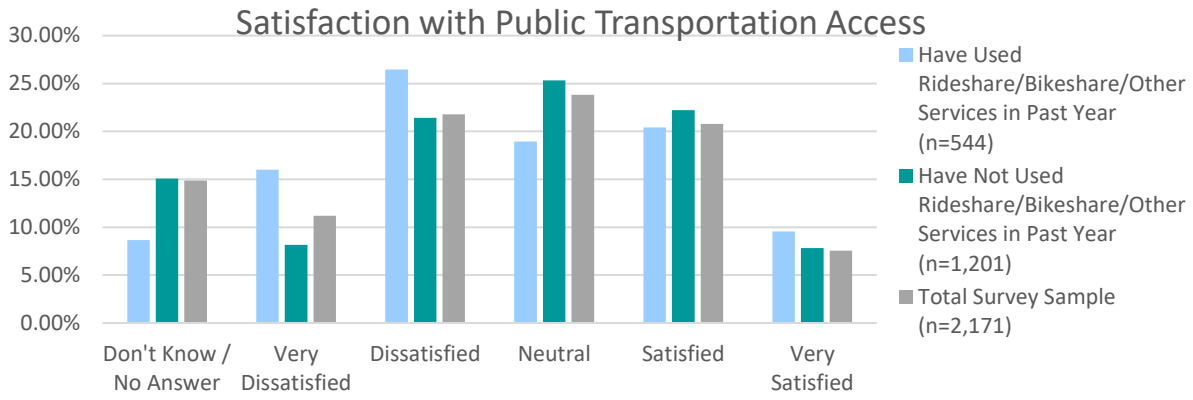


(d) Respondent Indicated Race/Ethnicity.

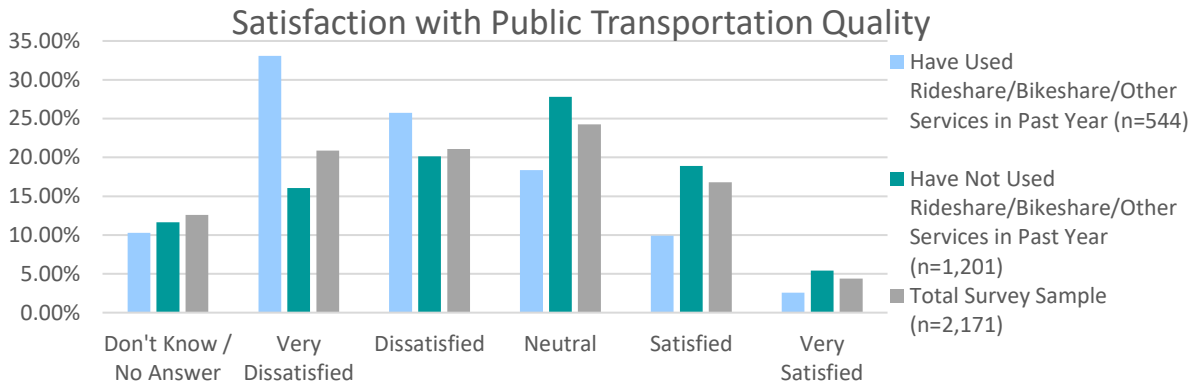


(e) What Is Your Gender Identity?

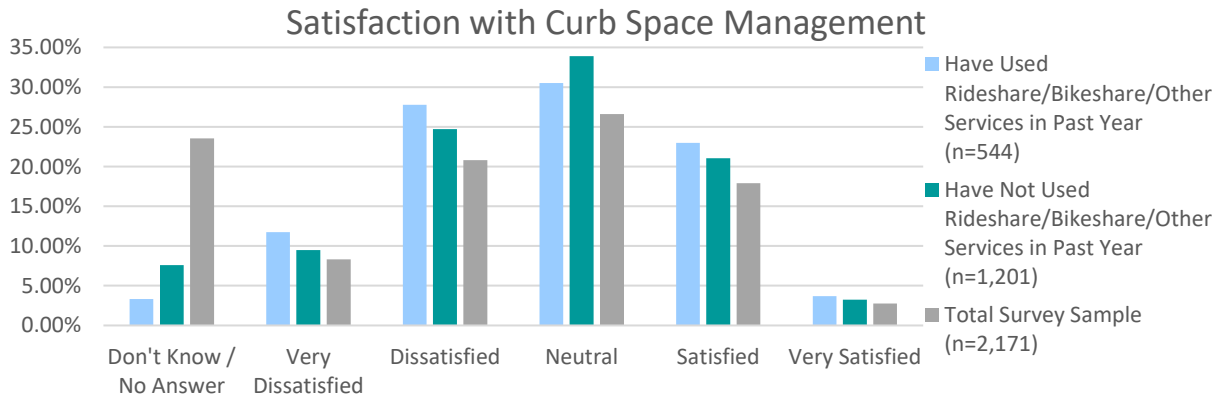
Figure A-2 continued



(a) How Satisfied Are You With Access to Public Transportation?



(b) How Satisfied Are You With the Overall Quality of Public Transportation?



(c) How Satisfied Are You With Curb Space Management (e.g. on-Street Parking, Rideshare)?

Figure A-3: Satisfaction Levels Based off of Use of Rideshare/Bikeshare Within the Past Year.

APPENDIX 2: 2017 NHTS WEIGHTED STATISTICAL ANALYSIS

Appendix 2 provides the 2017 NHTS weighted statistical analysis. The first section pertains to weighted summary statistics for both the taxi/ridesharing frequency and the rideshare app usage questions. The second section provides weighted cross tabulations for both questions.

2017 NHTS Weighted Summary Statistics

Taxi or Ridesharing Frequency of Use Summary Statistics

In Census Division 6, a total of 20.2% of respondents use taxi or rideshare with 15.7% using a few times a year, 3.9% using a few times a month, 0.7% using a few times a week, and 0.0% using daily, as seen in Figure A-4. At the national level, 34.0% of respondents use taxi or ridesharing services with 24.1% using a few times a year, 7.4% using a few times a month, 2.0% using a few times a week, and 0.5% using daily. In both Census Division 6 and the US, at least 10.5% of respondents gave a non-response answer (I don't know, I prefer not to answer, or not ascertained).

Ridesharing App Usage Summary Statistics

As seen in Figure A-5, 3.6% of respondents in Census Division 6 purchased a ride using a smartphone rideshare app in the past 30 days. At the national level, 8.3% of respondents purchased a ride in the past 30 days. The non-response percent was higher for the ridesharing app question compared to the taxi/ridesharing frequency questions at 15-16%.

2017 NHTS Weighted Cross Tabulations

Taxi or Ridesharing Frequency of Use Cross Tabulation

As seen in Table A-1, the weighted cross tabulations for the question "How often do you use Taxi service or ridesharing to get from place to place?" was completed for Census Division 6 and the US.

Of those who reported using taxi or ridesharing services, one- or two-person households were most frequent. In the US, 29.1% of those who use these services were from one-person households while 25.6% of those who never use these services were from one-person households.

Similarly, households with zero or one vehicles were more likely to use taxis or ridesharing. In the US, 14.5% of those who use these services were from zero vehicle households while 5.1% of those who did not use these services were from zero vehicle households. Likewise, in the US, 34.0% of those who use these services had one vehicle in their household while 32.5% of those who reported not using these services were from one vehicle households.

The data suggest that people under the age of 55 were more likely to use taxi or ridesharing services. In the US, 18.7% of those who use these services were 45 to 54 years old whereas this group represents 17.6% of non-users. This trend continues in nationwide data for the younger age groups as well: 35 to 44 years old (22.4% use and 16.3% do not use); 25 to 34 years old (23.6% use and 13.1% do not use); and 18 to 24 years old (5.6% use and 3.9% do not use). Similar trends appear in the census division as well.

For Census Division 6, the most common education level for users of taxi/rideshare was a Bachelor's Degree, while a Graduate Degree or Professional Degree was most common for users of taxi/rideshare in the US data. The most common education level for those who do not use taxi or ridesharing services for both the census division and the US was Some College or Associate's Degree.

Taxi and rideshare users were more frequently employed. In the US, 73.7% of those who reported using taxi or ridesharing services were employed while 59.4% of those who do not use these services were employed.

High incomes were common for those using taxi or ridesharing. In the US, 37.2% (sum of $100,000 to $149,999 and $150,000 or more) of those who use taxi or rideshare have an annual household income of at least $100,000 compared to 18.9% of non-users in the US in these income brackets.

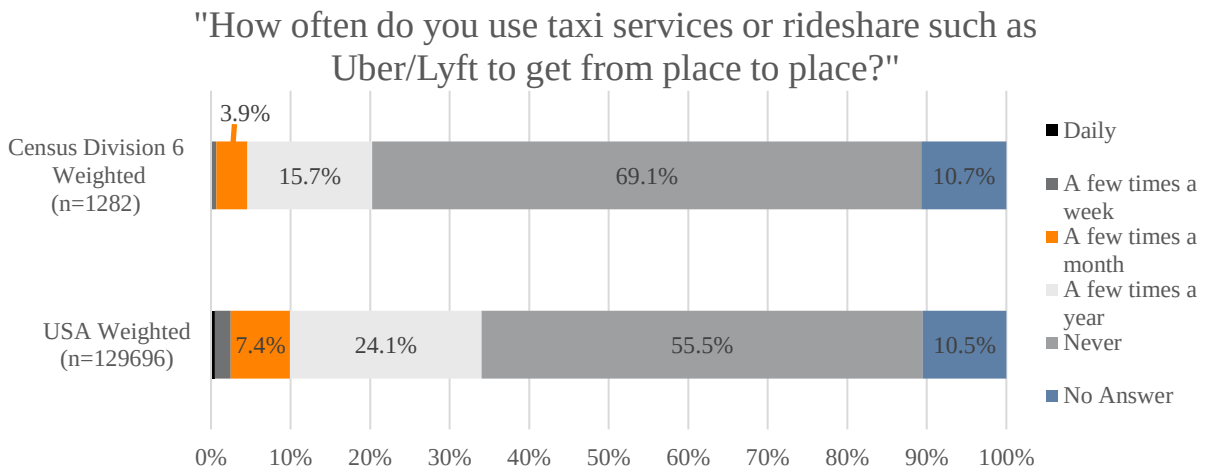


Figure A-4: Taxi and Rideshare Frequency of Use, Weighted Responses.

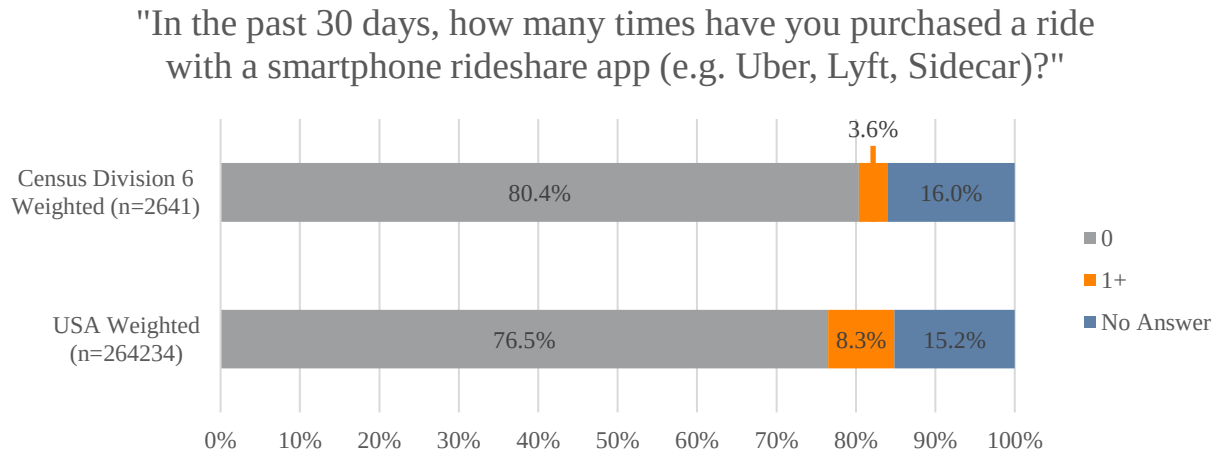


Figure A-5: Rideshare App Usage Over the Past 30 Days, Weighted Responses.

Table A-1: How Often Do You Use Taxi Services or Rideshare to Get From Place to Place? Weighted Cross Tabulation.

		Census Division 6								US							
		Never Uses		Uses		No Answer		Total		Never Uses		Uses		No Answer		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		5306168	100%	1556327	100%	820809	100%	7683304	100%	70069049	100%	42970759	100%	13282196	100%	126322004	100%
Count of Household Members	1	1333163	25.1%	516864	33.2%	346451	42.2%	2196478	28.6%	17953654	25.6%	12524272	29.1%	4939257	37.2%	35417183	28.0%
	2	1777174	33.5%	546036	35.1%	288612	35.2%	2611822	34.0%	23294547	33.2%	14060720	32.7%	4593336	34.6%	41948603	33.2%
	3	957937	18.1%	259597	16.7%	46572	5.7%	1264106	16.5%	11182467	16.0%	7088218	16.5%	1676438	12.6%	19947123	15.8%
	4	830110	15.6%	156492	10.1%	63023	7.7%	1049625	13.7%	10713363	15.3%	6388638	14.9%	1324701	10.0%	18426702	14.6%
	5	270342	5.1%	64955	4.2%	69556	8.5%	404853	5.3%	4431330	6.3%	2073905	4.8%	496384	3.7%	7001619	5.5%
	6	66088	1.2%	12383	0.8%	6595	0.8%	85066	1.1%	1688281	2.4%	595233	1.4%	182427	1.4%	2465941	2.0%
	7	37799	0.7%	0	0.0%	0	0.0%	37799	0.5%	490652	0.7%	152949	0.4%	44472	0.3%	688073	0.5%
	8	0	0.0%	0	0.0%	0	0.0%	0	0.0%	184007	0.3%	44278	0.1%	16138	0.1%	244423	0.2%
	9	33555	0.6%	0	0.0%	0	0.0%	33555	0.4%	82054	0.1%	35126	0.1%	3375	0.0%	120555	0.1%
	10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	35461	0.1%	6207	0.0%	5668	0.0%	47336	0.0%
	11	0	0.0%	0	0.0%	0	0.0%	0	0.0%	9207	0.0%	49	0.0%	0	0.0%	9256	0.0%
	12	0	0.0%	0	0.0%	0	0.0%	0	0.0%	688	0.0%	1164	0.0%	0	0.0%	1852	0.0%
	13	0	0.0%	0	0.0%	0	0.0%	0	0.0%	3338	0.0%	0	0.0%	0	0.0%	3338	0.0%
Count of Household Vehicles	0	235101	4.4%	181855	11.7%	128706	15.7%	545662	7.1%	3568036	5.1%	6225636	14.5%	2206659	16.6%	12000331	9.5%
	1	1602369	30.2%	517384	33.2%	366750	44.7%	2486503	32.4%	22741468	32.5%	14611686	34.0%	5008605	37.7%	42361759	33.5%
	2	1950213	36.8%	516745	33.2%	195035	23.8%	2661993	34.6%	24523032	35.0%	13804071	32.1%	3496591	26.3%	41823694	33.1%
	3	985853	18.6%	237132	15.2%	78005	9.5%	1300990	16.9%	11611496	16.6%	5279253	12.3%	1566348	11.8%	18457097	14.6%
	4	271713	5.1%	78585	5.0%	10496	1.3%	360794	4.7%	4966822	7.1%	1925326	4.5%	608523	4.6%	7500671	5.9%
	5	195260	3.7%	15604	1.0%	17249	2.1%	228113	3.0%	1719778	2.5%	688455	1.6%	250518	1.9%	2658751	2.1%
	6	47235	0.9%	6230	0.4%	12148	1.5%	65613	0.9%	538610	0.8%	213840	0.5%	87816	0.7%	840266	0.7%
	7	18424	0.3%	0	0.0%	12421	1.5%	30845	0.4%	232487	0.3%	128637	0.3%	38087	0.3%	399211	0.3%
	8	0	0.0%	2793	0.2%	0	0.0%	2793	0.0%	90319	0.1%	35123	0.1%	4809	0.0%	130251	0.1%
	9	0	0.0%	0	0.0%	0	0.0%	0	0.0%	39102	0.1%	20300	0.0%	4344	0.0%	63746	0.1%
	10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	16852	0.0%	11386	0.0%	2288	0.0%	30526	0.0%
	11	0	0.0%	0	0.0%	0	0.0%	0	0.0%	5675	0.0%	17558	0.0%	36	0.0%	23269	0.0%
	12	0	0.0%	0	0.0%	0	0.0%	0	0.0%	15374	0.0%	9489	0.0%	7572	0.1%	32435	0.0%
Imputed Age	Less Than 18	0	0.0%	0	0.0%	0	0.0%	0	0.0%	76917	0.1%	9226	0.0%	1028	0.0%	87171	0.1%
	18-24	318762	6.0%	106772	6.9%	0	0.0%	425534	5.5%	2726050	3.9%	2402477	5.6%	231289	1.7%	5359816	4.2%
	25-34	868659	16.4%	310231	19.9%	18370	2.2%	1197260	15.6%	9177854	13.1%	10121479	23.6%	859340	6.5%	20158673	16.0%
	35-44	954624	18.0%	342471	22.0%	52512	6.4%	1349607	17.6%	11418448	16.3%	9644351	22.4%	1269154	9.6%	22331953	17.7%
	45-54	798226	15.0%	310042	19.9%	163637	19.9%	1271905	16.6%	12336612	17.6%	8039735	18.7%	2406064	18.1%	22782411	18.0%
	55+	2365897	44.6%	486811	31.3%	586291	71.4%	3438999	44.8%	34333170	49.0%	12753491	29.7%	8515322	64.1%	55601983	44.0%

Table A-1 continued

		Census Division 6								US							
		Never Uses		Uses		No Answer		Total		Never Uses		Uses		No Answer		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		5306168	100%	1556327	100%	820809	100%	7683304	100%	70069049	100%	42970759	100%	13282196	100%	126322004	100%
Educational Attainment	High School Graduate or Less	1513148	28.5%	220944	14.2%	375844	45.8%	2109936	27.5%	17558604	25.1%	5061305	11.8%	5227309	39.4%	27847218	22.0%
	Some College or Associate's Degree	1729887	32.6%	333473	21.4%	218863	26.7%	2282223	29.7%	24825812	35.4%	9867167	23.0%	4131469	31.1%	38824448	30.7%
	Bachelor's Degree	1073871	20.2%	510101	32.8%	78427	9.6%	1662399	21.6%	15370048	21.9%	13699778	31.9%	1914091	14.4%	30983917	24.5%
	Graduate or Professional Degree	984848	18.6%	491809	31.6%	143807	17.5%	1620464	21.1%	12301361	17.6%	14328731	33.3%	1999087	15.1%	28629179	22.7%
	No Answer	4413	0.1%	0	0.0%	3868	0.5%	8281	0.1%	13225	0.0%	13779	0.0%	10241	0.1%	37245	0.0%
Worker Status	Is Employed	3102652	58.5%	1185458	76.2%	285353	34.8%	4573463	59.5%	41605007	59.4%	31683715	73.7%	6332453	47.7%	79621175	63.0%
	Is Not Employed	2203516	41.5%	370870	23.8%	535457	65.2%	3109843	40.5%	28463918	40.6%	11287045	26.3%	6949744	52.3%	46700707	37.0%
	No Answer	0	0.0%	0	0.0%	0	0.0%	0	0.0%	126	0.0%	0	0.0%	0	0.0%	126	0.0%
Household Income	Less than $25,000	1548682	29.2%	304373	19.6%	443245	54.0%	2296300	29.9%	16439387	23.5%	7740184	18.0%	4881798	36.8%	29061369	23.0%
	$25,000 to $49,999	1358542	25.6%	308919	19.8%	113848	13.9%	1781309	23.2%	17278867	24.7%	6970423	16.2%	3266402	24.6%	27515692	21.8%
	$50,000 to $74,999	930686	17.5%	237329	15.2%	107167	13.1%	1275182	16.6%	12660342	18.1%	5847378	13.6%	1506452	11.3%	20014172	15.8%
	$75,000 to $99,999	587804	11.1%	178017	11.4%	49353	6.0%	815174	10.6%	8493708	12.1%	5357821	12.5%	1095685	8.2%	14947214	11.8%
	$100,000 to $149,999	583396	11.0%	318117	20.4%	41567	5.1%	943080	12.3%	9090703	13.0%	7805008	18.2%	1063216	8.0%	17958927	14.2%
	$150,000 or more	160072	3.0%	199850	12.8%	17130	2.1%	377052	4.9%	4106594	5.9%	8174196	19.0%	764614	5.8%	13045404	10.3%
	No Answer	136986	2.6%	9723	0.6%	48500	5.9%	195209	2.5%	1999451	2.9%	1075751	2.5%	704030	5.3%	3779232	3.0%
Hispanic	Is Hispanic or Latino	150708	2.8%	70525	4.5%	7560	0.9%	228793	3.0%	9888270	14.1%	6992146	16.3%	2339266	17.6%	19219682	15.2%
	Is Not Hispanic or Latino	5155460	97.2%	1485802	95.5%	813250	99.1%	7454512	97.0%	60131035	85.8%	35926525	83.6%	10923381	82.2%	106980941	84.7%
	No Answer	0	0.0%	0	0.0%	0	0.0%	0	0.0%	49746	0.1%	52089	0.1%	19549	0.1%	121384	0.1%

Table A-1 continued

		Census Division 6								US							
		Never Uses		Uses		No Answer		Total		Never Uses		Uses		No Answer		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		5306168	100%	1556327	100%	820809	100%	7683304	100%	70069049	100%	42970759	100%	13282196	100%	126322004	100%
Presence of Medical Condition	Has a Medical Condition	670117	12.6%	123323	7.9%	247515	30.2%	1040955	13.5%	7453134	10.6%	3449298	8.0%	2362447	17.8%	13264879	10.5%
	No Medical Condition	4636051	87.4%	1433004	92.1%	573295	69.8%	6642350	86.5%	62596491	89.3%	39508407	91.9%	10905591	82.1%	113010489	89.5%
	No Answer	0	0.0%	0	0.0%	0	0.0%	0	0.0%	19426	0.0%	13055	0.0%	14158	0.1%	46639	0.0%
Race	White	3972341	74.9%	1177123	75.6%	509644	62.1%	5659108	73.7%	53644705	76.6%	30340990	70.6%	8404497	63.3%	92390192	73.1%
	Black or African American	1183823	22.3%	265841	17.1%	257399	31.4%	1707063	22.2%	8888765	12.7%	5608201	13.1%	2948856	22.2%	17445822	13.8%
	Asian	37855	0.7%	15573	1.0%	13600	1.7%	67028	0.9%	2129857	3.0%	3018216	7.0%	646215	4.9%	5794288	4.6%
	Other	107222	2.0%	92799	6.0%	36298	4.4%	236319	3.1%	5009505	7.1%	3603031	8.4%	1174569	8.8%	9787105	7.7%
	No Answer	4927	0.1%	4991	0.3%	3868	0.5%	13786	0.2%	396219	0.6%	400323	0.9%	108060	0.8%	904602	0.7%
Imputed Gender	Male	2085832	39.3%	777985	50.0%	307633	37.5%	3171450	41.3%	31048942	44.3%	20351400	47.4%	5680481	42.8%	57080823	45.2%
	Female	3220336	60.7%	778342	50.0%	513177	62.5%	4511855	58.7%	39020109	55.7%	22619360	52.6%	7601715	57.2%	69241184	54.8%
Residential Area Type	Urban	3111067	58.6%	1280985	82.3%	489377	59.6%	4881429	63.5%	54748987	78.1%	39966944	93.0%	10716786	80.7%	105432717	83.5%
	Rural	2195101	41.4%	275342	17.7%	331432	40.4%	2801875	36.5%	15320064	21.9%	3003816	7.0%	2565410	19.3%	20889290	16.5%

The data show a greater percentage of taxi/rideshare users than non-users at the census division and US levels (4.5% users compared to 2.8% non-users and 16.3% users compared to 14.1% non-users, respectively).

Similarly, almost 92% of all respondents using taxis or ridesharing do not have a medical condition that makes it difficult to travel. Those who do not have a medical condition account for 87-89% of all non-users.

It was found that the majority of users were white. In the US, 70.6% of users were white while 76.6% of non-users were white. Notably, although Asians are a small number of respondents nationwide (4.6%), there are more users (7.0%) compared to non-users (3.0%).

Gender was almost evenly split between taxi and ridesharing users. When comparing users versus non-users in the US, males tend to use these services more than females (47.4% of males use compared to 44.3% do not use, while 52.6% of females use these services compared to 55.7% who do not).

People living in an urban setting were more likely to use taxi or ridesharing than those in a rural setting. In the US, 93.0% of people who reported using these services were in an urban setting while 78.1% of people who reported not using taxi or rideshare services were in an urban setting.

Ridesharing App Usage Cross Tabulation

As seen in Table A-2, the weighted cross tabulations for the question "In the past 30 days, how many times have you purchased a ride with a smartphone rideshare app?" was created for Census Division 6 and the US.

Of those who reported buying a ride, households with fewer people were most common. In the US, 18.0% of those who purchased a ride were from one-person households while 13.4% of all those who have not purchased a ride were from one-person households. Likewise, in the US, 36.2% of those who purchased a ride were from two-person households while 32.0% of all those who have not purchased a ride were from two-person households.

Similarly, households with fewer vehicles were more likely to purchase ridesharing rides. For example, in the US, 12.3% of those who purchased a ride had no vehicles in their household while just 6.0% of those who did not purchase a ride were from a zero-vehicle household.

The data suggest that people under the age of 45 were more likely to purchase a ride using a smartphone ridesharing app. In the US, 21.1% of those who purchased a ride were 35 to 44 years old whereas this group represents 16.0% of non-users. This trend continues for the younger age groups as well: 25 to 34 years old (34.6% have and 14.6% have not purchased a ride) and 18 to 24 years old (16.9% have and 11.7% have not purchased a ride). Similar trends appear in the census division.

Of those who reported purchasing a ride through a smartphone application, the majority had some form of higher education. In Census Division 6, the most common education level for those who had purchased a rideshare ride was a Graduate Degree or Professional Degree while a Bachelor's Degree was most common for the US. For both Census Division 6 and the US, the most common education level for those who did not purchase a ride was High School Graduate or Less.

Between 80 and 83% of those who reported purchasing a ride were employed. Census Division 6 had a higher percentage of employed with 82.2% and lowest percentage of employed workers who did not purchase a ride with 59.1%.

High incomes were common for those purchasing rides through smartphones. In the US, 48.5% (sum of $100,000 to $149,999 and $150,000 or more) of those who purchased a ride have an annual household income of at least $100,000 compared to 26.6% of those who did not purchase a ride in these income brackets.

In Census Division 6, there were no Hispanic or Latino respondents that reported purchasing a ridesharing ride. For the US, 18.2% of those who reported purchasing a ride were Hispanic while 15.9% of those who did not purchase a ride were Hispanic.

More than 90% of all respondents who purchased a ride with a smartphone do not have a medical condition that makes it difficult to travel. In the US, 96.9% of those who purchased a ride reported not

Table A-2: In the Past 30 Days, How Many Times Have You Purchased a Ride With a Smartphone Rideshare App? Weighted Cross Tabulation.

		Census Division 6								US							
		0 Trips		1+ Trips		No Answer		Total		0 Trips		1+ Trips		No Answer		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		14247321	100%	640107	100%	2842701	100%	17730129	100%	230775471	100%	25088410	100%	45735287	100%	301599168	100%
Count of Household Members	1	2065971	14.5%	130508	20.4%	0	0.0%	2196479	12.4%	30872663	13.4%	4512022	18.0%	32498	0.1%	35417183	11.7%
	2	4922382	34.5%	224786	35.1%	91261	3.2%	5238429	29.5%	73750462	32.0%	9070708	36.2%	1775909	3.9%	84597079	28.0%
	3	3045622	21.4%	171215	26.7%	529153	18.6%	3745990	21.1%	46736657	20.3%	4882122	19.5%	7281651	15.9%	58900430	19.5%
	4	2618740	18.4%	93478	14.6%	1098261	38.6%	3810479	21.5%	46276401	20.1%	4619395	18.4%	17691824	38.7%	68587620	22.7%
	5	1050872	7.4%	20120	3.1%	671744	23.6%	1742736	9.8%	20344597	8.8%	1547628	6.2%	10497312	23.0%	32389537	10.7%
	6	347490	2.4%	0	0.0%	153889	5.4%	501379	2.8%	8457761	3.7%	324286	1.3%	4945243	10.8%	13727290	4.6%
	7	104838	0.7%	0	0.0%	135693	4.8%	240531	1.4%	2377775	1.0%	79015	0.3%	2013580	4.4%	4470370	1.5%
	8	0	0.0%	0	0.0%	0	0.0%	0	0.0%	1195540	0.5%	36353	0.1%	722524	1.6%	1954417	0.6%
	9	91406	0.6%	0	0.0%	162700	5.7%	254106	1.4%	450085	0.2%	15329	0.1%	510078	1.1%	975492	0.3%
	10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	214771	0.1%	1552	0.0%	205901	0.5%	422224	0.1%
	11	0	0.0%	0	0.0%	0	0.0%	0	0.0%	58403	0.0%	0	0.0%	35470	0.1%	93873	0.0%
	12	0	0.0%	0	0.0%	0	0.0%	0	0.0%	14729	0.0%	0	0.0%	10127	0.0%	24856	0.0%
	13	0	0.0%	0	0.0%	0	0.0%	0	0.0%	25627	0.0%	0	0.0%	13170	0.0%	38797	0.0%
Count of Household Vehicles	0	698203	4.9%	119699	18.7%	93543	3.3%	911445	5.1%	13864427	6.0%	3088610	12.3%	2067830	4.5%	19020867	6.3%
	1	3200439	22.5%	131204	20.5%	754306	26.5%	4085949	23.0%	55512900	24.1%	7496633	29.9%	10247684	22.4%	73257217	24.3%
	2	5370414	37.7%	201818	31.5%	1046669	36.8%	6618901	37.3%	80065427	34.7%	8672505	34.6%	20056396	43.9%	108794328	36.1%
	3	2868514	20.1%	140358	21.9%	695378	24.5%	3704250	20.9%	45565903	19.7%	3339055	13.3%	8750126	19.1%	57655084	19.1%
	4	1085667	7.6%	45179	7.1%	96977	3.4%	1227823	6.9%	22138661	9.6%	1649252	6.6%	3079172	6.7%	26867085	8.9%
	5	717223	5.0%	1848	0.3%	125376	4.4%	844447	4.8%	8580839	3.7%	589523	2.3%	1072877	2.3%	10243239	3.4%
	6	214853	1.5%	0	0.0%	26644	0.9%	241497	1.4%	2985389	1.3%	127955	0.5%	266153	0.6%	3379497	1.1%
	7	86420	0.6%	0	0.0%	3809	0.1%	90229	0.5%	1204451	0.5%	62251	0.2%	117633	0.3%	1384335	0.5%
	8	5588	0.0%	0	0.0%	0	0.0%	5588	0.0%	451797	0.2%	23922	0.1%	41243	0.1%	516962	0.2%
	9	0	0.0%	0	0.0%	0	0.0%	0	0.0%	189844	0.1%	11243	0.0%	28801	0.1%	229888	0.1%
	10	0	0.0%	0	0.0%	0	0.0%	0	0.0%	54043	0.0%	11539	0.0%	3042	0.0%	68624	0.0%
	11	0	0.0%	0	0.0%	0	0.0%	0	0.0%	75300	0.0%	0	0.0%	844	0.0%	76144	0.0%
	12	0	0.0%	0	0.0%	0	0.0%	0	0.0%	86489	0.0%	15923	0.1%	3487	0.0%	105899	0.0%
Imputed Age	Less than 18	351522	2.5%	0	0.0%	2842702	100%	3194224	18.0%	8019494	3.5%	362343	1.4%	45458245	99.4%	53840082	17.9%
	18-24	1719232	12.1%	119807	18.7%	0	0.0%	1839039	10.4%	27047449	11.7%	4237281	16.9%	40310	0.1%	31325040	10.4%
	25-34	2188394	15.4%	180128	28.1%	0	0.0%	2368522	13.4%	33689309	14.6%	8683491	34.6%	54213	0.1%	42427013	14.1%
	35-44	2319436	16.3%	140050	21.9%	0	0.0%	2459486	13.9%	36958115	16.0%	5295743	21.1%	33948	0.1%	42287806	14.0%
	45-54	2261820	15.9%	102019	15.9%	0	0.0%	2363839	13.3%	37072178	16.1%	3339454	13.3%	50842	0.1%	40462474	13.4%
	55+	5406918	38.0%	98102	15.3%	0	0.0%	5505020	31.0%	87988926	38.1%	3170097	12.6%	97730	0.2%	91256753	30.3%

Table A-2 continued

		Census Division 6								US							
		0 Trips		1+ Trips		No Answer		Total		0 Trips		1+ Trips		No Answer		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		14247321	100%	640107	100%	2842701	100%	17730129	100%	230775471	100%	25088410	100%	45735287	100%	301599168	100%
Educational Attainment	High School Graduate or Less	5341511	37.5%	66034	10.3%	410619	14.4%	5818164	32.8%	77286659	33.5%	2769921	11.0%	8480533	18.5%	88537113	29.4%
	Some College or Associate's Degree	4261258	29.9%	146597	22.9%	0	0.0%	4407855	24.9%	70245561	30.4%	5158538	20.6%	62314	0.1%	75466413	25.0%
	Bachelor's Degree	2485331	17.4%	200661	31.3%	0	0.0%	2685992	15.1%	46403745	20.1%	9107917	36.3%	47716	0.1%	55559378	18.4%
	Graduate or Professional Degree	2139762	15.0%	226814	35.4%	0	0.0%	2366576	13.3%	36610568	15.9%	8028416	32.0%	20965	0.0%	44659949	14.8%
	No Answer	19459	0.1%	0	0.0%	2432083	85.6%	2451542	13.8%	228937	0.1%	23619	0.1%	37123760	81.2%	37376316	12.4%
Worker Status	Is Employed	8423394	59.1%	526052	82.2%	0	0.0%	8949446	50.5%	136482177	59.1%	20401368	81.3%	104698	0.2%	156988243	52.1%
	Is Not Employed	5823928	40.9%	114053	17.8%	0	0.0%	5937981	33.5%	94284626	40.9%	4684670	18.7%	124697	0.3%	99093993	32.9%
	No Answer	0	0.0%	0	0.0%	2842702	100%	2842702	16.0%	8668	0.0%	2372	0.0%	45505893	99.5%	45516933	15.1%
Household Income	Less than $25,000	3507024	24.6%	141928	22.2%	831052	29.2%	4480004	25.3%	45820256	19.9%	2867903	11.4%	8489363	18.6%	57177522	19.0%
	$25,000 to $49,999	3269191	22.9%	98738	15.4%	649409	22.8%	4017338	22.7%	48960480	21.2%	3202852	12.8%	8118982	17.8%	60282314	20.0%
	$50,000 to $74,999	2369285	16.6%	131826	20.6%	251536	8.8%	2752647	15.5%	38280376	16.6%	3347664	13.3%	7113290	15.6%	48741330	16.2%
	$75,000 to $99,999	1845093	13.0%	22943	3.6%	385845	13.6%	2253881	12.7%	29747356	12.9%	3138821	12.5%	5922417	12.9%	38808594	12.9%
	$100,000 to $149,999	2112363	14.8%	139481	21.8%	578697	20.4%	2830541	16.0%	36866446	16.0%	5111217	20.4%	8696614	19.0%	50674277	16.8%
	$150,000 or more	786173	5.5%	105189	16.4%	122184	4.3%	1013546	5.7%	24457550	10.6%	7049879	28.1%	6525449	14.3%	38032878	12.6%
	No Answer	358192	2.5%	0	0.0%	23978	0.8%	382170	2.2%	6643007	2.9%	370074	1.5%	869173	1.9%	7882254	2.6%
Hispanic	Is Hispanic or Latino	468595	3.3%	0	0.0%	207825	7.3%	676420	3.8%	36706935	15.9%	4574481	18.2%	10616617	23.2%	51898033	17.2%
	Is Not Hispanic or Latino	13772503	96.7%	640106	100%	2634877	92.7%	17047486	96.1%	193834553	84.0%	20487030	81.7%	35078372	76.7%	249399955	82.7%
	No Answer	6224	0.0%	0	0.0%	0	0.0%	6224	0.0%	233983	0.1%	26899	0.1%	40299	0.1%	301181	0.1%

Table A-2 continued

		Census Division 6								US							
		0 Trips		1+ Trips		No Answer		Total		0 Trips		1+ Trips		No Answer		Total	
Category	Variable	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total		14247321	100%	640107	100%	2842701	100%	17730129	100%	230775471	100%	25088410	100%	45735287	100%	301599168	100%
Presence of Medical Condition	Has a Medical Condition	1801830	12.6%	53423	8.3%	62664	2.2%	1917917	10.8%	24061688	10.4%	779661	3.1%	642095	1.4%	25483444	8.4%
	No Medical Condition	12445492	87.4%	586683	91.7%	2780038	97.8%	15812213	89.2%	206643289	89.5%	24303760	96.9%	45033376	98.5%	275980425	91.5%
	No Answer	0	0.0%	0	0.0%	0	0.0%	0	0.0%	70494	0.0%	4989	0.0%	59817	0.1%	135300	0.0%
Race	White	10876760	76.3%	487457	76.2%	1803034	63.4%	13167251	74.3%	168420446	73.0%	17873955	71.2%	30726608	67.2%	217021009	72.0%
	Black or African American	2766167	19.4%	99538	15.6%	729199	25.7%	3594904	20.3%	29187487	12.6%	2730312	10.9%	6138414	13.4%	38056213	12.6%
	Asian	133141	0.9%	12485	2.0%	40755	1.4%	186381	1.1%	11699724	5.1%	2077738	8.3%	2172729	4.8%	15950191	5.3%
	Other	451825	3.2%	40625	6.3%	269714	9.5%	762164	4.3%	19785624	8.6%	2202684	8.8%	6350586	13.9%	28338894	9.4%
	No Answer	19428	0.1%	0	0.0%	0	0.0%	19428	0.1%	1682189	0.7%	203721	0.8%	346952	0.8%	2232862	0.7%
Imputed Gender	Male	6830368	47.9%	361585	56.5%	1416147	49.8%	8608100	48.6%	111661613	48.4%	13109644	52.3%	23267836	50.9%	148039093	49.1%
	Female	7416954	52.1%	278521	43.5%	1426555	50.2%	9122030	51.4%	119113858	51.6%	11978766	47.7%	22467452	49.1%	153560076	50.9%
Residential Area Type	Urban	8474901	59.5%	592245	92.5%	1964277	69.1%	11031423	62.2%	186016395	80.6%	24204060	96.5%	37042213	81.0%	247262668	82.0%
	Rural	5772420	40.5%	47860	7.5%	878424	30.9%	6698704	37.8%	44759076	19.4%	884350	3.5%	8693075	19.0%	54336501	18.0%

having a medical condition while 89.5% of those who did not purchase a ride did not have a medical condition.

It was found that the majority of those purchasing a ride were white. In the US, 71.2% of people purchasing a ride were white and 73.0% of people who did not purchase a ride were white. Notably, although Asians are a small number of respondents nationwide (5.3%), there are more users (8.3%) compared to non-users (5.1%).

Gender was almost evenly split for those whose who purchased a ride with a smartphone app. When comparing those who have and have not purchased a ride in the US, males purchase rides more than females (52.3% of males have compared to 48.4% have not purchased a ride while 47.7% of females have compared to 51.6% have not purchased a ride).

People living in an urban setting were more likely to purchase a ride than those in a rural setting. In the US, 96.5% of people who reported purchasing a ride were from an urban setting while 80.6% of people who reported purchasing a ride were from an urban setting.

APPENDIX 3: RESULTS OF ADDITIONAL RIDEHAILING QUESTIONS FROM POPULUS SURVEY

Appendix 3 provides additional summary statistics based on survey data collected by the company Populus Technologies, Inc. The first section pertains to use of financial instruments such as credit and debit cards and the use of smartphones. This is followed by a section with the results of additional ridehailing questions such as wait times and cancellations. The third section pertains to the impact ridehailing has on personal vehicle ownership and mode choice decisions. The final section presents information about ridehailing drivers.

Results of Financial Instrument and Smartphone Survey Questions

Figure A-6 shows the responses to several survey questions pertaining to the respondent's banking and smartphone usage. The first question asked respondents if they use a credit card, and about two-thirds of the entire sample said they used a credit card. Eighty-one percent (114 of 141) of those who used ridehailing when traveling use a credit card.

Respondents were also asked if they use a debit card. This was the most popular banking type for the overall sample with 82% of all respondents indicating that they use a debit card. This was most common among the group that used ridehailing when traveling (91%, 129 of 141) and those who used ridehailing in their city (87%, 179 of 205).

Prepaid cards were most popular among those who used ridehailing in their city (19%, 38 of 205), although this was a relatively small percentage compare to the previously mentioned credit card and debit card utilization percentages.

Almost everyone in the sample (95%) responded that they use a smartphone. Eight percent (41 of 506) of those who had heard of but never used ridehailing did not use a smartphone. This may be a contributing factor as to why they do not use ridehailing since ridehailing services are typically booked via a smartphone application.

Results of Additional Ridehailing Survey Questions

Several survey questions pertained to other aspects of ridehailing (Figure A-7). These questions were not asked of all respondents; the sample size for these questions is 258 unless otherwise noted.

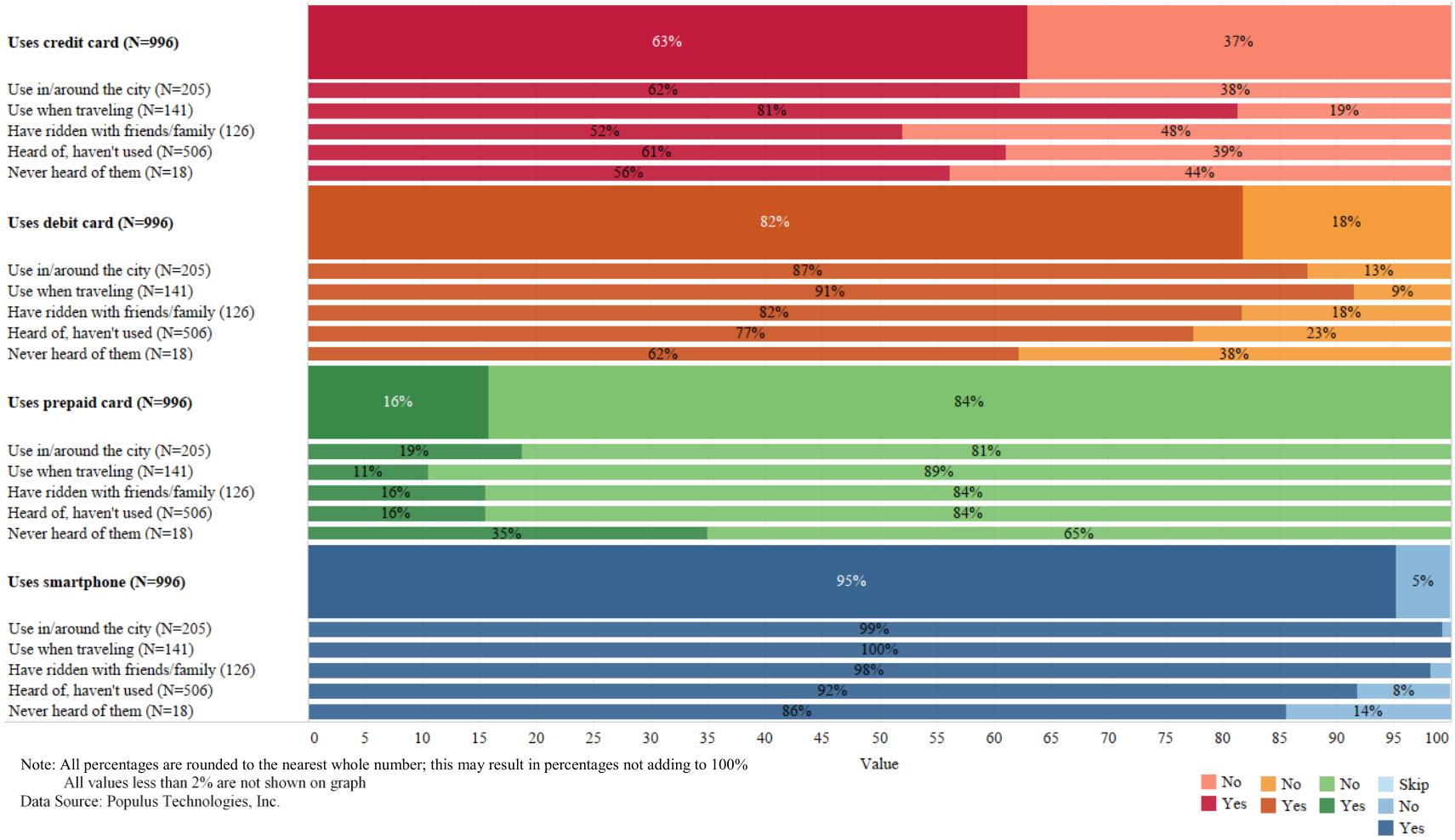
The first question asked respondents which days of the week they used ridehailing over the past month, and the answers were weekdays, weekends, or did not use. Respondents were allowed to select more than one option (i.e., for those respondents who used ridehailing both during the week and on the weekend). Thirty-eight percent (97 of 258) of respondents used ridehailing on the weekends within the past month, and 31% (81 of 258) used ridehailing during the week.

A follow-up question then asked respondents about the time periods throughout the day when they used ridehailing over the past month, and respondents could select more than one time period. The most popular time periods were 7pm to midnight (30%, or 78 of 258) and 4pm to 7pm (30%, 77 of 258). The two least common time periods were after midnight (10%, 27 of 258) and before 7am (8%, 21 of 258).

Respondents were asked to select their average estimated wait time when calling an Uber or Lyft from their home. The majority of respondents (70%) estimated a wait time of under 10 minutes, including 25% (64 of 258) waiting 8 to 10 minutes, 22% (56 of 258) waiting 6 to 7 minutes, 21% (55 of 258) waiting 2 to 5 minutes, and 2% (6 of 258) waiting less than 2 minutes.

Another survey question inquired about requesting a trip and then having it canceled by the driver. Sixty-one percent (157 of 258) of respondents reported never being cancelled on, and another 29% (75 of 258) reported they had been cancelled on less than 5% of the time.

Respondents were also asked how often they use Uber or Lyft to connect to public transit. Just 11% of respondents connected to public transit at least half of the time, including 7% (18 of 258) doing so half of the time, 2% (6 of 258) connecting to transit most of the time, and about 2% (3 of 258) always connecting



Note: All percentages are rounded to the nearest whole number; this may result in percentages not adding to 100%
All values less than 2% are not shown on graph
Data Source: Populus Technologies, Inc.

Figure A-6: Financial Instrument and Smartphone Survey Questions.

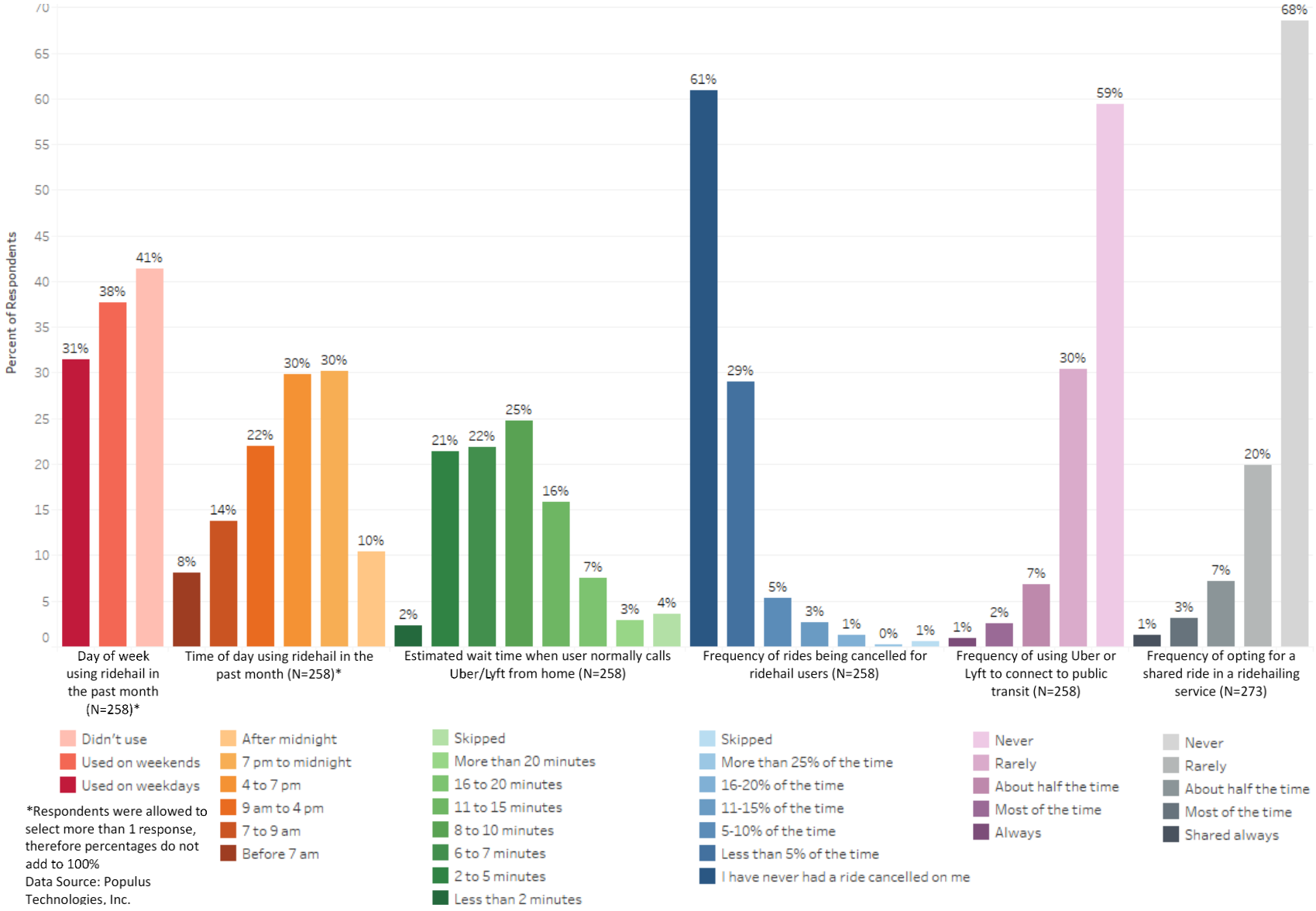


Figure A-7: Additional Ridehailing Questions.

to transit. The highest percentage of respondents (153 of 258, which is 59%) stated they never use ridehailing to connect to transit, and another 30% (78 of 258) stated that they rarely do so.

The final question in Figure A-7 asked how often respondents opted for a shared ride when using ridehailing services. In total, 12% opted for a shared ride at least half of the time. This percentage includes 7% (20 of 273) opting for a shared ride about half of the time, 3% (9 of 273) doing so most of the time, and 1% (4 of 273) always opting for a shared ride. Note that this question was asked to a slightly larger sample of 273 people.

Results of Ridehailing Impacts on Vehicle Ownership and Mode Choice Survey Questions

The survey included several questions pertaining to the impacts of ridehailing on other transportation modes and the broader transportation system. Figure A-8 shows the impacts that ridehailing has on vehicle ownership decisions. Eighty-two percent of respondents stated that their decisions had not been impacted by ridehailing, and this includes 73% (189 of 258) that have not reduced the number of vehicles they own and an additional 9% (24 of 258) that did not have a vehicle prior to using ridehailing. Just 7% of all respondents indicated that they had gotten rid of a vehicle since using ridehailing, including 4% (9 of 258) getting rid of a second vehicle and 3% (7 of 258) getting rid of their only vehicle.

Figure A-9 displays the impact of ridehailing on personal driving habits. Of the 200 people asked this question, 85% (171 of 200) stated that they drive about the same as they did before using ridehailing, 12% (23 of 200) stated that they drive less, and 3% (6 of 200) drive more than they did before using ridehailing.

Figure A-10 shows responses to the following question: “Since you started using on-demand services such as Uber and Lyft, do you find that you use the following transportation options more or less?”. These questions are shown for the entire sample size and then broken down into groups based on the response to the ridehailing familiarity and adoption question (discussed in the previous sections). The sample size for each transportation mode varies due to some respondents not using specific transportation modes. Three modes (walking, bus, and train) were answered by 258 people, and these three modes are the focus of the following discussion.

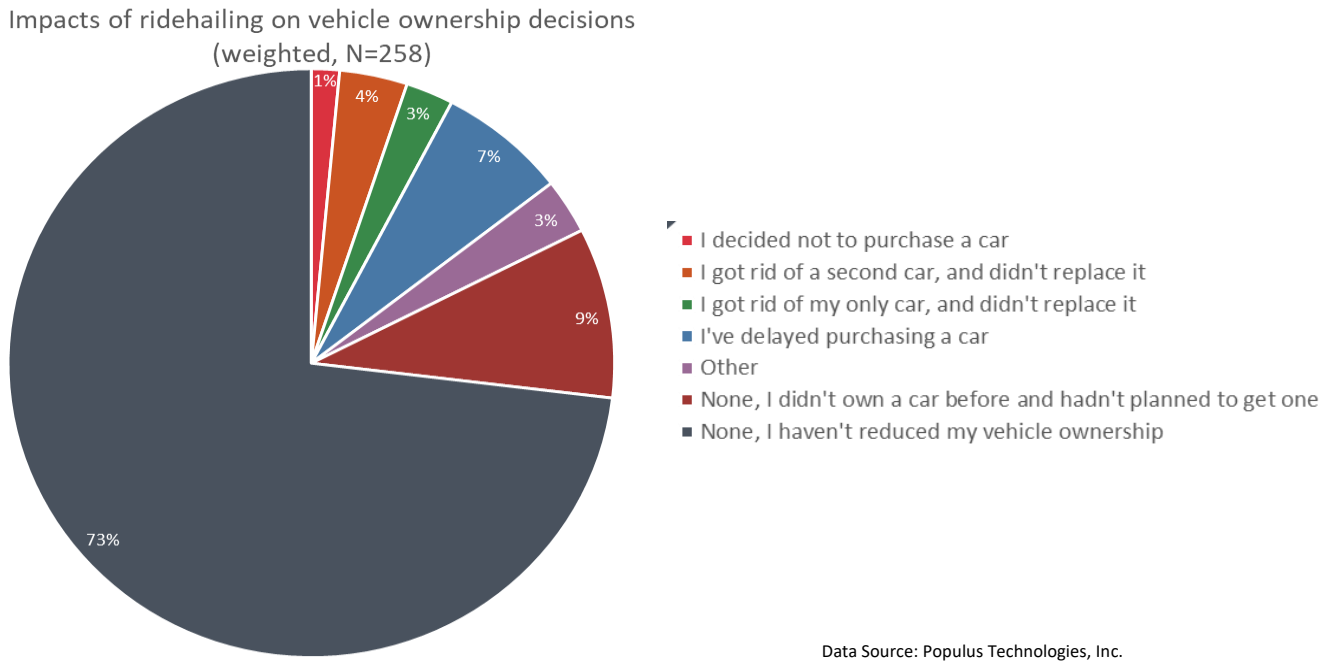
For walking, 21% of the sample said they walked less (9%, 23 of 258) or significantly less (12%, 30 of 258) while 9% of the sample reported they walked more (5%, 14 of 258) or significantly more (4%, 11 of 258). Twenty-seven percent of those who use ridehailing in their city (N=146) said they walked less (11%, 15 of 146) or significantly less (16%, 23 of 146) while 10% answered that they walked more (7%, 10 of 146) or significantly more (3%, 4 of 146).

For those who used the bus, 28% of the sample said they used the bus less (9%, 23 of 258) or significantly less (19%, 48 of 258) while only 6% of the sample indicated they used the bus more (4%, 10 of 258) or significantly more (2%, 5 of 258). Thirty-one percent of those who used ridehailing in their city reported they used the bus less (10%, 15 of 146) or significantly less (21%, 31 of 146) while 6% said they used the bus more (5%, 7 of 146) or significantly more (1%, 1 of 146).

For those who used the train, 27% of the sample said they used the train less (10%, 26 of 258) or significantly less (17%, 44 of 258) while only 5% of the sample reported they used the train more (3%, 7 of 258) or significantly more (2%, 5 of 258). Thirty-three percent of those who use ridehailing in their city indicated they used the train less (12%, 17 of 146) or significantly less (21%, 31 of 146) while only 3% said they used the train more (2%, 4 of 146) or significantly more (1%, 1 of 146).

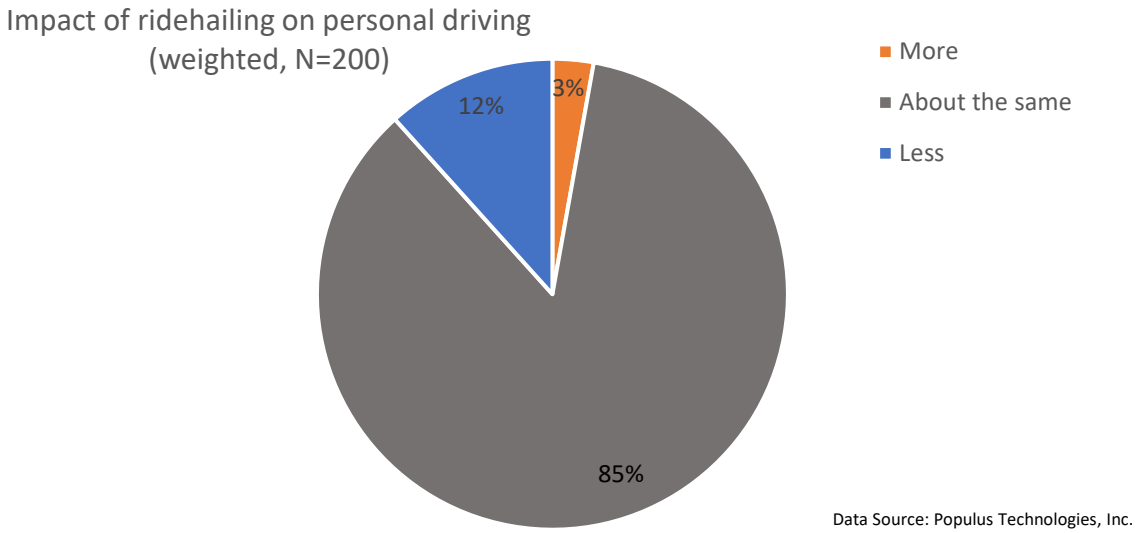
Results of Ridehailing Driver Survey Questions

The survey asked all respondents (N=996) whether they had ever driven for a ridehailing service. Respondents were given the ability to select several different services including Amazon Flex, DoorDash, Instacart, Lyft, Postmates, Uber, Via, other, and none. For Figure A-11, DoorDash, Instacart, and Postmates were combined into a single category called online food delivery while Amazon Flex, Via, and other were combined to be “other”. Of these services, Uber was the most common service for drivers (6%, 58 of 996)



Data Source: Populus Technologies, Inc.

Figure A-8: Impact of Ridehailing on Vehicle Ownership Decisions.



Data Source: Populus Technologies, Inc.

Figure A-9: Impact of Ridehailing on Personal Driving.

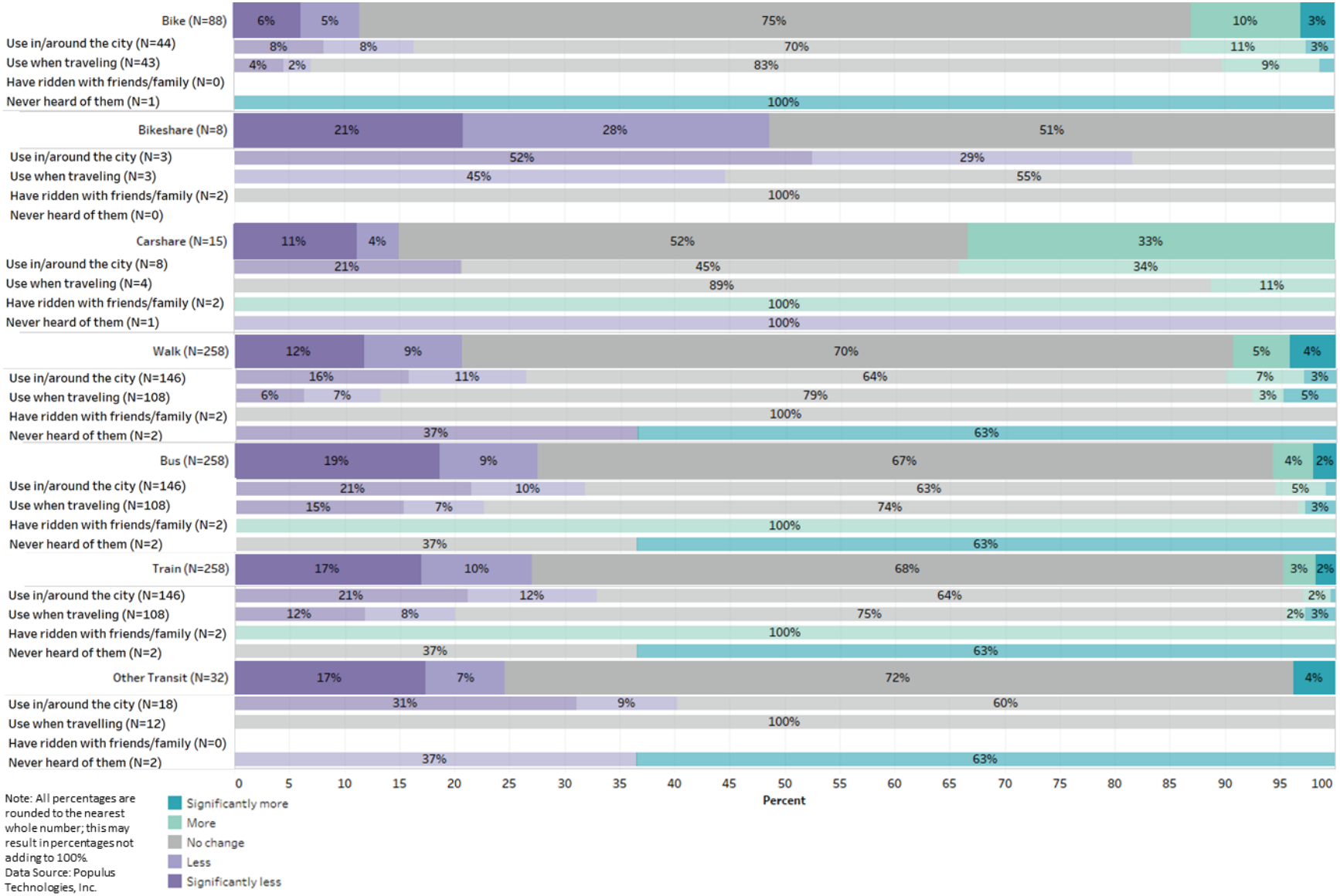
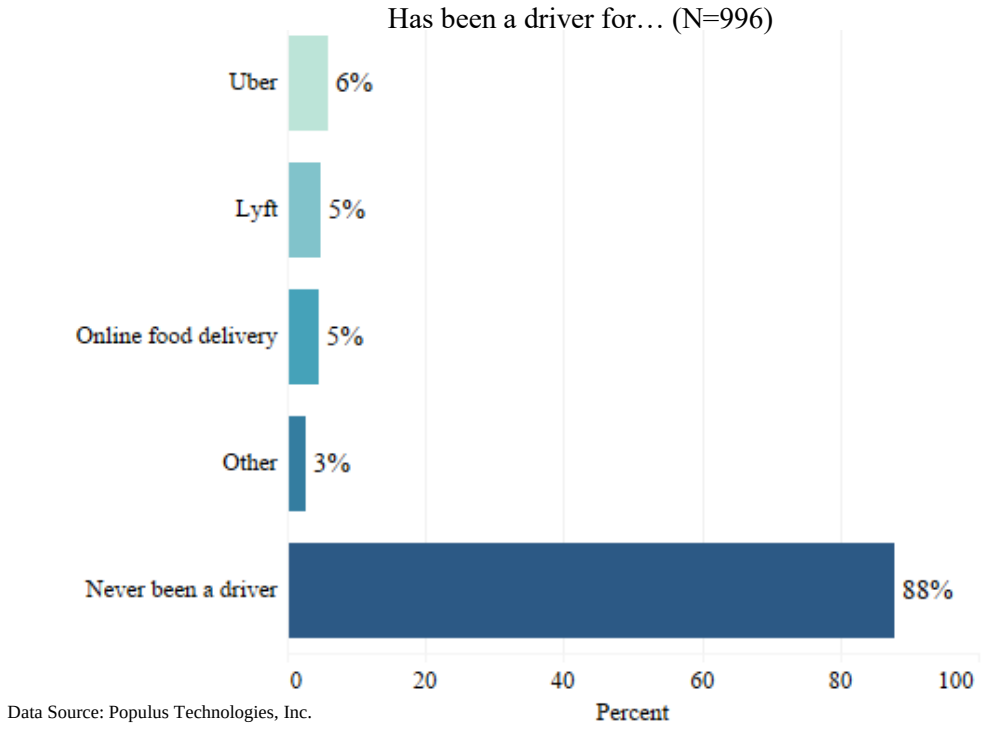


Figure A-10: Impact of Ridehailing on Other Modes of Transportation Questions.



Data Source: Populus Technologies, Inc.

Figure A-11: Has Been a Driver For...

followed by Lyft with 48 respondents (5%). Five percent of the respondents drove for online food delivery services (45 of 996). The majority of the respondents had never driven for any of these services before (88%, 874 of 996).

Eighty-two respondents were then asked how often they drove for Uber or Lyft over the past three months (Figure A-12). Thirty-nine percent (32 of 82) of the respondents said they had not driven in the past three months. An additional 3% (2 of 82) stated that they stopped driving within the past three months. Of the respondents that did drive over the past three months, the most common frequency was a few days a month (25%, 21 of 82) and a few days a week (21%, 17 of 82).

Sixty-nine respondents were asked then about their behavior as a ridehailing driver over the past month, and the results are shown in Figure A-13. The first question asked which days they drove for Uber/Lyft over the past month (weekdays or weekends), and drivers were able to select multiple answers for this question. More people drove for Uber/Lyft on weekdays (48%, 33 of 69) compared to the weekend (41%, 28 of 69). Of the 69 people that were asked this question, 17 did not answer (25%).

The second question asked what time of day the respondent drove for Uber/Lyft. Drivers were able to select multiple answers for this question. The most common times were 9am to 4pm (30%, 21 of 69), 7pm to midnight (20%, 14 of 69), and 4pm to 7pm (19%, 13 of 69). Of the 69 people that were asked this question, 25 people did not answer (36%).

Forty-one respondents were considered active drivers and were asked more questions about their current driving habits as seen in Figure A-14. Drivers were asked the average number of miles they drive each day without a passenger in their vehicle. The most common responses were 10 to 24 miles (34%, 14 of 41), 25 to 49 miles (25%, 10 of 41), and less than 10 miles (24%, 9 of 41).

Drivers were also asked the average number of miles per week they drove with passengers over the past month. The most common response was 100 to 199 miles with 31% (13 of 41), followed by 200 to 299 miles with 21% (9 of 41).

Drivers were asked what their average earnings per hour were before accounting for expenses. The most common responses were $20 to $24.99 per hour (23%, 9 of 41), $10 to $14.99 per hour (21%, 9 of 41), $15 to $19.99 per hour (16%, 7 of 41), and less than $5 per hour (16%, 7 of 41).

Drivers were then asked to select the reason they drive for Uber/Lyft. Drivers were only able to select one answer from the list. The most common responses were to keep busy (23%, 9 of 41) and wanting to meet new people (17%, 7 of 41).

Twenty-eight respondents were considered non-active drivers and were asked questions about their previous experience driving for ridehailing services. The results of these questions are shown in Figure A-15. Respondents were asked what their average earnings per hour were before accounting for expenses. The most common responses were $10 to $14.99 per hour (28%, 8 of 28), less than $5 per hour (20%, 6 of 28), $15 to $19.99 per hour (19%, 5 of 28), and $5 to $9.99 per hour (19%, 5 of 28).

The non-active drivers were also asked to select a reason for no longer driving for Uber/Lyft. Respondents were only able to select one answer from the list. The most common responses were making less money than anticipated (23%, 7 of 28), putting too much wear and tear on their vehicle (18%, 5 of 28), and only driving while in between jobs (17%, 5 of 28).

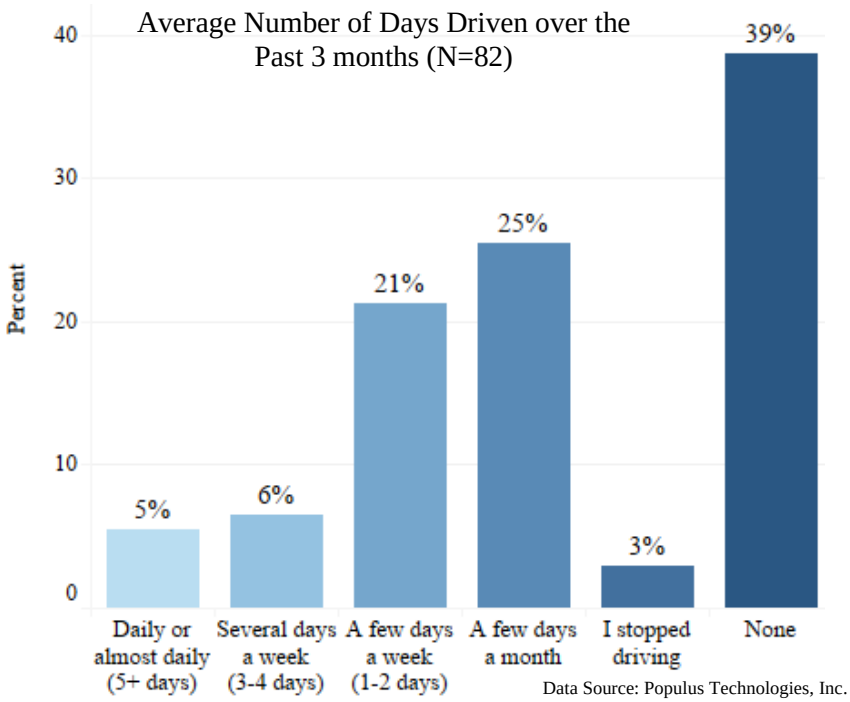
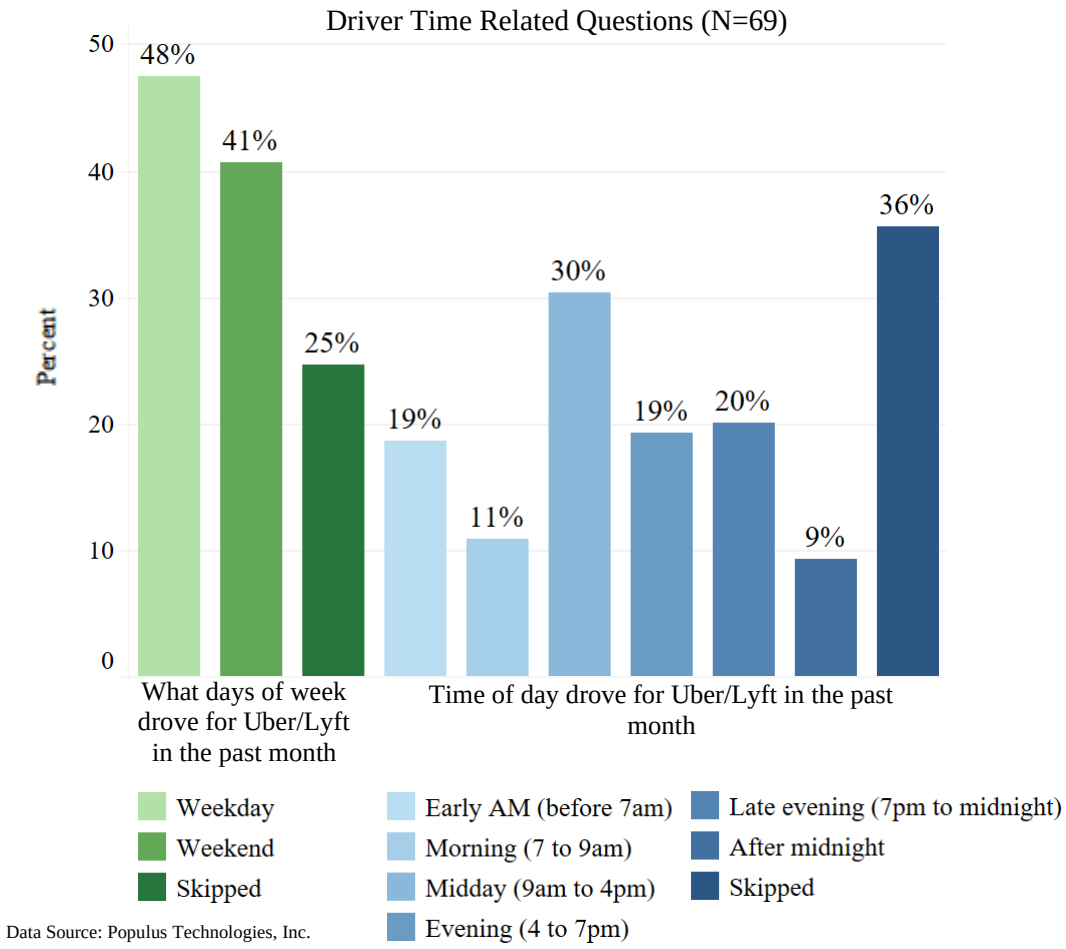


Figure A-12: Average Number of Days Driven for Uber, Lyft, or Other on-Demand Ride Service in the Past Three Months.



Data Source: Populus Technologies, Inc.

Figure A-13: Ridehailing Driver Time Related Questions.

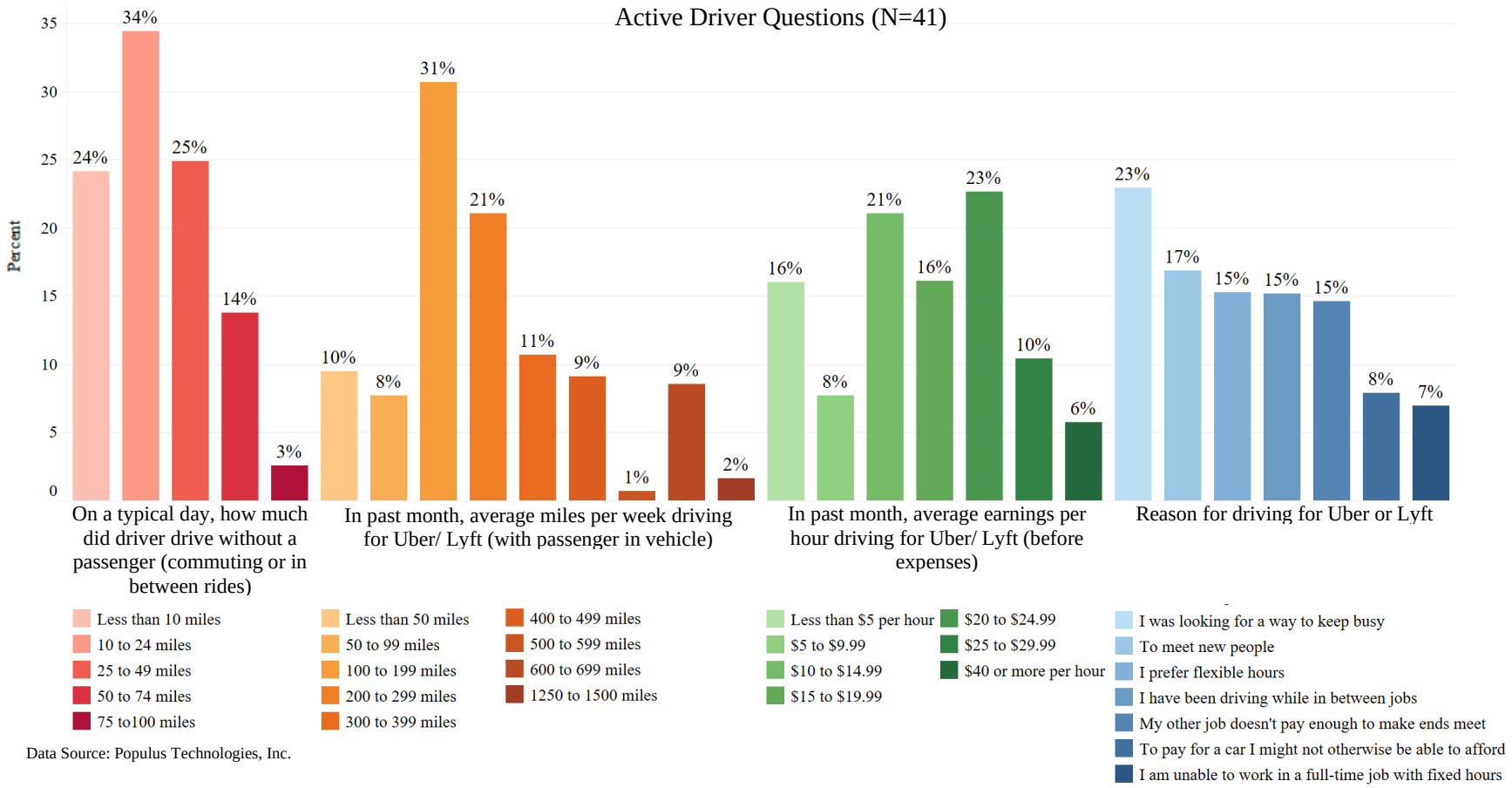


Figure A-14: Active Driver Questions.

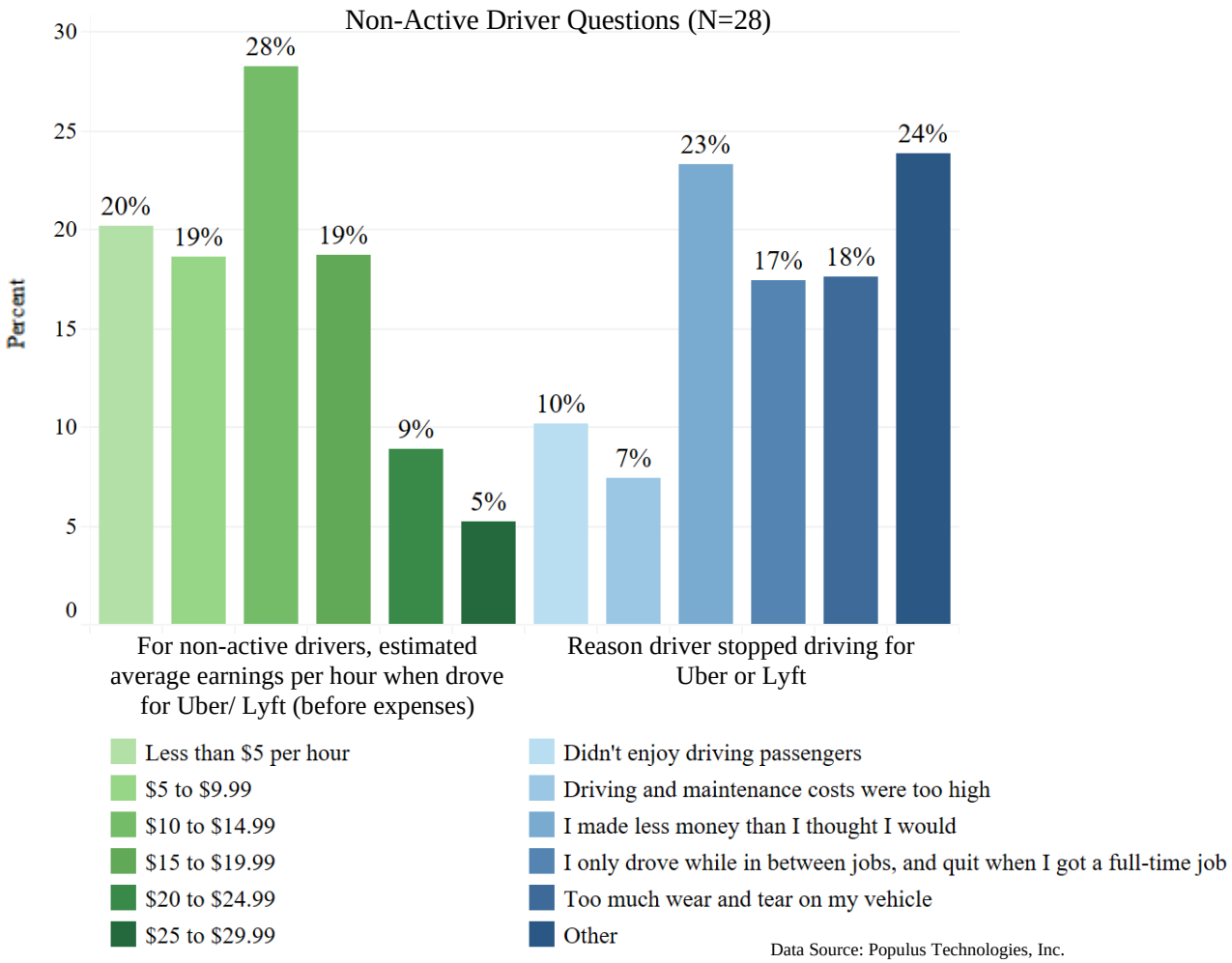


Figure A-15: Non-Active Driver Questions.

VITA

Cassidy Crossland was born and raised in Ellicott City, MD. She received her Bachelor of Civil Engineering from Auburn University in December 2018. During her undergraduate degree, Cassidy completed a summer internship with Maryland Department of Transportation, State Highway Administration in the Innovative Contracting Division as well as the Highway Hydraulics Division during the summer of 2017 and a summer internship with KCI Technologies in the Asset Management and Transportation Divisions during the summer of 2018. Cassidy began her Master of Science degree in Civil Engineering (Transportation) at the University of Tennessee in August 2019. She was named a Graduate Fellow as part of the Dwight David Eisenhower Transportation Fellowship Program in Fall 2020.