GEORGIA DOT RESEARCH PROJECT 16-31

FINAL REPORT

THE IMPACT OF EMERGING TECHNOLOGIES AND TRENDS ON TRAVEL DEMAND IN GEORGIA

GDOT

Georgia Department of Transportation

OFFICE OF PERFORMANCE-BASED MANAGEMENT AND RESEARCH

600 W. Peachtree St. NW

Atlanta, GA 30308

October 2019

1. Report No. FHWA-GA-19-1631	**2. Government Accession No.**	**3. Recipient's Catalog No.**

4. Title and Subtitle The Impact of Emerging Technologies and Trends on Travel Demand in Georgia	**5. Report Date** October 2019 **6. Performing Organization Code**
7. Author(s) Sung Hoo Kim; Patricia L. Mokhtarian, Ph.D.; Giovanni Circella, Ph.D.	**8. Performing Organ. Report No.** 16-31
9. Performing Organization Name and Address School of Civil and Environmental Engineering Georgia Institute of Technology 790 Atlantic Drive NW Atlanta, GA 30322	**10. Work Unit No.** **11. Contract or Grant No.** PI#: 0015283
12. Sponsoring Agency Name and Address Georgia Department of Transportation Office of Performance-based Management and Research 600 W. Peachtree St. NW Atlanta, GA 30308	**13. Type of Report and Period Covered** Final; September 2016 – October 2019 **14. Sponsoring Agency Code**

15. Supplementary Notes

Some data collection and other costs were contributed by the Tier 1 University Transportation Center for Teaching Old Models New Tricks (TOMNET), sponsored by the U.S. Department of Transportation through Grant No. 69A3551747116.

16. Abstract

This study aims to enhance understanding of the impact of new and emerging technologies on travel behavior/demand for the state of Georgia, and, thus, potentially contribute to improving transportation planning and demand forecasting for Georgia residents. In this project, the research team designed and implemented a wide-ranging travel survey that explores people's opinions about travel-related issues, together with how they use new mobility technologies and services, and travel in general. The study employed two sampling frames: (1) address-based stratified randomly sampled households, and (2) Georgia residents who participated in the 2017 National Household Travel Survey (NHTS) and agreed to be contacted for further surveys. The data were collected across about six months. The study explores five main themes: general travel behaviors, commute and work patterns, general opinions and attitudes, new and emerging technologies and services, and future transportation, with a specific focus on autonomous vehicles. Some findings include: despite the low levels of current ownership of alternative-fuel vehicles (2.2% of primary vehicles are hybrid/electric), respondents exhibit considerable interest in having such vehicles (59%); more than 5% "commute" by working at home, compared to 3% who use transit; overall, ridehailing services seem to have more substitution effects than complementarity and generation effects, including both car-for-car substitution and net reductions in the use of active transportation and public transit modes; and half of respondents (51%) said they are likely or very likely to own a self-driving car, whereas 27% and 12% are likely or very likely to use a driverless taxi alone/with others and with strangers, respectively. Based on results, the study provides some policy implications.

17. Key Words Attitudes, Autonomous vehicles, Ridehailing, Statewide survey, Technology use, Telecommuting, Transportation planning, Travel behavior, Vehicle ownership	**18. Distribution Statement**

19. Security Classification (of this report) Unclassified	**20. Security Classification (of this page)** Unclassified	**21. Number of Pages** 213	**22. Price**

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October 2019

ACKNOWLEDGMENTS

The research team offers our gratitude to the Georgia Department of Transportation (GDOT) staff for facilitating the project. In particular, Mr. Habte Kassa, our GDOT Technical/Implementation Manager, helped us obtain the contact information for the NHTS participants who agreed to be contacted for an additional survey. We are also grateful to Dr. Farzad Alemi, Dr. Sungtaek Choi, Ali Etezady, Dr. Yongsung Lee, Dr. Aliaksandr Malokin, Atiyya Shaw, and Xinyi Wang, who participated in the survey design and provided useful comments; Xiaodan Xu, who helped clean the vehicle-related variables; and Dr. Gwen Kash, who shared discussions on the NHTS data. Some data collection and other costs were contributed by the Tier 1 University Transportation Center for Teaching Old Models New Tricks (TOMNET), sponsored by the U.S. Department of Transportation through Grant No. 69A3551747116.

IMPORTANT

This report has been prepared in two parts. *Part 1: Research Design and Implementation* describes the survey design, administration, data cleaning, and weighting processes, while *Part 2: Empirical Findings* presents the analysis results. Each part contains its own Table of Contents, List of Tables, List of Figures, Executive Summary, and References, and is separately paginated. The page headers and leading text in the page numbers (e.g., “Part 1 - 37”) will orient readers to their location.

PART 1

Research Design and Implementation

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EXECUTIVE SUMMARY

PART 1

Understanding how and why people travel is fundamental to conducting urban/transportation planning and policymaking. In particular, travel survey data have offered instrumental input to that understanding. Although travel behavior, or demand, may have been somewhat stable in the past, we are facing disruptive technologies, new trends, and paradigms that are changing, and will change, behavior significantly. Advanced technologies are generating a number of changes with direct implications for travel demand in Georgia: working at home, online shopping, and new transportation products and services including ridehailing and carsharing. Additional technologies (such as autonomous vehicles, or AVs) are expected to impact how people travel in the near-to-medium-term future. These new options are transforming travel-related decision-making, in the population at large but especially among certain population segments, e.g., young adults ("millennials") and urban dwellers.

Accordingly, planning processes and travel demand forecasting models need to be updated to account for these new patterns, but this must be preceded by acquiring a better understanding of the new trends and processes at work. Unfortunately, although many transportation experts agree that we need to understand the impact of new and emerging technologies on travel behavior/demand, we often lack the proper data for doing so. The present study aims to address this gap for the state of Georgia, and together with GDOT Research Project (RP) 18-24 (Analysis of the Georgia Add-on to the 2016-2017 National Household Travel Survey), it provides important information for updating the Georgia Statewide Travel Demand Model (RP 16-12, The Integration of the Regional MPO Models into the Georgia Statewide Travel Demand Model – Phase 1, and RP 18-08, Improvement of the Georgia Statewide Travel Demand Model (GSTDM) – Phase 2). In this and many other ways, the present study can potentially contribute to improving transportation planning and demand forecasting for Georgia residents.

The research team designed and implemented a wide-ranging travel survey that seeks to capture people's opinions about travel-related issues, together with how they use technologies and travel in general. We devoted a year to designing the questionnaire, together with identifying effective sampling strategies. The study employed two sampling frames: (1) address-based stratified randomly sampled households, and (2) Georgia residents who participated in the 2017 National Household Travel Survey (NHTS) and agreed to be contacted for further surveys. We mailed out a survey packet inviting the sampled residents to take the survey through either completing a printed paper questionnaire or using a link to the online version of the survey. The data were collected across about 6 months (October 2017 – April 2018). By the end, we had retrieved a sizable number of completed surveys, with an overall 10.1 percent response rate. The two sampling frames had 6.5 percent and 31.0 percent response rates, respectively. A majority of responses were completed by paper and, thus, we spent about 7 months on data entry. After performing several procedures to improve data quality, we obtained a final dataset with 3,288 valid cases. In addition, we developed sample weights to achieve more representative results, and appended additional land-use variables that can be used in further analyses.

1. INTRODUCTION

1.1 Background and Research Need

The Georgia Department of Transportation (GDOT) has invested considerable effort and resources into improving travel demand models in support of transportation planning across the state. For example, a recent project (RP 16-12, The Integration of Regional MPO Models into the Georgia Statewide Travel Demand Model – Phase 1) developed a plan to integrate the Georgia Statewide Travel Demand Model (GSTDM) with the regional models that are directly developed and maintained by GDOT for Georgia's 14 metropolitan planning organizations (MPOs) outside of Atlanta, so as to simplify model maintenance and improve the accuracy of the model results (Circella et al., 2018). Another avenue for improving transportation demand models is to update and increase our understanding of how people travel and the corresponding key motivations and factors influencing their travel-related decisions. The Georgia subsample of the recent National Household Travel Survey (NHTS) provides an updated snapshot on *how* people travel, and another GDOT project (RP 18-24, Analysis of the Georgia Add-on to the 2016-2017 National Household Travel Survey) is underway to fully analyze the NHTS data. The present project (RP 16-31) offers insight into *why* people travel the way they do, as well as a glimpse of future intentions and expectations regarding emerging new technologies. These two projects are working synergistically with RP 16-12 and its successor, RP 18-08 (Improvement of the Georgia Statewide Travel Demand Model (GSTDM) – Phase 2), to support GDOT's statewide planning activities.

Although travel behavior, or demand, may have been somewhat stable in the not-too-distant past, we are facing disruptive technologies, new trends, and paradigms that are changing, and will change, behavior significantly. Advanced technologies are generating a number of changes with direct implications for travel demand in Georgia: working at home, online shopping, ridehailing services, and carsharing. Additional technologies (such as autonomous vehicles, or AVs) are expected to impact how people travel in the near- or medium-term future. These new options are transforming travel-related decision-making in the population at large—but especially among certain population segments such as “millennials” (loosely inclusive of 18–35-year-olds). These ongoing changes have a huge potential to modify the demand for housing, vehicle sales, the amount of travel by private vehicles, and the resulting gasoline tax revenues and emissions of greenhouse gases and criteria pollutants. Accordingly, travel demand forecasting models need to be updated to account for these new patterns; however, this must be preceded by acquiring a better understanding of the new trends and processes at work.

Unfortunately, although transportation experts agree that we need to understand the impact of new and emerging technologies on travel behavior/demand, we often lack the proper data for doing so. The present study aims to address this gap for the state of Georgia by providing a recent snapshot of what people think about transportation-related topics, and how they adopt new technologies, how they travel, and how they make decisions. As such, the study seeks to update our understanding in these areas, and, thus, potentially to contribute to improving transportation planning and demand forecasting for Georgia residents.

In view of respondents’ finite willingness to cooperate, nearly every survey represents a compromise between breadth and depth. The survey designed for the present study emphasized the former over the latter. Consequently, this study does not take a fine-grained look at each topic (e.g., going into great detail about Uber usage), but instead aims to supply a broad-brush view of overall travel patterns, opinions, and other characteristics that might be of interest to local governments or agencies. Similarly, this study does not seek to propose specific policy strategies (e.g., how much, or what, incentive should be offered to motivate people to use carpooling rather than driving alone). Rather, we expect this research to provide an overall sense of the transportation landscape from the users’ perspective, to serve as a beneficial reference in the context of developing statewide or MPO-level plans and policies.

1.2 Structure of This Report (Part 1)

The project comprises three phases: (1) survey design, (2) administration of the survey, and (3) data analysis. This final report describes details of the research design and implementation, and also analysis results and key takeaways. For convenience, we split the report into two parts: research design and implementation, and data analysis and implications. Part 1 describes details of the questionnaire design, sampling, data collection, and data preparation. Part 2 analyzes Georgia residents' opinions and behaviors, and it is organized by topic: general travel behaviors, commute and work patterns, general opinions and attitudes, recent technologies and services, and autonomous vehicles as a future transportation option. Part 1, in particular, consists of four chapters following this introduction:

- ***Survey Design***: This chapter describes the overall survey design process and survey contents. Section 2.2 delineates the structure of the survey and some rationales of the design.
- ***Sampling***: This chapter presents the sampling plan. The study contains two sampling frames, and the chapter explains each of those frames.
- ***Data Collection***: This chapter depicts the data collection process. In particular, Section 4.3 presents response rates by sampling frame and data collection channel.
- ***Data Preparation***: This chapter describes how the research team processed the data after collection. Topics include data entry, geocoding, cleaning, quality checks, developing sample weights, and appending additional variables.

2. SURVEY DESIGN

In this chapter, we review the survey design and implementation process. In the first section, we delineate the design effort, including our aims and survey design philosophy. The second section describes the contents of the survey.

2.1 Overview of the Survey Design Process

Data allow us to test theories and hypotheses about social phenomena and to estimate models to predict human behavior. Sometimes data are obtained through experimentation or monitoring of travel and activity pattern. In this study, however, we collect self-reported data through distribution of a survey. This allows us to ask questions about matters that cannot be directly observed, such as constraints, motivations, and attitudes. However, it is not easy to design a survey that obtains all desired information within a limited amount of space, accurately conveys our intention to respondents, and encourages respondents to fill it out completely and frankly. Hence, we developed and followed a strategic plan for survey implementation and put a year-long effort into maximizing the efficacy of our survey.

To address our research questions, we need to collect various types of information: attitudes, lifestyle, use of technology / transportation services, current travel behavior, future aspirations, and sociodemographics. Given the broad set of information we want to measure, the survey inevitably becomes complicated and long. Thus, we set the goal of not exceeding 16 pages to balance this tradeoff between respondents' burden (which is related to response rate and data quality) and richness of information. The final version of the paper survey is a 16-page booklet[1] (four 11″ × 17″ sheets, folded into 8½″ × 11″ halves and center-stapled), where the first page

[1] Technically, the survey also has wrap-around pages (i.e., it consists of a 20-page booklet). The front page of the wrap-around contains the title of the survey and the respondent's name and address that appear in the window of the envelope; the remaining three pages are blank. The wrap-around pages were used for logistical reasons, namely to make it easier to match the respondent's mailing address to the personalized information (name and access code) in the cover letter of the actual 16-page booklet.

contains the cover letter and the last page collects contact information (on a voluntary basis) and space for open-ended comments. As we designed the survey, we conducted four rounds of pretests (first on internal and then on external participants, for both paper and online survey modes). We asked the pretesters not only to take the survey normally and check how long it took, but also to look for and mark any typos, awkward statements, logical flaws, technical issues (online survey), and any other issues/opinions. We improved the survey based on the feedback from the pretesters, as described further in Section 2.2.

Before implementing the survey, it was necessary to obtain approval for our study from the Georgia Tech Institutional Research Board (IRB) because the research deals with "human subjects" (i.e., people). All research team members were certified by completing the online course in social/behavioral research. After IRB review of our survey protocol, the study was exempted from further review by the Georgia Tech IRB (under CFR 46 101b.2.) and was approved on August 3, 2017 (Protocol number H17288).

2.2 Contents of the Survey

This section describes the contents of the survey and general principles of its design. The actual survey document can be found in the Appendix. The questionnaire contains eight sections, which collect information on various travel behaviors and relevant key factors, such as attitudes, lifestyle, and sociodemographics. The eight sections are organized to support basic survey design principles and to maintain a logical/temporal flow. For example, the literature (e.g., Stopher, 2012) notes that it is preferable to order questions from general to specific or from easy to difficult. In our context, this suggests opening the survey with general attitudes/beliefs. In addition, attitudinal questions are more interesting to respondents than factual questions, and, therefore, help to draw respondents into the survey and solidify their commitment to completing it (Dillman, 2000).

The motivations and content for each section are as follows:

Section A: Your opinions on various topics contains 47 statements with which respondents were able to agree or disagree on a five-point Likert-type scale (i.e., “strongly disagree”, “disagree”, “neutral”, “agree”, or “strongly agree”). In the design stage, we identified several attitudinal dimensions that could be expected to influence the travel-related behaviors of interest to the study, based on a thorough review of the literature and our own judgment. The original attitudinal dimensions are as follows:

▪ Pro-exercise ▪ Pro-social ▪ Pro-environment ▪ Career-oriented ▪ Family/community-oriented ▪ Leisure-oriented ▪ Satisfaction ▪ Motion-sickness ▪ Mode preference	▪ Car-as-a-tool ▪ Must-have-car ▪ Possessive ▪ Pro-sharing ▪ Long-term-urbanite ▪ Pro-suburban ▪ Cost-sensitive ▪ Privacy-sensitive ▪ Safety-sensitive ▪ Adventurous	▪ Pro-technology ▪ Smartphone ▪ Tech-savvy ▪ Trend-setter ▪ Pro-multitasking ▪ Waiting ▪ Commute benefit ▪ Commute stress ▪ Travel-liking

In Chapter 4 of Part 2 of this report, we describe a technique called factor analysis, which is commonly used to quantify attitudes by forming composite scores from a set of variables (“items”) such as these. Although the literature on factor analysis suggests having three to five items for each hypothesized construct (e.g., Fabrigar et al., 1999), we aimed to ease the burden on the respondent and chose to have two attitudinal statements for each construct (and some dimensions even represented by single statements). In the resulting series of attitudinal statements, we varied the directionality of the statements to lead respondents to think about each item individually and, thus, avoid falling into an automatic response pattern (e.g., always “agreeing”). Likert (1932, p. 46) suggested that about half the items should be oriented in each direction, randomly distributed. However, we did not rely blindly on random assignment of directionality, but instead we carefully checked candidate wordings and orders for possible order/context effects. The attitudinal statements are mainly used in the analyses via the factor scores whose computation is described in Chapter 4 of Part 2.

Section B: Your use of technology collects information about the use of information and communications technology (ICT) devices (e.g., smartphone, laptop) and services (e.g., Facebook, Twitter), internet for transportation choices (e.g., "check traffic"), and online purchase activities (e.g., "buy goods", "pay bills"). Each question provides three to five usage frequency categories as response options. Given the purposes of the research, these technology-use frequencies are not only of interest in their own right, but also will be key covariates to understanding travel behavior and the adoption of new transportation options.

Section C: Key aspects of your lifestyle asks about residential location and living arrangements, to understand how these factors affect the way people organize their daily activities and the way they travel. In particular, this section collects the home address (either exact address or intersection of two streets near home). We obtained geocodes based on the home address, and those geocodes are connected to the respondent's residential characteristics or built environment attributes from external sources (e.g., census block group information). Respondents who work are additionally asked to provide work characteristics such as occupation, work schedule, telecommuting frequency, and work address.

Section D: How you travel collects information on various current travel choices. Travel choices include licensure, vehicle ownership, trip frequencies (by mode), experience with long-distance trips, and some commute characteristics (only for workers). Due to space limitations we cannot capture full "diary-type" trip information, but we can broadly capture the general characteristics of people's travel.

Section E: Evolving transportation services asks about various transportation services (either “at home”, i.e., when “in town”, or elsewhere, i.e. while “out of town”). The transportation services included are carsharing, on-demand ride services, and traditional taxi services. Specifically, we provided definitions and corresponding examples as follows:

- ***Carsharing***: using internet/smartphone apps to rent automobiles by the hour or day (e.g., Zipcar);
- ***On-demand ride services***: calling for rides by using smartphone apps (e.g., Uber, Lyft);
- ***Shared on-demand ride services***: sharing Uber/Lyft to reduce the cost (e.g., UberPOOL, Lyft Line);
- ***Traditional taxi services*** (e.g., Yellow Cab, Atlanta Checker Cab).

We collected information on familiarity with and trip purpose/usage frequency of these transportation services. Particularly regarding the on-demand ride services (e.g., Uber, Lyft), we additionally asked about perceptions of these services, willingness-to-wait, their impacts on other modes, and maximum fare that respondents paid in the past 6 months.

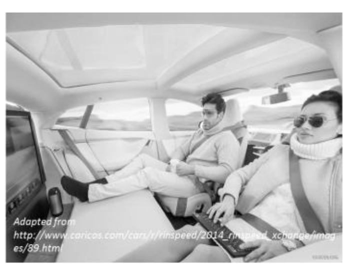
Section F: Your desires for future travel collects information on respondents’ expectations about where they will live and how they will travel 3 years after the time they took the survey. Questions include change of residential location / vehicle ownership, and interest in alternative-fuel vehicles. Motivations for having this section include wanting a sense of how millennials see their lives evolving as they age, and wanting to see how all respondents think emerging technologies might affect their future vehicle ownership and residential location decisions.

Section G: What if cars could drive themselves? asks for respondents’ opinions about self-driving cars. Due to the current lack of consensus on terminology (e.g., self-driving/driverless/autonomous/automated / Google cars/vehicles), we consistently use the term "self-driving cars" and sometimes "driverless cars" (both of which can be considered fairly self-explanatory and non-jargony). To avoid having to explore the choice between conventional and automated vehicles (which would require assumptions about their relative costs and safety that are impossible to make with confidence right now), we chose to focus on the era of full automation, in which *all* cars will be self-driving. Because self-driving cars are not yet commercially available, respondents may lack knowledge about them and may have different mindsets about the future. Hence, we provided a definition and examples with figures, which allow respondents to envision the future where self-driving technologies are fully mature. The descriptions are as follows:

Such vehicles [self-driving cars] drive themselves and control all operating and safety functions, and are even able to travel without a human inside. For our purposes, we want you to ***imagine*** a future where all cars are *fully automated* and do not need humans driving them (we will later ask you how far off you think this future is). Specifically, please assume that …

- Traditional cars can no longer be used in regular traffic – self-driving cars are the *only way to go by car*.
- Driverless cars are *at least as safe* as today's cars are, and *cost about as much* as today's cars do.
- You could *furnish* your self-driving car with a TV, kitchenette, recliner, light exercise equipment, etc.
- You could send an empty self-driving car somewhere to *pick up other people or things, or to park* after dropping you off at work or the ball game.
- You could let a self-driving car take you places *while you are sleeping*.

These figures may help you imagine the possibilities.



As noted unobtrusively on the figures, they were adapted from their original sources. In particular, we aimed to eliminate elements that are specific to conventional human-driven cars. For example, all steering wheels were removed in all figures. For the third illustration, we changed the driver of the adjacent car into a person reading a book, and additionally inserted blurred background trees to simulate the movement of the cars. Finally, all figures were changed into black-and-white for printing.

Section H: Some background about yourself collects information on basic sociodemographics (e.g., gender, age, race/ethnicity, education, household income). Sociodemographic information allows us to compare the data to the general population and to analyze key variables by different population segments. In particular, for the proper projection from the sample to the Georgia population, key sociodemographic information is employed to develop sample weights, as described in Section 5.4 of this report Part 1.

3. SAMPLING

The main purpose of this research is to illuminate the impacts of new technologies and emerging trends on travel behavior/demand in Georgia. Our target population is Georgia residents, specifically adults (18 years or older). It is ideal to collect responses from a representative sample of the target population, to provide the most accurate picture of Georgia adults' opinions or behaviors. Inevitably, however, final survey samples are always biased to some extent due to unavoidable coverage, sampling, and nonresponse biases. To help remedy this, we will employ a weighting process (described in Section 5.4) to replicate population distributions on key variables. While the weights are important for properly conducting the descriptive analysis of the data, they may not always be needed for modeling the effects of certain variables on others.

One of our primary focuses is geography. Georgia consists of 159 counties involving 16 metropolitan planning organizations, and the levels of urbanization/infrastructure notably vary by MPOs/cities (especially the Atlanta region versus other regions). Respondents' travel behavior and opinions about transportation could differ by residential location and, thus, it is crucial to reveal those heterogeneities to provide more fine-grained information for transportation planning and policymaking in each region, including updates of the MPO-based travel demand models.[2] Initially, in consultation with GDOT staff, we decided that because of (1) limited resources, and (2) relevance to the travel demand modeling of MPOs, we would target MPO regions, which contain about 80 percent of the Georgia population.[3] Accordingly, our initial address-based sampling frame (hereafter called "main") was limited to residents of the 15 Georgia-based MPOs (see Section 3.1). Our second sampling frame, however (hereafter called "NHTS", for reasons explained in Section 3.2), also included several hundred residents in the non-MPO (rural) parts of

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[2] Travel demand forecasting models for 14 of the 15 Georgia-based MPOs were developed and are continuously maintained by GDOT. The Atlanta MPO, the Atlanta Regional Commission, maintains its own regional model.

[3] 7,945,715 out of 10,006,693, according to the American Community Survey (ACS) 2015 5-year estimate data.

the state, and so we took advantage of the opportunity to at least partially represent that sector of the population at a relatively small marginal cost.

3.1. Main Sample

The main sample was obtained by employing address-based stratified random sampling. Various vendors sell residential data, which are mostly purchased for commercial purposes (e.g., targeted marketing mailings). The research team compared various vendors and ultimately purchased an address list from Infogroup (http://www.infogroup.com/). Infogroup provides U.S. residential data that are updated monthly from more than 70 contributing sources (Internal Infogroup white paper titled "Business and Residential Data", no date). We requested two randomized sampling processes from the vendor: (1) address-based random selection of households for each "MPO county", and (2) random selection of adult within household.

For the first randomization, we started with selecting target counties and planning the number of invitations for each county. Among the 16 MPOs[4] and again in consultation with GDOT staff, the Chattanooga MPO was excluded because it is based in, and mainly belongs to, the state of Tennessee. For the remaining 15 MPOs, one issue is that the definitions of MPO boundaries vary by document. Hence, we largely followed the boundaries defined by the GDOT Statewide Transportation Demand Model project (Circella et al., 2018). For convenient comparisons with other data (e.g., Census), we decided to sample by county base; however, a second issue is that MPO boundaries are not necessarily identical to county boundaries. Therefore, focusing on the urbanized areas within each MPO, we selected target counties to represent the 15 MPOs. The final geographical frame is 45 counties in 15 MPOs (Figure 3-1). A previously budgeted total of 30,000 invitations was household-proportionally assigned to each target county using the following steps:

[4] The Georgia Association of MPOs (GAMPO, http://www.gampo.org/) provides more details about MPOs in Georgia.

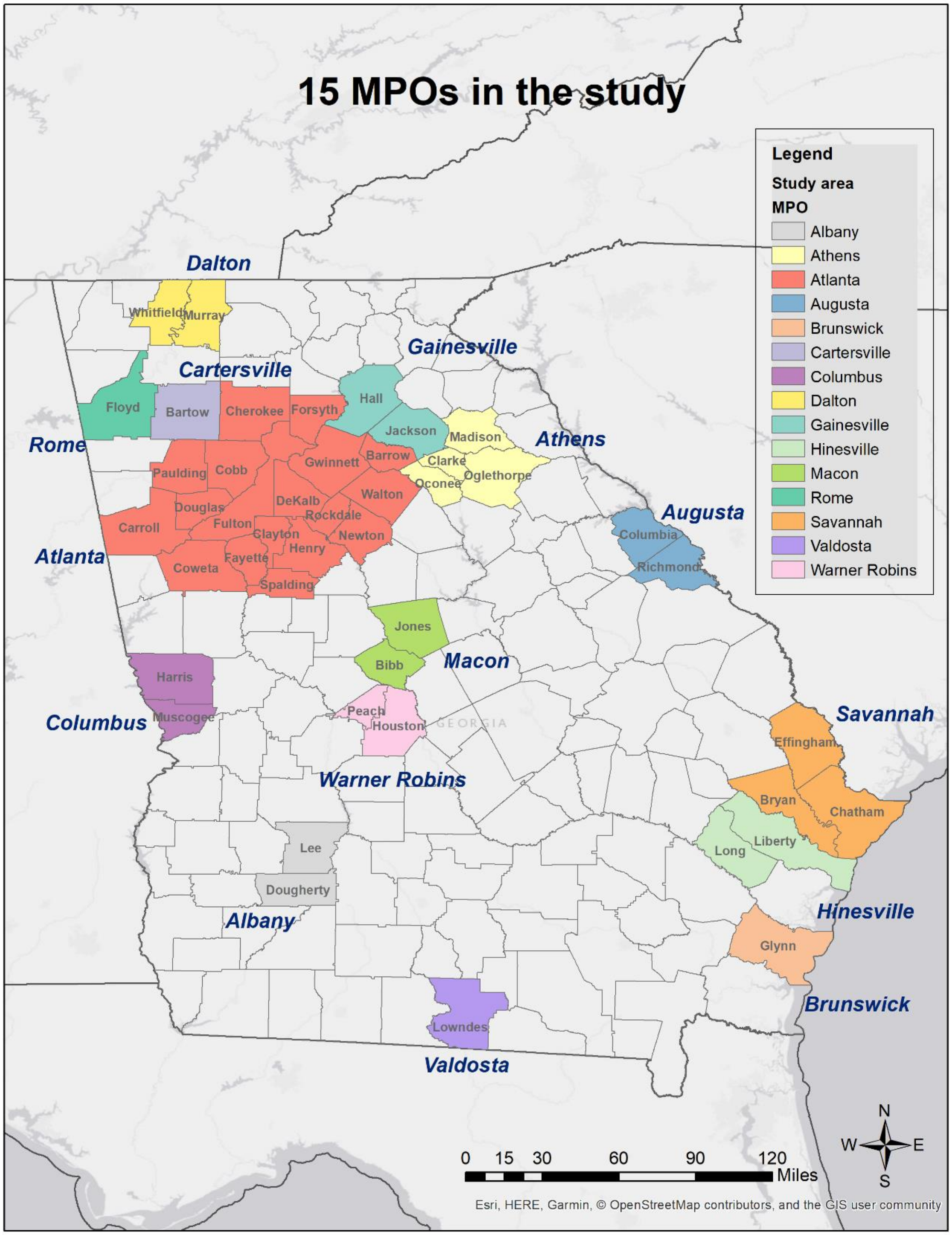

FIGURE 3-1

Geographical Frame for the Main Sample (45 Counties in 15 MPOs)

1. **Divide invitations between Atlanta MPO versus Non-Atlanta MPOs (for stratified sampling)**: The Atlanta MPO region contains 68 percent of the state's households.[5] In addition, we expected the Atlanta region to have a higher response rate than the rest of the state, due to having a younger, more tech-savvy population, as well as to the "Georgia Tech effect" (its influence may be strongest in its home region). Thus, if we had conducted simple random sampling, Atlanta-region residents would have dominated our final sample, leaving relatively small numbers of cases to represent the diversity of the rest of the state. Accordingly (and again in consultation with GDOT staff), we oversampled "non-Atlanta" MPO regions and undersampled Atlanta, allocating a share of 0.33 to invitations to households in the Atlanta MPO region (i.e., 30,000 × 0.33 = 9,900 invitations)—approximately half of its true share.
2. **Allocate invitations to each county**: Controlling for the two totals (i.e., 9,900 within the Atlanta region; the remaining 20,100 to the non-Atlanta MPO regions), invitations were assigned to each county proportional to its number of households. For example, an Atlanta-region county with 10 percent of the region's population would be allocated 990 (10% of 9,900) invitations, while a county in another MPO, having 10 percent of the population of the remaining MPOs, would be allocated 2,010 invitations.

Table 3-1 shows the sampling allocation to each target county. Our average sampling rate was a bit over 1 percent of the households in the 45 target counties of the state, but (as mentioned) that rate was about halved (0.53%) for the Atlanta region and doubled (2.27%) for the other MPO regions.

[5] Based on the 2015 ACS 5-year estimates, which were the latest estimates available when implementing the survey.

TABLE 3-1
Number of Households and Invitations by County (Main Sample)

County	MPO	Population (ACS15)	Households (ACS15)	Number of invitations (sampled households)
Dougherty	Albany	93,310	35,455	804
Lee	Albany	28,946	10,015	227
Clarke	Athens	120,905	43,356	984
Madison	Athens	28,232	10,195	231
Oconee	Athens	34,400	11,880	270
Oglethorpe	Athens	14,688	5,542	126
Barrow	Atlanta	72,012	23,560	126
Carroll	Atlanta	112,595	40,074	214
Cherokee	Atlanta	225,944	79,133	422
Clayton	Atlanta	267,234	88,793	474
Cobb	Atlanta	719,133	268,616	1,434
Coweta	Atlanta	133,416	48,777	260
DeKalb	Atlanta	716,331	267,396	1,428
Douglas	Atlanta	136,520	47,079	251
Fayette	Atlanta	108,655	38,535	206
Forsyth	Atlanta	196,236	62,295	333
Fulton	Atlanta	983,903	379,957	2,029
Gwinnett	Atlanta	859,234	274,017	1,463
Henry	Atlanta	211,512	70,281	375
Newton	Atlanta	102,645	34,641	185
Paulding	Atlanta	147,400	49,110	262
Rockdale	Atlanta	86,901	29,623	158
Spalding	Atlanta	63,873	22,717	121
Walton	Atlanta	86,201	29,667	158
Columbia	Augusta	136,204	45,488	1,032
Richmond	Augusta	201,291	71,724	1,627
Glynn	Brunswick	81,743	32,311	733
Bartow	Cartersville	101,336	35,732	811
Harris	Columbus	32,776	11,570	262
Muscogee	Columbus	200,285	72,760	1,651
Murray	Dalton	39,401	14,236	323
Whitfield	Dalton	103,456	34,575	784
Hall	Gainesville	187,916	61,992	1,406
Jackson	Gainesville	61,420	21,048	478
Liberty	Hinesville	64,427	22,943	521
Long	Hinesville	16,588	5,017	114
Bibb	Macon	154,816	57,111	1,296
Jones	Macon	28,738	10,326	234
Floyd	Rome	96,169	34,874	791
Bryan	Savannah	33,151	11,441	260
Chatham	Savannah	279,290	104,912	2,380
Effingham	Savannah	54,630	18,432	418
Lowndes	Valdosta	113,203	39,328	892
Houston	Warner Robins	147,570	53,771	1,220
Peach	Warner Robins	27,086	9,941	226
Total	-	**7,711,722**	**2,740,246**	**30,000**

3.2. NHTS Sample

When conducting the 2017 National Household Travel Survey (NHTS), the Federal Highway Administration (FHWA) partnered with state departments of transportation (DOTs), MPOs, and regional councils of government, and the survey partners purchased additional survey data for their local areas (i.e., the add-on program).[6] The NHTS respondents were asked several partner-specific questions, such as (in some cases, including Georgia), "Would you be willing to participate in a follow-up survey?" (Westat, 2018). With the aid of GDOT, we obtained the names and addresses of Georgia NHTS respondents who were willing to take a follow-up survey. We wanted to invite these participants to our GDOT study for two major reasons: (1) we can enrich future analyses by combining responses from both our survey and the NHTS survey (e.g., connecting the attitudinal information in the present study's survey to the travel behavior reported in NHTS's full travel diary that each respondent was asked to complete); and (2) these respondents are more likely to return our survey than randomly selected new respondents, thus allowing us to increase the sample size at a very modest marginal cost.[7]

GDOT purchased 8,000 add-on households (TRB, 2016), and we obtained a list of 5,150 of those participants who reported a willingness to be surveyed further.[8] Table 3-2 exhibits the number of invitations by MPO sent to this NHTS sample. As mentioned in the introduction to Section 3, this list included 572 households (11.1% of the total) in non-MPO regions. These households were included to represent rural residents of Georgia, and to allow us to conduct further interesting studies (e.g., comparisons of MPO residents versus non-MPO residents).

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[6] Refer to http://nhts.ornl.gov/addOn.shtml, http://nhts.ornl.gov/participant.shtml.

[7] Of course, even though the 2017 NHTS also employed address-based sampling, this self-selected-to-be-helpful subset of respondents will be less representative of the population than newly randomly selected respondents will be. However, our weighting process will partially counteract this bias, as will combining this sample with the main sample.

[8] The original contact list of 5,161 was reduced to 5,150 because 11 respondents were not Georgia residents.

TABLE 3-2
Number of Invitations by MPO (NHTS Sample)

MPO	Count	Percent of MPO-resident subsample	Percent of total sample
Albany	145	3.2%	2.8%
Athens	304	6.6%	5.9%
Atlanta	1541	33.7%	29.9%
Augusta	450	9.8%	8.7%
Brunswick	133	2.9%	2.6%
Cartersville	101	2.2%	2.0%
Columbus	321	7.0%	6.2%
Dalton	114	2.5%	2.2%
Gainesville	273	6.0%	5.3%
Hinesville	78	1.7%	1.5%
Macon	227	5.0%	4.4%
Rome	96	2.1%	1.9%
Savannah	477	10.4%	9.3%
Valdosta	122	2.7%	2.4%
Warner Robins	196	4.3%	3.8%
Non-MPO	572	-	11.1%
Sum of MPOs	4,578	100.0%	88.9%
Total invitations	5,150	-	100.0%

4. DATA COLLECTION

4.1. Overview of Data Collection

We distributed the surveys by mail, using the traditional method of sending a large envelope containing a cover letter of explanation, the questionnaire, and a pre-addressed, postage-paid, business reply mail return envelope (Babbie, 2012). A majority of recent surveys are implemented only online, because internet surveys offer an easier, cheaper, and faster way to gather data (Babbie, 2012; Stopher, 2012). However, despite being currently prevalent, online surveys have some disadvantages. The most critical issue is that internet accessibility is still uneven, particularly in a diverse demography (Adler et al., 2002; Wright, 2005). According to the Census, there are gaps in age, race, and income with respect to using computers and the internet. In general, as householders are older and have lower incomes, the percentage of computer/internet users decreases. In addition, specific ethnicities (e.g., Black) have lower accessibility. The Pew Research Center[9] estimates that the share of U.S. adults using the internet in 2018 was approximately 89 percent, but there are distinct discrepancies in that share by age, income, and education. In other words, an online survey certainly has a greater coverage bias than does a survey mailed to randomly selected residential addresses, and is also more likely to involve a sampling bias (since there is not a geographically based systematic directory of email addresses as there is for physical addresses). These biases could be more severe in the case of online opinion panels, i.e., people who self-register to take online surveys in return for financial or other rewards. The research team considered these issues to be crucial because the survey spotlights responses to emerging technologies and new trends; hence, the results from a biased sample (e.g., younger, affluent, highly educated, and "tech-savvy" respondents) could provide a misleading view of the population-wide effects of technologies and new trends.

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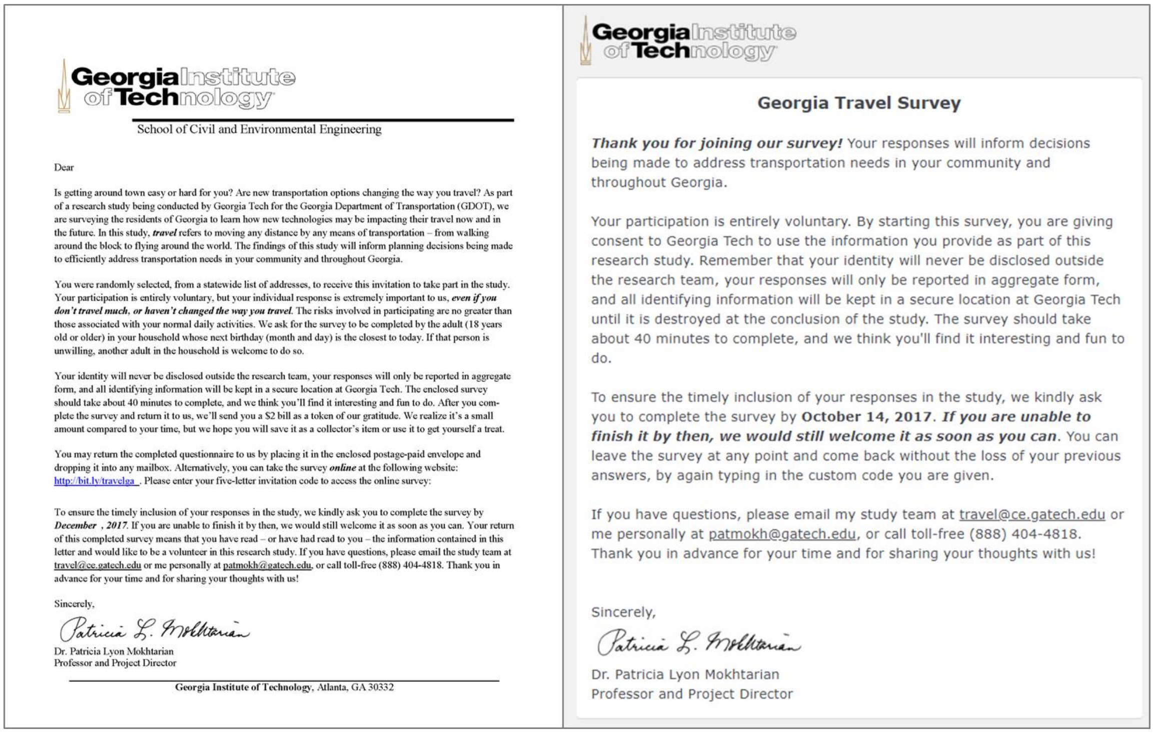
[9] http://www.pewinternet.org/fact-sheet/internet-broadband/ (accessed on May 22, 2018).

However, although our initial recruitment was through paper (including enclosure of the paper survey with the initial mailing), in terms of actual data retrieval we provided online as well as paper options for taking the survey. Knowing that some individuals prefer to respond online (Greaves et al., 2015), we expected that providing two channels would encourage more respondents to take the survey. Accordingly, the cover letter to the paper survey included a link to the online version of the survey, together with a unique five-letter access code (see Figure 4-1 for the paper cover letter and the online welcome message). The survey packets were printed, assembled, and delivered to the post office by Georgia Tech Printing & Copying Services (PCS).

The cover letter provided an overall description of the study purpose and invited recipients to share their opinions with us. We considered alternative salutations—specifically, generic versus personalized—from the perspective of their possible effects on the response rate. Studies (e.g., Heerwegh, 2005; Joinson and Reips, 2007) have found that personalized salutations generally improve the response rate, but this decision is not straightforward. Personalization makes the survey seem more inviting and less like spam (Dillman, 2000; Dillman et al., 2007), on balance (although some may find it disconcerting that total strangers could match their name to where they live), but greatly increases the chances that the survey will be discarded if the named person no longer lives at that address. On the other hand, a generic salutation is applicable to everyone, but is much less friendly and inviting. Ultimately, we decided to use a hybrid version for the main sample: "Dear #full name# or current resident," as an acceptable compromise between the two approaches. For the NHTS sample, we used "Dear #full name#", since we were re-inviting the respondent into the survey. We made the same choices for the addressee names on the outer envelope of the survey packet.

To avoid making an open-ended request, we set a target return date (close enough to prevent indefinite procrastination, but far enough away to give a reasonable amount of time—or so we hoped; see Section 4.3) and encouraged respondents to return the survey by the target date while still welcoming it thereafter. As a token of our appreciation (and as a modest incentive to encourage respondents to take the survey), the cover letter promised to send a $2 bill to those who completed the survey. Of course, the monetary value of this token per se is small, but we thought it would be appealing because the $2 bill is not in common circulation (and indeed, we had to order them in advance from the bank).



Georgia Institute of Technology

School of Civil and Environmental Engineering

Dear

Is getting around town easy or hard for you? Are new transportation options changing the way you travel? As part of a research study being conducted by Georgia Tech for the Georgia Department of Transportation (GDOT), we are surveying the residents of Georgia to learn how new technologies may be impacting their travel now and in the future. In this study, ***travel*** refers to moving any distance by any means of transportation – from walking around the block to flying around the world. The findings of this study will inform planning decisions being made to efficiently address transportation needs in your community and throughout Georgia.

You were randomly selected, from a statewide list of addresses, to receive this invitation to take part in the study. Your participation is entirely voluntary, but your individual response is extremely important to us, ***even if you don't travel much, or haven't changed the way you travel***. The risks involved in participating are no greater than those associated with your normal daily activities. We ask for the survey to be completed by the adult (18 years old or older) in your household whose next birthday (month and day) is the closest to today. If that person is unwilling, another adult in the household is welcome to do so.

Your identity will never be disclosed outside the research team, your responses will only be reported in aggregate form, and all identifying information will be kept in a secure location at Georgia Tech. The enclosed survey should take about 40 minutes to complete, and we think you'll find it interesting and fun to do. After you complete the survey and return it to us, we'll send you a $2 bill as a token of our gratitude. We realize it's a small amount compared to your time, but we hope you will save it as a collector's item or use it to get yourself a treat.

You may return the completed questionnaire to us by placing it in the enclosed postage-paid envelope and dropping it into any mailbox. Alternatively, you can take the survey ***online*** at the following website: http://bit.ly/travelga . Please enter your five-letter invitation code to access the online survey:

To ensure the timely inclusion of your responses in the study, we kindly ask you to complete the survey by ***December , 2017***. If you are unable to finish it by then, we would still welcome it as soon as you can. Your return of this completed survey means that you have read – or have had read to you – the information contained in this letter and would like to be a volunteer in this research study. If you have questions, please email the study team at travel@ce.gatech.edu or me personally at patmokh@gatech.edu, or call toll-free (888) 404-4818. Thank you in advance for your time and for sharing your thoughts with us!

Sincerely,

Patricia L. Mokhtarian

Dr. Patricia Lyon Mokhtarian
Professor and Project Director

Georgia Institute of Technology, Atlanta, GA 30332

Georgia Institute of Technology

Georgia Travel Survey

Thank you for joining our survey! Your responses will inform decisions being made to address transportation needs in your community and throughout Georgia.

Your participation is entirely voluntary. By starting this survey, you are giving consent to Georgia Tech to use the information you provide as part of this research study. Remember that your identity will never be disclosed outside the research team, your responses will only be reported in aggregate form, and all identifying information will be kept in a secure location at Georgia Tech until it is destroyed at the conclusion of the study. The survey should take about 40 minutes to complete, and we think you'll find it interesting and fun to do.

To ensure the timely inclusion of your responses in the study, we kindly ask you to complete the survey by **October 14, 2017**. ***If you are unable to finish it by then, we would still welcome it as soon as you can***. You can leave the survey at any point and come back without the loss of your previous answers, by again typing in the custom code you are given.

If you have questions, please email my study team at travel@ce.gatech.edu or me personally at patmokh@gatech.edu, or call toll-free (888) 404-4818. Thank you in advance for your time and for sharing your thoughts with us!

Sincerely,

Patricia L. Mokhtarian

Dr. Patricia Lyon Mokhtarian
Professor and Project Director

FIGURE 4-1

Cover Letter (Paper Invitation, left; Online Cover, right)

4.2. Data Collection

Our initial order for printing/delivery was on September 7, 2017. Because of the large number of surveys involved (i.e., 29,984 for the main sample and 5,159 for the NHTS sample), PCS processed them in three batches. It took 3–4 weeks after placing the order for the surveys to be placed with the U.S. Postal Service (USPS) and then delivered to respondents, and, thus, approximately a month was required to receive the first response. For the online channel, this study used Qualtrics (https://www.qualtrics.com/), which is licensed by Georgia Tech and is a popular online survey platform. We developed the online survey to mirror the paper survey to the extent feasible and practical. A few question formats were not identical with those in the paper survey due to limitations on the formats available in Qualtrics. On the other hand, the online survey provided several additional information fields such as date/time stamps (for when a survey was started and finished), IP address, IP address-based geocode, and the time required for completing the entire survey or a specific section.

We received the first response on October 2, 2017, and the final response on April 4, 2018, and, thus, data collection lasted 185 days. Figure 4-2 shows the survey response over time. Because the main-sample surveys were released first, we received only main-sample surveys (blue solid line) for a month before beginning to obtain NHTS surveys (red dotted line). We additionally sent out a postcard to remind people of the survey or access code and to express our gratitude to respondents who had already taken the survey. The two batches of postcards (main sample on October 30, 2017, and NHTS on November 10, 2017) were associated with surges in the response rate, although exact contributions are difficult to trace due to lags in mail time and overlap of the main sample reminder postcard with the NHTS sample original mailing. Eighty percent of the surveys retrieved were returned within the first 2 months of data collection. Although the figure does not distinguish between paper and online surveys, our retrieval date is determined differently between the two types. For online surveys, the date is automatically recorded after survey completion and, thus, the received date is the same as the date on which the respondent actually completed the survey. For paper surveys, however (which are the majority), the received date is somewhat later than the actual survey-completed date because of the intervals between survey completion and respondent mailing, arrival at Georgia Tech’s primary mail processing facility, and distribution to our research team (which was typically in batches at erratic intervals).

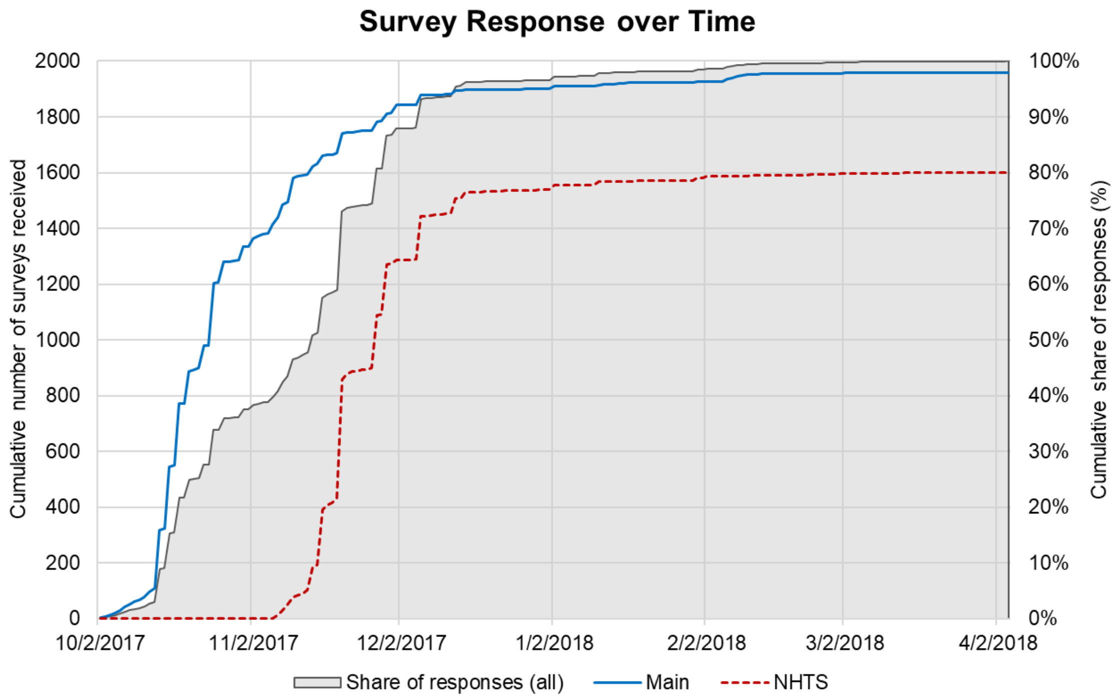


FIGURE 4-2

Survey Response over Time

4.3. Response Rate, Distribution, and Costs

Table 4-1 and Table 4-2 respectively exhibit the response rate by sampling frame, and the data composition by sampling frame and data collection channel. The overall response rate (overall 10.1%) is somewhat lower than expected. One reason is likely to be the fact that a sizable portion of people received the survey close to or even later than the target date given in the cover letter (October 14, 2017, for the main sample and October 30, 2017, for the NHTS sample). We placed the printing/delivery order a full month ahead of the deadline; however, several issues caused nontrivial delays:

1. The time estimates provided by the PCS office proved to be too optimistic—in other words, it took substantially longer for printing/stuffing than we were led to expect, and, thus, the surveys were placed with the USPS too close to the deadlines.

2. Georgia, particularly its coastal area, was hard hit by the Category 5 Hurricane Irma in September 2017. We postponed the survey implementation process for a week or two to provide some time for at least initial recovery, but we could not wait too long, and there is no doubt that in areas with considerable damage, the response rate suffered due to irregular mail delivery and the low priority given to random surveys during a time of crisis.
3. There were additional unexpected delays. For example, we sent out the survey to the research team members' addresses to monitor delivery times. For some team members, even though living near Atlanta, it took more than 2 months to receive the survey. Some delay could be attributed to our use of bulk mail to reduce costs, but delays of this length again exceeded all expectations.

TABLE 4-1
Response Rate by Subsample

Type	Number of invitations	Number of surveys received	Response rate
Main sample	29,975	1,950	6.5%
NHTS	5,150	1,598	31.0%
Total	35,125	3,548	10.1%

TABLE 4-2
Data Composition

	Online	Paper	Total
Main sample			
Count	**435**	**1515**	**1950**
Percent by row	22.3%	77.7%	100.0%
Percent by total	12.3%	42.7%	55.0%
NHTS			
Count	**301**	**1297**	**1598**
Percent by row	18.8%	81.2%	100.0%
Percent by total	8.5%	36.6%	45.0%
Total	**736**	**2812**	**3548**
Percent	20.7%	79.3%	100.0%

As mentioned, the cover letter assured respondents that the deadline was a soft one, stating: "To ensure the timely inclusion of your responses in the study, we kindly ask you to complete the survey by #deadline#, 2017. If you are unable to finish it by then, we would still welcome it as soon as you can." Although we hoped that invitation would be taken as blanket permission to return the survey even after the deadline, many (30 or more) people called or emailed us to check if they could still return the surveys and to complain about the unreasonable deadline. While those people who contacted us were likely to complete and return the survey, it is certain that for every one who took the trouble to call or write, many more will simply have discarded the survey.

In terms of the response rate, there are two intriguing patterns to note. First, the two sampling frames have markedly different response rates: 6.5 percent for the main sample versus 31.0 percent for the NHTS sample. Although it is not surprising that the NHTS sample, which was self-selected to be friendly toward completing another transportation survey, has a much higher response rate than our "cold-call" main sample, it might be surprising that (1) the NHTS response rate was *only* 31 percent—demonstrating that even among a nominally willing sample, many factors (e.g., the delays described above, changes in circumstances or attitude, just hitting at a busy or stressful time) conspired to keep the "repeat" rate well below 50 percent; and (2) the NHTS rate was *so* much (nearly five times) higher than that of the main sample—demonstrating how much more difficult it is to elicit opinions from "random" people compared to people who are positively predisposed toward taking the survey.

Second, even though we provided two channels—paper and online—the majority of respondents chose to complete the paper version of the survey (77.7% of main-sample respondents and 81.2% of NHTS respondents). This could support the position that paper surveys are still useful (and potentially a key strength of this study), in that a sizable share of people prefer to use a paper survey rather than its online counterpart—at least when the paper survey is readily at hand, whereas the online counterpart may require booting up a computer and opening an internet browser, as well as typing in a URL and then a 5-letter access code. However, we do not know how many paper respondents would have returned the survey online if that had been the only option. Also, our final sample is biased toward older respondents, who are more likely to prefer paper. Even among the younger cohort (18–44 years old) in the final combined sample, however, 63 percent chose the paper option.

Ultimately, even after the adverse circumstances described above, 6.5 percent is not out of line with typical response rates being seen for this type of survey; the phenomenon of falling response rates is universal and widely remarked in the survey design and administration community (Groves, 2011; Morton et al., 2012; Pew Research Center, 2017).

The response rate provides a key basis for evaluating the cost of conducting a survey, which is a metric of interest to both researchers and funding agencies. Table 4-3 shows some important unit costs by task.[10] We purchased a contact list of 30,000 people for $1,800, thus having a unit cost of $0.06. Mailing out the survey (including printing, postage, and stuffing) cost $1.19 each, and survey implementation (including mailout and retrieval) required $13.95 per survey. In total, after taking into account data entry cost (which will be described in Section 5.1), $19.85 per survey was required. However, we need to use caution as it is possible that the costs are partly overestimated and partly underestimated compared to the usual survey. First, we have two sampling frames and one of them (NHTS sample) was cost-free to obtain. Furthermore, it has much higher response rate than typical random sampling and, thus, unit cost of typical surveys could be a bit higher (many cost elements are a function of number of surveys retrieved). In addition, two data collection channels were employed: one does not require data entry, but we had more papers that required data entry. It is challenging to compare the results with other survey studies or other types of research since: (1) cost is very context-specific (e.g., each survey has its own unique circumstances, like those above), and (2) few studies have reported cost information.

[10] Unit costs are best estimates, not necessarily actual cost.

TABLE 4-3
Some Important Unit Costs

Task	Unit cost [a]	Basis
Contact list (30,000 cases)	$ 0.06	Main sample (30,000)
Survey mailout (printing, envelopes, stuffing, postage)	$ 1.19	All invitations (35,125)
Survey implementation (mailout + retrieval)	$ 13.95	Completed surveys (3,548)
Data entry cost (for paper surveys) [b]	$ 4.58	Completed paper surveys (2,812)
Grand cost (with respect to final working dataset) [c]	$ 19.85	Final working dataset (3,288)

a. Unit costs are best estimates.
b. The study employed double data entry to improve data quality.
c. Note that we have two sampling frames (one cost-free) and two data collection channels (one not requiring data entry, but the majority of surveys returned on paper, which required data entry). Also, marginally, some data entry was performed by unpaid students receiving research credits. Hence, the unit costs of this survey in some ways overestimate and in other ways underestimate what others might experience.

5. DATA PREPARATION

5.1. Data Entry

Since we received a majority of the responses on paper, the process of data entry was not trivial. Some 13 Georgia Tech undergraduate students participated in data entry, either for pay or for unpaid research credits. To enter the data, we employed the same Qualtrics platform that hosted the online version of the survey. The students entered the paper surveys as if they were online respondents, except that for this purpose we removed the skipping logic from the online survey to allow capture of the raw responses even if they were logically inconsistent.[11] We took several steps to ensure the quality of data entry. First, we hired students based on an interview, at which we described the task they would work on and asked about their experience with similar work and their commitment to this work. Second, throughout the data entry process we asked them to report any issues (e.g., mistakes, poor quality of responses) and checked issues or specific surveys on a daily basis. To minimize fatigue, we set a maximum limit of two consecutive hours of data entry, with a break of at least an hour before resumption. In addition, we monitored quality by checking samples of the data the students input. Lastly and most importantly, in keeping with common practice, each survey was entered twice, by different people, to capture most of the random mistakes that are inevitable in such an endeavor. After the two sets of data were created, we compared them and addressed discrepancies. Overall, the data entry took about 7 months (October 26, 2017 – May 17, 2018). As shown in Table 4-3, it ultimately cost about $4.58/completed paper survey.[12]

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[11] While this may seem undesirable, it is better for the *raw* data to reflect the respondent's thinking as closely as possible, which allows for greater flexibility in dealing with inconsistencies down the line, and offers the opportunity to analyze the extent, nature, and causes of inconsistencies in their own right. However, to the extent practical, we reconciled inconsistencies in preparing the *working* dataset.

[12] This is an estimate rather than an exact number. We paid about $12,888.50 for data entry (this figure may include some other duties performed by the same assistants). We divided the cost by the number of paper surveys retrieved (2,812). As mentioned in Chapter 4, the actual unit cost could be a bit higher because some surveys were entered by unpaid students (receiving research credit).

5.2. Home Address and Geocoding

The residential location is very important information for several reasons. It could be a target variable to be analyzed/modeled (e.g., what factors affect the choice of the residential location) or a key covariate (e.g., it may affect vehicle ownership or use of public transit). Potentially, we can append more information on land use or built environment characteristics based on the home address. Furthermore, importantly, this information is utilized for developing weights. The share of the population returning the survey will vary geographically, not only because of the stratified random recruitment process we employed (undersampling Atlanta residents, as described in Section 3), but also because inclination to respond will differ across the map. To correct these imbalances and have the sample be representative of the population, we need information on the home address. Although we only require some aggregate level (e.g., county) of residential location for developing the weights, it is desirable to be as precise as possible from the perspective of relating land use or built environment characteristics to travel behavior. After reviewing all records case by case, we cleaned the home address information that involved data entry errors, typing errors, incomplete addresses, missing values, etc. In particular, for some missing values, we imputed home addresses from our original contact list, if the respondent was the one invited or was likely to be a household member of the invited person. Based on the cleaned information, we obtained geocodes by employing a Google Maps application programming interface (API).[13] Figure 5-1 shows the geocodes of the respondents by sampling frame. Of note from Figure 5-1 is that a majority of respondents in non-MPO regions are NHTS respondents (by our sampling design).

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[13] We ran multiple rounds of calling the Google API because sometimes it yielded clearly incorrect locations (e.g., a place that obviously could not be a residential location) and sometimes it produced reasonable results.

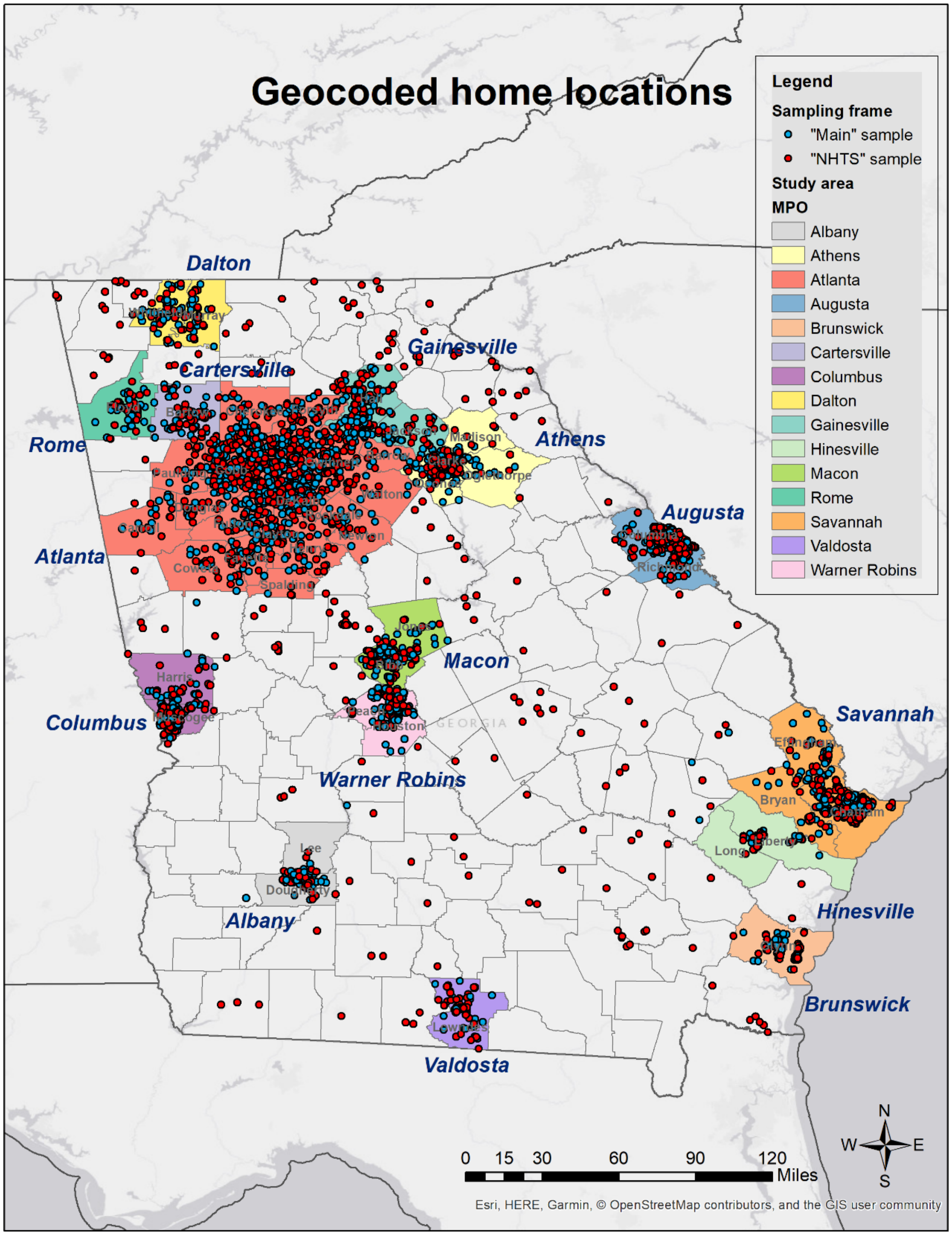

FIGURE 5-1

Home Address Geocodes (by Sampling Frame)

5.3. Data Cleaning and Quality Checks

No matter how carefully designed a survey is, there will always be missing and inconsistent responses. Addressing those imperfections involves making somewhat subjective tradeoffs between greater purity and sample size and representativeness (i.e., excluding *all* cases with *any* problems would greatly reduce the sample size and its representativeness, while including cases with some problems reduces the quality of the data overall), and between the benefits of improvement (e.g., through missing data imputation and reconciliation of inconsistencies) and the costs of time and other resources. This section provides a general idea of how we checked and processed the data to improve its quality. For brevity, we do not describe every detail.

We designed multiple strategies for identifying problematic cases. First, we identified "dealbreaker" problems which, in our judgment, required filtering out the case altogether. We identified each such case with a "hard" flag. After filtering the sample to exclude cases with hard flags, we further checked each remaining case for outliers, number of missing values, inconsistencies, etc. For these, we compiled a series of "soft" flags, indicating the presence of a possible issue. We did not permanently remove cases based on the soft flags as there are various reasons for a soft flag, they are not equally important, and some quality fails may not affect the specific analysis. Rather, we would check for relevant flags as we conducted later analyses and handle them as needed.

5.3.1. Hard Flags

Inherently, it is important for survey data to accurately reflect respondents' attitudes, traits, and behavior. However, respondents differ in their motivation to answer as accurately as possible. Even among well-intentioned respondents there may be random lapses of attention or increasing fatigue as the survey progresses. Some respondents may be indifferent to the need for accuracy, and just provide answers quickly and carelessly. In the worst case, whether through mischief or malice, a respondent may intentionally try to sabotage some or all of the survey by giving random or nonsense answers.

We implemented several steps to help identify such cases. The first step was actually taken during the survey design phase. A common practice (though not a universal one, and one whose effectiveness is, in fact, debated) is to insert "trap" questions as both a check on, and a motivation for, respondent attentiveness (e.g., Oppenheimer et al., 2009; Berinsky et al., 2014; Liu and Wronski, 2018). In keeping with this practice, we included two trap questions in the survey, at the beginning (Section A) and near the end (Section G) (see Section 2.2 for an overview of the survey contents). They were placed in the middle of the associated section, among a set of questions that use the same format, to identify (some of) the people who were not reading the questions carefully and were, therefore, marking "random" answers. The two trap questions say, "To confirm you're really reading this, please select 'strongly disagree' here." Upon reflection, we decided not to immediately filter out respondents who answered "strongly agree", on the assumption that they might have misread the word rather than have been randomly marking responses. This would call for a soft flag, indicating a lower quality record (and later on we filtered out cases having many soft flags), but not necessarily an altogether unusable one. The cases which checked "disagree", "neutral", and "agree" were given hard flags and excluded.

Second, for online survey respondents, we examined the time it took for the survey to be completed, to identify "speeders". Considering the length of the survey, it is unlikely that a careful respondent would finish it in a very short time. Hence, we filtered out cases that completed the survey in less than 15 minutes, and gave a soft flag to the cases that took between 15 and 25 minutes to finish.

Third, we identified and filtered out "flatliners", i.e., those who repeated the same answers to a certain block of questions. For example, it is highly unlikely that a respondent would "strongly agree" with many attitudinal statements that capture various dimensions. Accordingly, we filtered out respondents who marked 40 or more answers the same (out of 47 statements) in Section A. We identified flatliners in other sections that have repeated question formats (typically the 5-point Likert-type scale). However, we decided it was possible to legitimately have repeated answers in those cases, for example when the questions dealt with situations having high uncertainty.

Lastly, we filtered out cases that have many missing values (particularly in some important sections). For example, there are about 200 questions in the survey that apply to everyone; we filtered out cases having missing values on more than 60 of these. In all, these steps resulted in about 300 cases being dropped.

5.3.2. Outliers

Some questions provided an open-ended blank, to allow respondents to write numeric values (e.g., commute time). When the response to such a question is unusually large but physically possible, it could represent the reality that in a sample of several thousand observations, unusual events are to be expected (and excluding such cases would actually make the sample *less* representative of an aggregate population that inevitably encompasses unusual situations). Alternatively, it could represent a keystroke error, inattention, misunderstanding, or deliberate falsehood. Other responses could be realistically impossible, but sometimes the truth can be guessed on the basis of deduction and/or responses to other questions. We identified the following cases as some to be considered suspicious. We reviewed records case by case and treated some outliers as missing values or recoded them into the upper or lower bound.

- ***Weekly work hours***: A few cases reported working more than 70 hours a week (~10 hours a day for 7 days). However, the maximum reported value of 100 hours is plausible, albeit with low probability. As a result, we did not alter this variable.
- ***Licensure age***: A few respondents reported the age at which they obtained their driver's license to be very low or high (below 16 or above 50 years). In Georgia, people can take a

driver education course as young as 14 and obtain a learner's permit at 15 years.[14] In addition, there is no upper limit. Accordingly, we did not alter this variable.

- ***Number of vehicles***: A few cases reported having more than 10 household vehicles. In particular, one respondent reported 42 vehicles, but wrote a note saying "not a misprint". We did not alter this variable.
- ***Number of long-distance trips***: Some respondents reported very extreme values for the number of long-distance trips made in the past 12 months. We put a cutpoint of 180 (we were explicitly asking for "trips involving an overnight stay") and treated responses above the cutpoint as missing values.
- We also reviewed vehicle year, vehicle miles driven, single maximum Uber fare, age, and household size, and there were no notable outliers.

5.3.3. Inconsistent Responses

A sizable number of respondents gave inconsistent answers to several questions. We awarded soft flags for inconsistent responses and recoded some of the answers if possible. Table 5-1 exhibits some of the inconsistencies we identified.

[14] https://www.dmv.org/ga-georgia/teen-drivers.php

TABLE 5-1
Type and Number of Selected Inconsistencies

Theme	Description	Count
Household	Household correction (rescued missing values by using other variables)	218
	Household size (H5) [a] and sum of people by age group (H6) are not equal	4
	"I live alone" (C7), but respondent also checked other options (C7)	2
	Live with partner/husband/wife/boyfriend/girlfriend (C7), but relationship is single (C5), OR; Live with partner/husband/wife/boyfriend/girlfriend (C7), but household size is 1 (H5)	33
	Licensure (D1) + other household licensures (D2) should be equal to or less than household size (H5)	125
Work	Worker, but also checked "I don't work"	1
	Reported "No, I only work or take classes from home" (C14), but telecommuting is "Not possible/not allowed" or "Never"	66
	Reported "No, I only work or take classes from home" (C14), but also reported some commuting answers (D6–D12)	25
Transportation use	"I've not used [carsharing]" (E3_a_1=1), but checked trip purposes (E3_a)	1
	Have not used carsharing (E1_a), but checked at least one trip purpose (E3_a), or checked trip frequency (E4_a)	120
	"I've not used [an on-demand ride] service" (E3_b), but checked trip purposes (E3_b)	2
	Have not used an on-demand ride service (E1_b), but checked at least one trip purpose (E3_b), or checked trip frequency (E4_b)	42
	"I've not used [a shared on-demand ride] service" (E3_c), but checked trip purposes (E3_c)	4
	Have not used a shared on-demand ride service (E1_c), but checked at least one trip purpose (E3_c), or checked trip frequency (E4_c)	102
	"I've not used [a traditional taxi] service" (E3_d_1=1), but checked trip purposes (E3_d)	3
	Have not used a traditional taxi service (E1_d), but checked at least one trip purpose (E3_d), or checked trip frequency (E4_d)	135
Long-distance trip	Have overnight stays (D16), but total number of trips is zero (SUM(D15))	124
	Have no overnight stays (D16), but total number of trips is at least one (SUM(D15))	45
	1–10 nights away from home (D16), but total number of trips (SUM(D15)) is greater than 10, or 11–25 nights away from home (D16), but total number of trips (SUM(D15)) is greater than 25, or 25–50 nights away from home (D16), but total number of trips (SUM(D15)) is greater than 50	101

a. Section and number of the associated survey question.

5.3.4. Data Recoding

In some cases, we want respondents to select the single-most appropriate answer, while in other cases we want to allow all answers that apply. The online survey can restrict the number of answers respondents can select, whereas on the paper survey, respondents may mark multiple answers even when we ask for a single one. We used the following recoding logic in cases of multiple answers:

a) If it is obvious that one of the answers would be more proper, select it (e.g., if there are multiple answers for "highest education level attained", select the highest one).

b) If a particular combination of responses to a legitimately multiple-answer question has a sizable number of cases or makes sense for any other reason, make a new code (e.g., give the frequently appearing combination of {3,4} a new code of "6").

c) Other cases: We reviewed the cases and made a decision either to choose the selection that seemed most appropriate, or to treat them as missing values.

Some questions offer a response category of "other (please specify)" because we cannot always provide collectively exhaustive categories or respondents cannot fit their situations into ordinal categories due to the complexity. We examined the specified "other" responses, and used the following recoding logic:

a) If the answers could fit into one or more of the original categories, we recoded them into the appropriate category(ies).

b) If the answers were irrelevant to the question, we treated them as missing values.

c) If there were frequently appearing answers that did not fit into the original categories but which were relevant, we recoded them into new categories. For example:
   - "Retirement community" in response to a question about type of home (C2);
   - "Flight" in response to a question about the primary commute mode (D8).

d) If the case did not fall under the above situations, we preserved the original record.

5.4. Development of Sample Weights

If the purpose of a study is to estimate descriptive statistics for a population, it is critical that the sample be representative of the target population, whether through obtaining a true random sample or through weighting the cases in a sample to achieve representativeness (by giving greater weight to the cases belonging to underrepresented groups, and less weight to groups that are overrepresented). If the purpose is to model or estimate causal effects, the weighting issue becomes more nuanced (Solon et al., 2015), and the presence or absence of weighting may not be critical (Babbie, 2012). This study aims to understand the pertinent opinions and travel-related choices of adult residents of Georgia, and employs both descriptive statistics and models. Hence, we need to represent the population of Georgia as faithfully as possible, and accordingly we developed sample weights.

There are multiple ways to develop weights (e.g., Kalton and Flores-Cervantes, 2003; Stopher, 2012); we used a combination of cell weighting and iterative proportional fitting (IPF). Cell weighting is a standard procedure that adjusts the sample weights so that the sample shares conform to the population shares on a cell-by-cell basis, whereas IPF operates only on the marginal distributions (Kalton and Flores-Cervantes, 2003). In general, cell weighting is employed when we know population segments cell-by-cell and IPF is used when we only know the marginal distributions of target variables. We examined multiple relevant projects (e.g., the NHTS) to decide on the target variables for developing the weights. We identified nine target dimensions: residential location (MPO tier[15]), household income, household size, number of vehicles, sex, education, race, age, and work status. Some demographics that are often used in other studies were dropped either because our survey does not have such information (e.g., number of workers in the household) or because the sample has too few cases and, thus, inclusion of the variable was likely to lead to extreme values of weights (e.g., Hispanic origin).

Considering (a) the number of target variables, (b) the fact that the target variables are a mixture of individual and household characteristics, and (c) the fact that only marginal distributions are available for some combinations of variables, we designed an iterative weighting process that

[15] We defined four MPO tiers: Atlanta MPO (1st), mid-sized MPOs whose population is over 200,000 (2nd), small-sized MPOs whose population is under 200,000 (3rd), and non-MPO areas (4th). This reduces the cognitive load and provides more statistically robust results by combining smaller subsamples across multiple MPOs, while offering at least a first-level stratification by region size. The geographic locations of each MPO tier can be found in Figure 1-1 in Part 2 of the report.

includes four rounds of cell-weighting and IPF. As depicted in Figure 5-2, for the *first round*, cell weights are created for the crosstabulation of MPO tier by income. Incorporating the weights from the first round, in the *second round* we crosstabulate household size by vehicle ownership (VO, number of vehicles in household) and again develop cell weights for the combinations of those two variables. For the *third round*, we apply stretched IPF (i.e., one of the marginal distributions is actually the "stretched" combination of two variables—sex and education—rather than a single variable) to a crosstabulation (of sex/education and race) that incorporates weights from the second round. In the same fashion, cell weighting is applied in the *fourth round* to a crosstabulation (of work status by age) that incorporates weights from the third round. This series of steps iteratively continues until convergence (i.e., there is no additional update of weights from the previous weights). Once converged, the weighted four crosstabulations exactly mirror the same crosstabulations in the population. We use the 2016 ACS 5-year estimates to build the baseline population.[16] Because we referred to the ACS classifications for key variables when we designed the survey, we were able to match our variables' categories to those in the ACS data (e.g., our household income categories are combinations of categories in the ACS). We experimented not only with various combinations of variables, but also various categories within each variable, to find a solution that avoids extreme weights as much as possible. Table 5-2 exhibits the target variables and their categories for developing weights.

[16] When we designed the sampling, it was based on 2015 ACS 5-year estimates. However, as the 2016 estimates became available, we employed them. In addition, we used 5-year estimates because 1-year estimates are available for only some parts of Georgia.

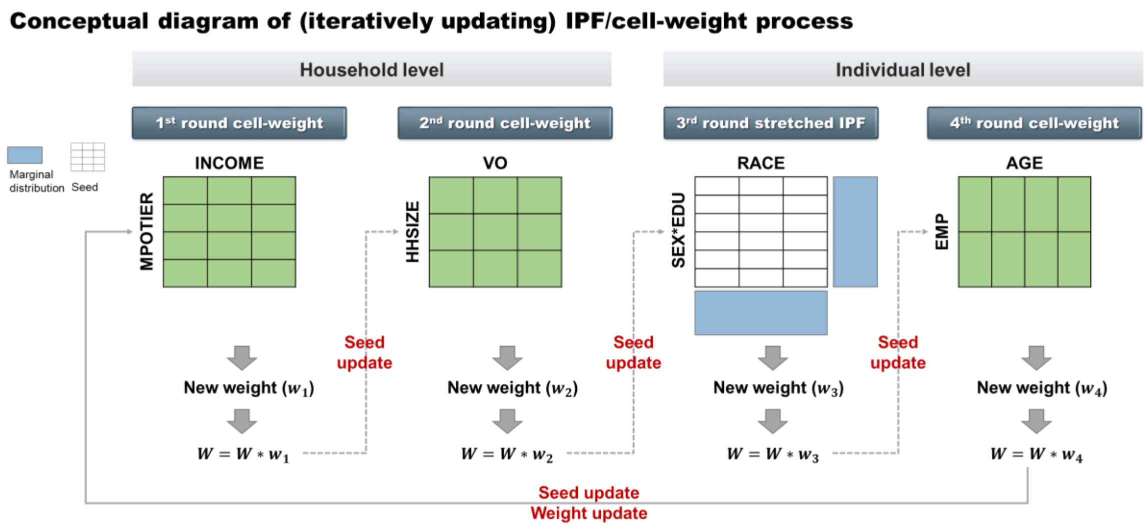

FIGURE 5-2

Conceptual Diagram of Weighting Process

TABLE 5-2
Target Variables and Categories for Developing Sample Weights

Household level		Individual level	
MPO TIER	1. Atlanta MPO 2. Mid-sized MPOs (POP>200,000) 3. Small-sized MPOs (POP<200,000) 4. Non-MPO areas	SEX by EDUCATION	1. Female; No college 2. Male; No college 3. Female; Some college 4. Male; Some college 5. Female; BA or higher 6. Male; BA or higher
INCOME	1. Less than $50,000 2. $50,000–$99,999 3. $100,000+	RACE	1. White alone 2. Black alone 3. Else
HOUSEHOLD SIZE	1. 1-person household 2. 2-person household 3. 3+-person household	AGE	1. 18–34 2. 35–44 3. 45–64 4. 65+
VEHICLE	1. 0 vehicle 2. 1 vehicle 3. 2+ vehicles	WORK STATUS	1. Working 2. Not working

One of the issues with using sample weights is that excessively large weights can unduly inflate the variances of survey-based estimates (Chowdhury et al., 2007). Hence, at the end, many studies "trim" extreme weights (i.e., cut them back to a specified maximum value). Such trimming of weights can introduce a degree of bias in estimates, and, thus, the ultimate goal of trimming is to reduce the mean squared error by reducing the variance more than enough to compensate for the possible increase in bias (Potter, 1990; Potter and Zheng, 2015). We used a common trimming strategy called the interquartile range (IQR)[17] method. After trimming, we renormalized the weights so that the sum of weights preserves the sample size (and thence the precision of sample statistics). Table 5-3 summarizes the descriptive statistics by both unweighted and weighted samples. Because we trimmed the weights, the weighted sample does not exactly mirror the population distribution. In particular, young people (18–34), the less educated (no college), those with low household income (less than $50,000), non-MPO residents, and those in households of size three or more are underrepresented.

[17] In the interquartile range (IQR) method, the following equation is employed: $median(w) + k * IQR(w)$, where w is a vector of weights, IQR is a measure of the dispersion of the weights (the difference between the 75th and 25th percentiles), and k is an integer-valued constant determined by the researcher, typically 4–6. In this study, we used $k = 5$. Weights larger than this number are considered to be extreme values that should be trimmed.

TABLE 5-3
Demographic Statistics (N=3,288)

Variable	Population [a b]		Unweighted sample [c]		Weighted sample [c]	
	Count	*Percent*	*Count*	*Percent*	*Count*	*Percent*
Gender						
Female	3,952,817	52.0%	1,602	48.7%	1,707	51.9%
Male	3,651,328	48.0%	1,686	51.3%	1,581	48.1%
Generation						
18–34	2,393,663	31.5%	292	8.9%	738	22.4%
35–44	1,375,596	18.1%	331	10.1%	561	17.1%
45–64	2,588,591	34.0%	1,329	40.4%	1,302	39.6%
65+	1,246,295	16.4%	1,336	40.6%	687	20.9%
Race						
White alone	4,703,643	61.9%	2,526	76.8%	2,039	62.0%
Black alone	2,297,725	30.2%	573	17.4%	983	29.9%
Else	602,777	7.9%	189	5.7%	266	8.1%
Education						
No college	3,269,740	43.0%	430	13.1%	1,081	32.9%
Some college	2,312,038	30.4%	980	29.8%	1,047	31.8%
BA or grad	2,022,367	26.6%	1,878	57.1%	1,160	35.3%
Work status						
Work	4,421,659	58.1%	1,816	55.2%	2,049	62.3%
Non-work	3,182,486	41.9%	1,472	44.8%	1,239	37.7%
MPO tier						
ATL MPO	1,883,257	52.1%	1,063	32.3%	1,696	51.6%
2nd MPO	497,175	13.8%	1,189	36.2%	592	18.0%
3rd MPO	398,141	11.0%	831	25.3%	441	13.4%
Non-MPO	833,133	23.1%	205	6.2%	559	17.0%
Income						
Less than $50,000	1,769,581	49.0%	1,050	31.9%	1,394	42.4%
$50,000–$99,999	1,070,953	29.7%	1,196	36.4%	1,041	31.7%
$100,000+	771,172	21.4%	1,042	31.7%	853	26.0%
Household size						
1 person	970,912	26.9%	925	28.1%	970	29.5%
2 persons	1,182,306	32.7%	1,430	43.5%	1,220	37.1%
3+ persons	1,458,488	40.4%	933	28.4%	1,098	33.4%
Number of vehicles						
0 vehicles	247,816	6.9%	81	2.5%	176	5.4%
1 vehicle	1,217,560	33.7%	890	27.1%	1,121	34.1%
2+ vehicles	2,146,330	59.4%	2,317	70.5%	1,990	60.5%

a. 2016 ACS 5-year estimates of Georgia (159 counties).
b. The total population is 7,604,145 (ages 18+) and total number of households is 3,611,706.
c. Counts are rounded. Total sample size is 3,288.

5.5. Appending Land-use Variables

As described in Section 5.2, we collected home address geocodes of the survey respondents. Based on their location, we appended more land-use variables that are expected to be key factors affecting travel behaviors. Multiple sources are available for land-use variables. In this study, we employed the Census summary data, Smart Location Database of the Environmental Protection Agency (EPA), and AllTransit. The EPA Smart Location Database (Ramsey and Bell, 2014) provides more than 90 different measures of the built environment, using the "D" variables schema popularized by Cervero and Kockelman (1997; also see Ewing and Cervero, 2010). This database is publicly available, but one drawback is that it is somewhat outdated (most of its variables were developed based on 2010 statistics). Hence, we updated some key variables (e.g., population density, household density, job density) based on the recent ACS and Longitudinal Employer–Household Dynamics (LEHD) data.[18] AllTransit[19] data provide transit-related indicators that are developed based on the National Transit Database and the publicly available General Transit Feed Specification (GTFS) data. We purchased the dataset from the Center for Neighborhood Technology (CNT). Both the EPA Smart Location Database and the AllTransit data are based on the census block-group unit of geography, and, thus, we appended the variables associated with the block group containing the geocoded home address of the respondent.

[18] https://lehd.ces.census.gov/
[19] https://alltransit.cnt.org/

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APPENDIX: Questionnaire

Georgia Institute of Technology

School of Civil and Environmental Engineering

Dear

Is getting around town easy or hard for you? Are new transportation options changing the way you travel? As part of a research study being conducted by Georgia Tech for the Georgia Department of Transportation (GDOT), we are surveying the residents of Georgia to learn how new technologies may be impacting their travel now and in the future. In this study, ***travel*** refers to moving any distance by any means of transportation – from walking around the block to flying around the world. The findings of this study will inform planning decisions being made to efficiently address transportation needs in your community and throughout Georgia.

You were randomly selected, from a statewide list of addresses, to receive this invitation to take part in the study. Your participation is entirely voluntary, but your individual response is extremely important to us, ***even if you don't travel much, or haven't changed the way you travel***. The risks involved in participating are no greater than those associated with your normal daily activities. We ask for the survey to be completed by the adult (18 years old or older) in your household whose next birthday (month and day) is the closest to today. If that person is unwilling, another adult in the household is welcome to do so.

Your identity will never be disclosed outside the research team, your responses will only be reported in aggregate form, and all identifying information will be kept in a secure location at Georgia Tech. The enclosed survey should take about 40 minutes to complete, and we think you'll find it interesting and fun to do. After you complete the survey and return it to us, we'll send you a $2 bill as a token of our gratitude. We realize it's a small amount compared to your time, but we hope you will save it as a collector's item or use it to get yourself a treat.

You may return the completed questionnaire to us by placing it in the enclosed postage-paid envelope and dropping it into any mailbox. Alternatively, you can take the survey ***online*** at the following website: http://bit.ly/travelga . Please enter your five-letter invitation code to access the online survey:

To ensure the timely inclusion of your responses in the study, we kindly ask you to complete the survey by ***December , 2017***. If you are unable to finish it by then, we would still welcome it as soon as you can. Your return of this completed survey means that you have read – or have had read to you – the information contained in this letter and would like to be a volunteer in this research study. If you have questions, please email the study team at travel@ce.gatech.edu or me personally at patmokh@gatech.edu, or call toll-free (888) 404-4818. Thank you in advance for your time and for sharing your thoughts with us!

Sincerely,

Patricia L. Mokhtarian

Dr. Patricia Lyon Mokhtarian
Professor and Project Director

Georgia Institute of Technology, Atlanta, GA 30332

Section A: Your opinions on various topics

This section asks for your opinions about a number of subjects related to transportation and everyday life. ***There are no right or wrong answers*** – we want only your true feelings.

1. For each item, please mark the box that best expresses your opinion. ***Even if you don't know much about a subject or it doesn't exactly apply to you, we would still like to have your general thoughts about it.***

	Strongly disagree	*Disagree*	*Neutral*	*Agree*	*Strongly agree*
a. I like exploring new places.	☐1	☐2	☐3	☐4	☐5
b. I prefer to minimize the amount of things I own.	☐1	☐2	☐3	☐4	☐5
c. I like the idea of public transit as a means of travel for me.	☐1	☐2	☐3	☐4	☐5
d. At this stage of my life, having fun is more important to me than working hard.	☐1	☐2	☐3	☐4	☐5
e. I like to juggle two or more activities at the same time.	☐1	☐2	☐3	☐4	☐5
f. I see myself living long-term in a suburban or rural setting.	☐1	☐2	☐3	☐4	☐5
g. Learning how to use new technologies is often frustrating for me.	☐1	☐2	☐3	☐4	☐5
h. Having to wait can be a useful pause in a busy day.	☐1	☐2	☐3	☐4	☐5
i. It's very important to me to achieve success in my work.	☐1	☐2	☐3	☐4	☐5
j. I am fine with not owning a car, as long as I can use/rent one any time I need it.	☐1	☐2	☐3	☐4	☐5
k. My phone is so important to me, it's almost part of my body.	☐1	☐2	☐3	☐4	☐5
l. I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	☐1	☐2	☐3	☐4	☐5
m. I am committed to exercising regularly.	☐1	☐2	☐3	☐4	☐5
n. The functionality of a car is more important to me than the status of its brand.	☐1	☐2	☐3	☐4	☐5
o. I'm uncomfortable being around people I don't know.	☐1	☐2	☐3	☐4	☐5
p. Family/friends play a big role in how I schedule my time.	☐1	☐2	☐3	☐4	☐5
q. My travel to/from work (or school) is usually pleasant.	☐1	☐2	☐3	☐4	☐5
r. I like sticking to a routine.	☐1	☐2	☐3	☐4	☐5
s. I like the idea of walking as a means of travel for me.	☐1	☐2	☐3	☐4	☐5
t. I definitely want to own a car.	☐1	☐2	☐3	☐4	☐5
u. I'm too busy to have as much leisure time as I'd like.	☐1	☐2	☐3	☐4	☐5

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
v. Cost or convenience takes priority over environmental impacts (e.g. pollution) when I make my daily choices.	☐1	☐2	☐3	☐4	☐5
w. It's okay to give up a lot of time with family and friends to achieve other worthy goals.	☐1	☐2	☐3	☐4	☐5
x. I consider myself to be a sociable person.	☐1	☐2	☐3	☐4	☐5
y. My commute is a useful transition between home and work (or school).	☐1	☐2	☐3	☐4	☐5
z. I would/do enjoy having a lot of luxury things.	☐1	☐2	☐3	☐4	☐5
aa. I prefer to live in a spacious home, even if it's farther from public transportation or many places I go to.	☐1	☐2	☐3	☐4	☐5
ab. A job is just a way to earn money for things I want/need.	☐1	☐2	☐3	☐4	☐5
ac. I generally enjoy the act of traveling itself.	☐1	☐2	☐3	☐4	☐5
ad. To confirm you're really reading this, please select "strongly disagree" here.	☐1	☐2	☐3	☐4	☐5
ae. I like the idea of bicycling as a means of travel for me.	☐1	☐2	☐3	☐4	☐5
af. I am confident in my ability to use modern technologies.	☐1	☐2	☐3	☐4	☐5
ag. I prefer to do one thing at a time.	☐1	☐2	☐3	☐4	☐5
ah. I usually go for the basic ("no-frills") option rather than paying more money for extras.	☐1	☐2	☐3	☐4	☐5
ai. Technology is creating more jobs than it is eliminating.	☐1	☐2	☐3	☐4	☐5
aj. As a general principle, I'd rather own things myself than rent or borrow them from someone else.	☐1	☐2	☐3	☐4	☐5
ak. I like the idea of driving as a means of travel for me.	☐1	☐2	☐3	☐4	☐5
al. Having to wait is an annoying waste of time.	☐1	☐2	☐3	☐4	☐5
am. I tend to feel sick if I read while in a moving vehicle.	☐1	☐2	☐3	☐4	☐5
an. I often introduce new trends to my friends.	☐1	☐2	☐3	☐4	☐5
ao. The importance of exercise is overrated.	☐1	☐2	☐3	☐4	☐5
ap. I often worry about safety during my daily travels.	☐1	☐2	☐3	☐4	☐5
aq. I like to wait a while rather than being first to buy new products.	☐1	☐2	☐3	☐4	☐5
ar. I am committed to an environmentally-friendly lifestyle.	☐1	☐2	☐3	☐4	☐5
as. I wish I could instantly be at work (or school) – the trip itself is a waste of time.	☐1	☐2	☐3	☐4	☐5
at. I'm worried that technology invades my privacy too much.	☐1	☐2	☐3	☐4	☐5
au. I am generally satisfied with my life.	☐1	☐2	☐3	☐4	☐5

Section B: Your use of technology

In this section, we are interested in learning about your use of technology and in understanding how it relates to your lifestyle and travel choices.

1. **How often do you use** each of the following devices and services?

	Never / rarely	*Sometimes*	*Often*	*"Constantly"*
a. Basic cell phone (only calling or texting)	☐1	☐2	☐3	☐4
b. Smartphone	☐1	☐2	☐3	☐4
c. Desktop computer	☐1	☐2	☐3	☐4
d. Laptop, tablet, iPad®, or e-reader	☐1	☐2	☐3	☐4
e. Wearable technology, smart watch, or Fitbit®	☐1	☐2	☐3	☐4

Check or post on...	*Never*	*Monthly or less*	*Weekly*	*Daily*	*"Constantly"*
f. Facebook	☐1	☐2	☐3	☐4	☐5
g. Twitter	☐1	☐2	☐3	☐4	☐5
h. Instagram	☐1	☐2	☐3	☐4	☐5
i. Open forum (e.g. Reddit, Quora)	☐1	☐2	☐3	☐4	☐5
j. WhatsApp, WeChat, Viber, or similar	☐1	☐2	☐3	☐4	☐5

2. In connection with your travel, **how often do you use the internet** (including mobile internet devices, smartphone apps, or GPS in-vehicle) to do each of the following things?

	Never / rarely	*At least once a **year***	*At least once a **month***	*At least once a **week***	*Daily*
a. Check traffic to plan my route or departure time	☐1	☐2	☐3	☐4	☐5
b. Check when a bus or train will be arriving at my stop	☐1	☐2	☐3	☐4	☐5
c. Decide which means of travel to use	☐1	☐2	☐3	☐4	☐5
d. Identify places of interest (e.g. café, repair shop)	☐1	☐2	☐3	☐4	☐5
e. Learn how to get to a new place	☐1	☐2	☐3	☐4	☐5
f. Navigate in real time (e.g. Google Maps, GPS in-vehicle)	☐1	☐2	☐3	☐4	☐5

3. **In the past six months**, how often have you done these things **online**, whether for yourself or someone else?

	Not during the last six months	*Once or twice*	*Three or more times*
a. Buy train, bus, or airline tickets	☐1	☐2	☐3
b. Make lodging reservations (e.g. hotel, Airbnb)	☐1	☐2	☐3
c. Buy goods (e.g. books, flowers, medicine)	☐1	☐2	☐3
d. Pay bills / purchase services (e.g. insurance, plumber)	☐1	☐2	☐3
e. Buy fresh food (e.g. vegetables, dairy products)	☐1	☐2	☐3

Section C: Key aspects of your lifestyle

Learning more about your residential location and living arrangements will help us understand how these factors affect the way you organize your daily activities and the way you travel.

1. How would you characterize the area where:

	Urban part of a city / region	*Suburban part of a city / region*	*Small town*	*Rural area*
a. You grew up (mainly)	□1	□2	□3	□4
b. You live now	□1	□2	□3	□4

2. What best describes the home you currently live in?
   - □1 Stand-alone house
   - □2 Attached home / duplex / townhouse
   - □3 Apartment / condo
   - □4 Dormitory / group housing
   - □5 Mobile home
   - □6 Other (please specify): ___________________

3. Knowing more about your neighborhood will help us put your transportation choices and opinions in context. Please give your address or, if you prefer, an intersection (two streets that cross) near your **home**.

   Street address: ____

   City: _______________________________ Zip code: ___________________________

4. Please give the year in which you *moved* to your current neighborhood.

   Year: ________ (e.g. 1995) **OR** □ I've lived in this neighborhood since I was born

5. What is your relationship status?
   - □1 Married
   - □2 In a relationship
   - □3 Single *(go to Question 7)*

6. Where does your relationship partner live?
   - □1 With me
   - □2 Different place within 5 miles
   - □3 Farther than 5 miles away

7. Who lives with you? Please check ***ALL*** that apply to you.
   - □1 Partner / husband / wife / boyfriend / girlfriend
   - □2 Child(ren) or grandchild(ren)
   - □3 Parent(s) or grandparent(s)
   - □4 Other relative(s) (e.g. siblings, in-laws)
   - □5 Other people (e.g. roommates, caregivers)
   - □6 I live alone (or only with animal companions)

8. What is your current **employment situation**? Please check ***ALL*** that apply.
   - □1 I work full-time for pay
   - □2 I work part-time for pay
   - □3 I am self-employed for pay
   - □4 I have two or more paying jobs
   - □5 I do unpaid work
   - □6 I am a homemaker / caregiver
   - □7 I am retired
   - □8 I do not work
   - □9 Other: ___________________

9. Which statement most accurately describes your current **student status**?
   - □1 I am a full-time student
   - □2 I am a part-time student
   - □3 I am not a student

NOTE: *If you* ***don't work for pay and don't go to school****, please go to Section D.*
If you're a ***non-working student****, please go to Question 14.*
If you work for pay*, please continue with Question 10.*

10. Which option best describes your main **occupation?**
    □1 Professional / technical
    □2 Manager / administrator
    □3 Arts / crafts
    □4 Sales / marketing
    □5 Production / construction
    □6 Service / repair
    □7 Clerical / administrative support
    □8 Other: __________________

11. On average, **how many hours** do you do paid work in a week? ______ hours per week

12. Which one of the following options *most closely* characterizes your **work schedule**?
    Fixed shift: □1 Daytime □2 Evening (swing) □3 Night (graveyard)
    □4 Variable start time / rotating shift
    □5 Compressed work week (e.g. 40 hours in 4 days, or 80 hours in 9 days, with the other days off)
    □6 Flexible (e.g. I organize my own work hours)
    □7 Other (please specify):____

13. On average, how often do you work from home *instead of* going to a regular workplace (i.e., **telecommute**)?
    □1 Not possible / not allowed
    □2 Never
    □3 Less than once a month
    □4 1-3 times a month
    □5 1-3 times a week
    □6 4 or more times a week

14. Please give your **work/school address** or, if you prefer, an intersection (two streets that cross) near your work/school. If you go to both work and school, please provide the place where you go more often.
    □ I only work / take classes from home.

    Street address: ____

    City: _______________________________ Zip code: ___________________________

Section D: How you travel

In this section, we would like to get a sense of the travel you currently do.

1. At what age did you get your driver's license? _____ (□ I don't have a license)

NOTE: In this survey, a **household** means "people who live together and *share at least some financial resources*." Unrelated roommates would usually not be considered household members.

2. How many ***other*** people in your household (***NOT including yourself***) hold a driver's license? _____

3. How many cars (including light truck, minivan, SUV, and motorcycle) does your household have? _____

4. What are the make, model, and year of the vehicle you drive **most often**? □ Not applicable

   Make:___________________ Model:___________________ Year:___________________

5. Do you have any physical conditions or anxieties that prevent or limit you from…

	No limitation	*Limits how often/how long*	*Absolutely prevents*
a. Driving during the day?	□1	□2	□3
b. Driving at night?	□1	□2	□3
c. Driving on the freeway?	□1	□2	□3
d. Taking public transit?	□1	□2	□3
e. Walking?	□1	□2	□3
f. Riding a bicycle?	□1	□2	□3

6. Please indicate **how often** you typically make **local** (i.e. not overnight) trips using each of the following means of transportation. ***Your best guess is fine!*** Please keep the following important points in mind:
   - A **trip** is a movement from one place to another – for any purpose, by any means of travel. Include things like walking the dog or riding a bike for fun.
   - If you make *multiple stops with different purposes,* count them as different trips (e.g. dropping kids at school on the way to work means two trips).
   - Don't count the *return-home* trip.
   - If a trip *to a single place has more than one purpose* (e.g. you go to work, but also eat lunch there), only report it under the more important purpose.
   - If *more than one means of travel* is used on a given trip, count just the one used for the longest distance.

All local trips EXCEPT going to your work or school (including shopping, eating/drinking, social/recreational, bringing/taking others, religious services, etc.)

	Never	*Less than once a **month***	*1-3 times a **month***	*1-2 times a **week***	*3-4 times a **week***	*5 or more times a **week***
a. Car driver (alone)	□1	□2	□3	□4	□5	□6
b. Car driver (with others)	□1	□2	□3	□4	□5	□6
c. Car passenger	□1	□2	□3	□4	□5	□6
d. Bus or train	□1	□2	□3	□4	□5	□6
e. Walking	□1	□2	□3	□4	□5	□6
f. Bicycle	□1	□2	□3	□4	□5	□6

NOTE: *If you **do not travel to work or school**, please check this box □ and go to Question 13.*
***Otherwise**, please continue answering the following questions.*

Going to your work or school (commuting)

	Never	*Less than once a **month***	*1-3 times a **month***	*1-2 times a **week***	*3-4 times a **week***	*5 or more times a **week***
a. Car driver (alone)	□1	□2	□3	□4	□5	□6
b. Car driver (with others)	□1	□2	□3	□4	□5	□6
c. Car passenger	□1	□2	□3	□4	□5	□6
d. Bus or train	□1	□2	□3	□4	□5	□6
e. Walking	□1	□2	□3	□4	□5	□6
f. Bicycle	□1	□2	□3	□4	□5	□6

7. How far do you live **from work/school**? If you go to more than one place for work/school, choose the one you go to **most often**. ________ miles

8. What is your primary means of transportation **to this work or school location**? Please check *only one*.
   - □1 Car driver (alone)
   - □2 Car driver (with others)
   - □3 Car passenger
   - □4 Uber or Lyft
   - □5 Bus or train
   - □6 Walk
   - □7 Bicycle
   - □8 Other (please specify): ______________________

9. How long (on average) does it take you to get **from home to this work/school location**? ________ minutes

10. Some people may want to use their travel time productively (e.g. make phone calls, work on a laptop), while others may just want to relax (e.g. nap or listen to music). To what extent do conditions during your trip to work/school allow you to do the things you might want to do while traveling?

    Hardly at all □1 □2 □3 □4 □5 *Almost completely*

11. In terms of its ***value to you***, how would you rate the time you ***now*** spend on your typical trip to work/school?

    Mostly wasted time □1 □2 □3 □4 □5 *Mostly useful time*

12. If you could choose, what would be your **ideal one-way travel time to work/school**? ________ minutes

13. Now considering your travel for *all* purposes, **how many miles** do you **personally drive** in a typical week? If you are a professional driver (e.g. bus, truck, taxi, or Uber/Lyft driver), please do ***not*** include the miles you cover as part of your job. Your answer doesn't have to be exact – ***your best guess is fine***!

    ________ miles per week

14. How far away from home is the **most distant place you go to** in a typical week? Please consider any purpose **by any means of travel**.
    - □1 Less than 5 miles
    - □2 5-15 miles
    - □3 16-40 miles
    - □4 41-75 miles
    - □5 76-150 miles
    - □6 More than 150 miles

Turning now to longer trips, we'd like for you to think of the business trips, vacations, and visits to friends and relatives you've made ***over the past 12 months***. Again, ***your best guesses are fine!***

15. **How many trips** involving an *overnight stay* did you make? Please do not double-count trips – just classify them under their most distant destination, the travel means used for the longest portion of the trip, and the most important purpose. If you did not travel to a certain destination, check the "*None*" box for that row.

		Business/work/school-related				*Leisure/recreation/social (e.g. vacation)*			
	None	*Car*	*Bus*	*Plane*	*Other*	*Car*	*Bus*	*Plane*	*Other*
Example	□	*2*	___	*1*	___	*3*	___	*1*	___
a. Within Georgia	□	___	___	___	___	___	___	___	___
b. Within Tennessee, Florida, North/South Carolina, or Alabama	□	___	___	___	___	___	___	___	___
c. Elsewhere in the U.S.	□	___	___	___	___	___	___	___	___
d. Canada, Mexico, or the Caribbean	□	___	___	___	___	___	___	___	___
e. Elsewhere in the world	□	___	___	___	___	___	___	___	___

16. Over the past 12 months, how many nights ***in all*** have you been away from home?
    - □1 None
    - □2 1-10 nights
    - □3 11-25 nights
    - □4 26-50 nights
    - □5 More than 50 nights

Section E: Evolving transportation services

In this section, we ask about your experience with various transportation services, whether "at home" or elsewhere. *Your answers are important even if you're not familiar with all of these services.* Please consider:

- **Carsharing**: using internet / smartphone apps to rent automobiles by the hour or day (e.g. Zipcar)
- **On-demand ride services**: calling for rides by using smartphone apps (e.g. Uber, Lyft)
- **Shared on-demand ride services**: sharing Uber/Lyft to reduce the cost (e.g. UberPOOL, Lyft Line)
- **Traditional taxi services** (e.g. Yellow Cab, Atlanta Checker Cab)

1. How *familiar* are you with the following transportation services? Please check the single most appropriate answer for *each* service below.

	I've never heard of it	*I've heard of it but not used it*	*I have used it*
a. Carsharing (e.g. Zipcar)	☐1	☐2	☐3
b. On-demand ride service (e.g. Uber, Lyft)	☐1	☐2	☐3
c. Shared on-demand ride service (e.g. UberPOOL)	☐1	☐2	☐3
d. Traditional taxi service (e.g. Yellow Cab)	☐1	☐2	☐3

2. Are the following transportation services *available* where you live?

	Yes	*No*	*I don't know*
a. Carsharing (e.g. Zipcar)	☐1	☐2	☐3
b. On-demand ride service (e.g. Uber, Lyft)	☐1	☐2	☐3
c. Shared on-demand ride service (e.g. UberPOOL)	☐1	☐2	☐3
d. Traditional taxi service (e.g. Yellow Cab)	☐1	☐2	☐3

3. What were the *purposes* of the trips for which you used each of the following transportation services (in either direction)? Please check ***ALL*** purposes that apply to you.

	I've not used this service	*Work/ school related*	*Shopping*	*Eating/ drinking*	*Social/ recreational*	*Airport*	*Other (e.g. medical)*
a. Carsharing	☐1	☐2	☐3	☐4	☐5	☐6	☐7
b. On-demand ride service	☐1	☐2	☐3	☐4	☐5	☐6	☐7
c. Shared on-demand ride service	☐1	☐2	☐3	☐4	☐5	☐6	☐7
d. Traditional taxi service	☐1	☐2	☐3	☐4	☐5	☐6	☐7

4. Please indicate *how often* you typically use each of the following transportation services.

	Never used / No longer use	*Less than once a **month***	*1-3 times a **month***	*1-2 times a **week***	*3 or more times a **week***
a. Carsharing	☐1	☐2	☐3	☐4	☐5
b. On-demand ride service	☐1	☐2	☐3	☐4	☐5
c. Shared on-demand ride service	☐1	☐2	☐3	☐4	☐5
d. Traditional taxi service	☐1	☐2	☐3	☐4	☐5

Questions 5 and 6 ask about Uber/Lyft. Your opinions are important ***even if you have not used these services.***

5. Please indicate your impressions of Uber/Lyft ***as a (potential or actual) passenger***, with respect to each of these characteristics.

	Very bad	*Bad*	*Neutral*	*Good*	*Very good*
a. Ease of use and payment	□1	□2	□3	□4	□5
b. Cost	□1	□2	□3	□4	□5
c. Service area or availability	□1	□2	□3	□4	□5
d. Waiting time	□1	□2	□3	□4	□5
e. Travel time compared to my usual means of transportation	□1	□2	□3	□4	□5
f. Comfort	□1	□2	□3	□4	□5
g. Safety	□1	□2	□3	□4	□5
h. No need to park	□1	□2	□3	□4	□5
i. Can avoid driving myself or asking a friend	□1	□2	□3	□4	□5
j. Riding with strangers (driver / passengers)	□1	□2	□3	□4	□5
k. Getting around at night	□1	□2	□3	□4	□5
l. Convenient when carrying things	□1	□2	□3	□4	□5
m. Drivers (skill and friendliness)	□1	□2	□3	□4	□5
n. Overall effect on traffic congestion	□1	□2	□3	□4	□5

6. In general, if you were to use Uber/Lyft, how long would you be willing to wait for the vehicle to arrive?
   □1 Less than 3 min □2 3-5 min □3 6-10 min □4 11-15 min □5 More than 15 min

NOTE: *Please answer Questions 7 and 8 with respect to your use of Uber/Lyft.*
If you ***<u>have NOT used Uber/Lyft</u>****, please check this box □ and go to Section F.*

7. Please think about the **most recent trip** you made by Uber/Lyft. How did your choice of Uber/Lyft affect your use of other means of transportation? Please check ***ALL*** that apply.
   - □1 ***Reduced*** the amount of driving that I did (or that a friend / relative would have done for me)
   - □2 ***Reduced*** my use of taxi
   - □3 ***Reduced*** the amount of walking / biking I did
   - □4 ***Reduced*** my use of public transportation
   - □5 ***Increased*** the amount of walking / biking I did
   - □6 ***Increased*** my use of public transportation by providing a better way to access public transportation services, from a location not directly served by transit
   - □7 ***Increased*** my use of public transportation by providing a ride (e.g. back home at night) outside of scheduled public transportation service hours
   - □8 It was a ***new trip*** I would not have made by other means
   - □9 Other (please specify): ____

8. What is the maximum fare you have paid for a **single Uber/Lyft trip** in the **past 6 months**? Please provide your best estimate:
   $ ________ OR □ I have not used Uber/Lyft within the past 6 months

Section F: Your desires for future travel

We are interested in your expectations about where you'll live and how you'll travel a few years from now. Remember: there are no right or wrong answers – we only want to know ***what you think may happen***.

1. **Within the next three years**, how likely is each of the following changes to happen to you?

	Very unlikely	*Unlikely*	*Neutral*	*Likely*	*Very likely*
a. Move to a different home	□1	□2	□3	□4	□5
b. Start a new job / change my job	□1	□2	□3	□4	□5
c. Leave / retire from my job	□1	□2	□3	□4	□5
d. Start to study, or move to a new school	□1	□2	□3	□4	□5
e. Get married	□1	□2	□3	□4	□5
f. Have / adopt a child	□1	□2	□3	□4	□5
g. Have some members of my household move away (e.g. "children leaving the nest")	□1	□2	□3	□4	□5

2. Imagine that you are moving to a different home. Would you like to…?

□1 Move to a more urban part of a city / region
□3 Move to a small / college town
□2 Move to a more suburban part of a city / region
□4 Move to a more rural area
□5 Stay in the same type of area in which I live now

3. **Three years from now,** how much would you like to travel by each of these means?

	Less *than I currently do*	*About the* ***same***	***More*** *than I currently do*
a. By walk	□1	□2	□3
b. By bike	□1	□2	□3
c. By local bus/train	□1	□2	□3
d. By car	□1	□2	□3
e. By inter-city bus	□1	□2	□3
f. By air	□1	□2	□3

4. What do you expect will happen to your household's car ownership **within the next three years**?

□1 No change – will not add or get rid of a car
□3 Decrease the number of cars
□2 Replace one or more cars, keeping the same total
□4 Increase the number of cars

5. What do you expect to do regarding your use of carsharing (such as ZipCar) **within the next three years**?

□1 Continue *not* using carsharing
□3 *Begin* using carsharing
□5 *Stop* using carsharing
□2 *Resume* using carsharing
□4 *Keep* using carsharing
□6 I'm not sure

6. Would you *ever* be interested in buying or leasing a vehicle that runs on any of these **alternative fuels**?
Check here □1 if not interested, otherwise please check ***ALL*** that apply.

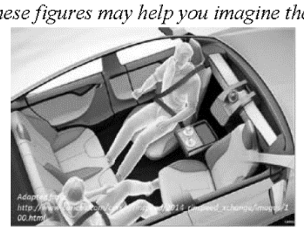
□2 Gasoline hybrid (e.g. Toyota Prius)
□6 Flex-fuel vehicle (runs on gasoline or ethanol)
□3 Diesel
□7 Hydrogen fuel cell (e.g. Honda Clarity)
□4 Battery electric (e.g. Nissan Leaf, Tesla Model S)
□8 I don't know
□5 Compressed Natural Gas (CNG)
□9 Other (please specify): ________________

Section G: What if cars could drive themselves?

In this section, we'd like to know your opinions on ***self-driving (or driverless) cars***. Such vehicles drive themselves and control all operating and safety functions, and are even able to travel without a human inside. For our purposes, we want you to ***imagine*** a future where all cars are *fully automated* and do not need humans driving them (we will later ask you how far off you think this future is). Specifically, please assume that …

- Traditional cars can no longer be used in regular traffic – self-driving cars are the *only way to go by car*.
- Driverless cars are *at least as safe* as today's cars are, and *cost about as much* as today's cars do.
- You could *furnish* your self-driving car with a TV, kitchenette, recliner, light exercise equipment, etc.
- You could send an empty self-driving car somewhere to *pick up other people or things, or to park* after dropping you off at work or the ball game.
- You could let a self-driving car take you places *while you are sleeping*.

These figures may help you imagine the possibilities.



1. We are interested in your *awareness of* or *familiarity with* the concept of a self-driving car before you started taking this survey. Please check the response that best describes you.

   ☐1 I had *never heard* of it
   ☐2 I had heard of it but am *not familiar* with it
   ☐3 I had heard of it and am *somewhat familiar* with it
   ☐4 I had heard of it and am *very familiar* with it

2. For ***each*** of the following statements, please check the response that best expresses your opinion. ***Your impressions are important*** even if you're not very sure about some of the topics mentioned.

	Strongly disagree	*Disagree*	*Neutral*	*Agree*	*Strongly agree*
a. A self-driving car would enable me to get to places faster than if I had to drive myself.	☐1	☐2	☐3	☐4	☐5
b. I would gain a lot of useful time by sending my vehicle to do certain things (e.g. pick up dry cleaning) without me.	☐1	☐2	☐3	☐4	☐5
c. I would miss the joy of driving and the feeling of being in control.	☐1	☐2	☐3	☐4	☐5
d. I am concerned that the self-driving car would lead to spending less time with family or friends (e.g. because of having more work trips).	☐1	☐2	☐3	☐4	☐5
e. I would more often travel even when I am tired or sleepy.	☐1	☐2	☐3	☐4	☐5
f. A self-driving car would reduce by too much the exercise I get through walking or biking.	☐1	☐2	☐3	☐4	☐5

	Strongly disagree	*Disagree*	*Neutral*	*Agree*	*Strongly agree*
g. A self-driving car would enable me to enjoy traveling more (e.g. watching the scenery).	☐1	☐2	☐3	☐4	☐5
h. To confirm you're still really reading this, please select "strongly disagree" here.	☐1	☐2	☐3	☐4	☐5
i. Even if I could do other activities in the car while it drove itself, I would not gain that much useful time.	☐1	☐2	☐3	☐4	☐5
j. I would be able to travel more often when under the influence of alcohol or medicines.	☐1	☐2	☐3	☐4	☐5
k. I am concerned that the self-driving car would lead to me using a car too much.	☐1	☐2	☐3	☐4	☐5
l. Having the vehicle drive itself would allow me to be more comfortable on trips.	☐1	☐2	☐3	☐4	☐5
m. I would reduce my parking costs because my self-driving car could drive itself to a cheaper parking space.	☐1	☐2	☐3	☐4	☐5

3. If self-driving cars were the only cars available, how likely would you be to ***own*** a self-driving car, ***use*** self-driving services (such as a driverless taxi), or do both?

	Very unlikely	*Unlikely*	*Somewhat likely*	*Likely*	*Very likely*
a. I would own a self-driving car.	☐1	☐2	☐3	☐4	☐5
b. I would use a driverless taxi alone or with others I know.	☐1	☐2	☐3	☐4	☐5
c. I would use a driverless taxi with other passengers who are strangers to me (like UberPOOL).	☐1	☐2	☐3	☐4	☐5

4. For *each* pair of options below, please mark an "X" at the place that best reflects how close your general inclination is to one side or the other, as shown in the following example. ***Please imagine yourself in each situation***, even if it would not normally apply to you.

Example

Between the two options, if you are somewhat more inclined to watch a movie, mark like this…

Option A	*I'm more inclined to:*	*Option B*
Read a book on weekend	├──┼──┼──×──┼──┤	Watch a movie on weekend

I'm more inclined to:

Option A		*Option B*
Walk/bike for 20 minutes to get to a transit station	├──┼──┼──┼──┼──┤	Take a self-driving car to get to a transit station
Walk/bike for 20 minutes to get to work/school	├──┼──┼──┼──┼──┤	Take a self-driving car to get to work/school
Walk/bike for 20 mins to go shopping	├──┼──┼──┼──┼──┤	Take a self-driving car to go shopping
Walk/bike for 20 mins to social activities or to do personal business	├──┼──┼──┼──┼──┤	Take a self-driving car to social activities or to do personal business
Take a bus or train to get to work/school	├──┼──┼──┼──┼──┤	Take a self-driving car to get to work/school

Option A	*I'm more inclined to*:	Option B
Take a bus or train to go shopping	├──┼──┼──┼──┼──┤	Take a self-driving car to go shopping
Take a bus or train to social activities or to do personal business	├──┼──┼──┼──┼──┤	Take a self-driving car to social activities or to do personal business
Fly to a vacation in a distant state	├──┼──┼──┼──┼──┤	Take a self-driving car to a vacation in a distant state
For a one-day trip, fly for 3 hours each way (including access/wait time)	├──┼──┼──┼──┼──┤	For a one-day trip, take a self-driving car for 6 hours each way
Go with the car to bring my child	├──┼──┼──┼──┼──┤	Send an empty self-driving car to bring my child
Go with the car to bring other people who are not able to drive	├──┼──┼──┼──┼──┤	Send an empty self-driving car to bring others who are not able to drive
Go with the car to pick up meals	├──┼──┼──┼──┼──┤	Send an empty self-driving car to pick up meals

5. How likely is it that self-driving cars would **change your behavior**, in each of the following ways?

I would…	*Very unlikely*	*Unlikely*	*Somewhat likely*	*Likely*	*Very likely*
a. Eat out in restaurants more often.	☐1	☐2	☐3	☐4	☐5
b. Go to grocery stores or shopping malls more often.	☐1	☐2	☐3	☐4	☐5
c. Travel to social/leisure activities more often.	☐1	☐2	☐3	☐4	☐5
d. Go to more distant restaurants.	☐1	☐2	☐3	☐4	☐5
e. Go to more distant grocery stores or shopping malls.	☐1	☐2	☐3	☐4	☐5
f. Socialize with people who live farther away.	☐1	☐2	☐3	☐4	☐5
g. Travel to more distant locations for leisure.	☐1	☐2	☐3	☐4	☐5
h. Eliminate some overnight trips because it would be easier to come back the same day.	☐1	☐2	☐3	☐4	☐5
i. Make more overnight trips by car because it would be less burdensome to travel long distances.	☐1	☐2	☐3	☐4	☐5
j. Go to work/school at a different time to avoid traffic jams, since I can sleep/work in the car.	☐1	☐2	☐3	☐4	☐5
k. Take part in more leisure activities after dark, because I wouldn't need to drive myself.	☐1	☐2	☐3	☐4	☐5
l. Take vacations more often.	☐1	☐2	☐3	☐4	☐5
m. Reduce my time at the regular workplace and work more in the self-driving car.	☐1	☐2	☐3	☐4	☐5
n. Sleep less time at home and more time in the car, to be more efficient.	☐1	☐2	☐3	☐4	☐5
o. More often eat meals in a self-driving car instead of at home or in a restaurant.	☐1	☐2	☐3	☐4	☐5
p. Cultivate new hobbies or skills with the time I saved.	☐1	☐2	☐3	☐4	☐5

6. Where would you prefer to live, if self-driving cars were available? Please check the *single* best answer.
   - □1 I would like to move closer to the locations I travel to most often (e.g. workplace or school).
   - □2 Having a self-driving car would not influence me to move somewhere else.
   - □3 I would like to move to a more attractive location, even if it means being farther from the locations I travel to most often.

7. Considering **the number of cars** your household currently owns, how would that change if self-driving cars were the only cars available?

   □1 Very likely to own *fewer* cars　□2 Somewhat likely to own *fewer* cars　□3 Most likely to own the *same* number of cars　□4 Somewhat likely to own *more* cars　□5 Very likely to own *more* cars

8. How many years do you think it will take for **all cars** to be ***fully*** self-driving?

   □1 10 years or less　□2 11-20 years　□3 21-30 years　□4 More than 30 years　□5 Never

Section H: Some background about yourself

Your responses in this section enable us to expand the results from this small sample to the population as a whole.

1. Are you… □1 Female □2 Male □3 Other

2. In what year were you born? Year: ________ (e.g. 1975)

3. How would you describe yourself? Please check *ALL* that apply to you.

   □1 Asian / Pacific Islander　□3 Hispanic / Latino　□5 White / Caucasian
   □2 Black / African American　□4 Native American　□6 Other (please specify): _______

4. What is your educational background? Please check the highest level attained.

   □1 Some grade/high school　□3 Some college/technical school　□5 Some graduate school
   □2 Completed high school or GED　□4 Bachelor's degree　□6 Completed graduate degree(s)

5. How many people (***including yourself***) live in your household? As a reminder, unrelated roommates are usually not considered household members.

   _______ people

6. Please **write the number** of your household members (***including yourself***) falling into the different age groups shown below (your answers should add up to the number of people indicated in Question 5).

   ____ persons under 6　____ persons 15-17　____ persons 27-34　____ persons 51-65
   ____ persons 6-14　____ persons 18-26　____ persons 35-50　____ persons over 65

7. Please check the category that contains your approximate annual *household* income before taxes.

   □1 Less than $25,000　□3 $50,000 to $74,999　□5 $100,000 to $149,999
   □2 $25,000 to $49,999　□4 $75,000 to $99,999　□6 $150,000 or more

To send you our token of appreciation, we need to know how to contact you. *We will only use this information for the purposes you authorize*. However, if you wish to return the survey completely anonymously (forgoing the $2 bill), you don't need to provide your contact information.

For what purposes may we contact you? Please check ***ALL*** that apply.

- ☐ To send the token of appreciation.
- ☐ For any questions about this survey.
- ☐ For a follow-up survey sometime in the future.

In what ways may we contact you? Please provide ***ALL*** that apply.

Name: ____

Telephone: ______________________ or ______________________

E-mail: ____

Mail: ________________________________

____

____

We would value any additional comments you may have, on self-driving cars or any other topics in this survey. Please write them in the space below, and/or attach another page.

Thank you for your participation in this study!

PART 2

Empirical Findings

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EXECUTIVE SUMMARY

PART 2

The research team designed and implemented a wide-ranging survey that aims to capture Georgians' opinions about various travel-related issues, their use of travel-related technologies, and their travel behavior along a number of dimensions (for more details about the study and survey design, please refer to Part 1 of this report). The working sample from this survey contains 3,288 cases. We developed and applied case weights to render the sample representative of the adult population of Georgia with respect to nine geographic and demographic variables; all statistics presented in this report are based on the weighted sample, unless otherwise specified. Further, we enriched the dataset through appending a variety of land use variables in support of our analyses.

The study explores five main themes: general travel behaviors, commute and work patterns, general opinions and attitudes, new and emerging technologies and services, and future transportation (with a specific focus on autonomous vehicles). Among other segmentations, we stratified many of the variables analyzed by four metropolitan planning organization (MPO)-based tiers: the Atlanta region, mid-size MPO areas (those with populations greater than 200,000), small MPO areas, and rural areas.

General Travel Behaviors (Chapter 2) describes the population of Georgia with respect to several key travel indicators. We first investigate two of the most fundamental travel-related decisions: vehicle ownership and the choice to drive. We then examine local travel (in terms of general indicators of trip frequency and distance) and long-distance trips. Some selected key findings are:

- Residents of larger MPO areas tend to have fewer vehicles. For example, only 25 percent of Atlanta-region residents have 3 or more vehicles per household, whereas 38 percent of non-MPO area (i.e., rural) residents do.

- The Atlanta region has a notably higher fraction of (only) one-car-per-adult households (51%), whereas households in the smaller MPO areas have a greater tendency to own "surplus" vehicles.
- Despite the low levels of current ownership of alternative-fuel vehicles (2.2% of primary vehicles are hybrid/electric), respondents exhibit considerable interest in buying/leasing such vehicles, with more than half (59%) indicating the appeal of one or more alternative fuels.
- Drivers' licensing differs substantially with income, employment status, and regional and local geography.
- There is no clear difference in the frequency of solo-driver commuting across the MPO regions of the state, with 70–74 percent of commuters driving alone for 5 or more times a week. Of course, there can be substantial differences *within* MPO category.
- Residents of the smaller MPO areas (and to some extent, rural residents) are substantially more likely than Atlanta-area residents to occasionally carpool: for example, 65 percent of Atlanta-region respondents never drive other passengers on their commute, whereas only 51–54 percent of other respondents never do so.
- Sixty-six percent of higher-income people traveled by airplane over the past 12 months, whereas only 18 percent of lower-income people did. Similarly, 90 percent of higher-income people traveled long-distance by car, whereas only 55 percent of lower-income people did.

Commute and Work Patterns (Chapter 3) explores the commute patterns of Georgia residents. Some selected key findings are:

- Nearly 14 percent of workers report being self-employed (multiple answers were allowed), and more than 6 percent hold two or more paying jobs.

- A fixed shift is by far the most common work schedule (65% of workers), followed by flexible schedules (19% of workers). Only 4 percent have compressed work weeks (e.g., 9/80 or 4/40).
- In terms of primary commute mode, nine out of 10 workers commute by car, eight of them by driving alone. More than 5 percent “commute” by working at home, compared to 3 percent who use transit. Two percent bicycle or walk to work.
- On average, Georgia residents commute 16.6 miles and 30 minutes. Atlanta-region residents have the longest average commute time (34 minutes).
- More than half (58%) of all workers are either not able/allowed to telecommute (33.3%) or never do so (24.3%).
- In general, workers in the Atlanta region are better able to telecommute than others, and do so more frequently.
- Twenty-one percent of higher-income people are not able/allowed to telecommute, whereas that share is almost doubled (41%) for lower-income people. Thirty-four percent of higher-income people telecommute once or more per week, whereas only 15 percent of lower-income people do.

General Opinions and Attitudes (Chapter 4) portrays Georgians’ general attitudes on several transportation-related dimensions. Some selected key findings are:

- Georgians are decidedly favorable toward owning and driving cars, not just as a matter of necessity but also out of liking.
- Atlanta region residents tend to be more tech-savvy, pro-exercise, and urbanite than others, and less pro-suburban.
- On average, Atlanta residents perceive less benefit from commuting compared to residents in smaller MPO areas—presumably a function of the recurrent heavy congestion in the Atlanta region.

- On average, younger people tend to be more work-oriented, tech-savvy, pro-exercise, travel-liking, and favorable to non-car alternatives.

New and Emerging Technologies and Services (Chapter 5) describes how people use technologies and emerging services, such as information and communications technology (ICT) devices and shared mobility (ridehailing, in particular) services. Some selected key findings are:

- On average, younger people and higher-income people use ICT devices more frequently. Approximately 65 percent of millennials (ages 18–34) use a smartphone "constantly", whereas only 38 percent of those age 45–64 do; 77 percent of higher-income people use laptops or similar devices often or "constantly", whereas 42 percent of lower-income people do.
- On average, 58 percent of Atlanta region residents check traffic to plan their route or departure time at least once a week, whereas only about 30 percent of residents in other areas check traffic via the internet with the same frequency.
- Younger people, those with higher incomes, Atlanta region residents, and urban dwellers use ridehailing more frequently than others. For example, 22 percent of residents in the Atlanta area reported using ridehailing at least once a month, while fewer than 10 percent of residents in other areas did.
- More than 40 percent of ridehailing service users have used them in connection with eating/drinking activities, and nearly half for accessing the airport.
- Compared to others, Atlanta region residents and urban area residents have distinctively higher fractions of ridehailing use for work/school-related, eating/drinking, and airport access purposes.
- With respect to the most recent use, ridehailing services seem to have more substitution effects than complementarity and generation effects, including both car-for-car substitution (about 70–80 percent of people reported that use of Uber/Lyft reduced driving by

themselves or other friends/relatives, but of course it increased car travel in the ridehailing vehicles) and net reductions in the use of active transportation and public transit modes.

- A non-trivial fraction (12%) of most-recent ridehailing trips constituted new (vehicle) travel.

Future Transportation: Autonomous Vehicles (Chapter 6) explores how people perceive autonomous vehicles (AVs), and how they envision their behavior in a (possible) future era when all cars will be autonomous. Although these views will certainly evolve over time, the glimpse into current opinions is still valuable, and provides a benchmark against which to monitor the evolution. Some selected key findings are:

- Only 7.7 percent of the sample have never heard of AVs; on average, the residents of the Atlanta region are more familiar with AVs than residents in other areas.
- Respondents perceive a number of benefits of AVs, such as increased comfort and enjoyment of travel, and time savings. They tend not to be concerned about many potential disadvantages of AVs. However, they would miss the joy of driving and the sense of control, and do not believe that an AV trip will be faster than if driving themselves.
- Residents of the larger MPO areas, higher-income people, and younger people perceive/ expect more potential benefits from AVs.
- The more private the vehicle, the more willing the respondent to use it. Half of respondents (51%) said they are likely or very likely to *own* a self-driving car, whereas 27 percent and 12 percent are likely or very likely to use a driverless taxi alone/with others and with strangers, respectively. Especially considering that multiple answers were allowed, this indicates that a sizable fraction of people are disinclined to use AVs at all: 22 percent of respondents are unlikely or very unlikely to use *any* of these options.

- More than half of the sample (57%) expect to own the same number of cars as today and 38 percent of people expect to shed one or more cars, whereas 5 percent of people expect to increase the number of cars in the household.
- In terms of current vehicle ownership, 41 percent of people having two or more vehicles expect to shed one or more vehicles, whereas only 28 percent of people having one vehicle expect to reduce the number of vehicles. Ninety-six percent of carless individuals expect to continue not to own any vehicles.
- In terms of residential location, three-quarters (77%) of the sample expect that AVs would not influence their residential location choice.
- In the AV era, higher shares of residents in more urban areas would prefer to move (either closer to the locations they travel most often or to a more attractive but possibly more distant location), compared to residents of less urban areas.

Some planning and/or policy implications of these findings include the following:

- The high level of interest in alternative-fuel vehicles suggests considerable receptivity to policies promoting their adoption, potentially including tax credits or other price-lowering instruments; increased density of charging stations to ameliorate range anxiety; and support of research and development of technologies that would increase range and/or lower cost (Section 2.1.3).
- Carpooling has not been found to be an especially popular commute mode, and the present study is no exception (Section 2.3.1 and Section 3.2.1). However, new technologies have improved the ability to match drivers and passengers in real time, and simplify the financial transaction. There may be scope for increasing commute carpooling through promoting such technological applications.
- The disparity in driver's licensing between workers and non-workers, and higher versus lower incomes, is striking (Section 2.2), and the direction of causality is not clear. However,

research has shown (Blumenberg and Pierce, 2014; 2017) that lack of access to a car restricts access to employment opportunities. Accordingly, additional investigation into the causes of lower licensing rates for non-workers and lower-income people may identify barriers amenable to policy intervention.

- Although there is a somewhat irreducible share of jobs that cannot be telecommuted, there may be considerable scope for increasing the approval of telecommuting among organizations/managers who currently do not allow it, and for increasing its adoption among workers who currently do not engage in it (Section 3.2.3).
- The increasing adoption of ridehailing, though expanding the mobility options for many and allowing some to forgo vehicle ownership (while still relying on *others'* personal vehicles) is not altogether benign, in view of its apparent impacts on transit, active transportation, and trip generation (Section 5.3.2). Ingenuity is called for in identifying ways to promote the benefits of ridehailing while mitigating its disbenefits.
- People show a marked disinclination to share rides with strangers, both currently (Section 2.3.1, Section 3.2.1, and Section 5.3.2) and in an automated-vehicle future (Section 6.2.1). To avoid some of the proliferation of vehicular travel that is already underway and likely to accelerate in an AV era, it will be important to find meaningful incentives to promote sharing rides.
- On the other hand, a sizable fraction of people expects to be able to shed a car in the AV era (Section 6.2.3). Incentivizing that inclination could lead to more efficient use of the vehicle fleet, and benefits to those travelers who can reduce their car-related expenses while still fulfilling their mobility needs. However, from a societal perspective it would be important that a reduction in household vehicles not be accompanied by a sizable amount of deadheading by the remaining vehicle(s), as they reposition themselves to serve the needs of multiple household members. More research is needed to improve our

understanding of the personal and societal tradeoffs among household vehicle ownership, deadheading travel, and sharing rides.

- The AV era has the potential to greatly increase the set of residential locations considered feasible by a household (Section 6.2.3). Among the minority who anticipate an AV-stimulated move, current inclinations are fairly evenly split between moving "closer" and moving "farther away". However, it will be important to monitor these preferences over time, as there can be substantial implications for urban decentralization and exurban development—i.e. for more resource-intensive urban forms.

1. INTRODUCTION

1.1. Background and Research Need[1]

The Georgia Department of Transportation (GDOT) has invested considerable effort and resources into improving travel demand models in support of transportation planning across the state. For example, a recent project (RP 16-12, The Integration of Regional MPO Models into the Georgia Statewide Travel Demand Model – Phase 1) developed a plan to integrate the Georgia Statewide Travel Demand Model (GSTDM) with the regional models that are directly developed and maintained by GDOT for Georgia's 14 metropolitan planning organizations (MPOs) outside of Atlanta, so as to simplify model maintenance and improve the accuracy of the model results (Circella et al., 2018). Another avenue for improving transportation demand models is to update and increase our understanding of how people travel and the corresponding key motivations and factors influencing their travel-related decisions. The Georgia subsample of the recent National Household Travel Survey (NHTS) provides an updated snapshot on *how* people travel, and another GDOT project (RP 18-24, Analysis of the Georgia Add-on to the 2016-2017 National Household Travel Survey) is underway to fully analyze the NHTS data. The present project (RP 16-31) offers insight into *why* people travel the way they do, as well as a glimpse of future intentions and expectations regarding emerging new technologies. These two projects are working synergistically with RP 16-12 and its successor, RP 18-08 (Improvement of the Georgia Statewide Travel Demand Model (GSTDM) – Phase 2), to support GDOT's statewide planning activities.

Although travel behavior, or demand, may have been somewhat stable in the not-too-distant past, we are facing disruptive technologies, new trends, and paradigms that are changing, and will change, behavior significantly. Advanced technologies are generating a number of changes with direct implications for travel demand in Georgia: working at home, online shopping,

[1] This section repeats Section 1.1 of Part 1, for those who begin reading with Part 2.

ridehailing services, and carsharing. Additional technologies (such as autonomous vehicles, or AVs) are expected to impact how people travel in the near- or medium-term future. These new options are transforming travel-related decision-making in the population at large—but especially among certain population segments such as "millennials" (loosely inclusive of 18–35-year-olds). These ongoing changes have a huge potential to modify the demand for housing, vehicle sales, the amount of travel by private vehicles, and the resulting gasoline tax revenues and emissions of greenhouse gases and criteria pollutants. Accordingly, travel demand forecasting models need to be updated to account for these new patterns; however, this must be preceded by acquiring a better understanding of the new trends and processes at work.

Unfortunately, although transportation experts agree that we need to understand the impact of new and emerging technologies on travel behavior/demand, we often lack the proper data for doing so. The present study aims to address this gap for the state of Georgia by providing a recent snapshot of what people think about transportation-related topics, and how they adopt new technologies, how they travel, and how they make decisions. As such, the study seeks to update our understanding in these areas, and, thus, potentially to contribute to improving transportation planning and demand forecasting for Georgia residents.

In view of respondents' finite willingness to cooperate, nearly every survey represents a compromise between breadth and depth. The survey designed for the present study emphasized the former over the latter. Consequently, this study does not take a fine-grained look at each topic (e.g., going into great detail about Uber usage), but instead aims to supply a broad-brush view of overall travel patterns, opinions, and other characteristics that might be of interest to local governments or agencies. Similarly, this study does not seek to propose specific policy strategies (e.g., how much, or what, incentive should be offered to motivate people to use carpooling rather than driving alone). Rather, we expect this research to provide an overall sense of the transportation landscape from the users' perspective, to serve as a beneficial reference in the context of developing statewide or MPO-level plans and policies.

1.2. Outline of the Report (Part 2)

This is Part 2 of a two-part report on *The Impact of Emerging Technologies and Trends on Travel Demand in Georgia*. This part presents analyses based on the data collected. All details about how the study and survey were designed and implemented, and how the data were collected and processed, are described in Part 1. All descriptive statistics are reported based on the weighted sample, to be more population-representative (please refer to Part 1 for details about the weights). The full sample size of the study is 3,288, but the number of cases on which descriptive statistics are based could fluctuate by variable since (1) some variables have a qualifying condition for inclusion (e.g., work-related), and (2) each variable has a different number of cases with missing values. The sample size will be reported appropriately. For descriptive statistics, we provide some crosstabulations of key variables by population segment. The major population segments of interest are MPO size (where people live), age cohort, household income, and neighborhood type. In particular, we define four MPO tiers in Georgia: the Atlanta MPO area, mid-sized MPO areas, small-sized MPO areas, and non-MPO areas (refer to Part 1 for more details). Figure 1-1 shows the MPO classification used in this study.

In addition to the descriptive statistics, for some core variables we present a model. These models identify the joint effects of multiple factors on the target variable, and are intended to support other modeling and planning activities at GDOT and in specific regions of the state.

Part 2 consists of six chapters after this Introduction:

- ***General Travel Behaviors***: This chapter describes various travel behaviors of the general population, including one of the most fundamental travel-related decisions: vehicle ownership. Then, it presents routine travel (trip quantity and length), and long-distance trips that are distinctive from daily travel.

- ***Commute and Work Patterns***: This chapter shows how people work and commute, for people who work. In particular, the chapter discusses primary commute mode, commute time/distance, and telecommuting.
- ***General Opinions and Attitudes***: This chapter presents residents' opinions on transportation-related topics and their general attitudes. This information helps us understand how people think about transportation and can be used to help explain their behavior.
- ***New and Emerging Technologies and Services***: This chapter exhibits how people use technologies and relatively new transportation options. In particular, the ways in which people use information and communications technology (ICT) devices and how they use ridehailing services (i.e., Uber and Lyft) constitute the core of the chapter.
- ***Future Transportation: Autonomous Vehicles***: This chapter describes how people perceive autonomous vehicles, and how they expect their short-term, interim, and long-term decisions related to travel to change once AVs become ubiquitous.
- ***Conclusions and Recommendations***: This chapter offers some brief reflections on the value of the present project to statewide planning and policy, provides some implementation recommendations, and suggests several topics to which future surveys would be well suited.

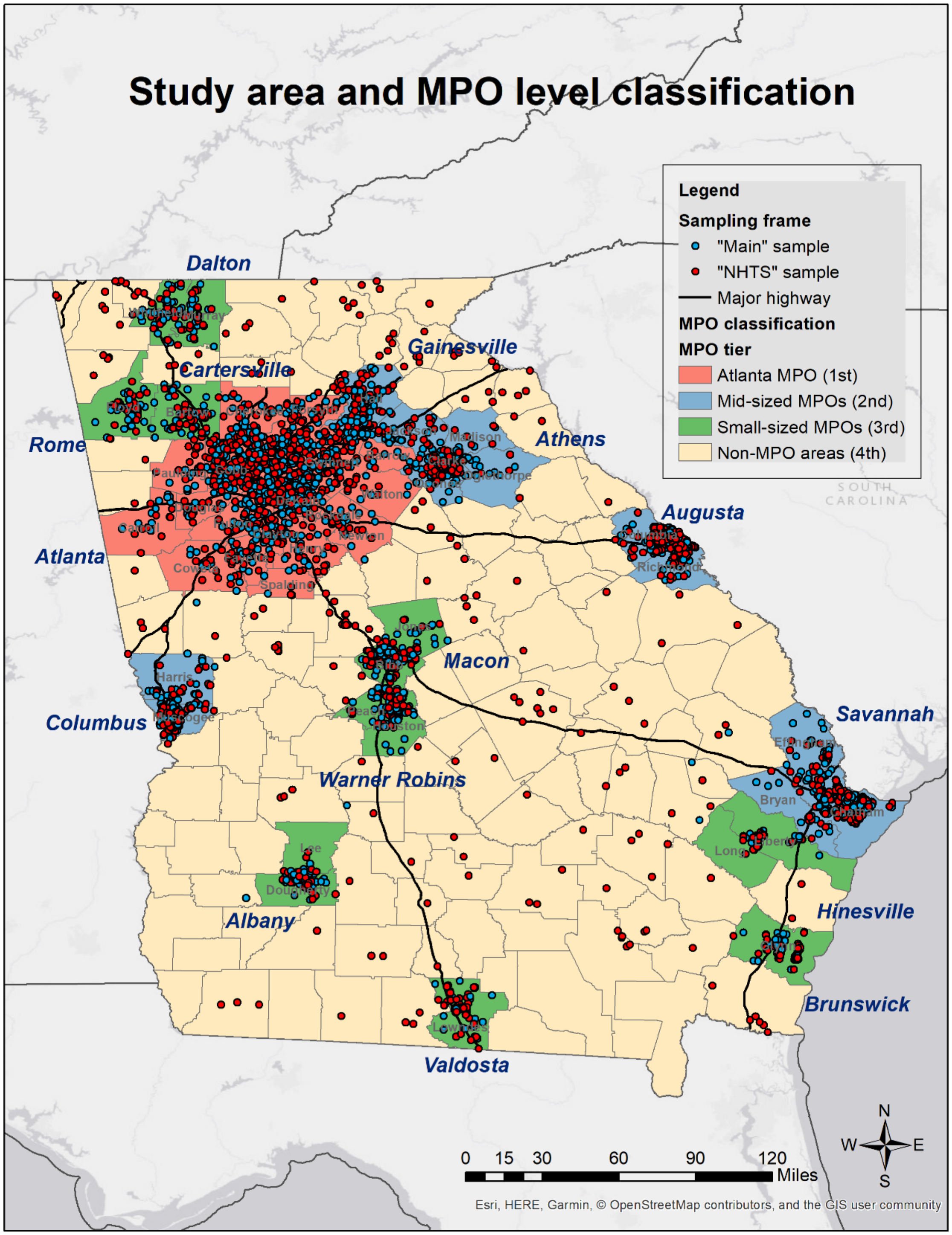

FIGURE 1-1

Study Area and MPO Level Classification

2. GENERAL TRAVEL BEHAVIORS

This chapter describes various travel behaviors of the general population. First, we consider one of the most fundamental travel-related decisions—vehicle ownership—followed by a brief analysis of who drives. Then, we analyze local travel (i.e., trip quantity and length), followed by long-distance trips that are distinctive from daily travel.

2.1. Vehicle Ownership

This section explores several aspects of vehicle ownership: number of vehicles (Section 2.1.1), vehicle type and age (Section 2.1.2), and interest in alternative-fuel vehicles (Section 2.1.3).

2.1.1. Number of Vehicles

Vehicle ownership is a key input for regional planning and transportation policies. It is potentially associated with congestion, emissions, fuel tax revenue, transit revenue, and numerous other travel-related indicators. In this section we first examine vehicle ownership statistics statewide and by segment. Then, we present a multinomial logit model of vehicle ownership, to enable analysis of the simultaneous effect of multiple variables on this important household decision.

2.1.1.1. Descriptive analysis

Table 2-1 presents descriptive statistics for Georgia statewide household vehicle ownership. On average, households have 2.01 vehicles, with 5.36 percent reporting zero vehicles, 34.11 percent of households reporting one vehicle, 32.62 percent of households reporting two vehicles, and 27.91 percent reporting 3 or more vehicles. In general, the average number and distribution of vehicles in our survey sample are similar to those of the Georgia subsample of the roughly contemporaneous (2016–2017) National Household Travel Survey (NHTS). The current study has a slightly higher number of household vehicles compared to that of NHTS. This difference could result from a combination of reasons (e.g., time frame, sampling plan, weighting method, and measurement error).

We can further investigate vehicle ownership by decomposing by population segment or by taking into account household size (in particular, driving age). Figure 2-1 and Figure 2-2 show the number of vehicles by MPO size and income level. On average, the residents of larger MPO areas tend to have a smaller number of vehicles. For example, 25 percent of Atlanta region residents have 3 or more vehicles per household, whereas 38 percent of non-MPO area residents do. We can also observe a difference in vehicle ownership by income. Not surprisingly, households with higher income levels tend to have more vehicles (Figure 2-2). For instance, almost half of households earning less than $50,000 have one vehicle in the household, whereas a majority of households earning $100,000 or more have two or more vehicles. It is common to examine not only the number of vehicles per se, but also a ratio of number of vehicles to some measure of household size, since, all else equal, larger households can be expected to "need" more vehicles. Sometimes the denominator is simply the number of household members; in other cases, it is the number of licensed drivers or the number of driving-age household members. In this study, we use the latter measure (specifically, the number of adults) as the denominator, to represent the potential for competition for vehicles among eligible household members and for consistency with the GDOT-funded analysis of the NHTS survey being conducted in parallel with this study (GDOT RP 18-24, Analysis of the Georgia Add-on to the 2016-2017 National Household Travel Survey).

Table 2-2 shows the distribution of vehicle sufficiency after taking into account the number of adults in the household. Fifty-four percent of households are vehicle sufficient (i.e., the number of vehicles is equal to the number of adults). When looking into vehicle sufficiency by MPO size, the Atlanta region has a notably higher fraction of (only) one-car-per-adult households (61%) whereas, on average, households living in the smaller MPO areas have a greater tendency to have surplus vehicles (Figure 2-3). Two counteracting tendencies are at work there: Atlanta-region households tend to have higher incomes (which makes them less likely to have zero vehicles), but are more likely to live in denser areas where owning more cars can be costly and inconvenient (making them less likely to have a surplus of vehicles).

TABLE 2-1
Household Vehicle Ownership

	Current study (whole sample, N=3,288)	NHTS (Georgia subsample)
Average number of vehicles	2.01	1.92
Number of vehicles		
0	5.36 %	6.95 %
1	34.11 %	33.65 %
2	32.62 %	34.56 %
3	17.37 %	15.65 %
4+	10.54 %	9.20 %

TABLE 2-2
Overall Vehicle Sufficiency (N=3,270)

Category	Count	Share (%)
Zero-vehicle	176	5.4%
Vehicle-deficit (vehicles < people 18+)	490	15.0%
Vehicle-sufficient (vehicles = people 18+)	1773	54.2%
Vehicle-surplus (vehicles > people 18+)	832	25.4%

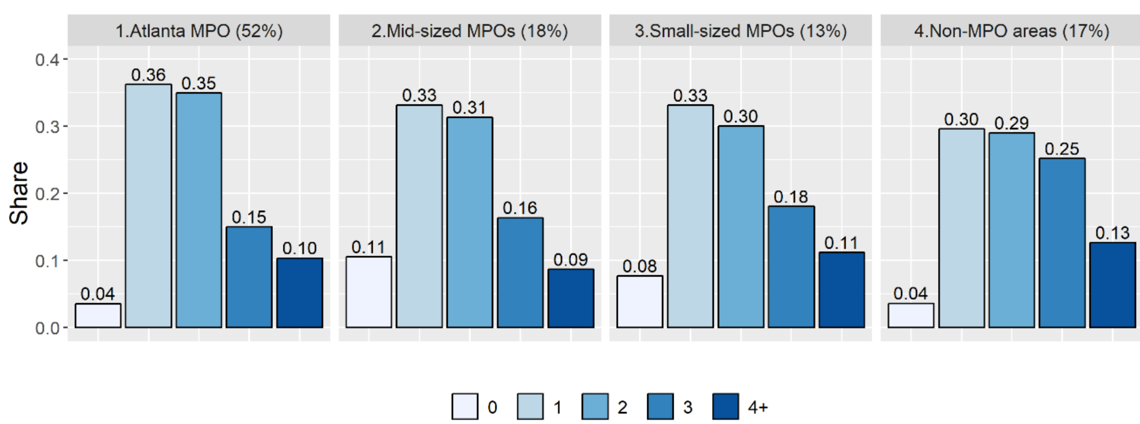

FIGURE 2-1
Number of Vehicles (by MPO size) (N=3,288)

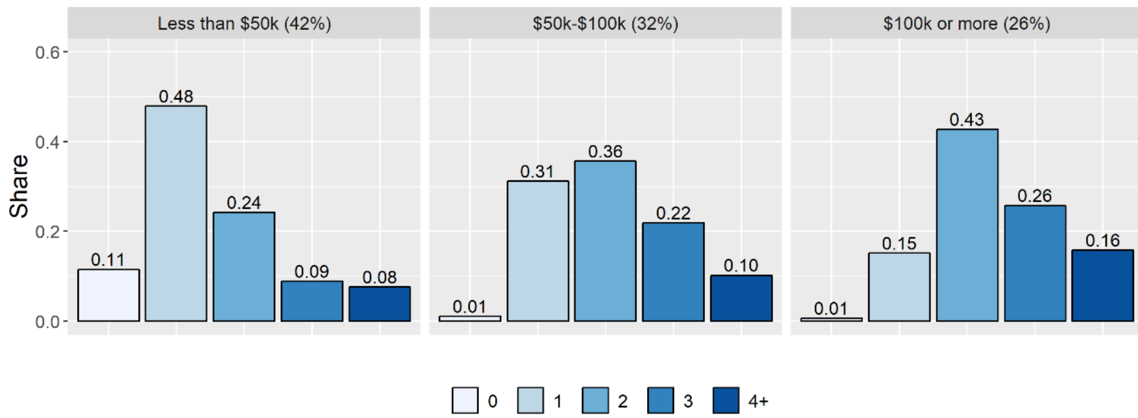

FIGURE 2-2

Number of Vehicles (by annual household income) (N=3,288)

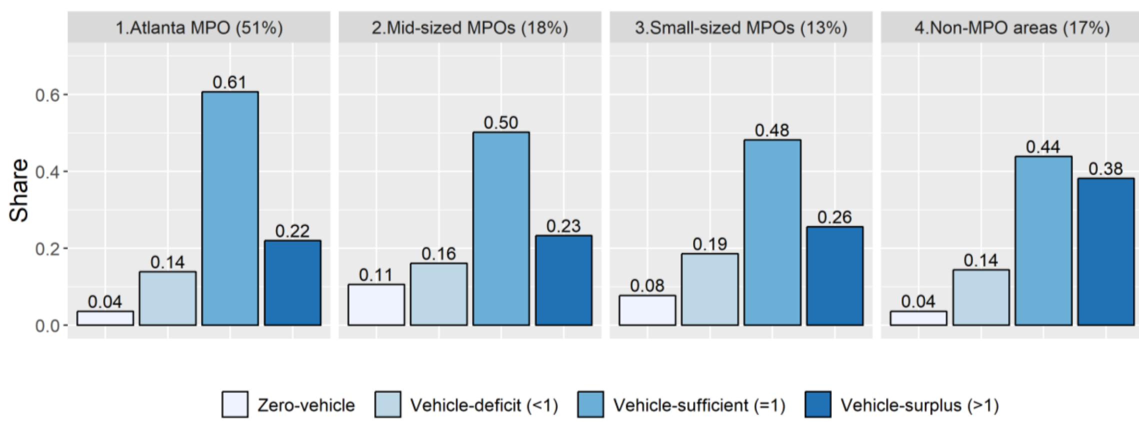

FIGURE 2-3

Vehicle Sufficiency with Respect to People 18+ (by MPO size) (N=3,270)

2.1.1.2. Modeling vehicle ownership

Most demand modeling frameworks (e.g., activity-based models) include a vehicle ownership module as one of several long-term household decision models. Because vehicle ownership is so central to a number of subsequent travel choices (e.g., mode and destination for individual trips), it is a key target for policy intervention, and for both of those reasons understanding it is critical. Based on the literature, we modeled household vehicle ownership with various combinations of factors. In particular, we modeled four levels of number of vehicles (0, 1, 2, and 3 or more) with a weighted multinomial logit model (MNL).[2] Table 2-3 shows the estimation results of the final vehicle ownership model, which could be used to evaluate a number of policy (e.g., land-use densification) and/or demographic (e.g., falling household sizes, or rising incomes) scenarios.

Overall, compared to typical vehicle ownership models, the fit of the model is good ($\rho^2 = 0.28$). Most coefficients are statistically significant. In terms of household characteristics, as income and size increase, households tend to increase the number of vehicles they own. Attitudes are also important determinants of vehicle ownership.[3] Holding income and size constant, pro-suburban and pro–car-owning households tend to have more vehicles (as indicated by the positive signs and gradually increasing magnitudes of these coefficients), whereas urbanite households tend to have fewer vehicles (as indicated by negative coefficients and gradually increasing magnitudes). Three selected land use variables are also important factors affecting vehicle ownership. As activity (sum of population and employment) density, number of stores nearby (within 1 mile), and transit score (a function of number of transit stations/lines and service frequency) increase, households tend to decrease their number of vehicles. Activity density and number of stores measure the degree of urbanization where households live. The transit score also indirectly represents urbanization level, but explicitly it indicates the extent to which people have viable transit options and, thus, a lower need for vehicles.

We experimented to see whether any technology use or adoption of ridehailing indicators affected vehicle ownership. In this sample we could not find a clear relationship between vehicle ownership and those factors. Vehicle ownership may be a long-term decision that is relatively stable and, hence, less influenced by such technology adoption. However, we recommend continuing to

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[2] For brevity, this report does not describe the theoretical background of the model; for this, please consult other references such as Ben-Akiva and Lerman, 1985.

[3] Technically, vehicle ownership is a household-level decision, whereas attitudes were measured by individual. However, although attitudes can certainly vary within household, there is also likely to be greater homophily within household than between households; hence, some studies have used individual attitudes as proxies for the propensities of the household, while acknowledging the potential measurement gap (e.g., Kim and Mokhtarian, 2018).

monitor vehicle ownership trends and decision processes to see if such impacts could become significant as these technologies become more ubiquitous in the near future.

TABLE 2-3

Vehicle Ownership Model (base: zero vehicles, N=3,287)

Dimension	Variable	Category	Coefficient	t-value
Intercept	Intercept	VO=1	3.548	10.00
		VO=2	2.004	5.48
		VO=3+	0.928	2.46
Household characteristics	Middle income (\$50k–\$99k)	VO=1	1.923	5.77
(base: low income, below \$50k)		VO=2	2.912	8.54
		VO=3+	3.300	9.52
	High income (\$100k+)	VO=1	2.492	5.00
		VO=2	4.303	8.53
		VO=3+	4.752	9.34
	Household size	VO=1	−0.056	−0.59
		VO=2	0.672	6.99
		VO=3+	0.899	9.22
MPO level	Mid-sized MPOs	VO=1	−1.071	−4.64
(base: Atlanta MPO)		VO=2	−1.238	−4.96
		VO=3+	−1.224	−4.71
	Small-sized MPOs	VO=1	−1.060	−3.59
		VO=2	−1.457	−4.64
		VO=3+	−1.283	−3.99
	Non-MPO areas	VO=1	−1.026	−2.95
		VO=2	−1.245	−3.46
		VO=3+	−0.750	−2.06
Land-use characteristics	Activity density	VO=1	−0.020	−1.99
	(population + employment)	VO=2	−0.024	−2.09
		VO=3+	−0.030	−2.17
	Number of stores	VO=1	−0.049	−3.17
	(within a mile from home)	VO=2	−0.090	−5.63
		VO=3+	−0.097	−5.87
	Transit score [b]	VO=1	−0.620	−1.40
		VO=2	−1.015	−2.13
		VO=3+	−1.386	−2.75
Attitudes [a]	Pro-suburban	VO=1	0.170	1.94
		VO=2	0.199	2.10
		VO=3+	0.283	2.88
	Urbanite	VO=1	−0.138	−1.60
		VO=2	−0.194	−2.08
		VO=3+	−0.296	−3.05
	Pro–car-owning	VO=1	0.535	7.23
		VO=2	0.771	9.37
		VO=3+	0.778	9.01
Model Summary				
Log-likelihood at $\hat{\beta}$	−3292.816			
Log-likelihood at constants [c]	−4094.195			
Log-likelihood at zero	−4557.404			
ρ^2 (equally-likely base)	0.277			
$\bar{\rho}^2$ (equally-likely base)	0.269			

a. Factor scores—please refer to Chapter 4 for details.

b. Transit score that measures the level of transit service. It ranges between 0 and 1.

c. Market shares, specifically in the dataset modeled, are zero vehicles 5% (176), one vehicle 34% (1,121), two vehicles 33% (1,072), and three or more vehicles 28% (918).

2.1.2. Vehicle Type and Age

The type and age of vehicle are relevant to traffic operations, emissions, and other public concerns. Thus, it is of interest to know what kinds of vehicles Georgia residents primarily use. The survey asked respondents to report the make, model, and year of the vehicle they drive most often. We[4] classified vehicles into five categories based on the reported make and model: automobile/car/station wagon, van (mini/cargo/passenger), SUV (e.g., Santa Fe, Tahoe, Jeep), pickup truck, and motorcycle/motorbike (Table 2-4). This classification is a subset of the NHTS classification because our sample does not include small-share vehicle types (e.g., recreational vehicles). Overall, more than half of the "primary" vehicles are in the automobile/car/station wagon category. Figure 2-4 and Figure 2-5 show vehicle type by MPO size and income, respectively. In particular, as shown in Figure 2-4, the Atlanta region has a higher fraction of automobiles/ cars/station wagons (59%) than other areas, whereas non-MPO areas have the smallest fraction (43%). In addition, small-sized MPO areas have the highest portion of pickup trucks (24%) and the Atlanta region has the smallest portion of pickup trucks (10%). Figure 2-5 presents the association between vehicle type and income. Especially, middle- or high-income ($50,000 or more) groups have distinctive shares of SUVs (above 30%) compared to that of the low-income group (18%). The shares of van and motorcycle/motorbike are relatively low, and they do not vary greatly across population segments.

[4] The authors are grateful to Xiaodan Xu for performing this task.

TABLE 2-4
Overall Share of Vehicle Type (N=2,833)

Vehicle type	Count	Share (%)
Automobile/Car/Station Wagon	1510	53.3%
Van (Mini/Cargo/Passenger)	129	4.6%
SUV (Santa Fe, Tahoe, Jeep, etc.)	765	27.0%
Pickup Truck	419	14.8%
Motorcycle/Motorbike	9	0.3%
Total	2833	100.0%

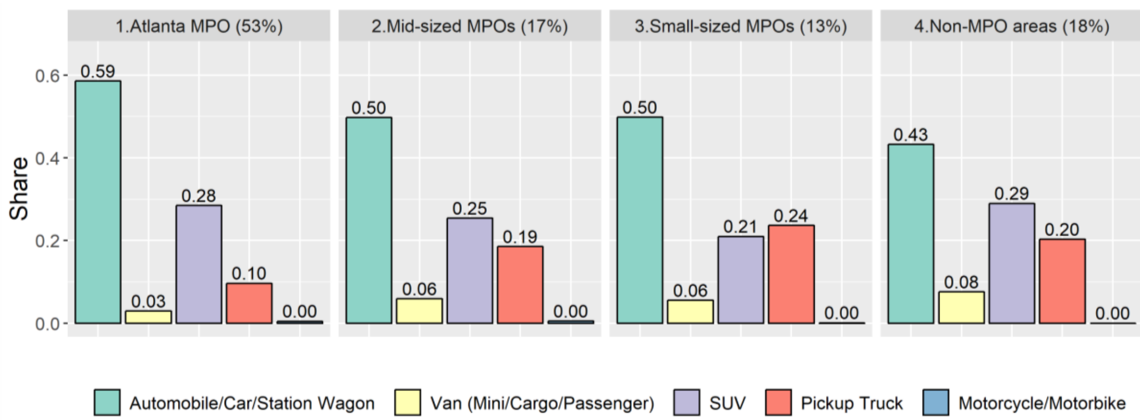

FIGURE 2-4

Vehicle Type (by MPO size) (N=2,828)

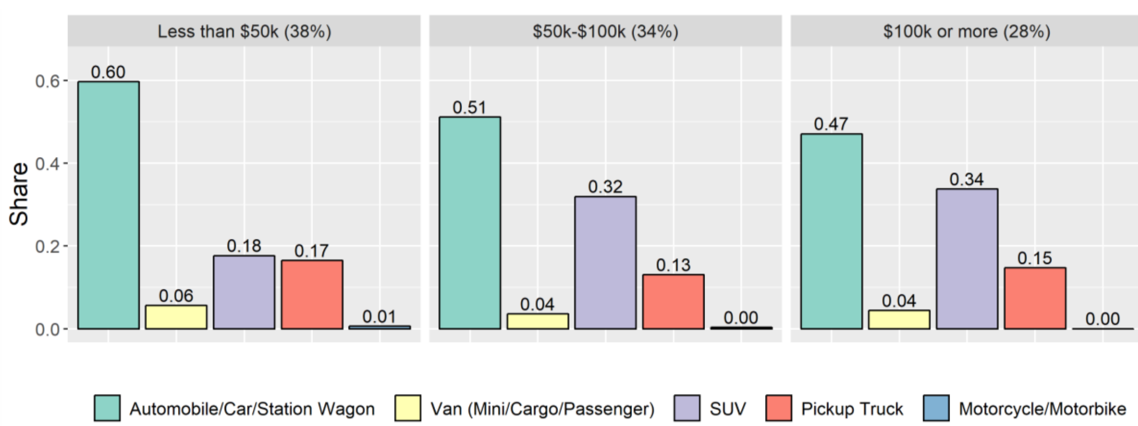

FIGURE 2-5

Vehicle Type (by income) (N=2828)

Figure 2-6 exhibits the distribution of primary vehicle age in 2017, the year of data collection (calculated based on vehicle year). The average age of primary vehicles is 8.39 years. According to AutoAlliance[5], the average age of vehicles in Georgia is 11.9 years. One likely reason for the difference is that our survey collected information on a single primary vehicle, whereas AutoAlliance reported statistics for vehicle registrations, i.e. for all "potentially driven" vehicles. It is likely that the vehicles primarily used by our respondents will tend to be the newer members of the household's fleet. Table 2-5 shows descriptive statistics of vehicle age by MPO size and income. On average and as expected, the bigger MPO areas have newer primary vehicles, and higher-income people tend to drive newer vehicles.

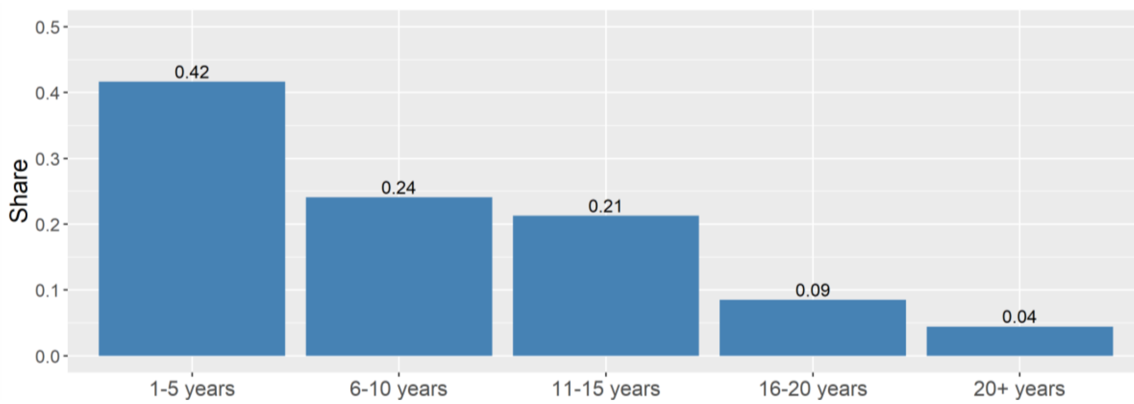

FIGURE 2-6

Age of Primary Vehicle Based on Vehicle Year (N=2,943)

TABLE 2-5
Descriptive Statistics of Vehicle Age by Population Segment (N=3,079)

MPO size			Income		
Category	*Mean*	*Std.*	*Category*	*Mean*	*Std.*
Atlanta MPO area	7.32	5.61	Less than $50k	10.48	7.26
Mid-sized MPOs	8.00	6.53	$50k–$100k	7.29	5.76
Small-sized MPOs	8.32	6.76	$100k or more	6.36	5.34
Non-MPO areas	9.21	6.93			

5 https://autoalliance.org/in-your-state/GA/pdf/?export

2.1.3. Interest in Alternative-Fuel Vehicles

2.1.3.1. Descriptive analysis

In our sample, 2.2 percent of primary vehicles are hybrid/electric vehicles.[6] From an environmental-policy perspective, it is important to know the public's interest in buying or leasing an alternative-fuel vehicle. Although this interest does not necessarily lead to actual acquisition, people who have such an interest could be targeted for marketing efforts. Table 2-6 depicts the statewide interest in *ever* acquiring an alternative-fuel vehicle, while Figure 2-7 exhibits the interest by MPO size. Overall, despite the low levels of *current* ownership, respondents exhibit considerable *interest* in having such vehicles, with more than half (59%) indicating the appeal of one or more alternative fuels. This suggests extensive scope for (resuming) the promotion of alternative-fuel vehicles through policy instruments such as tax rebates.

Across fuel types, people have relatively lower interest in diesel and compressed natural gas, and highest interest in gasoline hybrid and battery electric vehicles. The latter is specifically true of Atlanta region residents, which might be attributable to the fact that the Atlanta region has more charging facilities compared to other areas. In general, as the MPO size gets smaller, average interest in alternative fuels decreases.

[6] AutoAlliance reported 1.05 and 0.25 percent of registered vehicles in Georgia are hybrid and electric vehicles, respectively (source: https://autoalliance.org/in-your-state/GA/pdf/?export). Again, it is not surprising that hybrid/electric vehicles would have a higher share among primary vehicles than among all registered vehicles.

TABLE 2-6

Overall Interest in Alternative-Fuel Vehicles (N=3,261) ("check all that apply")

Alternative fuel type	Count	Share (%)
Not interested	803	24.62
Gasoline hybrid (e.g., Toyota Prius)	1324	40.60
Diesel	520	15.93
Battery electric (e.g., Nissan Leaf, Tesla Model S)	1263	38.73
Compressed natural gas (CNG)	380	11.65
Flex-fuel vehicle (runs on gasoline or ethanol)	847	25.98
Hydrogen fuel cell (e.g., Honda Clarity)	552	16.93
I don't know	639	19.58
Other	30	0.92

Note: Among current owners of alternative-fuel vehicles, all but one person expressed interest in owning or leasing one in the future, so in essence the measure of future interest also includes present ownership.

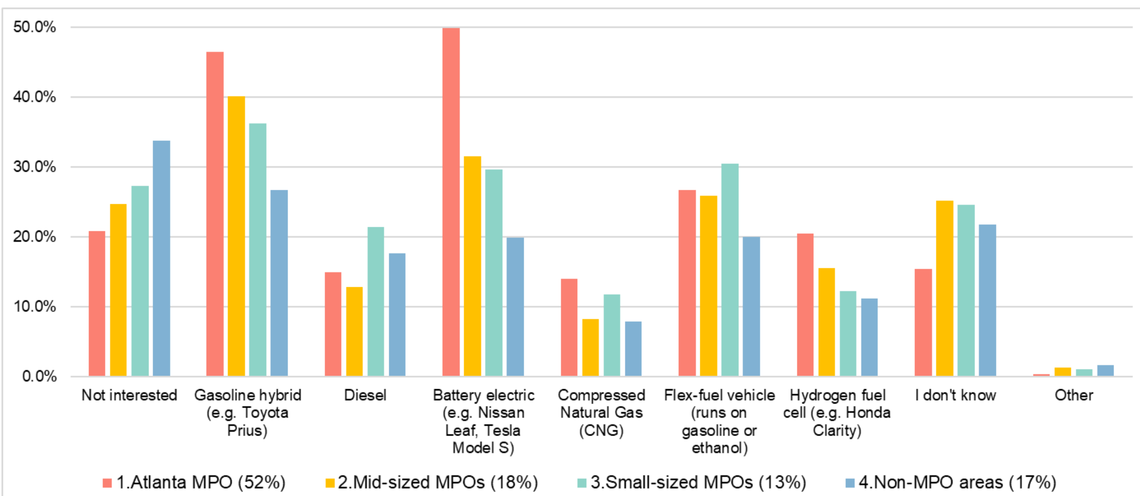

FIGURE 2-7

Interest in Alternative-Fuel Vehicles by MPO Size ("check all that apply")

2.1.3.2. Modeling the interest in electric vehicles

Georgia formerly had a tax credit incentive to purchase electric vehicles (EVs), which ended in 2015. While that policy was in effect, Georgia was ranked second among U.S. states in number of registered EVs. However, since the tax credit expired in June 2015, Georgia places around tenth with respect to number of newly registered EVs (July 2015 – Dec 2018).[7] Because the current survey does not contain details on the adoption of EVs, the study cannot analyze the effectiveness of the tax credit at increasing EV sales. However, we *can* identify how many people are interested in EVs and analyze the factors associated with their interest, which may assist in targeting those potential customers.

The survey asked respondents about their interest in "*ever* buying or leasing a vehicle that runs on any of these **alternative fuels**". This section specifically focuses on the interest in EVs rather than other alternative-fuel vehicles.[8] As shown in Table 2-6, nearly 2 out of 5 (38.73% of) respondents reported an interest in EVs—a healthy share that bodes well for possible future policy incentives. We estimated a weighted binary logit model[9] of the interest in EVs (interested versus not interested), and Table 2-7 presents the estimation results. Overall, the fit of the model is good ($\rho^2 = 0.245$). Most of the coefficients are statistically significant. In terms of sociodemographics, sex, race, work status, age, income, and education are important factors. On average, male, white, worker, young, higher income, and highly educated people are more likely to be interested in buying or leasing EVs. Compared to Atlanta MPO residents, people in other areas have distinctly lower interest levels.

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[7] https://autoalliance.org/energy-environment/advanced-technology-vehicle-sales-dashboard/

[8] Gasoline hybrids such as the Prius are another relatively common fuel type, but hybrids were not considered as low-emission vehicles eligible for tax credits even when the tax credit policy was in effect (https://dor.georgia.gov/sites/dor.georgia.gov/files/related_files/document/LATP/Publication/Credit%20summaries%209.19.18.pdf). Other alternative-fuel types are less common.

[9] For brevity, this report does not describe the theoretical background of the model; please refer to other sources, such as Ben-Akiva and Lerman, 1985.

TABLE 2-7

Binary Logit Model of Interest in EVs (Base: not interested, N=3,256)

Dimension	Variable	Coefficient	t-value
Intercept	Intercept	−2.156	−9.18
Sociodemographics	Sex (female=1)	−0.531	−5.91
	Race (white=1)	0.617	6.28
	Work status (work=1)	0.261	2.45
	Age 18–34 (base: 35–64)	0.151	1.39
	Age 65+ (base: 35–64)	−0.600	−4.21
	Middle income \$50k–\$99k (base: below \$50k)	0.053	0.49
	High income \$100k+ (base: below \$50k)	0.270	2.18
	Education (college=1)	0.356	3.08
	Education (bachelor or graduate =1)	0.657	5.10
Land-use characteristics	Population density (pop/acre)	0.049	3.94
	Land-use entropy [a]	0.459	2.68
MPO level	Mid-sized MPOs	−0.524	−4.47
(base: Atlanta MPO)	Small-sized MPOs	−0.379	−2.76
	Non-MPO areas	−0.807	−5.72
Behaviors	Current vehicle: automobile/car/station wagon (base: no car) [b]	0.668	4.61
	Current vehicle: other (base: no car) [b]	0.314	2.06
	Activity radius in a typical week (76+ mi=1)	−0.696	−4.18
	Use of social media [c]	0.040	2.84
Attitudes [d]	Tech-savvy	0.414	7.98
	Pro-environmental	0.282	6.23
	Pro–non-car-modes	0.185	4.25
	Pro-exercise	0.106	2.37
Model Summary			
Log-likelihood at $\hat{\beta}$	−1704.041		
Log-likelihood at constants [e]	−2173.571		
Log-likelihood at zero	−2257.069		
ρ^2 (equally-likely base)	0.245		
$\bar{\rho}^2$ (equally-likely base)	0.235		

a. A commonly used measure of land-use diversity based on shares of eight types of employment. Values range between 0 and 1, where the higher the value, the more mixed the land use.
b. Based on primary vehicle that respondent drives.
c. Sum of frequency indicators of various types of social media (Facebook, Twitter, Instagram, etc.).
d. Factor scores—please refer to Chapter 4 for details.
e. Market shares, specifically in the dataset modeled, are: ‘not interested in EVs’ 61% (1,995) and ‘interested in EVs’ 39% (1,261).

TABLE 2-8
Availability of EV Facilities Near Home Location by MPO Size

EV charging station statistics based on home location *	Atlanta MPO	Mid-sized MPOs	Small-sized MPOs	Non-MPO Areas
Average number of EV charging stations within a mile	1.48	0.51	0.25	0.13
Mean distance (mi.) of the 20 closest EV charging stations	5.86	9.58	21.48	27.91
Median distance (mi.) of the 20 closest EV charging stations	6.24	7.61	23.25	29.97
Average distance (mi.) to the closest EV charging station	2.34	3.58	3.99	12.03

* We produced these statistics based on information in Open Charge Map. We employed the API service of Open Charge Map and collected the number of EV charging stations (up to 20) based on the geocode of the home location.

In addition, with respect to land use characteristics, as population density and land use entropy increase, people are more likely to be interested in EVs. These MPO level and land use variables might be representing the accessibility of EV facilities (e.g., number of charging stations) or familiarity with EVs in that, on average, the Atlanta region and more-urban areas (highly populated and with diverse land uses) have more facilities. Table 2-8 exhibits the comparison, across MPO size, of EV charging station availability near the home location.[10] Clearly, the bigger the MPO area, the denser the availability of EV facilities. We experimented with various combinations of variables in the model to see the effect of availability of EV facilities. Although we tried to include dummy variables for both MPO size and availability of EV facilities in the model, the coefficient of EV facility availability became statistically insignificant when MPO size was also in the model. We suspect this is because of collinearity between these two sets of variables. We ultimately kept the two aforementioned land-use characteristics and dummy variables for MPO

[10] We collected the number of EV charging stations (up to 20) based on the geocode of the home location by using the application programming interface (API) service of Open Charge Map (https://openchargemap.org/site/).

size in the final model, because they capture not only the availability of EV facilities but also other merits of larger cities and denser areas.

A number of other lifestyle and activity indicators are associated with interest in EVs. For example, compared to people without cars, car owners are more likely to be interested in EVs. In particular, on average, automobile/car/station wagon drivers are more interested in EVs than are drivers of other types of vehicles (e.g., SUV, pickup truck). People whose activity radius in a typical week is more than 75 miles are less likely to be interested in having an EV, perhaps due to range anxiety. People who use social media more often are more likely to be interested in EVs, perhaps because they are more tech-savvy, and/or are more exposed to EV news and, thus, more familiar with EVs. Lastly, attitudes can also stimulate interest in EVs: more tech-savvy, pro-environmental, pro–no-car-modes, and pro-exercise people are more likely to be interested in buying/leasing EVs.

The model is limited in that it only predicts/explains interest in EVs, falling short of predicting actual acquisition. Nevertheless, interest is presumably a necessary condition for acquisition, and the model suggests some useful recommendations for increasing interest, as well as some potentially receptive marketing targets:

1. Increasing charging station availability is likely to generate greater interest in EVs: more frequent unpurposive encounters with charging stations will increase familiarity with the concept, heighten a sense that many people are adopting the technology, serve as conversation starters, and provide reassurance regarding range anxiety.
2. Elevating values of the actionable explanatory variables in the model would provide other ways to generate more interest. Examples include heightening pro-environmental sentiment through social marketing; increasing land-use density and diversity, which facilitates shorter trips and thereby also helps alleviate range anxiety; and increasing effective income through offering tax credits or other financial incentives to purchase EVs.

3. To some extent, allowing interest to increase spontaneously over time will be effective, as the values of some associated variables (such as tech-savviness, and use of social media) may increase through natural evolution.
4. Converting interest to acquisition suggests targeting marketing campaigns particularly toward the most receptive segments of the population: people who use social media often; people who live in denser urban environments and in the Atlanta region; and people who are car owners, tech-savvy, pro-environmental, pro–non-car-modes, pro-exercise, and higher income. With respect to the latter factor, there was about a 70 percent increase in EV sales between 2017 and 2018 across the U.S., and Tesla Model 3 was the highest selling model (i.e., about half of total EV sales were Tesla models).[11] Targeted marketing firms collect a wealth of behavior, lifestyle, and attitudinal data on every household possible, and offer the ability to tailor mailings or other media pitches to a fairly carefully described audience.[12]

Although the breadth of our survey did not permit an in-depth investigation of EV adoption, it would be desirable for future studies to build on these results by collecting data on intention and purchase behavior, enabling the development of models predicting the response to policies or conditions such as tax credits, increased charging station availability, and increased range.

2.2. Who are the Drivers?

Since automobile trips compose the vast majority of travel in Georgia, it is important to understand what share of the eligible population can drive.[13] Table 2-9 presents this information by segment.

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[11] https://www.theicct.org/publications/surge-EVs-US-cities-2019
[12] See, e.g., http://www.experian.com/marketing-services/marketing-services.html, accessed July 10, 2019.
[13] In this study, we define "driver" to be essentially synonymous with "license holder". Question D1 in the survey asks, "At what age did you get your driver's license?", with the option to check "I don't have a license". Those who provided an age are considered drivers/license holders; those who checked "I don't have a license"

Overall, 4.0 percent of our sample does not drive, but the share of non-drivers varies substantially by segment. For example, 7.1 percent of those with annual household incomes less than $50,000 do not drive, compared to 2.0 percent of those with higher incomes. Similarly, 7.0 percent of non-workers do not drive, compared to 2.2 percent of workers. Interestingly, there are higher shares of non-drivers among those of middle ages (6.7% for 35–44-year-olds) than in the youngest (4.4%) and oldest (2.0%) age groups. This is not the case for the Georgia subsample of the NHTS, which conforms to expectations with the shares of non-drivers being highest in the youngest (14.6%) and oldest (16.3%) age groups, and lowest for the middle two groups (5.8% and 8.0%, respectively).[14] However, in our sample the 35–44-year-old age group is the smallest of the four, and so sampling and/or weighting fluctuations, as well as varying definitions[15], could account for the result. In general, the numbers of non-drivers are small in most segments, and therefore comparisons across segment should be viewed with some caution.

Geography matters as well: at a regional scale, 6–8 percent of those in mid- and small-sized MPO areas do not drive, compared to 2–4 percent in the Atlanta and non-MPO areas. With respect to the local scale, some interesting patterns emerge. The share of non-drivers is lowest (0.9%) in rural areas (although the sample size is especially small here), which is understandable in view of the lack of effective alternatives to the automobile and the role of driving in agricultural operations. It is next lowest (2.2%) in suburbia, where there may also be few effective alternative means of travel. It is second highest (6.5%) in urban areas, which is also understandable, and highest (6.7%) in small towns, which may reflect income, employment, and other effects.

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are considered non-drivers, and if a response to the question is missing, driver status is missing. This definition could involve some misclassifications in each direction: some people who were ever licensed may be more inclined to give the age of licensing than to check "I don't have a license", even if they have stopped driving, while some who admitted not having a license may actually drive. However, we believe such cases will be few, and that this simple definition will suffice for our purposes.

[14] Thanks to Akash Bhatt for performing this calculation for us.

[15] The NHTS asked if the individual drove, rather than if s/he had a license.

Most drivers drive; in a typical week, fewer than 5 percent of the drivers in any of the population segments studied did not drive at all. We discuss the vehicle-miles driven (VMD) further in Section 2.3.2.

TABLE 2-9
Driver Statistics by Segment

Segment	Category	N	Drivers		Non-drivers		% Drivers with zero vehicle-miles driven (VMD) *
			Count	*%*	*Count*	*%*	
Overall		3,288	3,156	96.0%	132	4.0%	2.1%
MPO size	Atlanta MPO area	1,696	1,661	97.9%	36	2.1%	1.6%
	Mid-sized MPO areas	592	543	91.7%	49	8.3%	4.3%
	Small-sized MPO areas	441	414	94.0%	27	6.0%	2.9%
	Non-MPO areas	559	539	96.4%	20	3.6%	0.9%
Age cohort	18–34	738	705	95.6%	33	4.4%	3.0%
	35–44	561	523	93.3%	37	6.7%	1.8%
	45–64	1,302	1,255	96.4%	47	3.6%	1.8%
	65+	687	673	98.0%	14	2.0%	2.0%
Income level	Less than $50,000	1,394	1,295	92.9%	99	7.1%	3.3%
	$50,000–$99,999	1,041	1,025	98.5%	16	1.5%	0.8%
	$100,000 or more	853	836	98.0%	17	2.0%	1.9%
Work status	Worker	2,049	2,004	97.8%	45	2.2%	1.3%
	Non-worker	1,239	1,153	93.0%	86	7.0%	3.4%
Neighborhood type	Urban part of a city / region	555	519	93.5%	36	6.5%	4.2%
	Suburban part of a city / region	1,517	1,483	97.8%	33	2.2%	2.0%
	Small town	602	562	93.3%	40	6.7%	1.7%
	Rural area	539	534	99.1%	5	0.9%	0.9%

* Note: There are 142 cases of missing values in the VMD variable. This column is calculated as the ratio of the number of drivers with zero VMD to the number of drivers (4th column in the table).

2.3. How Much People Travel (Locally)

How much people travel is a primary interest of transportation planning. Although the survey was not designed to capture all trips in individual detail[16], the study takes a broader view of trip quantity and provides a general snapshot. This section explores the frequency of local trips (i.e., those not involving an overnight stay), and two measures of distance traveled; the following section (2.4) analyzes longer-distance travel.

2.3.1. Local Trip Frequency

Table 2-10 summarizes overall trip frequency by mode and trip purpose. Overall, most local trips of Georgia residents are by car, in particular driving alone. The majority of Georgia residents rarely use a non-car option. The survey distinguished three car options: driving alone, driving with passengers, and riding as a passenger. Figure 2-8 presents the frequency of *commute* trips (to work or school) by car option, while Figure 2-9 does the same for *all other* trips. Note that the sample sizes differ for these two figures, with Figure 2-8 based only on the 1800+ respondents who commute.

Turning first to commute trips (Figure 2-8), there is no clear difference in frequency of solo-driving across the MPO regions of the state, with 70–74 percent of commuters driving alone for 5 or more times a week (rural residents show somewhat lower rates, with only 64 percent driving alone that often). Interestingly, despite that similarity, residents of the smaller MPO areas (and to some extent, rural residents) are substantially more likely than Atlanta-area residents to occasionally carpool: for example, 65 percent of Atlanta-region respondents never drive other passengers on their commute, whereas only 51–54 percent of other respondents never do so. Still, more than half of all commuters never use carpooling options, either as a driver or as a passenger (51–71 percent by MPO size by option).

[16] This would have required a full travel diary or GPS/app-based data collection.

Comparing these commute trip patterns to the non-work trip patterns in Figure 2-9, it is evident that the shares of frequent solo-drivers are lower for non-work purposes than for commuting, regardless of MPO size. For example, 70 percent of Atlanta region commuters drive alone 5 or more times a week for commuting, whereas only 55 percent of Atlanta region residents drive alone 5 or more times a week for non-work purposes. Conversely, carpool options see substantially higher frequencies of non-work trips than commuting trips (Figure 2-8 and Figure 2-9). In other words, in general, people tend to drive alone for commuting, but they more frequently take private vehicles with others for non-work trips.

As shown in Figure 2-10, trip frequencies by non-car options (bus/train, walk, or bike) are marginal compared with trip frequencies by car options. Compared to other areas, a greater share of Atlanta region residents uses public transit, but residents of mid-size MPO areas also use transit to some extent. For example, 12 percent of residents of both MPO categories take a bus or train one or more times a month, whereas only 5 percent and 3 percent of small-sized MPO and non-MPO area residents do.

TABLE 2-10
Overall Trip Frequency by Mode and Trip Purpose

Travel Mode	Category	Commute trips		Non-commute trips	
		Count	*Share (%)*	*Count*	*Share (%)*
Driving alone	Never	99	5.4	214	6.7
	Less than once a month	58	3.2	108	3.4
	1–3 times a month	43	2.3	234	7.3
	1–2 times a week	111	6.0	465	14.5
	3–4 times a week	239	13.0	618	19.3
	5 or more times a week	1287	70.1	1568	48.9
	Total	**1838**	**100.0**	**3207**	**100.0**
Taking a car with others	Never	1089	59.7	330	10.3
	Less than once a month	211	11.6	387	12.1
	1–3 times a month	125	6.8	575	18.0
	1–2 times a week	113	6.2	721	22.5
	3–4 times a week	129	7.1	567	17.7
	5 or more times a week	157	8.6	622	19.4
	Total	**1823**	**100.0**	**3202**	**100.0**
Taking a car as a passenger	Never	1228	67.4	362	11.5
	Less than once a month	189	10.4	715	22.7
	1–3 times a month	113	6.2	759	24.0
	1–2 times a week	115	6.3	727	23.0
	3–4 times a week	75	4.1	298	9.4
	5 or more times a week	100	5.5	297	9.4
	Total	**1821**	**100.0**	**3158**	**100.0**
Taking a bus or train	Never	1597	87.4	2405	74.9
	Less than once a month	83	4.6	492	15.3
	1–3 times a month	46	2.5	166	5.2
	1–2 times a week	14	0.7	47	1.4
	3–4 times a week	26	1.4	40	1.2
	5 or more times a week	60	3.3	61	1.9
	Total	**1826**	**100.0**	**3211**	**100.0**
Walking	Never	1601	87.8	1274	39.7
	Less than once a month	52	2.9	495	15.4
	1–3 times a month	39	2.1	457	14.3
	1–2 times a week	33	1.8	318	9.9
	3–4 times a week	34	1.9	262	8.2
	5 or more times a week	64	3.5	401	12.5
	Total	**1823**	**100.0**	**3207**	**100.0**
Biking	Never	1722	94.3	2544	79.2
	Less than once a month	41	2.2	334	10.4
	1–3 times a month	15	0.8	171	5.3
	1–2 times a week	6	0.3	73	2.3
	3–4 times a week	9	0.5	35	1.1
	5 or more times a week	33	1.8	55	1.7
	Total	**1826**	**100.0**	**3212**	**100.0**

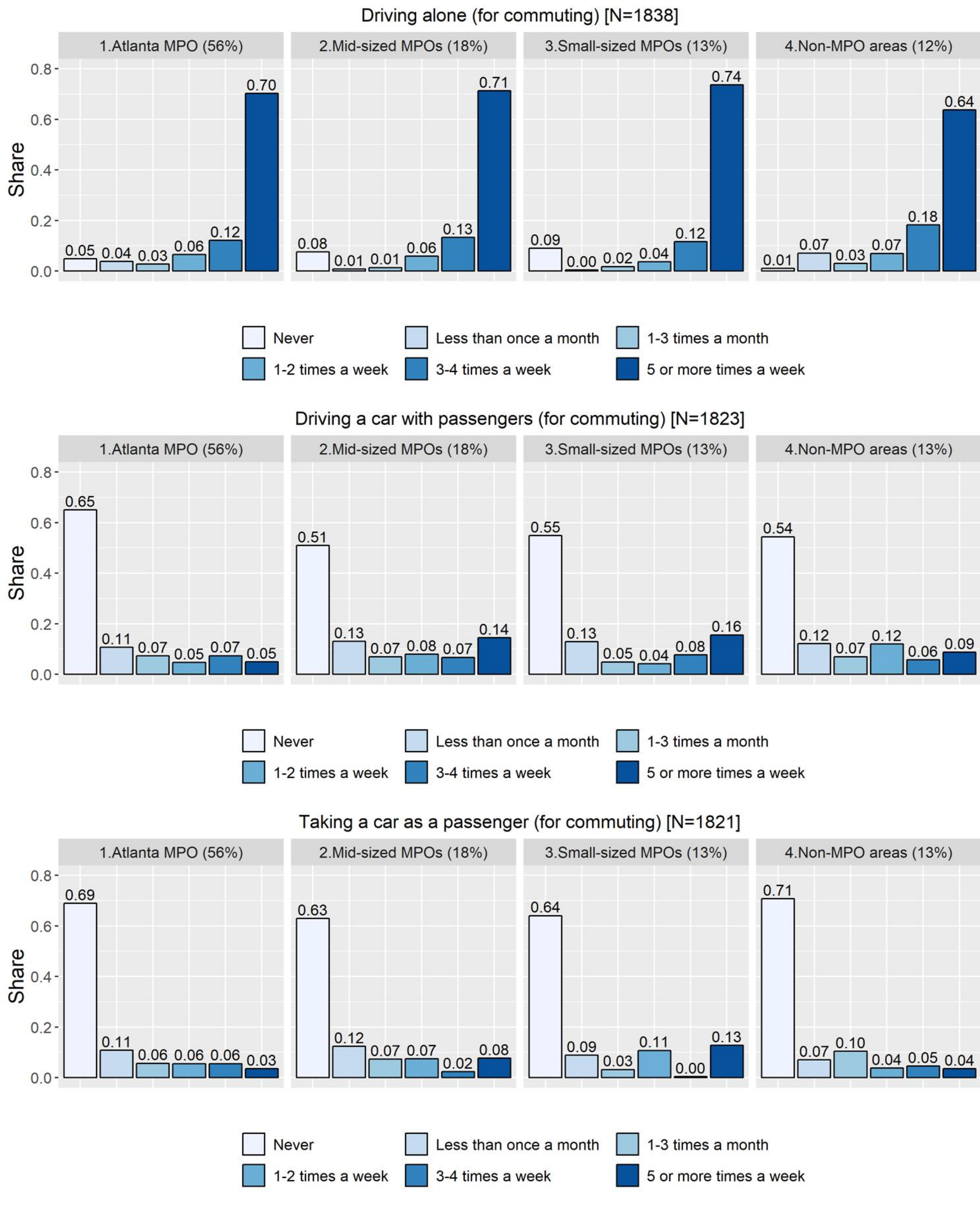

FIGURE 2-8

Frequency of Commute Trips by Car Option and MPO Size

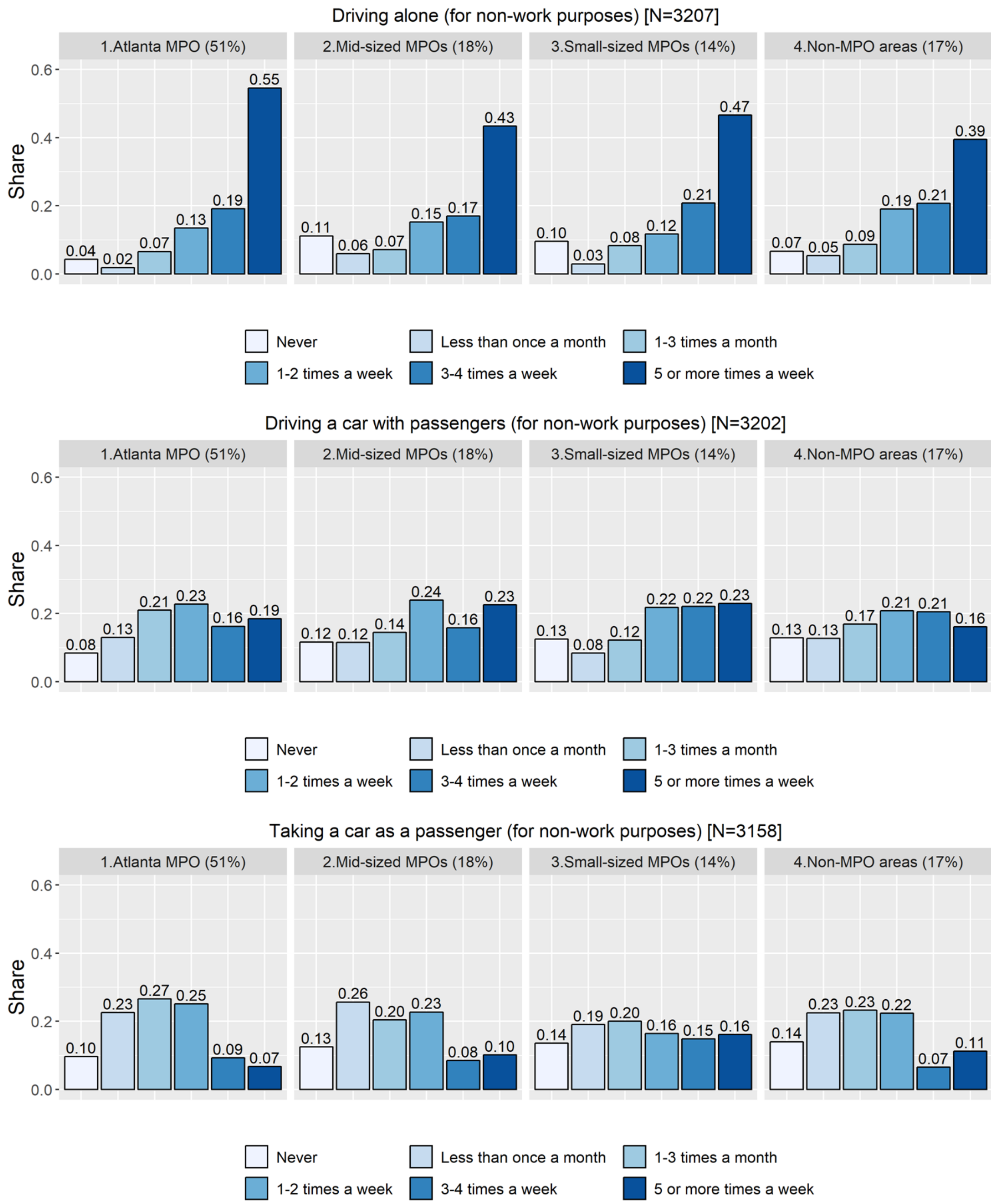

FIGURE 2-9

Frequency of Non-commute Trips by Car Option and MPO Size

FIGURE 2-10

Trip Frequency of Non-commute Trips by Non-car Options

2.3.2. Distance Traveled

The quantity of travel can be viewed from at least two dimensions: frequency of trips and distance traveled. We discussed trip frequencies in Section 2.3.1; here, we discuss various measures of distance traveled. In view of the dominance of the personal automobile and its importance to measures of congestion, air quality, and greenhouse gas emissions, a frequently used measure of travel distance is the total vehicle-miles driven (VMD). The time period for VMD varies across studies (e.g., daily, weekly, monthly, yearly); here, we measure weekly VMD. Whatever the time period, VMD is a function of distance and frequency of trips. We cannot precisely decompose VMD into those two dimensions without an actual travel diary, which was beyond the scope of this survey. However, in this section, we first examine weekly VMD per driver (and per person). Then, we explore the general activity radius (for all respondents, not just drivers), which (for those who drive) can provide a glimpse of the basis for a respondent's VMD, and (for everyone) is a marker for the geographic range of that individual's typical activity patterns. Finally, we present a regression model that predicts VMD as a function of a variety of factors.

2.3.2.1. Descriptive analysis of VMD and activity radius

The survey asked for the total VMD in a typical week (for all purposes), to capture an approximate measure of how much people drive. The average weekly per-driver and per-person VMD of the sample are 144.69 miles and 141.94 miles, respectively. Figure 2-11 shows a histogram of weekly vehicle miles driven per driver, which shows that the distribution of weekly VMD is spread out and skewed (i.e., with a "long tail"), meaning that there is substantial variation across the population as a whole, and probably by segment, as well. Accordingly, Table 2-11 and Table 2-12 exhibit per-driver and per-person VMD statistics by several population segments of interest.[17] A general

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[17] As noted earlier, here we defined "drivers" as people who have a license. Thirty-one "non-drivers" reported non-zero VMD. We decided to keep those values as they are, to preserve the (potentially correct, even if dissonant) information that people reported. This meant that the "driving non-drivers" are excluded in Table 2-14, but included in Table 2-12. Retaining those cases in Table 2-12 does not materially affect the results; however, one anomaly should be noted. Although the per-driver statistics should be greater than the

observation is that the means are always substantially higher than the medians, signifying the presence of large-value outliers pulling up the mean. This is also clear from Figure 2-11 and from comparisons of the final two columns of Table 2-11 and Table 2-12, where 90 percent of the cases in each segment have VMDs of 400 miles or lower, whereas the maximum values tend to be 3–5 times higher than the 90th percentile. Nevertheless—although it is important to keep that in mind—because of the utility of the arithmetic mean as a per-unit multiplier, we follow standard practice and focus our analysis on the means.

With respect to MPO size, given the sprawling nature of the Atlanta region it is not surprising that it has the highest average VMD (156.26 miles), but it might be unexpected that mid-size MPO areas have the lowest average VMD (122.48 miles). Perhaps these regions have found a "livability sweet spot" that achieves enough density and compactness to minimize automobile trip distances: their settlement densities tend to be neither as high nor as low as those of the Atlanta region, while the densities of the small MPO and rural areas tend to be so low that automobile travel, and for longer-than-average distances, is a necessity for meeting daily needs.

There are also notable differences across age cohort, income level, work status, and neighborhood type. Those of ages 35-–44, higher incomes ($100,000 or more), workers, and suburban residents have higher average VMD, whereas those ages 65+, with lower incomes (less than $50,000), non-workers, and urban residents have lower average VMD. These patterns are entirely typical, with higher VMD springing from economic (working, having higher incomes), demographic (having larger and more active households), and geographic (living in lower density areas) sources. With respect to the latter, urban residents have the lowest average VMD for several reasons: destinations are closer together so that car trips are shorter and walking is more often an option, and densities are higher so that more attractive transit service can be offered. However,

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corresponding per-person statistics because the per-driver denominator is smaller, one median value (for urban dwellers) has the opposite pattern. This may be because some non-drivers reported VMD made a small difference in the value ordering near the 50th percentile.

residential location is correlated with the economic and demographic factors described above, so the VMD differences seen by neighborhood type cannot be attributed completely to the built environment as a *cause*.

The survey also asked (of all respondents, not just drivers), "How far away from home is the most distant place you go to in a typical week?", which is an approximate measure of the respondent's activity radius and, thus, a proxy for the distance dimension. The activity radius varies by work status (Figure 2-12) and residential neighborhood type (Figure 2-13). Workers range farther from home (only 32 percent of workers normally travel within 15 miles of home, whereas 47 percent of non-workers do), and so do rural residents (46 percent of urban residents usually travel within 15 miles from home, whereas only 29 percent of rural residents do). In other words, economic and geographic factors, again, affect how far from home people travel, but it should again be kept in mind that these characteristics are correlated with other traits that are also influential.

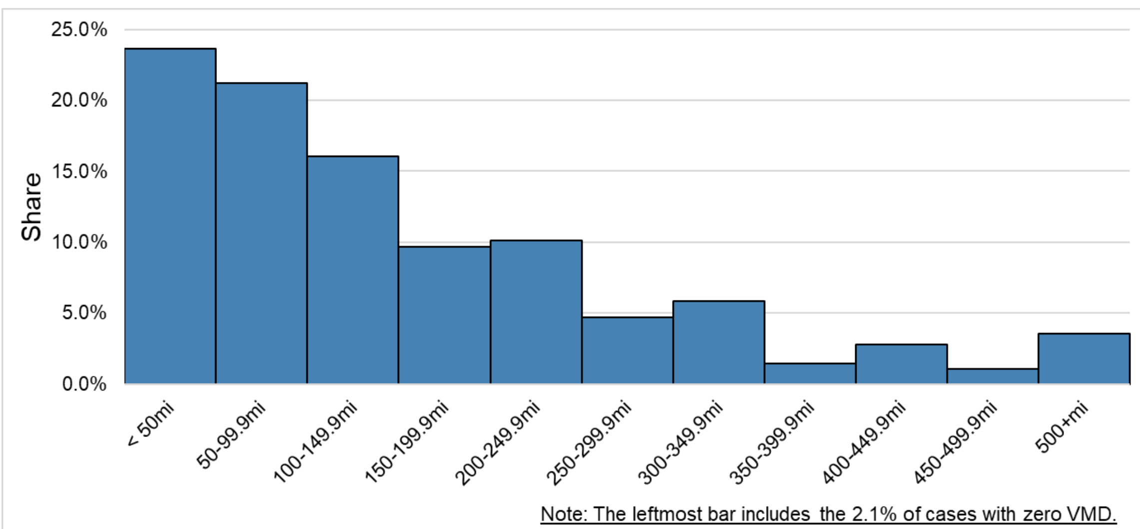

FIGURE 2-11

Histogram of Weekly Vehicle-Miles Driven (N=3,014)

TABLE 2-11
Descriptive Statistics of Weekly Vehicle-Miles Driven per Driver (N=3,014)

Segment	Category	Count	Mean	Std. deviation	Median	90th percentile	Max
Overall		3014	144.69	144.54	100	300	1420
MPO size	Atlanta MPO	1582	156.26	150.18	100	350	1150
	Mid-sized MPOs	517	122.48	134.98	80	300	1200
	Small-sized MPOs	401	131.26	152.53	90	300	1420
	Non-MPO areas	514	141.90	125.22	100	300	600
Age cohort	18–34	684	139.84	136.82	100	300	1000
	35–44	515	181.66	176.50	150	400	1200
	45–64	1194	153.92	147.73	100	350	1420
	65+	621	101.68	99.61	70	250	1200
Income level	Less than $50,000	1195	103.63	113.80	70	250	1420
	$50,000–$99,999	997	168.32	152.66	120	350	1200
	$100,000 or more	822	175.68	159.58	141	400	1200
Work status	Worker	1947	174.53	156.62	140	400	1200
	Non-worker	1067	90.23	98.35	60	200	1420
Neighborhood type	Urban part of a city / region	488	98.28	107.41	63	217	1420
(N=2,964)	Suburban part of a city / region	1432	165.45	161.31	110	400	1200
	Small town	527	140.16	137.06	100	300	1000
	Rural area	517	140.35	124.13	100	300	1000

TABLE 2-12

Descriptive Statistics of Weekly Vehicle-Miles Driven per Person (N=3,106)

Segment	Category	Count	Mean	Std. deviation	Median	90th percentile	Max
Overall		3106	141.94	143.72	100	300	1420
MPO size	Atlanta MPO	1597	155.75	149.83	100	350	1150
	Mid-sized MPOs	547	119.24	132.81	75	300	1200
	Small-sized MPOs	428	125.10	149.98	80	300	1420
	Non-MPO areas	534	137.40	125.20	100	300	600
Age cohort	18–34	707	137.05	135.76	100	300	1000
	35–44	551	172.04	175.11	125	350	1200
	45–64	1223	151.93	147.06	100	337	1420
	65+	625	101.43	99.46	70	250	1200
Income level	Less than $50,000	1260	100.49	112.23	65	250	1420
	$50,000–$99,999	1012	166.89	152.39	120	350	1200
	$100,000 or more	833	174.35	159.29	140	400	1200
Work status	Worker	1980	172.94	156.15	130	400	1200
	Non-worker	1126	87.46	97.23	52	200	1420
Neighborhood type	Urban part of a city / region	514	98.08	105.87	70	209	1420
(N=3,049)	Suburban part of a city / region	1452	163.44	161.10	100	400	1200
	Small town	564	132.82	136.27	100	300	1000
	Rural area	518	140.13	124.08	100	300	1000

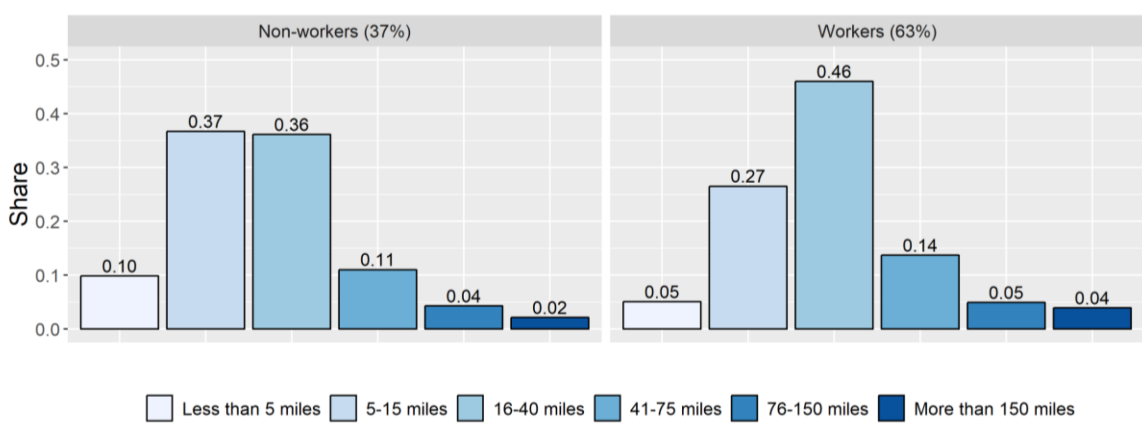

FIGURE 2-12

Miles to the Most Distant Place in a Typical Week (by work status) (N=3,214)

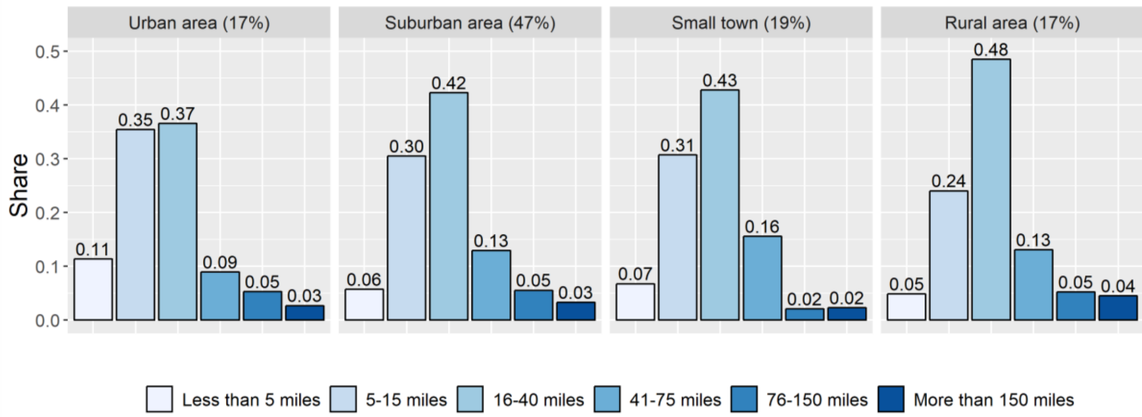

FIGURE 2-13

Miles to the Most Distant Place in a Typical Week (by neighborhood type) (N=3,141)

2.3.2.2. Modeling vehicle-miles driven

To quantify the effects of various factors on VMD (i.e., how much people drive), we developed a regression model. As shown in Figure 2-11, the distribution of VMD is highly skewed; hence, we transformed it by applying the logarithm to reduce deviation from the normal distribution (consistent with other studies, such as Handy et al, 2005; Circella et al., 2017; and Singh et al., 2018)[18]. As a result, the coefficients of the model can be interpreted as the percentage change in VMD resulting from a one-unit change in the associated explanatory variable. Table 2-13 shows the estimation results of a weighted log-linear regression model. The model has a moderate R-squared ($R^2 = 0.266$), an acceptable value considering the goodness of fit of typical travel behavior models.

In the final model, various sociodemographics are found to have statistically significant effects on an individual's VMD. Male, white, higher income, and highly educated people tend to drive more in a typical week. Consistent with the descriptive statistics in Table 2-11, the middle age cohort (35–64) drives more, in keeping with their lifecycle stage (peak earning, pre-empty-nest years). People who have a partner living separately tend to drive more, perhaps reflecting the

[18] To avoid taking the logarithm of zero (which is negative infinity), we added 1 to each value before the log-transformation (i.e., $\ln(VMD + 1)$). This also transforms a VMD of 0 to $\ln(1) = 0$.

inability to spread household-serving trips across multiple driving-age household members, as well as trips between the multiple residences of the split household (e.g., taking children to visit a separated parent). Work status impacts VMD a great deal: on average, switching from being a non-worker to being a worker leads to a 76 percent increase ((exp(0.563) – 1) * 100) in VMD.[19] Overall, Atlanta MPO residents tend to drive more than other area residents. Four land-use characteristics are also found to have significant effects on VMD. As population/job densities, number of stores (within a mile from home), and transit score increase, people tend to drive less. This corroborates numerous studies in the land use literature finding that densification is associated with less driving. It is particularly striking that even after controlling for density, transit score is still statistically significant, suggesting that a key mechanism for decreasing VMD is not just through shortening trip lengths because of higher densities, but also through diversion to transit when service levels are attractive.

Telecommuting generally reduces VMD (see Section 3.2.3 for additional analysis of telecommuting in this sample). Hence, encouraging people to telecommute could be important in terms of reducing VMD overall. For example, all else equal, people who telecommute 1–3 times a week have 18 percent lower VMD than those who do not telecommute, on average; those who do so 4 or more times a week have 34 percent lower VMD. People who use ridehailing services at least once a week on average tend to drive less, but after taking ridehailing drivers' miles into account, it is unclear whether using ridehailing services is adding or reducing VMD on the system level. Finally, attitudes also matter for VMD: travel-liking, pro–car-owning, and less-environmentally-concerned people tend to drive more.

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[19] Technically, in VMD + 1, per footnote 18.

TABLE 2-13
Estimation Results of Log-Transformed VMD Model (N=2,892)

Dimension	Variable	Coefficient	t-value
Intercept	Intercept	4.412	67.22
Land use characteristics	Population density (pop/acre)	−0.018	−3.12
	Job density (jobs/acre)	−0.012	−3.40
	Number of stores (within a mile)	−0.009	−3.65
	Transit score [b]	−0.384	−4.46
Behaviors	Telecommute frequency (less than once a month) [c]	−0.004	−0.06
	Telecommute frequency (1–3 times a month) [c]	−0.092	−1.24
	Telecommute frequency (1–3 times a week) [c]	−0.198	−2.86
	Telecommute frequency (4 or more times a week) [c]	−0.408	−5.92
	Use Uber/Lyft weekly base	−0.361	−3.39
MPO level	Mid-sized MPO area	−0.343	−7.29
(base: Atlanta MPO)	Small-sized MPO area	−0.374	−6.96
	Non-MPO area	−0.190	−3.70
Sociodemographics	Female	−0.275	−8.22
	White	0.206	5.64
	Middle income ($50k–$99k per year, household)	0.229	5.54
	High income ($100k+ per year, household)	0.253	5.02
	Age 18–34 (base: 35–64)	−0.080	−1.88
	Age 65+ (base: 35–64)	−0.113	−2.34
	Education (some college=1)	0.148	3.41
	Education (bachelor’s degree or beyond =1)	0.152	3.07
	Work status (work=1)	0.563	12.92
	Have partner living separately	0.111	1.95
Attitudes [a]	Travel-liking	0.071	4.33
	Pro–car-owning	0.110	6.58
	Pro-environmental	−0.052	−3.12
Model summary			
R-square	0.266		
Adjusted R-square	0.260		

a. Factor scores—please refer to Chapter 4 for details.
b. A score measuring the level of transit service (as a function of number of transit stations/lines and service frequency). It ranges between 0 and 1.
c. Base is people who do not telecommute.

2.4. Long-distance Trips

The definitions of long-distance trip can differ by study, in that trips can be considered "long-distance" in one or more of several aspects: duration, distance, or destination. Any single one of these dimensions is incomplete, since a trip might be relatively short-distance but long in duration (e.g., spending a few days with family members living 100 miles away), or conversely (flying 400 miles and back for a same-day business meeting). Most studies, however, use a single criterion for their definition. Some have defined long-distance trips by travel time or distance (e.g., 100 miles or more), but in this study we define them as *trips involving an overnight stay*.

2.4.1. Shares of People Making Long-distance Trips

Before delving into more detailed patterns, it is useful to examine the most basic statistic: how many people have taken long-distance trips over the past 12 months, by mode, geographic region, and other variables (Table 2-14). Eighty-two percent of the sample has traveled long distance (i.e., involving overnight) at least once over the past 12 months. Private vehicles were used by more people (72.3%) than any other mode for long-distance travel, and more people traveled to the five states adjacent to Georgia than any other destination region (even edging out "within Georgia" itself, although the picture changes when we look at *number of trips* in Section 2.4.2).

Figure 2-14 and Figure 2-15 show the shares of people making any long-distance trips (for any purpose, mode, and place) by MPO size and by income, respectively. The Atlanta region has the highest fraction of long-distance travelers (87%). There is a clear difference in the share of long-distance travelers across income level. Only 3 percent of the higher-income group has not taken a long-distance trip over the past 12 months, whereas 32 percent of the lower-income group has not done so.

The survey asked about four types of mode: car, bus, plane, and other. However, only small fractions of people reported using bus and other modes; hence, we focus on car and airplane. Clearly, for most population segments, the share of car users is higher than that of airplane passengers. MPO size (Figure 2-16) and income (Figure 2-17) matter for long-distance trips segmented by mode. In other words, on average, residents of larger MPO areas and those with higher incomes are more likely than their counterparts to have made long-distance trips by car, and similarly by airplane. For example, 66 percent of higher-income people traveled by airplane over the past 12 months, whereas only 18 percent of lower-income people did. Similarly, 90 percent of higher-income people traveled long-distance by car, whereas only 55 percent of lower-income people did.

TABLE 2-14
Incidence of at Least One Long-distance Trip (over the past year) (N=3,207)

Made at least one long-distance trip …	Count	Share (%)
Overall	2637	82.2
*Mode**		
By car	2320	72.3
By bus	107	3.4
By airplane	1190	37.1
By other modes	163	5.1
*Destination**		
Within Georgia	1864	58.1
Within TN, FL, NC, SC, or AL**	1981	61.8
Elsewhere in the U.S.	1468	45.8
Canada, Mexico, or the Caribbean	433	13.5
Elsewhere in the world	395	12.3

* Multiple answers are possible.
** Tennessee (TN), Florida (FL), North Carolina (NC), South Carolina (SC), and Alabama (AL) are the five states bordering Georgia.

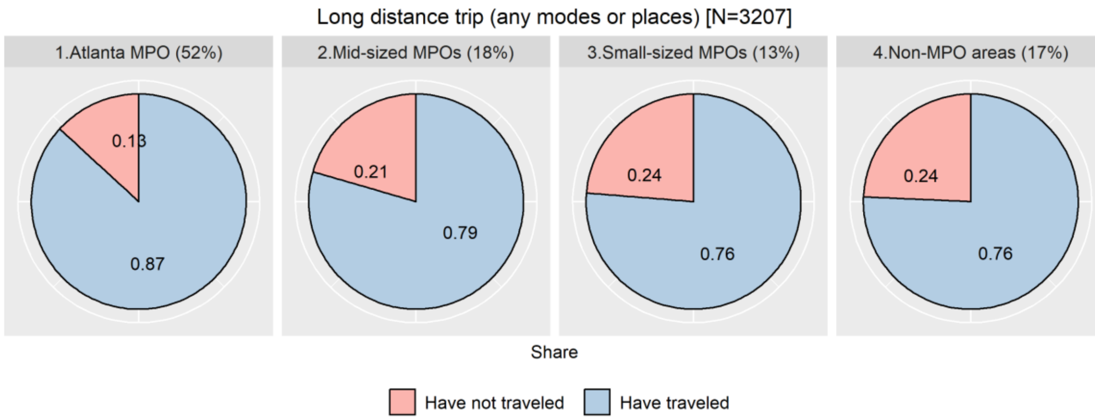

FIGURE 2-14

Share of People who Made at Least One Long-distance Trip (by MPO size)

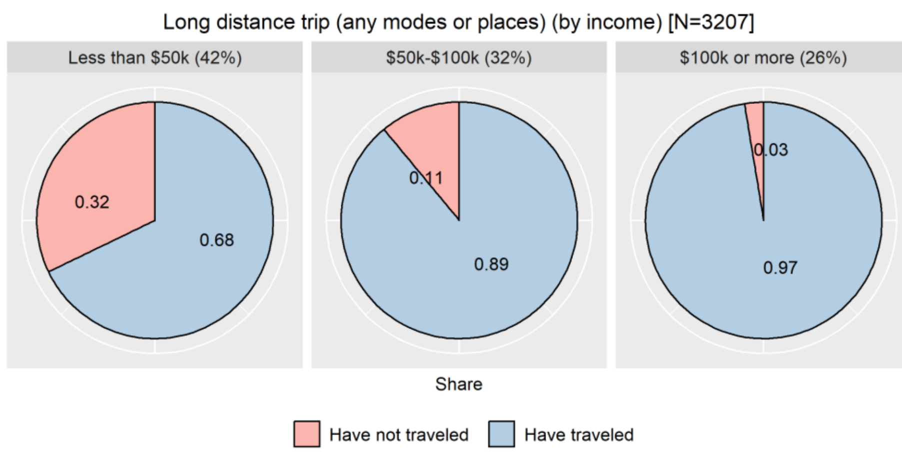

FIGURE 2-15

Share of People Who Made at Least One Long-distance Trip (by income)

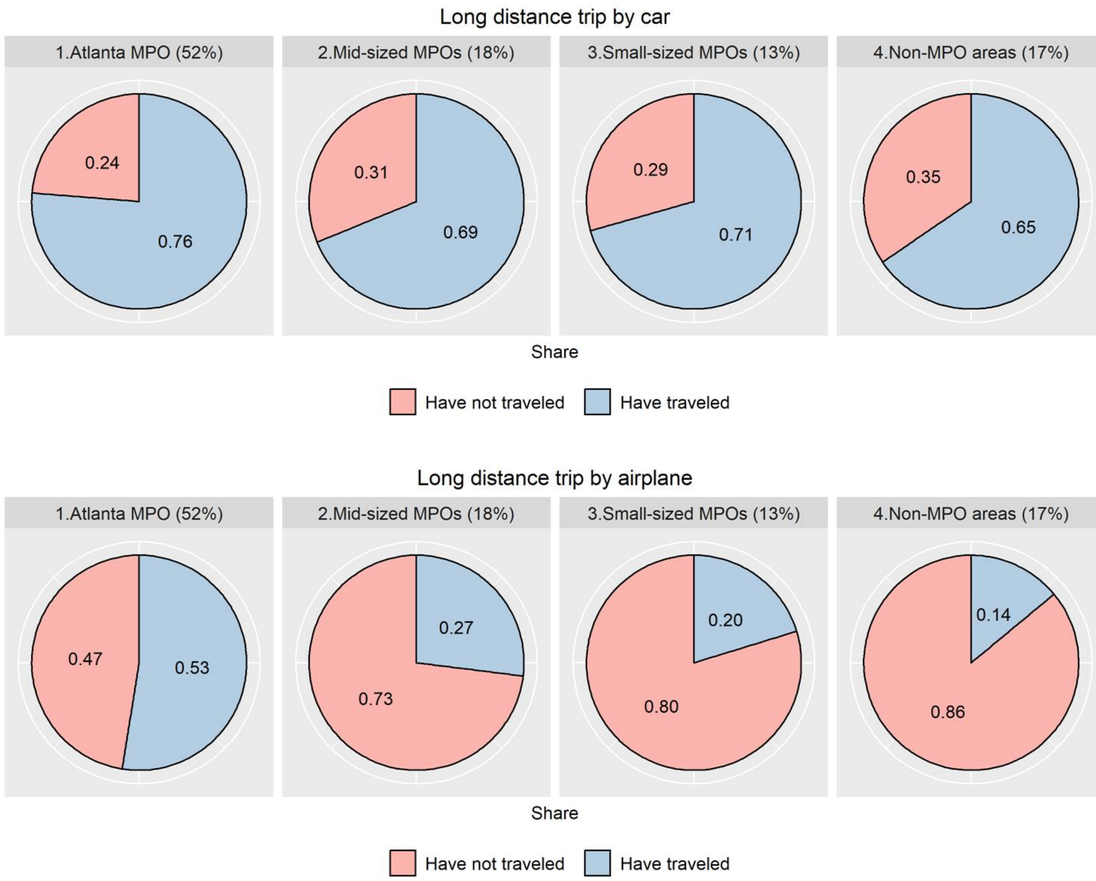

FIGURE 2-16

Share of Long-distance Travelers (by mode [car and airplane] and MPO size)

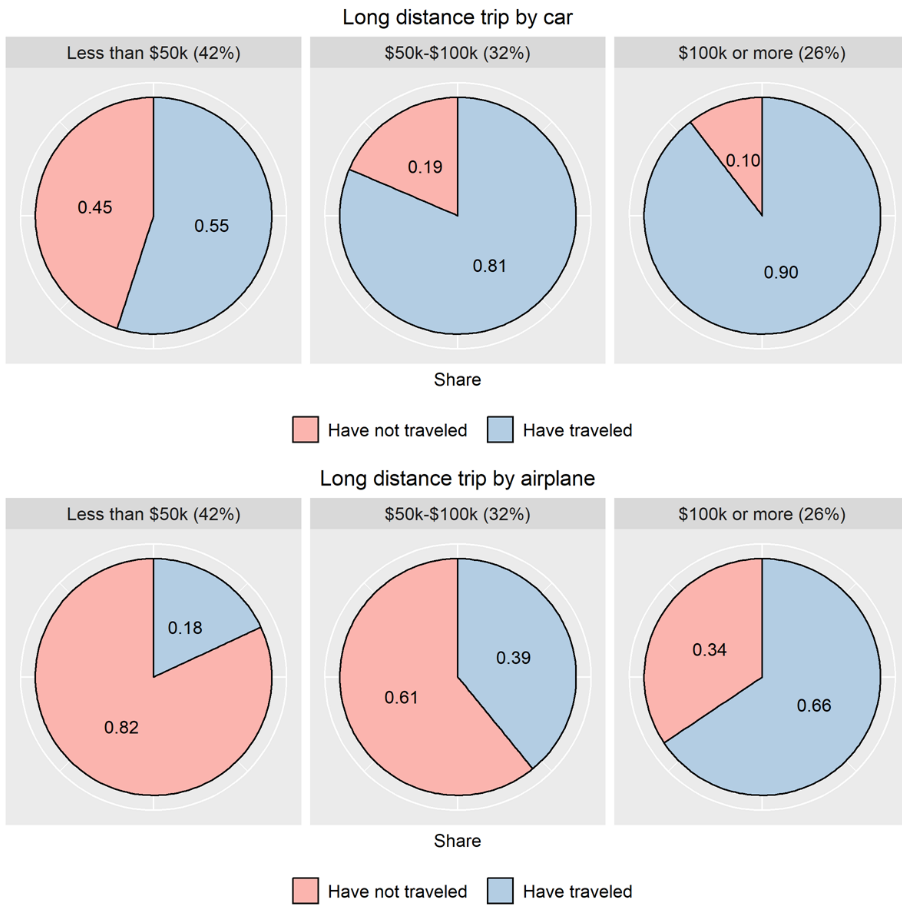

FIGURE 2-17

Share of Long-distance Travelers (by mode [car and airplane] and income)

2.4.2. Number of Long-distance Trips

Section 2.4.1 dealt with the distribution of long-distance *tripmakers*, without regard to how many *trips* a given tripmaker actually took. In the present section, we present the average number of long-distance *trips* by mode and destination, disaggregated by MPO size (Table 2-15) and income (Table 2-16). Some notable observations include:

1. On average, respondents made 9.2 long-distance trips in the 12 months before the survey. Averages range from 10.55 to 5.93 in descending order of MPO size, and from 5.74 to 15.68 in ascending order of income category.

2. For the overall population, any MPO segment, or any income group, car is the most frequently used mode for long-distance travel (being the primary mode for almost three quarters, 74.3 percent[20], of the trips overall). It is followed by airplane (22.7%), other modes (2.2%), and bus (0.8%), in that order.
3. The most popular destinations, for the overall population, any MPO segment, or any income group, are within Georgia (constituting the most distant destination for 41.6 percent of the trips overall). This is followed by adjacent states (28.4%), elsewhere in the U.S. (23.4%), and outside the U.S. (6.6%). One exception to this pattern is that the higher-income group, on average, travels slightly more to elsewhere in the U.S. than to adjacent states.
4. Residents of small MPO areas have the highest average frequency of long-distance trips by car. In concert with the fact that this same group has the highest average frequency of long-distance trips with destinations in Georgia, it seems likely that members of this group may (relatively) often need to travel somewhere within Georgia (e.g., Atlanta) and decide to stay overnight rather than coming back on the same day.
5. Atlanta region residents have a notably higher average frequency of long-distance trips by airplane. This is not surprising in view of the convenient presence of the Hartsfield–Jackson Atlanta International Airport in this region, but that factor is also confounded with income, occupation type, and other characteristics being associated with MPO size. For example, 27 percent of the respondents in the Atlanta region have household incomes above $100,000 a year, compared to only 16 percent of respondents in small-sized MPO areas (result not tabulated).

[20] These percentages are computed as the total number of trips in the row category that are reported by people falling into the column segment, divided by the samplewide column total number of trips and converted to a percentage, *not* as the column-specific average of each *individual's* percentage of trips that fall into the row category.

6. Higher-income groups make notably more long-distance trips, by both car *and* air, than other income groups do.

TABLE 2-15
Average Frequency of Long-distance Trips by MPO Size (N=3,207)

	Atlanta MPO area	Mid-sized MPO areas	Small-sized MPO areas	Non-MPO areas	Total
Overall	10.55	7.93	10.02	5.93	9.22
Mode					
By car	6.34	5.72	9.00	4.87	6.33
By bus	0.06	0.16	0.04	0.02	0.07
By airplane	3.51	1.05	0.55	0.27	2.12
By other modes	0.20	0.17	0.07	0.19	0.18
Destination					
Within Georgia	3.60	4.08	6.79	3.25	4.05
Within TN, FL, NC, SC, or AL*	2.97	2.13	2.04	1.65	2.47
Elsewhere in the U.S.	2.97	1.39	0.95	0.89	2.07
Canada, Mexico, or the Caribbean	0.42	0.15	0.13	0.08	0.27
Elsewhere in the world	0.59	0.18	0.11	0.07	0.36

Note: The averages shown are obtained by dividing the samplewide total number of reported trips in the cell by the number of respondents falling into the column segment.
* Tennessee (TN), Florida (FL), North Carolina (NC), South Carolina (SC), and Alabama (AL) are the five states bordering Georgia.

TABLE 2-16
Average Frequency of Long-distance Trips by Income (N=3,207)

	Less than $50,000	$50,000–$99,999	$100,000 or more	Total
Overall	5.74	8.55	15.68	9.22
Mode				
By car	4.31	6.03	9.96	6.33
By bus	0.09	0.06	0.04	0.07
By airplane	0.44	1.79	5.26	2.12
By other modes	0.10	0.29	0.16	0.18
Destination				
Within Georgia	3.40	3.50	5.75	4.05
Within TN, FL, NC, SC, or AL*	1.39	2.62	4.04	2.47
Elsewhere in the U.S.	0.76	1.86	4.44	2.07
Canada, Mexico, or the Caribbean	0.09	0.21	0.65	0.27
Elsewhere in the world	0.10	0.36	0.80	0.36

Note: The averages shown are obtained by dividing the samplewide total number of reported trips in the cell by the number of respondents falling into the column segment.
* Tennessee (TN), Florida (FL), North Carolina (NC), South Carolina (SC), and Alabama (AL) are the five states bordering Georgia.

2.4.3. Number of Nights Away from Home

Making three trips in a year means one thing if they each involve two *nights* away from home; it means something quite different if they each involve two *weeks* away from home. To obtain a sense of the total combined duration of all trips, the survey asked respondents to report how many nights they spent away from home in all during the past 12 months, offering five ordinal response categories. Figure 2-18, Figure 2-19, and Figure 2-20 present the number of nights away from home by various population segments. They show that residents of larger MPO areas, younger people, and higher-income people spent more nights away from home over the past 12 months. In particular, income is naturally very relevant; for example, 45 percent of higher-income people spent more than 25 nights away from home in the past year, whereas only 15 percent of lower-income people did.

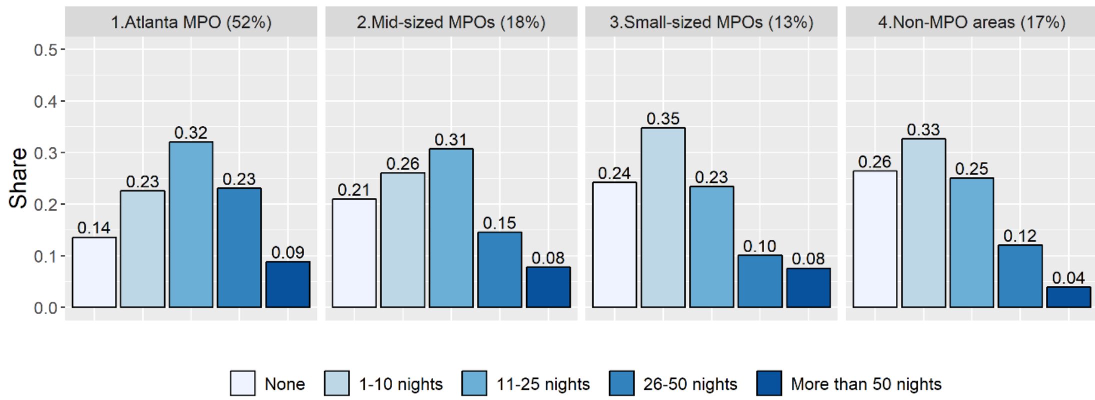

FIGURE 2-18

Number of Nights Away from Home (by MPO size) (N=3,141)

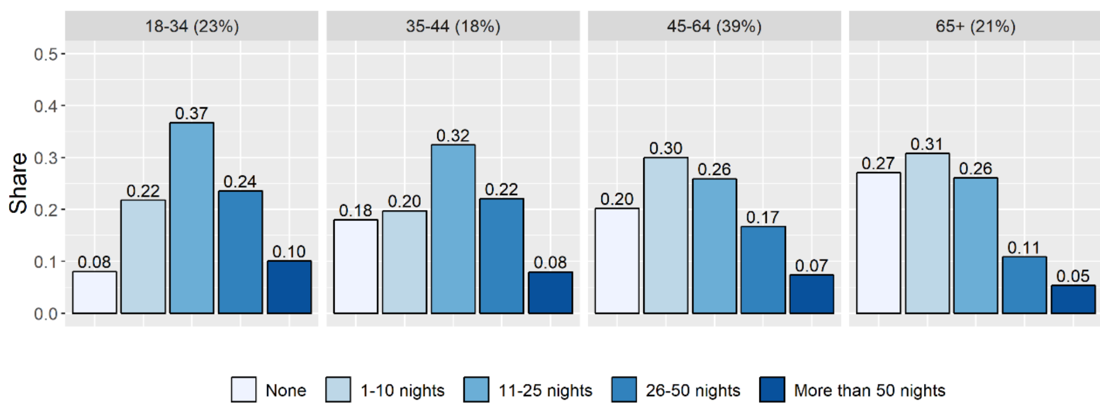

FIGURE 2-19

Number of Nights Away from Home (by age cohort) (N=3,141)

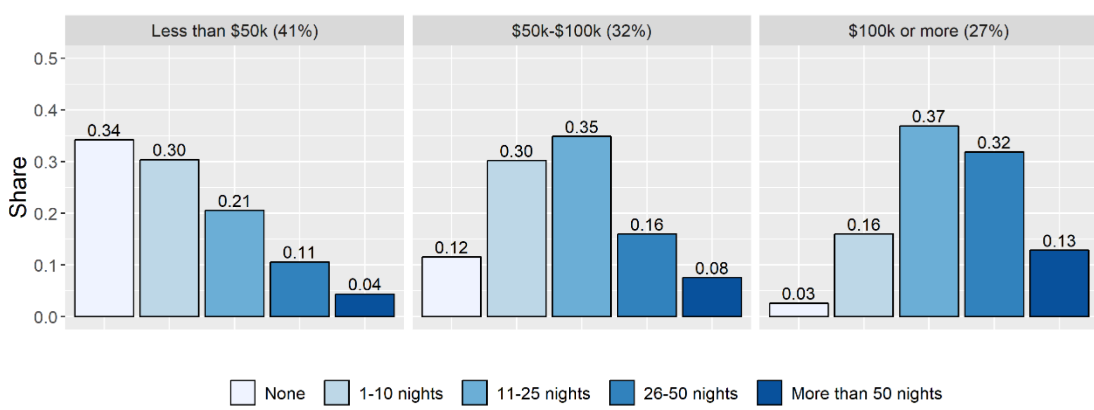

FIGURE 2-20

Number of Nights Away from Home (by income) (N=3,141)

3. COMMUTE AND WORK PATTERNS

Commuting is a major activity whose frequency and spatiotemporal concentration is a key contributor to congestion and its correlates (such as emissions, energy consumption, and crashes). In this chapter, we explore the commute patterns of Georgia residents. We begin by analyzing work patterns (Section 3.1), and continue with characteristics of commuting (Section 3.2).

3.1. How People Work

There are 2,049 workers in the (weighted) sample, 62.3 percent of the total (3,288). Table 3-1 shows the distribution of employment status among workers. Multiple answers could apply, so the total exceeds 100 percent. Three quarters of the sample works full-time; nearly 14 percent are self-employed; 6 percent hold more than one job. As shown in Table 3-2, a fixed shift is by far the most common work schedule (65% of workers), followed by flexible schedules (19% of workers). Only 4.4 percent have a compressed work week (e.g., 4/40 or 9/80), suggesting considerable scope for more aggressive promotion of this long-standing transportation demand management (TDM) strategy. Table 3-3 shows the average working hours of the population as a whole, together with that of some segments of the population. On average, workers work 40.9 hours per week; Atlanta-region residents, those ages 35–44, and higher-income people work more than other population segments. These results are consistent with expectations.

TABLE 3-1
Employment Status Among Workers (N=2,049) ("check all that apply")

Employment status	Count	Share (%)
I work full-time for pay	1536	75.0
I work part-time for pay	276	13.5
I am self-employed for pay	279	13.6
I have two or more paying jobs	131	6.4

TABLE 3-2
Work Schedule (N=2,004)

Work schedule	Count	Share (%)
Fixed shift (daytime, evening, or night)	1309	65.3
Variable start time / rotating shift	178	8.9
Compressed work week	89	4.4
Flexible (e.g., I organize my own work hours)	390	19.5
Other	38	1.9

TABLE 3-3
Average Working Hours in a Week (N=1,972)

	Mean	Std. deviation	Count
Total sample	40.92	12.78	1972
MPO size			
Atlanta MPO area	41.65	12.85	1143
Mid-sized MPO areas	40.98	11.65	335
Small-sized MPO areas	40.87	12.31	247
Non-MPO areas	37.54	13.84	248
Age			
18–34	40.09	11.50	565
35–44	43.49	11.51	431
45–64	41.43	13.11	865
65+	31.34	15.95	111
Income			
Less than $50,000	37.28	15.93	575
$50,000–$99,999	40.68	9.90	707
$100,000 or more	44.21	11.54	691

3.2. How People Commute

This section investigates several key indicators of commute patterns. First, we examine the primary commute mode, both with and without considering telecommuting. Next, we briefly summarize average commute times and distances. Finally, we explore the availability and frequency of telecommuting. We presented commute trip frequencies by mode in Section 2.3.1.

3.2.1. Primary Commute Mode

Because commuting is a major source of traffic, commute mode shares are important for planning. Respondents were asked to report their "primary means of transportation" to the work or school[21] location they go to most often. In this report, we have two versions of commute mode shares: mode share among commuters (i.e., without people who mainly work at home) and mode share among all workers (i.e., including people who mainly work at home).[22] Table 3-4 and Table 3-5 compare the commute mode shares of the study with those of the ACS 5-year estimates for the State of Georgia (2017). In general, the results of the study approximate the ACS estimates. The sample has a bit higher share of "drive alone" and lower share of "car with others". However, these comparisons need to be viewed with caution in that (1) the study sample sizes for some categories are rather small (particularly when segmenting the sample); and (2) there are differences between this survey and the ACS in the way this question was worded.[23]

Both tables show that the vast majority (90% or more) of workers rely on cars. In particular, more than four out of five workers (85.7% and 81.8%) primarily commute by driving alone, while another 8–9% drive or ride with others. Public transit (bus or train) and walk/bike pertain to about 3 and 2 percent of workers, respectively. The share of telecommuting or work at

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[21] Although we have excluded non-working students from this portion of the analysis, school may be the more frequently visited location for some working students.

[22] Both sets of statistics are widely used. The survey originally focused on the former; hence, it asked people who "do not travel to work or school" to skip several questions, including the one asking for primary commute mode (which did not include the option of "telecommuting/work at home"). For people who *only* worked at home, there is no ambiguity about their primary commute "mode". The uncertainty arises when people telecommuted some of the time, but were, in effect, asked for a primary mode only with respect to the days on which they physically *commuted*. However, for comparability with other sources (e.g., ACS estimates), we created a new variable for primary commute mode that includes "telecommuting/ work at home", based on other information in the survey. Specifically, we compared the reported telecommuting frequency (question C12) to commuting frequencies by other modes (D6). We then (1) recoded respondents' primary commute mode as "telecommuting" if their telecommuting frequency was greater than the maximum commute frequency by any other mode; or (2) otherwise considered their original answer to question D8 to be their primary mode. This solution will not be error-free, but we believe it to be the best option considering the data available.

[23] This study asked respondents, "What is your **primary** means of transportation to this work or school location?", while the ACS asked respondents, "How did this person **usually get to work LAST WEEK**?" Hence, although both studies aimed to capture the typical most-used mode, the ACS took a snapshot of "last week", while this survey had a broader, more diffuse temporal focus.

home is 5.4 percent—notably exceeding the share of transit, in keeping with nationwide trends. Although we had intended this question to identify working from home as a direct substitute for commuting to one's regular workplace, it is possible that anyone who worked at home, e.g., as a farmer, a live-in domestic worker, or self-employed in a home-based business, could have also reported "telecommuting". Accordingly, this mode should probably be interpreted as "telecommuting/work at home of all kinds", rather than purely as salaried workers staying at home from their regular workplace. The ACS numbers also include such cases, and indeed, the telecommute/work at home primary mode shares are very similar between the two surveys.

Although driving alone dominates the primary commute mode share, there are some differences in mode share across population segments:

- The Atlanta region and mid-sized MPO areas have more diverse commute modes than small-sized MPO areas or rural areas. (Figure 3-1)
- Small MPO areas have the highest share of driving alone (87%), while rural areas exhibit the most ridesharing (14%). (Figure 3-1)
- The Atlanta region has the highest share of "primarily" working at home (8%); rural areas have the next highest share (4%), albeit probably for different reasons. (Figure 3-1)
- On average, urban residents have the most diverse commute modes and have the lowest share of driving alone (76%) compared to residents in other areas. However, ridesharing (16%) and working at home (7%) are most prominent in small towns and suburban areas, respectively. (Figure 3-2)
- Lower-income people use public transit or walk/bike more than other income groups, although the absolute amounts are still small at 4% each. Their ridesharing use is larger (11%) than that of other income groups. (Figure 3-3)
- The higher-income group has the greatest share (8%) of "primary" telecommuters compared to other income groups, and the lowest share of carpooling (6%). It essentially

ties with the lower-income group in transit share (4%); our data do not permit a more in-depth investigation, but we speculate that higher-income people are more likely to be using premium transit services such as express buses. (Figure 3-3)

TABLE 3-4
Overall Primary Commute Mode Share Among Commuters

Commute mode	Current study		ACS 2017 5-year estimates	
	Count	*Share*	*Count*	*Share*
Drive alone	1,527	85.7%	3,622,783	84.0%
Car with others [a]	153	8.6%	466,180	10.8%
Bus/train	55	3.1%	97,418	2.3%
Walk/bike	39	2.2%	79,186	1.8%
Other	8	0.4%	49,585	1.1%
Total	**1,782**	100.0%	**4,315,152**	**100.0%**

a. For the current study, this includes carpool driver, carpool passenger, and Uber/Lyft.

TABLE 3-5
Overall Primary Commute Mode Share Among Workers

Commute mode	Current study		ACS 2017 5-year estimates	
	Count	*Share*	*Count*	*Share*
Drive alone	1,478	81.8%	3,622,783	79.6%
Car with others [a]	144	8.0%	466,180	10.2%
Bus/train	51	2.8%	97,418	2.1%
Walk/bike	32	1.8%	79,186	1.7%
Other means	6	0.3%	49,585	1.1%
Work at home	97	5.4%	238,180	5.2%
Total	**1,808**	**100.0%**	**4,553,332**	**100.0%**

a. For the current study, this includes carpool driver, carpool passenger, and Uber/Lyft.

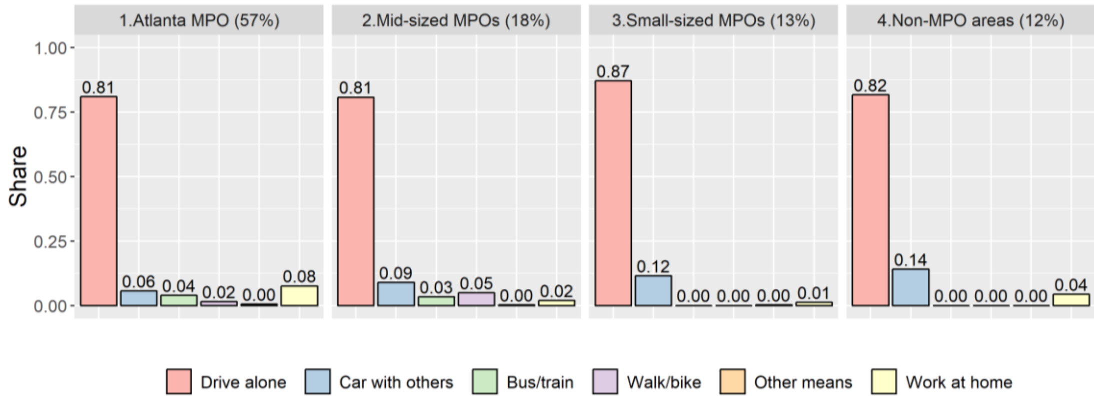

FIGURE 3-1

Primary Commute Mode (by MPO size) (N=1,808)

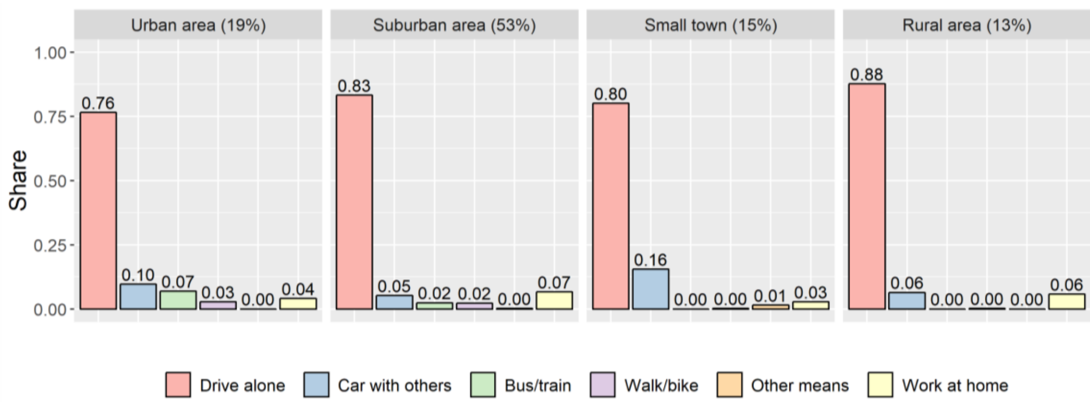

FIGURE 3-2

Primary Commute Mode (by neighborhood type) (N=1,778)

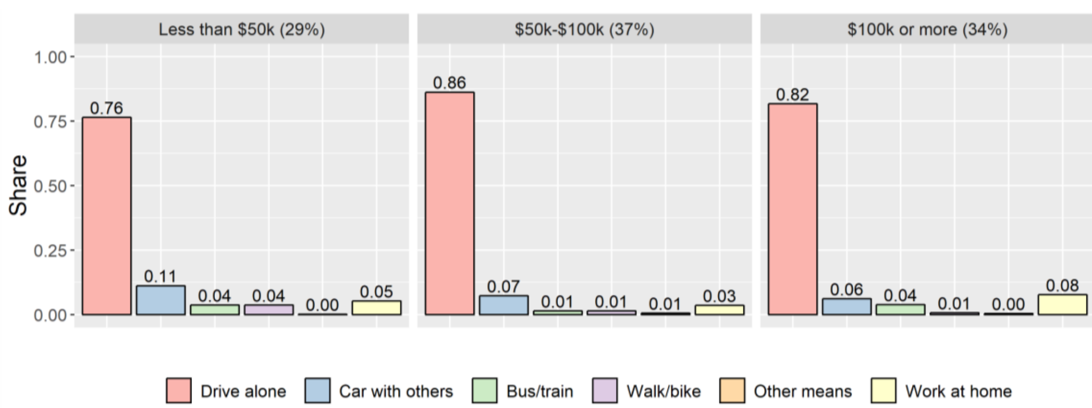

FIGURE 3-3

Primary Commute Mode (by income) (N=1,808)

3.2.2. Commute Time and Distance

Table 3-6 and Table 3-7 present descriptive statistics of commute distance and time.[24] On average, Georgians' commutes are 16.6 miles and 30 minutes long. Atlanta-area residents have the longest average commute time (34 minutes) and the second longest average commute distance (17.4 miles). Mid-sized MPO residents have the shortest average and median commute distance (14.2 and 10 miles). However, small-sized MPO residents have the shortest average commute *time*. When investigating commute distance and time by income level, on average, higher-income people have longer commute distances and times, consistent with typical patterns in the U.S. Stratifying by neighborhood type, urban residents have distinctively shorter commute *distances* (a mean of 10.88 miles and a median of 7 miles) compared to those in other neighborhood types. However, urban residents have an average commute *time* similar to that of small-town and rural-area residents, indicating that their commutes occur at slower speeds (either because of using slower modes, or driving in congestion).

[24] Eight cases reported flight as a primary commute mode, with commute times and distances accordingly extremely large (e.g., 1,000 miles). Commuting by flight does occur, but the descriptive statistics (in particular, the mean and max) can be distorted by such extreme cases. Hence, we exclude those cases in this section. Another important note is that the original question did not provide a "flight" option for the primary commute mode. Such flight commuters were identified because they checked the "other" option and then specified "flight". We cannot rule out the possibility that some flight commuters reported a secondary option (like driving) because they did not find an appropriate option. Hence, some long-distance commutes among those we retained (e.g., one of 600 miles) could still, in fact, occur by flight. In general, the distances and times shown in the tables exhibit a "long tail" pattern, for which 90 percent of the cases fall far below the maximum.

TABLE 3-6
Descriptive Statistics of Self-reported Commute Distance (miles)

	Count	Mean	Std. deviation	Median	90th percentile	Max
Total	*1764*	*16.63*	*20.64*	*12*	*35*	*600*
MPO size (N=1,764)						
Atlanta MPO	1006	17.40	19.58	14	35	400
Mid-sized MPOs	315	14.20	18.88	10	30	225
Small-sized MPOs	226	15.19	27.17	12	29	600
Non-MPO areas	217	18.08	19.77	14	38	175
Income level (N=1,764)						
Less than $50,000	521	14.45	15.03	10	30	125
$50,000–$99,999	648	16.69	13.97	14	35	215
$100,000 or more	595	18.47	29.10	13	35	600
Neighborhood type (N=1,735)						
Urban part of a city / region	332	10.88	11.51	7	20	110
Suburban part of a city / region	914	18.19	21.03	14	40	400
Small town	263	17.73	29.02	10	40	600
Rural area	226	17.63	17.30	15	30	175

TABLE 3-7
Descriptive Statistics of Self-reported Commute Time (minutes)

	Count	Mean	Std. deviation	Median	90th percentile	Max
Total	*1773*	*29.54*	*21.96*	*25*	*60*	*240*
MPO size (N=1,773)						
Atlanta MPO	1013	33.79	22.30	30	62	120
Mid-sized MPOs	317	24.59	21.62	20	45	240
Small-sized MPOs	226	22.28	15.00	20	40	240
Non-MPO areas	217	24.47	22.52	15	45	210
Income level (N=1,773)						
Less than $50,000	526	26.31	19.90	20	55	120
$50,000–$99,999	653	30.36	22.88	25	60	240
$100,000 or more	594	31.50	22.40	27	60	210
Neighborhood type (N=1,743)						
Urban part of a city / region	336	24.49	14.92	20	40	120
Suburban part of a city / region	914	33.52	23.73	30	66	240
Small town	264	24.50	20.26	15	60	200
Rural area	229	25.80	22.21	20	45	240

3.2.3. Telecommuting

With the aid of information and communications technologies, people have the additional option of telecommuting for work. The increase in the number of telecommuters has the potential to contribute to reducing peak-hour congestion. Hence, it is of interest to know how many workers even *can* telecommute (whether the nature of work allows it or he/she is allowed to do so by manager or company, but also potentially including other perceived barriers, such as distractions or inadequate space at home), and how frequently they telecommute. In this section, we first present a descriptive analysis of the availability and frequency of telecommuting, and then a binary logit model of telecommuting adoption.

3.2.3.1. Descriptive analysis

As shown in Table 3-8, a third of workers reported that telecommuting is not possible or not allowed, and a quarter (24%) answered that they "never" telecommute (implicitly saying that they *can* telecommute, but are not doing so now). More than a fifth (21%) of workers telecommute once or more per week.[25]

Figure 3-4 shows the availability and frequency of telecommuting by MPO size. In general, workers in the Atlanta region are better able to telecommute, and do so more frequently. For example, 29 percent of Atlanta workers are not able/allowed to telecommute, whereas 43 percent of workers in small-sized MPO areas are not able/allowed. Consistent with other studies, telecommutability is related to income (or related factors such as occupation or position, Figure 3-5): 21 percent of higher-income people are not able/allowed to telecommute, whereas that share is almost doubled (41%) for lower-income people. Thirty-four percent of higher-income people telecommute once or more per week, whereas only 15 percent of lower-income people do.

Figure 3-6 presents the availability and frequency of telecommuting by neighborhood type. Overall, workers in more urban areas are better *able* to telecommute. However, there is no

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[25] The survey question (C13) reads, "On average, how often do you work from home *instead of* going to a regular workplace (i.e., **telecommute**)?" As touched on in Section 3.2.1, although we had intended this question to identify working from home as a direct substitute for commuting to one's regular workplace, non-zero responses likely (partially) include two groups of people we had tried to exclude: (1) those reporting with respect to after-hours working at home (e.g., checking email in the evenings), and (2) those who are primarily based at home (e.g., a farmer, a live-in domestic worker, or one who is self-employed in a home-based business). We have no way of separating out the first group, but it is less likely (though far from impossible) that they misinterpreted the question. With respect to the second, we have some information, but not enough. Specifically, question C8 asked, "What is your current **employment situation**? Please check ***ALL*** that apply." "I am self-employed for pay" was one response option, but because much self-employment consists of moonlighting outside of a regular paid job, it would not be appropriate to exclude all workers who gave that response from the set of telecommuters. In short, "telecommuting" in this report should probably be interpreted as "telecommuting/work at home of all kinds", rather than purely as salaried workers staying at home from their regular workplace.

The inclusion of both of these groups of "questionable telecommuters" probably accounts, in part, for the relatively high share of regular/frequent telecommuting shown in Table 3-8. In partial support of this supposition, 34.1 percent of the 423 cases in the two highest frequency categories reported "I am self-employed for pay" (possibly together with other employment situations) in response to question C8, compared to only 13.1 percent of the (coincidentally) same number of cases in the two lowest (but non-zero) categories.

clear difference in telecommuting frequency among urban, suburban, and small-town dwellers. One notable point is that rural areas have the highest share of cases in the most-frequent category (4 or more times a week); however, as discussed in footnote 22, this is consistent with our perception that some home-based workers (e.g., farmers and self-employed people) reported that they are telecommuting.[26]

TABLE 3-8
Availability/frequency of Telecommuting (N=1,997)

Category	Count	Share (%)
Not possible / not allowed	666	33.3
Never	486	24.3
Less than once a month	240	12.0
1–3 times a month	183	9.2
1–3 times a week	223	11.1
4 or more times a week	200	10.0

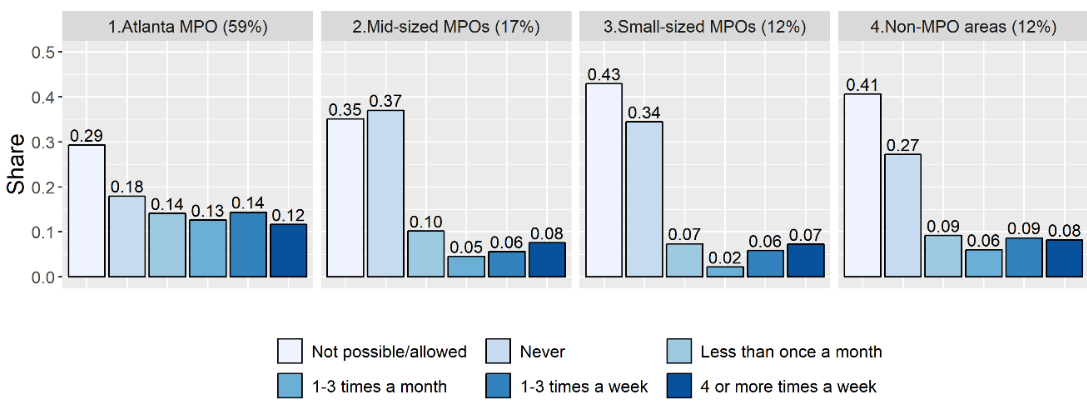

FIGURE 3-4
Availability/frequency of Telecommuting (by MPO size) (N=1,997)

[26] Among rural dwellers, 18 (48%) of the 37 cases in the two highest-frequency categories report being self-employed, compared to only 9 (23%) of the 38 cases in the two lower-frequency categories. Of course, the small sizes of these groups preclude definitive conclusions.

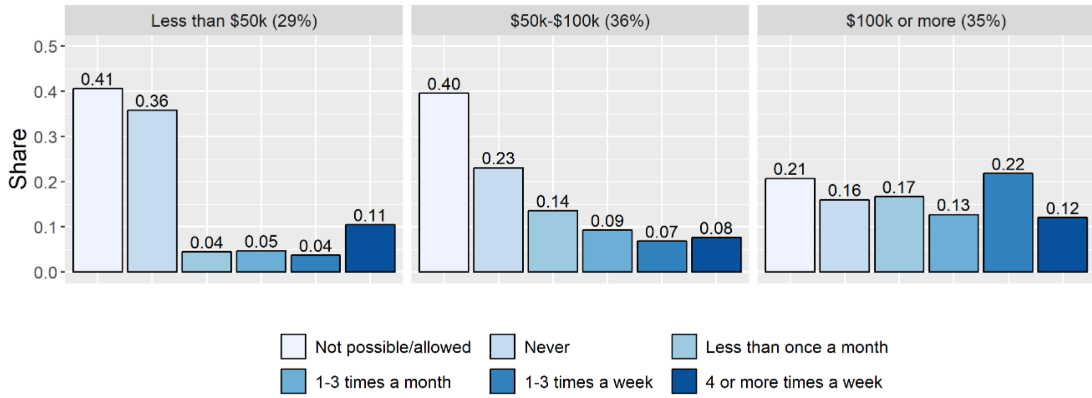

FIGURE 3-5

Availability/frequency of Telecommuting (by income) (N=1,997)

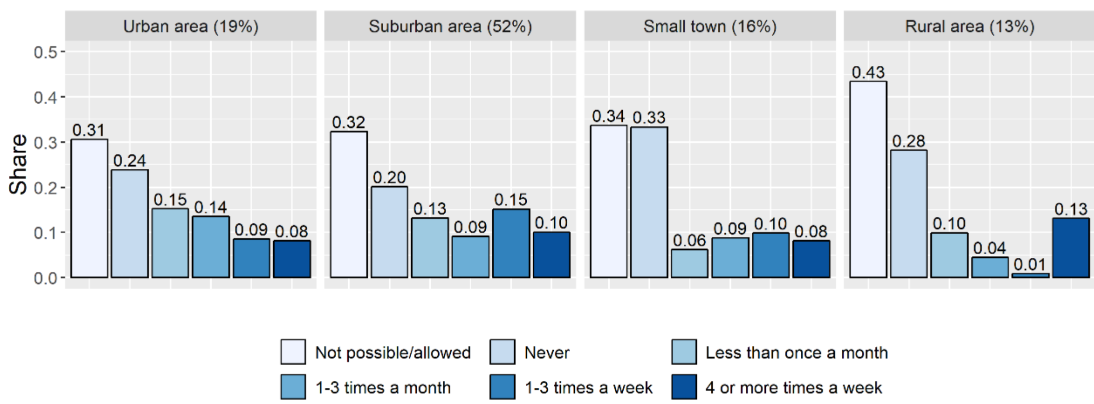

FIGURE 3-6

Availability/frequency of Telecommuting (by neighborhood type) (N=1,970)

3.2.3.2. Modeling the adoption of telecommuting

With respect to telecommuting, a major question is, who telecommutes or works at home, and who does not? Encouraging telecommuting is a key TDM strategy and, in fact, in Georgia, as in many other places around the country, the overall share of telecommuting has overtaken that of commuting by public transit (Table 3-5). Hence, it is desirable to understand the key drivers or factors influencing people to telecommute. Accordingly, in this section we model the adoption of telecommuting, to identify such factors.

Because there are some heterogeneities with respect to reasons to adopt and not to adopt telecommuting, it is important to place certain restrictions on the sample used for the model. In particular, we are most interested in understanding adoption by those who have the *choice* to telecommute or work at home, and those who may offer the greatest transportation benefit from working at home. With that in mind, we first filter out non-workers, and then workers who indicated that telecommuting or working at home was "not possible/not allowed". The latter could be due to a variety of constraints, such as job suitability, management willingness, or even perceived constraints at home, such as the distracting presence of other family members or lack of sufficient space or equipment. We also exclude the self-employed from our model, since they presumably do not need a public policy incentive to telecommute.

In addition, we focus on certain occupations (i.e., professional/technical, manager/ administrator, and clerical/administrative support) that are considered as having the greatest potential to telecommute. While there are always exceptions and gradations, other occupations (e.g., arts/crafts, sales/marketing, production/construction, service/repair) are more likely to involve location-dependent work. Such cases are less informative to TDM policy.

Table 3-9 shows the estimation results of a weighted binary logit model.[27] Overall, the fit of the model is good ($\rho^2 = 0.320$). With respect to sociodemographics, people who are younger,

[27] For brevity, the report does not describe the theoretical background of the model; please see a typical reference such as Ben-Akiva and Lerman, 1985.

have higher income, and live alone are more likely than others to adopt telecommuting. Higher income is likely indicative of greater autonomy and/or more senior rank. The impact of age seems reasonable in that younger people might be less *able* to telecommute overall (since they would tend to have *less* autonomy), but we are investigating their adoption probability *given that they are allowed to telecommute*. Among those allowed to telecommute, younger people may be more tech-savvy, and (at least stereotypically) are more apt to expect and desire workplace flexibility. For example, the 2016 Deloitte Millennial Survey[28] investigated 7,700 millennials in 29 countries and found that 75 percent of respondents want to start to or more frequently work from home or other locations, whereas 43 percent are actually doing it. Similarly, PwC's NextGen study[29] reported that 64 percent of millennials would like to occasionally work from home if the current job were more flexible. People living alone are more likely than others to adopt telecommuting, perhaps because they have fewer distractions and adequate space at home.

Job characteristics are important factors affecting the adoption of telecommuting: workers who are professional or managers, or who have more flexible work schedules are more likely than others to adopt it, while full-time workers are less likely than others to adopt it. The latter two results suggest that working at home complements other forms of employment flexibility (i.e., in the schedule and amount worked) rather than substituting for them, but they may also reflect an association of employment flexibility with *self-employment*—which is often home-based—as much as or more than with salaried employment. In other words, it is not clear whether this result would hold for salaried telecommuters only, or whether it is heavily influenced by the inclusion of home-based workers among the telecommuting group.

With respect to geography and land use characteristics, workers in the Atlanta region are more likely to adopt telecommuting. Workers in mid-sized or small MPO regions are less likely to

[28] Available at https://www2.deloitte.com/content/dam/Deloitte/global/Documents/About-Deloitte/gx-millenial-survey-2016-exec-summary.pdf, accessed on July 11, 2019.
[29] Available at https://www.pwc.com/gx/en/hr-management-services/publications/assets/pwc-nextgen.pdf, accessed on July 11, 2019.

telecommute, hence such MPOs may need more aggressive strategies to encourage telecommuting. Job density at the home location has a negative impact on adopting telecommuting, perhaps representing the availability of more transportation options (e.g., transit), which would make telecommuting less appealing for workers (e.g., Tang et al., 2011).[30] Attitudes are also relevant drivers of adopting telecommuting: people who perceive commuting to have some benefit are less likely to adopt, while those who are more tech-savvy are more likely to adopt telecommuting. One thing to note is that this model is for the *adoption* of telecommuting; the factors associated with the *frequency* of telecommuting could differ.

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[30] We speculated that job density was correlated with actual commute distance/time, but (1) the correlation was not strong, and (2) testing multiple measures of potential commute distance/time, such as block-group-level weighted commuting time or the reported commute distance, did not identify a clear relationship between commuting distance/time and adoption of telecommuting in our data. One problem is that those who telecommute all the time were not asked for their commute distance and time, and imputing those values to be zero would be counter to the expected relationship that *longer* commute distances/times would increase the propensity to telecommute.

TABLE 3-9

Binary Logit Model of Telecommuting Adoption (Base: never, N=886)

Dimension	Variable	Coefficient	t-value
Intercept	Intercept	0.863	1.63
Sociodemographics	Age	−0.027	−3.30
	Middle income \$50k–\$99k (base: below \$50k)	0.789	3.27
	High income \$100k+ (base: below \$50k)	1.547	6.08
	Live alone	0.710	3.27
Land use characteristics	Job density (jobs/acre) at residential location	−0.042	−3.18
MPO level	Mid-sized MPOs	−1.185	−5.06
(base: Atlanta MPO)	Small-sized MPOs	−1.249	−4.21
	Non-MPO areas	−0.620	−2.23
Job characteristics	Full-time employment	−0.420	−1.80
	Occupation (professional/manager=1)	0.725	2.95
	Work schedule (non-fixed shift=1)	0.932	4.63
Attitudes [a]	Commute benefit	−0.400	−4.66
	Tech-savvy	0.286	2.54
Model Summary			
Log-likelihood at $\hat{\beta}$	−417.126		
Log-likelihood at constants [b]	−534.185		
Log-likelihood at zero	−613.869		
ρ^2 (equally-likely base)	0.320		
$\bar{\rho}^2$ (equally-likely base)	0.298		

a. Factor scores—please refer to Chapter 4 for details.

b. Market shares, specifically in the dataset modeled, are ‘telecommuted’ 71% (628) and ‘did not telecommute (but could)’ 29% (258).

4. GENERAL OPINIONS AND ATTITUDES

In some respects, it is just as important to understand what people *think* about transportation as it is to understand what they *do* about it. For several decades, it has been empirically demonstrated that attitudes are key drivers of travel behavior, and are, thus, powerful predictors of that behavior. Attitudes give insight into the motivations behind people's choices, as well as the directions their choices might take if current constraints on their behavior were relaxed. This chapter aims to portray Georgians' general attitudes on several transportation-related dimensions (e.g., preferences regarding residential location, and environmental issues, among others).

Some details on how we designed the survey to capture attitudes are available in Section 2.2 in Part 1. Here, we first explore respondents' raw responses on each of 46 attitudinal statements (Section 4.1). Then, we describe how to estimate attitudinal propensities ("factor scores") from the raw attitudinal statements and present the results (Section 4.2). Finally, we explore attitudinal differences across some population segments (Section 4.3).

4.1. Descriptive Statistics on General Opinions

Table 4-1 presents some descriptive statistics (for the weighted pooled sample) regarding general opinions on a variety of transportation-related topics. The individual statements are measured on the 5-point Likert-type scale ("strongly disagree", "disagree", "neutral", "agree", "strongly agree") and are sorted by relevant dimensions (which will be described in the next section). These responses are numbered 1 through 5, respectively, and a higher mean value indicates greater agreement with the specific statement itself. However, in some cases (for reasons explained in Section 2.2 of Part 1) the statement is oriented oppositely to the dimension with which it is associated. For example, the statement "The importance of exercise is overrated" is oriented oppositely to the pro-exercise direction of the dimension, and so for this statement, a *lower* mean value indicates an attitude more favorable toward exercise. The following opinions have means that are notably different from neutral (3):

- It's very important to me to achieve success in my work (4.27);
- The functionality of a car is more important to me than the status of its brand (4.12);
- The importance of exercise is overrated (2.02);
- I like exploring new places (4.29);
- I definitely want to own a car (4.32);
- I am fine with not owning a car, as long as I can use/rent one any time I need it (2.00);
- I like the idea of driving as a means of travel for me (4.07);
- As a general principle, I'd rather own things myself than rent or borrow them from someone else (4.34); and
- I am generally satisfied with my life (4.09).

One noteworthy observation is that multiple statements speak to a general favorability toward the driving option or having car(s). This is closely associated with the fact that driving is a dominant way to travel (as shown, for example, by the analysis in Chapters 2 and 3). However, favorability toward cars appears to be not just a matter of necessity, but also one of liking. We also see that, in general, Georgia residents are satisfied with their lives.

We present respondents with several statements ("items") relating to each attitudinal dimension, so as to capture multiple aspects of that dimension. In subsequent analyses, however, it is unwieldy to manage a large set of intercorrelated items. Accordingly, we combine responses to related statements into a single score on the underlying dimension or "factor", using the psychometric technique of factor analysis. The application of this approach, which has been extensively used in psychology, transportation, and other domains, is described in the following section.

TABLE 4-1 Descriptive Statistics for Opinions on Transportation-related Topics

Dimension	Statement	Mean	SD	Dist.
Non-car alternatives	I like the idea of walking as a means of travel for me.	2.93	1.20	
	I like the idea of bicycling as a means of travel for me.	2.48	1.20	
	I like the idea of public transit as a means of travel for me.	3.09	1.29	
Tech-savvy	Learning how to use new technologies is often frustrating for me.	2.69	1.31	
	I am confident in my ability to use modern technologies.	3.84	1.04	
Commute benefit	My commute is a useful transition between home and work (or school).	3.36	0.95	
	My travel to/from work (or school) is usually pleasant.	3.49	1.00	
	I wish I could instantly be at work (or school) – the trip itself is a waste of time.	2.94	1.14	
Modern urbanite	I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	3.44	1.26	
	My phone is so important to me, it's almost part of my body.	3.19	1.21	
Work-oriented	At this stage of my life, having fun is more important to me than working hard.	3.19	1.20	
	I'm too busy to have as much leisure time as I'd like.	3.22	1.16	
	It’s very important to me to achieve success in my work.	4.27	0.80	
Materialistic	I usually go for the basic (“no-frills”) option rather than paying more money for extras.	3.39	1.05	
	The functionality of a car is more important to me than the status of its brand.	4.12	0.95	
	I would/do enjoy having a lot of luxury things.	3.13	1.08	
	I like to wait a while rather than being first to buy new products.	3.81	0.91	
	I prefer to minimize the amount of things I own.	3.25	1.02	
Polychronic	I prefer to do one thing at a time.	3.33	1.05	
	I like to juggle two or more activities at the same time.	3.19	1.06	
Pro-environmental	Cost or convenience takes priority over environmental impacts (e.g. pollution) when I make my daily choices.	3.15	1.06	
	I am committed to an environmentally-friendly lifestyle.	3.51	0.91	
Pro-exercise	The importance of exercise is overrated.	2.02	0.95	
	I am committed to exercising regularly.	3.49	1.10	
Family/friends-oriented	Family/friends play a big role in how I schedule my time.	3.80	1.03	
	It’s okay to give up a lot of time with family and friends to achieve other worthy goals.	2.63	1.06	
Pro-suburban	I prefer to live in a spacious home, even if it’s farther from public transportation or many places I go to.	3.05	1.18	
	I see myself living long-term in a suburban or rural setting.	3.82	1.14	
Waiting-tolerant	Having to wait is an annoying waste of time.	3.49	1.07	
	Having to wait can be a useful pause in a busy day.	3.01	1.09	
Travel liking	I generally enjoy the act of traveling itself.	3.90	0.95	
	I like exploring new places.	4.29	0.81	
Sociable	I consider myself to be a sociable person.	3.78	0.93	
	I’m uncomfortable being around people I don’t know.	2.86	1.12	
Pro-car-owning	I definitely want to own a car.	4.32	0.93	
	I am fine with not owning a car, as long as I can use/rent one any time I need it.	2.00	1.18	
	I like the idea of driving as a means of travel for me.	4.07	0.93	
	As a general principle, I'd rather own things myself than rent or borrow them from someone else.	4.34	0.75	

* Note: The last column, “Distribution”, depicts the distributions of responses on the five-point Likert-type scale. The leftmost and the rightmost bars indicate “strongly disagree” and “strongly agree”, respectively.

4.2. Estimation of Attitudes Using Factor Analysis

This section describes how we conduct factor analysis as a means of estimating attitudes. It contains a number of technical details and can be skipped, if desired. To summarize this section, at the conclusion of the factor analysis, we produced, for each person, standardized scores on each attitudinal construct, representing the degree of agreement with that attitude. The scores are weighted combinations of the individual's responses to the specific statements shown in Table 4-2, where the weights are a function of the loadings shown in the table, i.e., higher for items more strongly associated with the factor.

Factor analysis is a method for uncovering psychological constructs, and quantifying individuals' measurements on those constructs. Many studies have used principal components analysis (PCA) as a data reduction method, but our aim is to identify latent constructs by modeling associations among indicator variables (here, attitudinal statements); hence, exploratory factor analysis (EFA) is more appropriate (Fabrigar et al., 1999). In this study, as described in Part 1, we designed 46 attitudinal statements in Section A of the survey, to capture several dimensions of attitudes. As a large body of literature has demonstrated that attitudes are key covariates of travel-related behaviors or choices, the attitudinal constructs identified will be informative and useful for explaining behaviors/choices that will be covered in later sections and future analyses.

Before conducting the factor analysis, we inspected the data for missing responses to the 46 statements in Section A. Most statistical techniques (including factor analysis) rely on having complete data for each case (i.e., the set of responses for a single individual), so missing data for a given case must either be imputed, or the entire case be discarded. Accordingly, dealing with missing data involves a tradeoff between imputing "too many values" (either for a given case, or for a given variable), and the loss of information associated with throwing away the entire case. After evaluation of the number and patterns of missing responses, we decided to discard cases missing eight or more responses to these attitudinal statements, and impute missing values for the remaining cases. In particular, we employed the predictive mean matching imputation method (Little, 1988; Van Buuren and Groothius-Oudshoorn, 2010; Van Buuren, 2018). Both because we were conservative about how many items to impute (after discarding 33 cases with eight or more missing items, we imputed only 866 responses for the remaining 3,515 cases, i.e., only 0.5 percent of the $46 \times 3{,}515 = 161{,}690$ total responses), and because the factor scores produced by the analysis are less sensitive to individual items, any differences between the imputed and true (but unreported) responses should not materially influence the results.

To find the best factor solution, we explored various solutions by controlling the number of items included (i.e., investigating the exclusion of items with low loadings), rotation method (varimax, oblimin, promax, etc.[31]), and the degree of rotation. The major challenge in factor analysis is selecting the number of factors, and many studies have suggested multiple principles or rules of thumb, such as the eigenvalue-greater-than-one rule or "elbow rule" (Cattell, 1966; Rummel, 1970). For selecting the optimal number of factors, we considered multiple quantitative and qualitative criteria: communalities (proportion of the variance of the variable that is common to other variables); factor loadings[32] (at least 0.3 in magnitude for the highest loadings for each item, and minimizing the number of items loading substantially on more than one factor); scree plot; and interpretability (see Figure 4-1). Throughout the experiments, we found several statements that did not load on any factors meaningfully (i.e., their highest loading was less than 0.3 in magnitude) and, thus, we ultimately excluded them from the factor analysis (while treating them as "standalone" items in future analyses). Some of them were intentionally designed to be standalone items (i.e., we did not include other related statements) and others were designed to

[31] The varimax method ensures that the attitudinal dimensions are orthogonal to each other (uncorrelated), whereas other rotations allow obliqueness (correlations) between factor dimensions. Since we use factor scores as explanatory variables, it would be desirable for them to be uncorrelated, but Fabrigar et al. (1999) summarized several rationales for why oblique rotation is preferred (e.g., conceptually some constructs are correlated to each other; oblique solutions provide more information).
[32] Items have "loadings" on each factor, representing the association of the item with each factor. Loadings generally range between −1 and 1, and higher magnitudes mean a stronger association (either in the same direction if positive, or oppositely oriented if negative).

represent certain constructs, but were not perceived as doing so by the respondents. These statements appear at the bottom of Table 4-1.

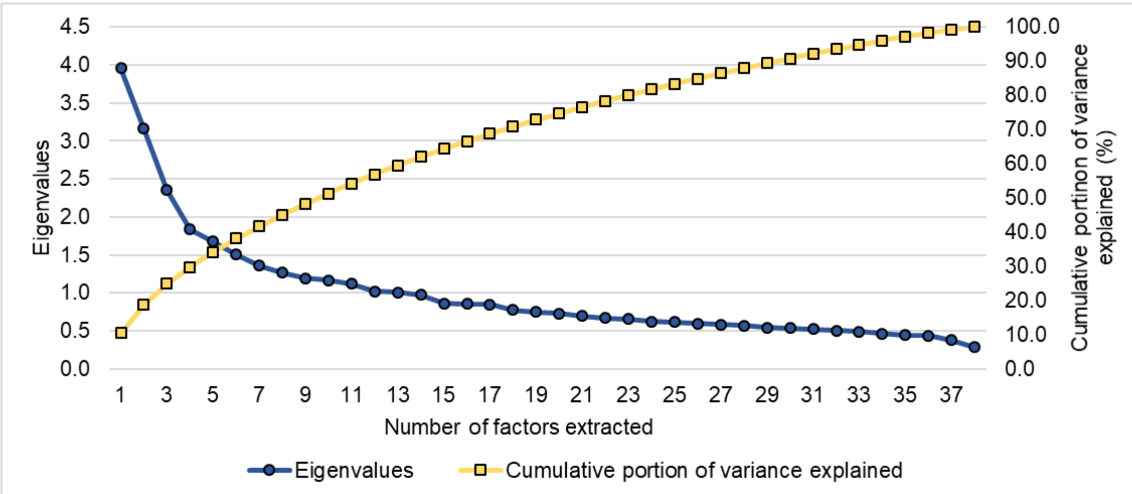

FIGURE 4-1

Initial Eigenvalues and Cumulative Portion of Variance Explained (by number of factors)

Using oblimin rotation (with delta=0)[33] on the 38 remaining statements, we chose the 15-factor solution. We labeled each factor based on the statements most highly loading on it (Table 4-2). In general, the empirical latent constructs found by factor analysis are similar to the conceptual constructs around which we designed the items. Some factors (e.g., tech-savvy, pro-environmental, pro-suburban) are expected to be key covariates in explaining travel behaviors and choices in later chapters, since they have been used as key variables in previous studies. It is worth noting that because we allow oblique rotation, the factors are correlated. The absolute value of correlation ranges from 0.013 to 0.412. Some correlations are more than moderate, but they are conceptually valid. For example, the correlation of −0.412 between *non-car alternatives* and *pro–car-owning* is

[33] The (direct) oblimin rotation, suggested by Jennrich and Sampson (1966), is an oblique rotation method that minimizes the objective function applied directly to the loadings rather than to the reference structure (which is common among other rotation methods). The oblimin method is preferred in that it is simpler than others and has a wider range of oblique solutions. The delta parameter controls the degree of rotation, and Harman (1976) suggested to set delta to zero or negative. The factors are most oblique when delta=0, and large negative values of delta lead to factors which are nearly orthogonal (Harman, 1976). We explored different values of delta to reduce factor correlations, but it resulted in having more “off-diagonal” loadings (i.e., items loading substantially on more than one factor); hence we use delta=0.

attributable to the logical (inverse) connection between driving and other modes—but the two factors represent conceptually different dimensions.

To further investigate attitudes and use them as covariates in modeling, we needed to obtain "factor scores" for each individual on each attitude. However, since common factor scores are mathematically indeterminate, we needed to *estimate* them (McDonald and Burr, 1967). In particular, we employed the Bartlett estimation method.[34] We standardized the resulting factor scores, as well as the responses to the individual standalone items, so that all attitudes were measured on commensurate scales. The outcome of this procedure is described in the first paragraph of this section.

[34] Refer to some comparisons among estimation methods in other studies such as DiStefano et al. (2009).

TABLE 4-2
Attitudinal Factors and Corresponding Factor Loadings

Factor	Statement	Pattern matrix loading[a]
Non-car alternatives	I like the idea of walking as a means of travel for me.	0.666
	I like the idea of bicycling as a means of travel for me.	0.628
	I like the idea of public transit as a means of travel for me.	0.336
Tech-savvy	Learning how to use new technologies is often frustrating for me.	−0.866
	I am confident in my ability to use modern technologies.	0.801
Commute benefit	My commute is a useful transition between home and work (or school).	0.677
	My travel to/from work (or school) is usually pleasant.	0.579
	I wish I could instantly be at work (or school)—the trip itself is a waste of time.	−0.428
Modern urbanite	I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	0.417
	My phone is so important to me, it's almost part of my body.	0.350
Work-oriented	At this stage of my life, having fun is more important to me than working hard.	−0.572
	I'm too busy to have as much leisure time as I'd like.	0.527
	It's very important to me to achieve success in my work.	0.298
Materialistic	I usually go for the basic ("no-frills") option rather than paying more money for extras.	−0.565
	The functionality of a car is more important to me than the status of its brand.	−0.431
	I would/do enjoy having a lot of luxury things. [c]	0.426
	I like to wait a while rather than being first to buy new products.	−0.357
	I prefer to minimize the amount of things I own.	−0.341
Polychronic	I prefer to do one thing at a time.	−0.834
	I like to juggle two or more activities at the same time.	0.697
Pro-environmental	Cost or convenience takes priority over environmental impacts (e.g., pollution) when I make my daily choices.	−0.914
	I am committed to an environmentally friendly lifestyle.	0.481
Pro-exercise [b]	The importance of exercise is overrated.	−0.669
	I am committed to exercising regularly.	0.663
Family/friends-oriented [b]	Family/friends play a big role in how I schedule my time.	0.612
	It's okay to give up a lot of time with family and friends to achieve other worthy goals.	−0.468
Pro-suburban	I prefer to live in a spacious home, even if it's farther from public transportation or many places I go to.	0.609
	I see myself living long-term in a suburban or rural setting.	0.387
Waiting-tolerant	Having to wait is an annoying waste of time.	−0.831
	Having to wait can be a useful pause in a busy day.	0.533
Travel liking [b]	I generally enjoy the act of traveling itself.	0.618
	I like exploring new places.	0.593
Sociable	I consider myself to be a sociable person.	0.563
	I'm uncomfortable being around people I don't know.	−0.507
Pro–car-owning	I definitely want to own a car.	0.748
	I am fine with not owning a car, as long as I can use/rent one any time I need it.	−0.576
	I like the idea of driving as a means of travel for me.	0.535
	As a general principle, I'd rather own things myself than rent or borrow them from someone else.	0.404

a. Factor loadings under 0.3 are suppressed.
b. For easier interpretation, we changed the direction of the factor by multiplying the original loadings by (−1).
c. This statement also had loadings greater than 0.3 on other constructs (0.319 on *Modern urbanite* and 0.361 on *pro-suburban*).

4.3 Attitudes by Population Segment

Average attitudes differ by population segment, and, thus, can contribute to different behaviors by segment. Hence, understanding attitudes by segment can deepen our knowledge of travel behavior. The factor scores, whose estimation was described in the previous section, are standardized, i.e., expressed in terms of standard deviations from the raw mean.[35] As such, individual scores generally lie between −3 and 3, while averages across groups of any size will tend to lie in a much narrower range around 0. Either way, we can interpret scores using directionality (positive or negative) and magnitude. For example, a pro–car-owning score of −0.3 indicates a moderately negative attitude toward having car(s) for an individual, but as an average across a large group of people, it can be viewed as portraying a *relatively strong* negative attitude for the group as a whole (taking any sizable group of people whose attitudes will inevitably vary, it is a lot harder for the *average* to be as low as −0.3 than it is for any *single* score to have that value). In this section, we describe the differences for selected attitudes and segments.

With respect to MPO size, on average, Atlanta area residents tend to be more tech-savvy, pro-exercise, and urbanite, and less pro-suburban (Figure 4-2). There are monotonic increases/decreases in mean scores by MPO size. Certain correlations are quite natural; for example, residential location preferences are associated with actual residential choice (i.e., the larger the MPO area, the less pro-suburban its residents are, on average). Related to mode use, people who live in the Atlanta region tend to be more favorable toward non-car alternatives than those living elsewhere in Georgia. In addition, on average, Atlanta residents perceive less benefit of commuting compared to residents in smaller MPO areas—presumably a function of the recurrent heavy congestion in the Atlanta region.

[35] For this analysis, we post-processed the raw factor scores obtained from the Bartlett estimation method. First, some factor scores are multiplied by (−1) to change directionality for easier interpretation (see Section 4.2). Then, because Bartlett estimation does not provide standardized scores, we standardized the scores by first dividing them by their standard deviation, and then recentering them by subtracting the weighted mean across the sample.

Figure 4-3 presents average attitudinal factor scores by age cohort. On average, younger people tend to be more work-oriented, tech-savvy, pro-exercise, travel-liking, and favorable to non-car alternatives. Although studies on generational differences have proliferated in recent years (e.g., comparisons between millennials and Generation X), investigations in Georgia have rarely been conducted. Our findings are consistent with other cohort-comparison studies and, thus, corroborate that Georgia also has similar patterns of generational difference. One thing to note is the result for the pro-environmental attitude is somewhat counterintuitive in that many studies have discussed that the younger generations are more pro-environmental. However, the debate on this conventional wisdom is ongoing. Some studies also have found that younger people are not necessarily pro-environmental, and that certain attitudes could be confounded with other factors such as life stage or income level. In our study, the pro-environmental factor is measured with two attitudinal statements (see Table 4-2), and they may not measure a purely pro-environmental dimension. For example, the statement of "Cost or convenience takes priority over environmental impacts (e.g., pollution) when I make my daily choices" loads heavily on the pro-environmental factor (see Table 4-2), but it is also seemingly related to other constructs such as cost-sensitivity.[36]

[36] On the other hand, it could be argued that "forcing" a tradeoff between personal benefit and the "greater good" is a more "true" indicator of environmental attitudes than eliciting an unconstrained preference. It is easy to be pro-environment when it is free and convenient.

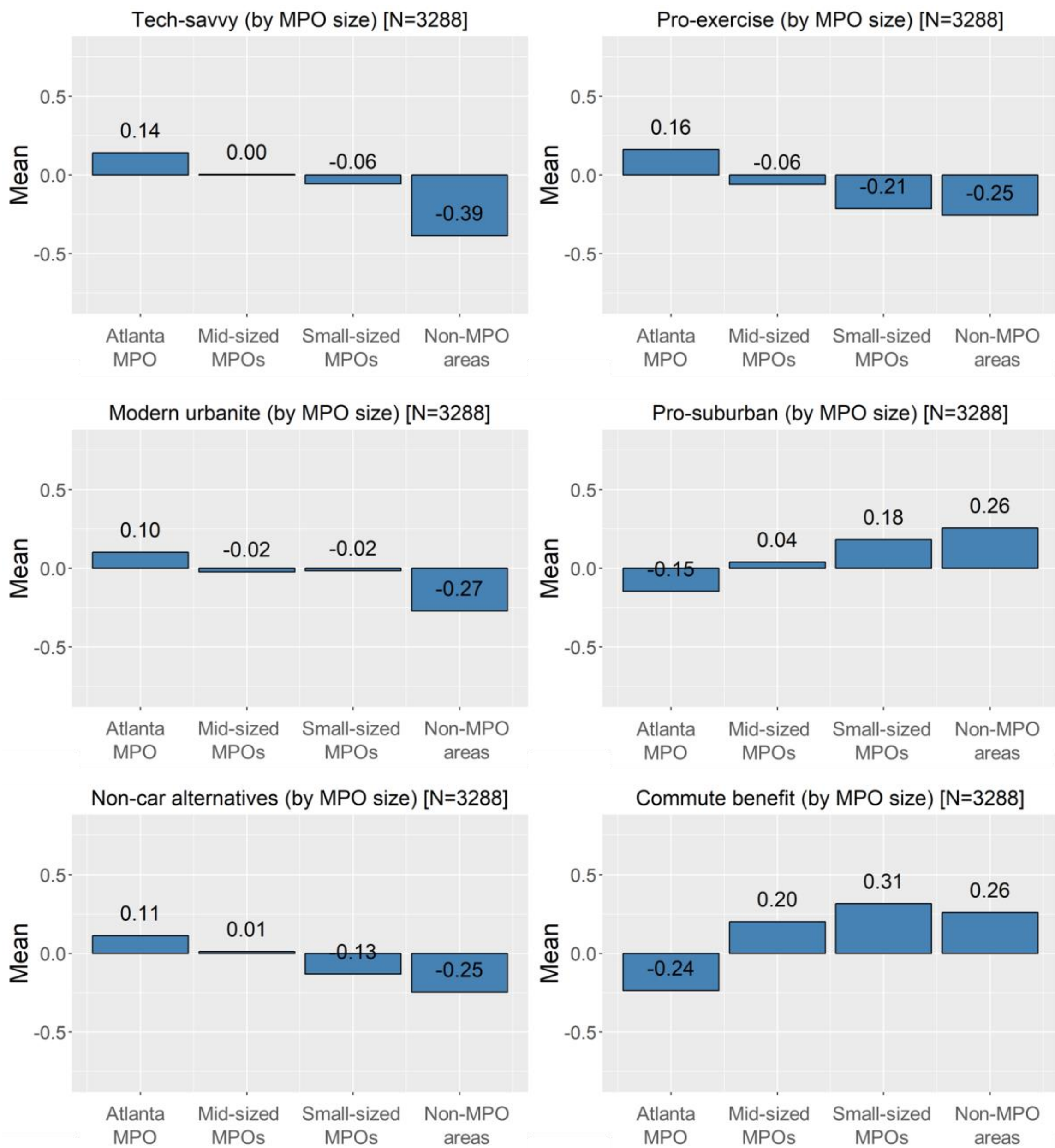

FIGURE 4-2

Selected Average Attitudinal Factor Scores (by MPO size) (N=3,288)

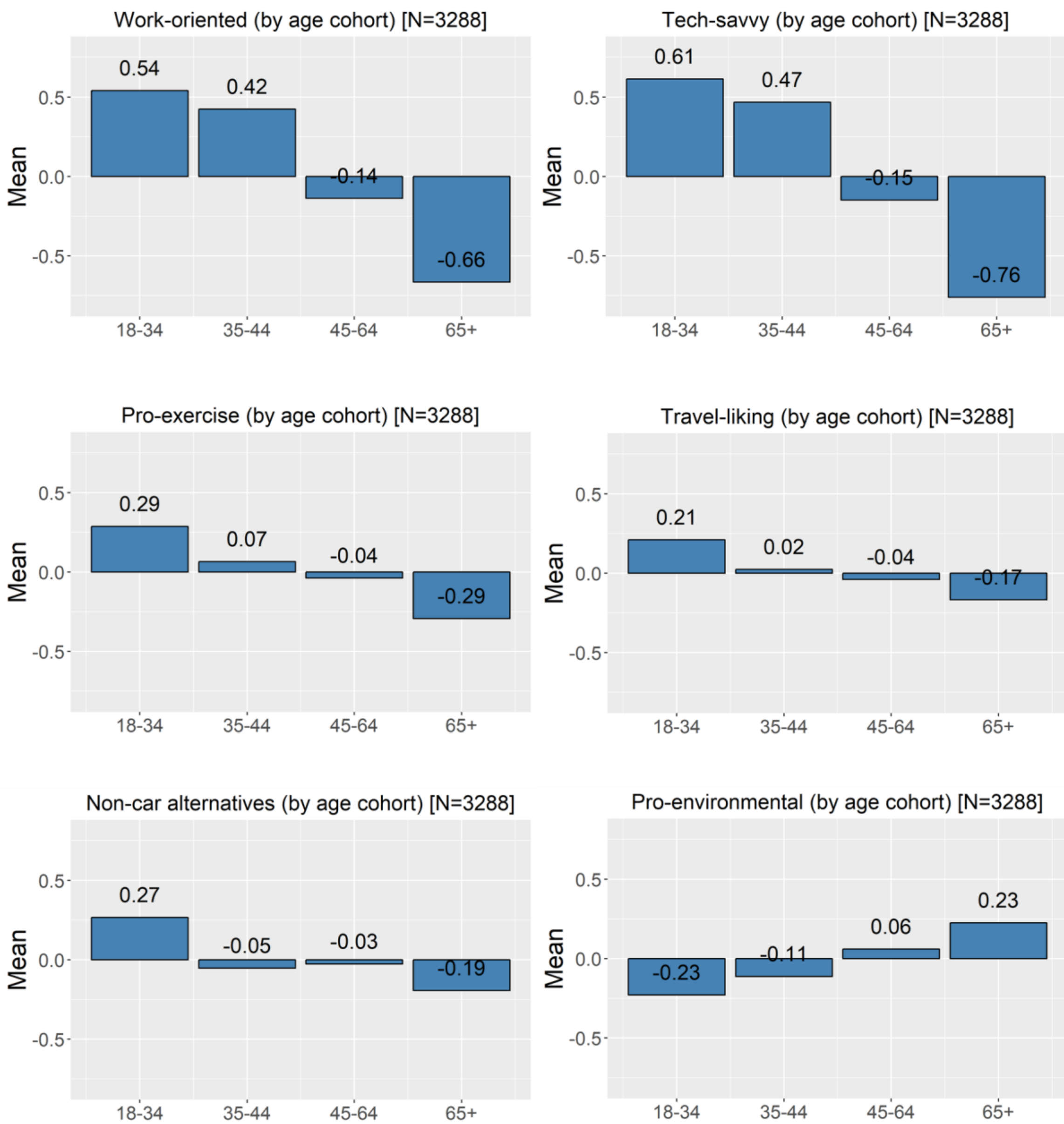

FIGURE 4-3

Selected Average Attitudinal Factor Scores (by age cohort) (N=3,288)

5. NEW AND EMERGING TECHNOLOGIES AND SERVICES

With increasing acceleration, the past two decades have seen a flurry of new technologies and services that either support transportation directly, or have indirect impacts on how, when, and whether we travel. This chapter provides a sketch of the extent to which and ways in which Georgians are using some of the most relevant technologies and emerging services. Section 5.1 explores the use of ICT devices and applications, while Section 5.2 and Section 5.3 investigate transportation services (especially ridehailing services).

5.1. Information and Communications Technology (ICT) Use

The impacts of ICT on travel behavior (e.g., trip generation, destination/mode choice, etc.) have been extensively studied throughout the past several decades. Depending on the context, ICT could generate new travel (*complementarity*), modify the characteristics of existing travel (*modification*), reduce travel (*substitution*), and/or have no relevant effect on travel (*neutrality*)—and often it does more than one of those things simultaneously (Mokhtarian et al., 2006). Given that ICT devices can have substantial impacts on travel, we need to understand how Georgia residents use them in their daily lives, including for their travel.

5.1.1. Use of ICT Devices

Because it is not easy to quantify the use frequency of ICT devices (such devices can be used numerous times per day), the survey relied on subjective frequency categories for this purpose. Table 5-1 shows that a majority of people use smartphones (41% use them "constantly" and 35% use them often), whereas a majority of people have *not* used or rarely use some other high-tech devices (such as wearable technology). The usage frequencies of desktop or laptop are quite evenly distributed. When investigating segment-specific device use, we can confirm the conventional wisdom that, on average, younger people and higher-income people use ICT devices more frequently. Figure 5-1 and Figure 5-2 show usage frequencies for smartphones and laptops or similar devices, respectively, by age cohort and income. For example, 65 percent of millennials (18–34) use a smartphone “constantly”, whereas only 38 percent of those age 45–64 do; 77 percent of higher-income people use laptops or similar devices often or “constantly”, whereas 42 percent of lower-income people do.

TABLE 5-1
Overall Frequencies of ICT Device Use

Device	Never/rarely	Sometimes	Often	“Constantly”
Basic cell phone (N=3,218)	26.1%	13.8%	37.9%	22.1%
Smartphone (N=3,254)	16.7%	6.5%	35.4%	41.4%
Desktop (N=3,242)	28.5%	22.3%	32.0%	17.3%
Laptop, tablet, iPad, or e-reader (N=3,274)	21.7%	20.9%	35.6%	21.8%
Wearable technology, smart watch, or Fitbit (N=3,262)	73.8%	9.7%	6.2%	10.3%

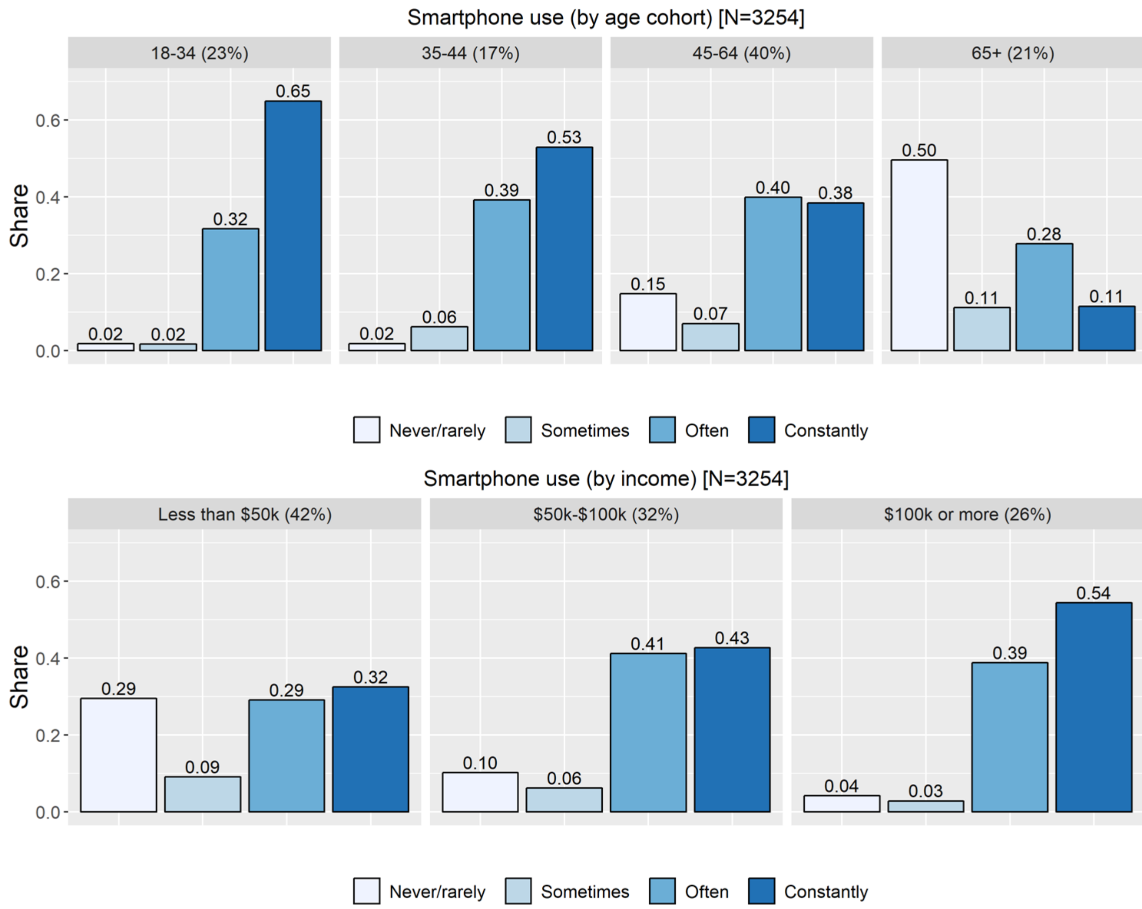

FIGURE 5-1

Frequency of Smartphone Use (by age cohort and income)

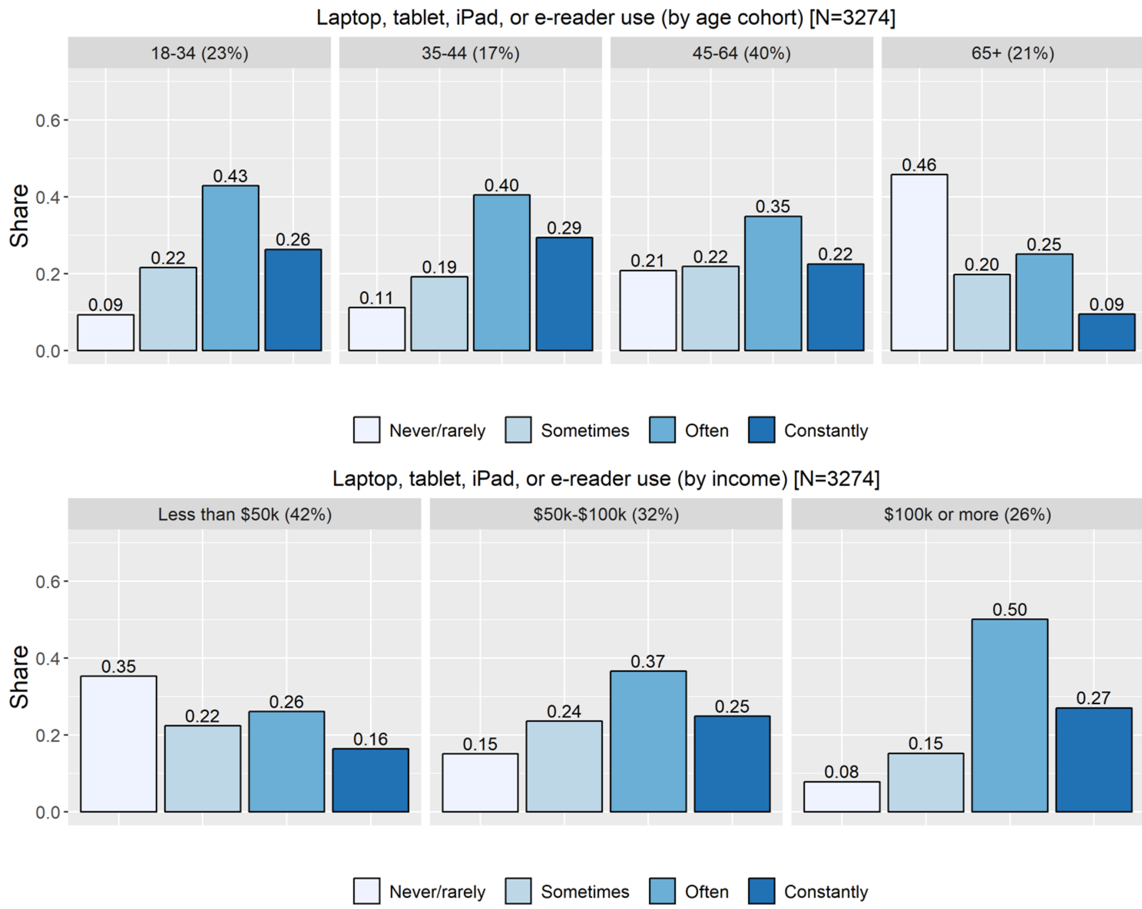

FIGURE 5-2

Frequency of Laptop, Tablet, iPad, or E-reader Use (by age cohort and income)

5.1.2. What Types of Travel-Related Internet Services Do People Use?

Information on transportation or locations can affect people's decisions on how, when, and where to travel. Table 5-2 portrays the overall frequency of internet use related to travel. Around 20 percent of people check traffic or navigate in real time on a daily basis. More than 40 percent of people use the internet to identify places of interest or learn how to get to a new place at least once a week or daily. However, because a majority of people use private vehicles, consulting the internet for checking transit arrivals or deciding which means of travel to use are less frequent.

Geography (MPO size and neighborhood type) is highly relevant to how frequently people use the internet for travel. Figure 5-3 and Figure 5-4 show internet use frequency by MPO size. On average, 58 percent of Atlanta area residents check traffic to plan their route or departure time at least once a week, whereas only about 30 percent or less of residents in other areas check traffic via the internet with the same frequency. More than half of the sample never or rarely check transit arrivals or use the internet to decide their travel mode, even if residing in the Atlanta region. The frequencies of using the internet for identifying places of interest, learning how to get to a new place, or navigating in real time are negatively correlated with MPO size. In other words, as people live in larger MPO areas, they tend to use the internet for those purposes more frequently.

Similar findings appear with respect to neighborhood type (Figure 5-5 and Figure 5-6). Fifty-six percent of urban dwellers, on average, check traffic via internet, whereas less than 30 percent of small-town or rural-area dwellers do. In addition, urban dwellers more frequently use the internet for checking transit arrivals or choosing their travel mode. Thus, geography and internet use for transportation are closely related, in part because more urbanized areas have more travel/activity options and more traffic.

TABLE 5-2
Overall Frequency of Internet Use Related to Travel

Purpose of internet use	Never / rarely	At least once a year	At least once a month	At least once a week	Daily
Check traffic to plan my route or departure time (N=3,262)	28.8%	10.0%	18.5%	23.4%	19.3%
Check when a bus or train will be arriving at my stop (N=3,274)	80.1%	8.6%	5.8%	2.4%	3.1%
Decide which means of travel to use (N=3,254)	63.4%	14.8%	9.3%	6.9%	5.6%
Identify places of interest (e.g., café, repair shop) (N=3,270)	17.8%	11.5%	28.5%	29.7%	12.4%
Learn how to get to a new place (N=3,264)	13.4%	14.2%	33.3%	27.9%	11.1%
Navigate in real time (e.g., Google Maps, GPS in-vehicle) (N=3,281)	14.5%	11.7%	25.9%	27.7%	20.2%

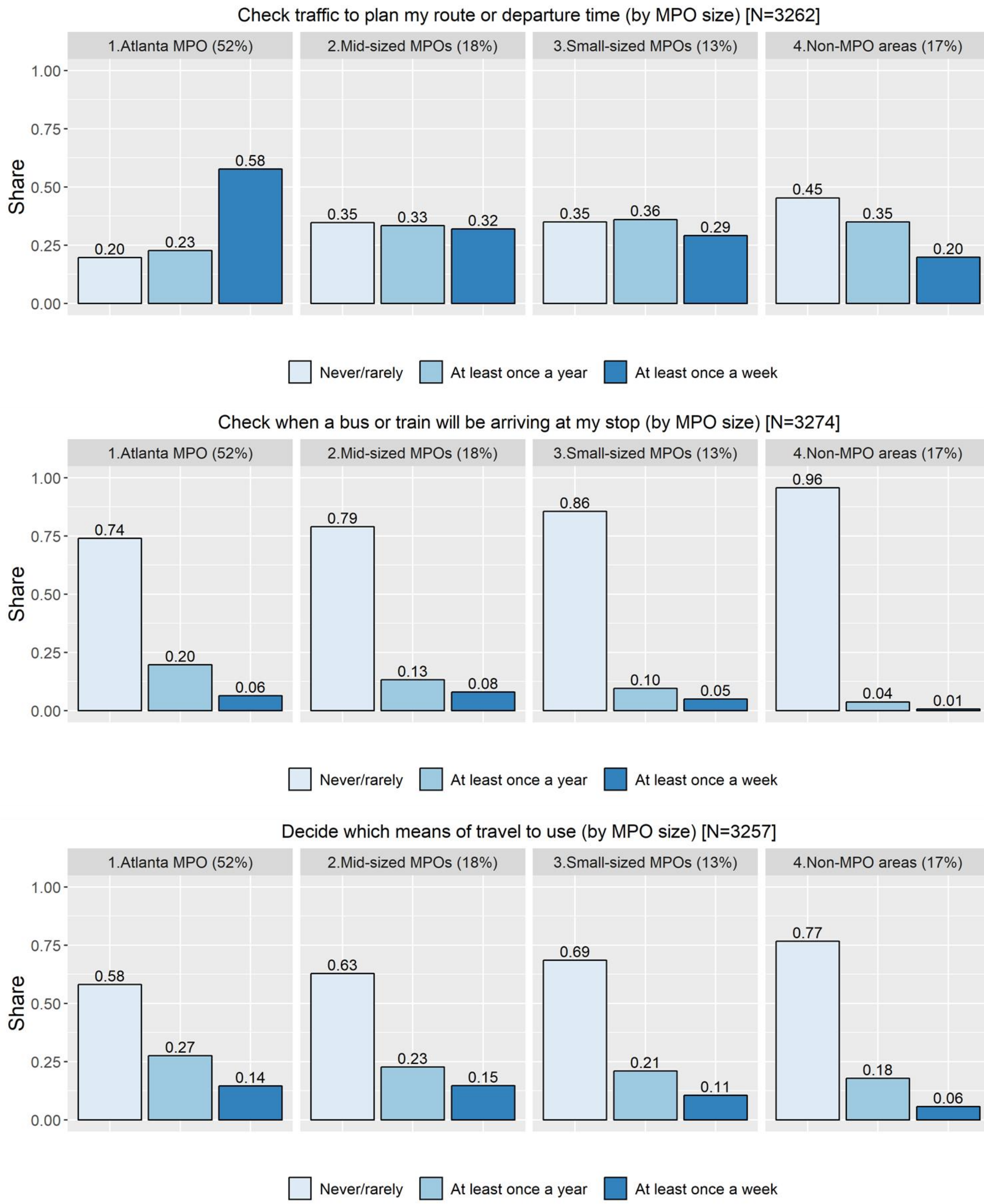

FIGURE 5-3

Internet Use for Travel (by MPO size)

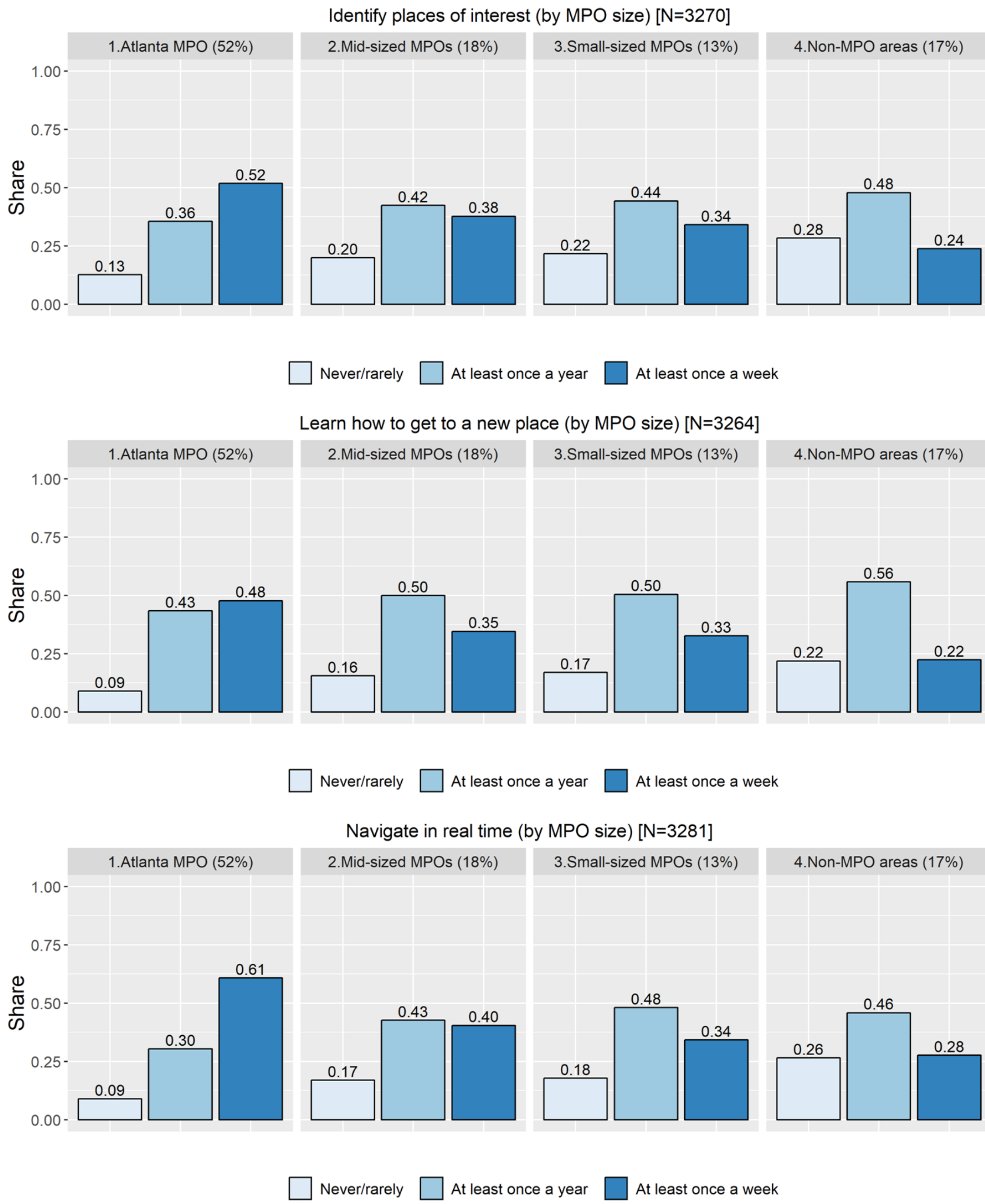

FIGURE 5-4

Internet Use for Navigation (by MPO size)

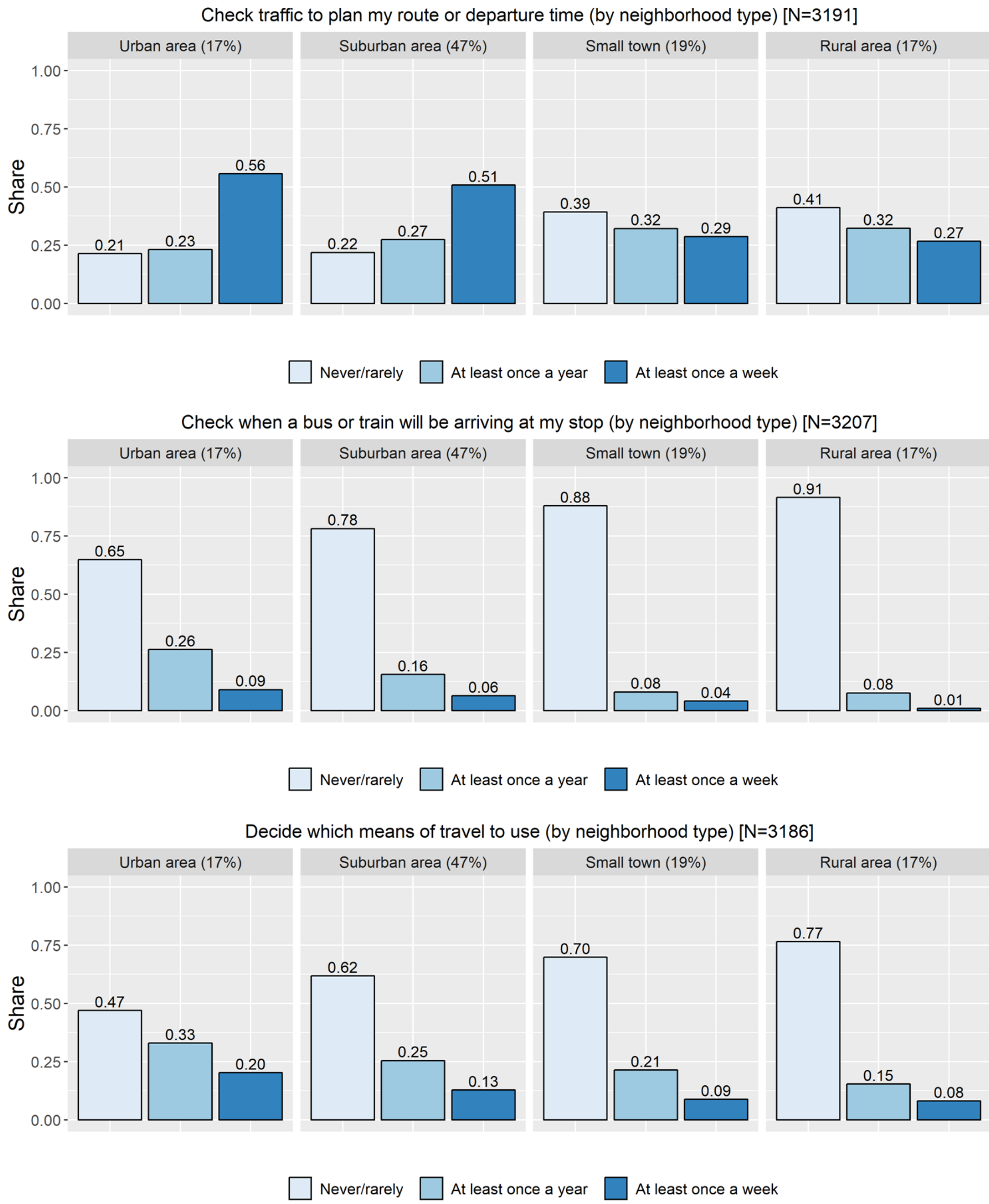

FIGURE 5-5

Internet Use for Travel (by neighborhood type)

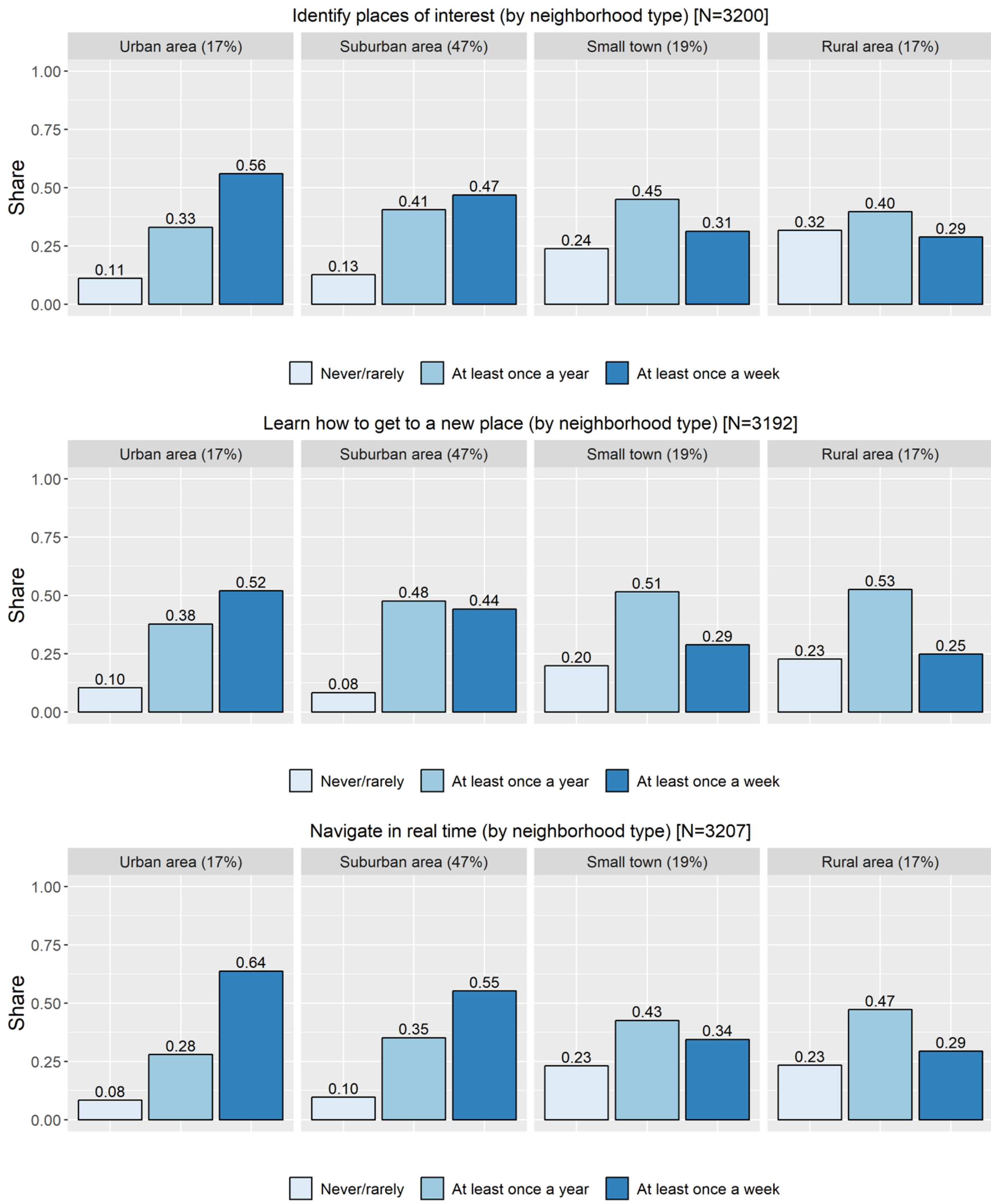

FIGURE 5-6

Internet Use for Navigation (by neighborhood type)

5.2. Use of Transportation Options

A variety of new transportation options has emerged within the past several years, enabled by the mobile internet and characterized by real-time matching of service sellers and buyers, or of vehicles and users. Mobility services such as carsharing, ridehailing, and bikesharing have become widely available and are increasingly appealing to travelers. In particular, ridehailing services such as Uber and Lyft are rapidly penetrating the transportation market in the U.S., certainly including Georgia. The study of how people adopt and use such services is expanding, signifying the importance placed on this subject by those in government, industry, and academia. The findings from this research are confirming that these new transportation services are, indeed, affecting our decisions. And yet, because most usage data from the privately operated service providers are not publicly available, our knowledge on how people use these services is still lacking. Limited evidence has been reported in some cities, such as San Francisco and New York, but to our knowledge, little work has been done in Georgia. Hence, in this section, we aim to offer a snapshot of how people use new transportation options, including:

- **Carsharing**: using internet / smartphone apps to rent automobiles by the hour or day (e.g., Zipcar);
- **Ridehailing services** [37]: calling for rides by using smartphone apps (e.g., Uber, Lyft);
- **Shared ridehailing services**: sharing Uber/Lyft (with unknown other travelers) to reduce the cost (e.g., UberPOOL, Lyft Line); and
- **Traditional taxi services** [38] (e.g., Yellow Cab, Atlanta Checker Cab).

We begin with a descriptive analysis of the familiarity with and use of these options, and follow with models of the adoption and usage frequency of ridehailing (non-shared or shared), in particular.

[37] Also known as on-demand ride services or transportation network services (TNCs). The survey used the term "on-demand ride services", but in this report, we use the also-common term "ridehailing services".
[38] Technically, taxi services are not new, but are included because of their commonality with the newer ridehailing services, making them a useful benchmark for comparison.

5.2.1. Descriptive Analysis

Table 5-3 and Table 5-4 present the overall familiarity with these evolving transportation options and their use frequencies. Some immediate observations are that: carsharing is much less popular than the (considerably more recent) ridehailing options, shared ridehailing is substantially less popular than the non-shared form, and regular ridehailing is already used more often than traditional taxi services. More specifically, 39 percent and 12 percent of Georgia residents have used ridehailing or shared ridehailing services, respectively. However, only 3.7 percent of people have used carsharing and 62.4 percent of people have not used carsharing even though they have heard of it. Fourteen percent and 4.8 percent of people are using ridehailing and shared ridehailing services, respectively, at least once a month.

Because the fractions of carsharing and taxi users are marginal, we explore details only with respect to the ridehailing options. Figure 5-7 and Figure 5-8 exhibit the use frequencies of ridehailing services by selected population segments. There are notable patterns in terms of the use of ridehailing services—the following population segments tend to use ridehailing services more often:

- *Younger people:* 31 percent of the 18–34 cohort is using the service at least once a month;
- *Higher-income:* more than 26 percent of those with household incomes greater than $50,000 a year are using the service at least once a month;
- *Atlanta area residents:* 21 percent are using the service at least once a month; and
- *Urban area residents:* 36 percent are using the service at least once a month.

TABLE 5-3
Familiarity with Transportation Options

Transportation option	Familiarity	Count	Share (%)
Carsharing (e.g., Zipcar)	I've never heard of it	1099	33.9
	I've heard of it but not used it	2025	62.4
	I have used it	120	3.7
Ridehailing service (e.g., Uber, Lyft)	I've never heard of it	235	7.3
	I've heard of it but not used it	1736	53.7
	I have used it	1264	39.1
Shared ridehailing service (e.g., UberPOOL)	I've never heard of it	1061	32.9
	I've heard of it but not used it	1752	54.3
	I have used it	411	12.8
Traditional taxi service (e.g., Yellow Cab)	I've never heard of it	98	3.0
	I've heard of it but not used it	1633	50.2
	I have used it	1520	46.8

TABLE 5-4
Overall Use Frequency of Transportation Options

Transportation option	Use frequency	Count	Share (%)
Carsharing (e.g., Zipcar)	Never used / No longer use	3097	95.1
	Less than once a month	104	3.2
	1–3 times a month	40	1.2
	1–2 times a week	8	0.2
	3 or more times a week	10	0.3
Ridehailing service (e.g., Uber, Lyft)	Never used / No longer use	2087	64.2
	Less than once a month	710	21.9
	1–3 times a month	360	11.1
	1–2 times a week	64	2.0
	3 or more times a week	29	0.9
Shared ridehailing service (e.g., UberPOOL)	Never used / No longer use	2817	86.8
	Less than once a month	275	8.5
	1–3 times a month	128	4.0
	1–2 times a week	18	0.6
	3 or more times a week	6	0.2
Traditional taxi service (e.g., Yellow Cab)	Never used / No longer use	2221	68.1
	Less than once a month	892	27.4
	1–3 times a month	119	3.7
	1–2 times a week	19	0.6
	3 or more times a week	7	0.2

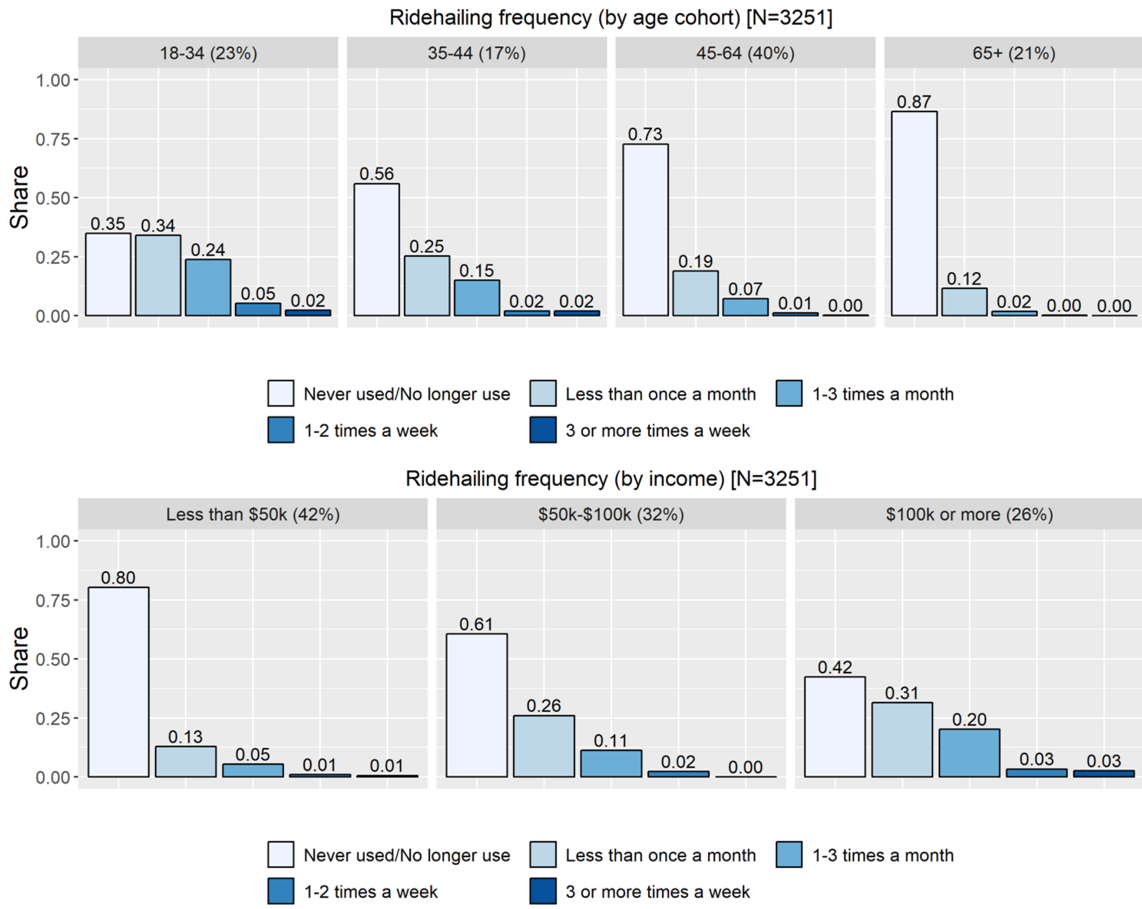

FIGURE 5-7

Use Frequency of Ridehailing Service (by age cohort and income)

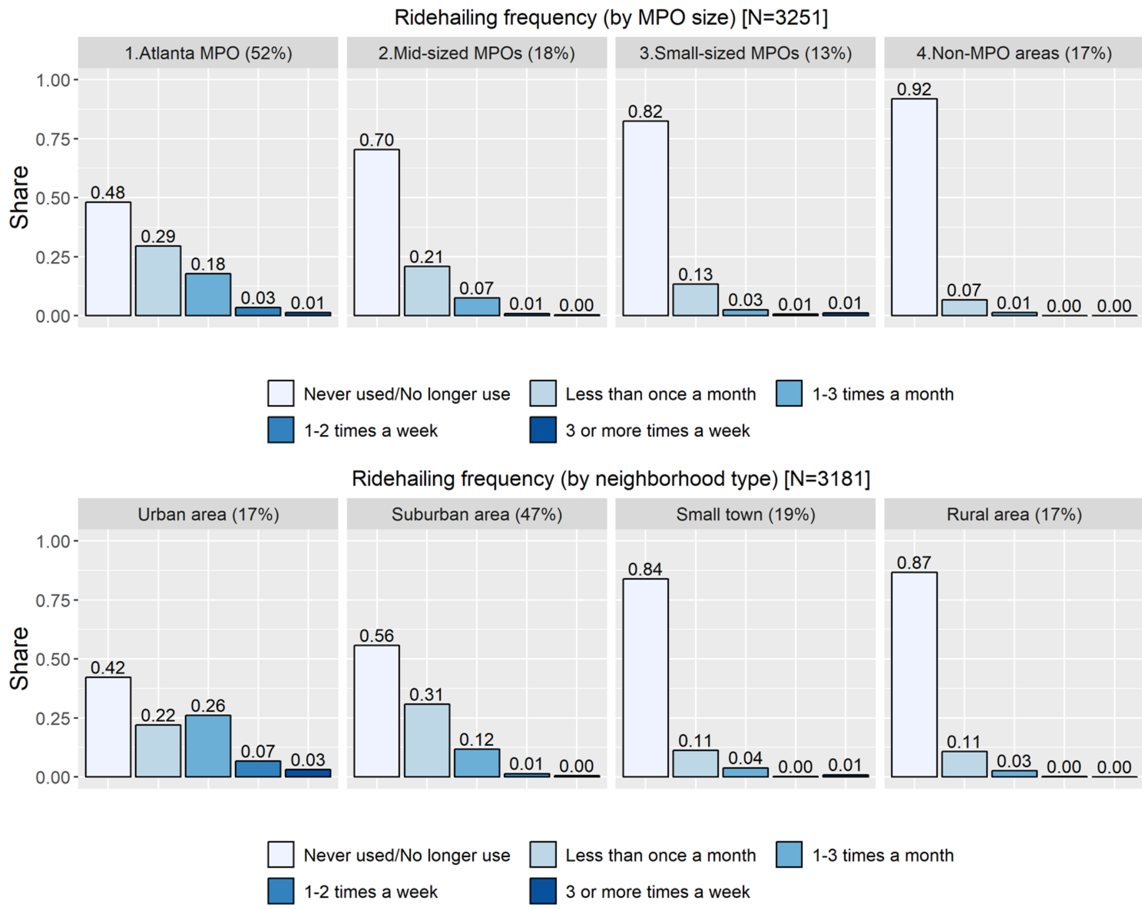

FIGURE 5-8

Use Frequency of Ridehailing Service (by MPO size and neighborhood type)

5.2.2. Modeling the Adoption of Ridehailing

The market for ridehailing services is growing in Georgia, as it is nationwide. Some studies have started to investigate the characteristics of ridehailing demand, i.e. to identify the kinds of people who are using such services (Circella, Alemi, et al., 2018; Lavieri and Bhat, 2019; Young and Farber, 2019). However, the number of studies is limited and the use of ridehailing services is highly subject to geographic context. In the absence of more specific knowledge about how Georgians in particular are using ridehailing services, we here model the adoption of those services (i.e., Uber/Lyft).[39]

[39] The binary dependent variable of our model distinguishes between people who have used any kind of

Table 5-5 presents the estimation results of a weighted binary logit model.[40] Overall, the goodness of fit of the model is moderately strong ($\rho^2 = 0.392$). With respect to sociodemographics, the findings are consistent with what other studies have found: white, younger people, and higher-income people are more likely to adopt ridehailing services. There are distinctively different adoption rates by MPO size (which, of course, is partly a function of service availability): the residents of larger MPOs are more likely to adopt Uber/Lyft. Multiple land use characteristics have significant and positive impacts on adoption. As activity density, transit score, and number of drinking establishments near their home increase, people are more likely to adopt ridehailing services. Those measures indicate the level of urbanization and presence of attractions conducive to the use of ridehailing services. One interesting observation is that transit score is still statistically significant even after controlling for degree of urbanization through the inclusion of the other two land use characteristics. However, it is difficult to disentangle the specific effects of multiple reasons: among other possibilities, transit score might be capturing a unique dimension of the urban area, or reflecting the complementarity of Uber/Lyft as a first-/last-mile service feeding public transit.

Other current behaviors are also closely related to the adoption of ridehailing services. As people use social media more often and travel long-distance by airplane more, they are more likely to adopt Uber/Lyft. Use of social media reflects a level of tech-savviness and social engagement (which may generate travel, as well as the converse), both of which lend themselves to using Uber/Lyft. As will be shown (in Table 5-7), a major trip purpose for ridehailing is airport access or egress; hence, Uber/Lyft use is relevant to long-distance trips. In terms of attitudes, people who are more tech-savvy and like travel are more likely to adopt ridehailing services, while those who like owning (and driving) cars are less likely to do so.

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ridehailing services (either non-shared or shared options) and people who have not used such services. The services may have been used anywhere, not necessarily in the respondent's "home town".

[40] For brevity, we do not describe the theoretical background of the model, which can be found in references such as Ben-Akiva and Lerman, 1985.

TABLE 5-5
Binary Logit Model of Uber/Lyft Adoption (Base: have not used, N=3,146)

Dimension	Variable	Coefficient	t-value
Intercept	Intercept	−2.393	−12.33
Sociodemographics	Race (white=1)	0.188	1.72
	Age 18–34 (base: 35–64)	1.261	9.72
	Age 65+ (base: 35–64)	−0.265	−1.84
	Middle income \$50k–\$99k (base: below \$50k)	0.614	5.15
	High income \$100k+ (base: below \$50k)	0.866	6.14
Land-use characteristics	Activity density (population+employment per acre)	0.022	2.04
	Transit score	1.031	4.28
	Number of bars (within a mile from home)	0.042	1.76
MPO level	Mid-sized MPOs	−0.630	−4.96
(Base: Atlanta MPO)	Small-sized MPOs	−1.094	−6.70
	Non-MPO areas	−1.177	−6.84
Behaviors	Number of long-distance trips by airplane past 12 months (log-transformed)	0.970	12.56
	Use of social media [b]	0.075	4.61
Attitudes [a]	Tech-savvy	0.266	4.54
	Pro–car-owning	−0.317	−6.36
	Travel-liking	0.178	3.52
Model Summary			
Log-likelihood at $\hat{\beta}$	−1324.605		
Log-likelihood at constants [c]	−2116.448		
Log-likelihood at zero	−2180.340		
ρ^2 (equally-likely base)	0.392		
$\bar{\rho}^2$ (equally-likely base)	0.385		

a. Factor scores—please refer to Chapter 4 for details.
b. Sum of frequency indicators for various types of social media (Facebook, Twitter, Instagram, etc.)
c. Market shares, specifically in the dataset modeled, are ‘never used’ 60% (1,889) and ‘used’ 40% (1,257).

5.2.3. Modeling the Frequency of Ridehailing

Next, we investigate how frequently people use ridehailing. Some of the same factors may apply here as for ridehailing adoption, but people may not necessarily have the same drivers for the quantity of use as for using it in the first place. The survey provided five frequency categories (including “never used/no longer use”), but we combine some of them to avoid having too few cases in some categories. The three ordered categories we modeled are “less than once a month”, “1–3 times a month”, and “at least once a week”. We also drop nonusers and past users, so that we are modeling the frequency of use conditional on being a current user. Considering the ordered nature of frequency, we use weighted ordered logit.[41] Table 5-6 shows the estimation results for frequency of ridehailing use. Overall, the fit of the model is good ($\rho^2 = 0.331$); however, it has a bit lower goodness of fit and fewer significant variables compared to the model of ridehailing adoption. This seems consistent with other studies (Circella, Alemi, et al., 2018; Lavieri and Bhat, 2019). In addition, having a somewhat different set of variables implies that the drivers to adopt ridehailing are not exactly the same as those affecting how much people use ridehailing.

Several variables *do* influence both decisions, though. For example, transit score and number of bars within a mile from home are statistically significant and positively influence use frequency, with the same interpretation as before. Interestingly, some of the sociodemographic drivers of adoption (gender and income) become statistically insignificant for frequency. However, younger people tend to use ridehailing more frequently. In terms of current behaviors, number of long-distance trips and use of social media tend to increase the frequency of ridehailing use, as they did for propensity to adopt. With respect to attitudes, travel-liking and sociable people tend to use ridehailing more frequently, while people who favor owning and driving their own cars tend to use it less often. The sociability variable may reflect a higher demand (more social trips, possibly involving drinking) or a willingness to ride with strangers (whether only the Uber/Lyft driver, or passengers as well, if shared).

[41] For brevity, we do not describe the theoretical background of the model, which can be found in references such as Train, 2009.

TABLE 5-6
Ordered Logit Model of Ridehailing Frequency (N=1,133)

Dimension	Variable	Coefficient	t-value
Constant	Threshold 1	2.040	7.79
	Threshold 2	4.412	14.95
Land-use characteristics	Transit score	1.321	5.33
	Number of bars (within a mile from home)	0.039	2.61
Behaviors	Number of long-distance trips by airplane in the past 12 months (log-transformed)	0.506	7.69
	Use of social media [b]	0.040	2.04
Sociodemographics	Age 18–34 (base: 35–64)	−0.319	−2.02
	Age 65+ (base: 35–64)	−0.962	−2.80
Attitudes [a]	Pro–car-owning	−0.335	−6.33
	Travel-liking	0.151	2.20
	Sociable	0.196	3.21
Model Summary			
Log-likelihood at $\hat{\beta}$	−831.9245		
Log-likelihood at constants [c]	−1000.199		
Log-likelihood at zero	−1244.349		
ρ^2 (equally-likely base)	0.331		
$\bar{\rho}^2$ (equally-likely base)	0.324		

a. Factor scores—please refer to Chapter 4 for details.
b. Sum of frequency indicators for various types of social media (Facebook, Twitter, Instagram, etc.).
c. Market shares, specifically in the dataset modeled, are ‘less than once a month’ 61% (687), ‘1–3 times a month’ 30% (343), and ‘at least once a week’ 9% (10).

5.3. More about Ridehailing Services

Ridehailing services can generate new trips, as well as shift existing trips away from other modes. Accordingly, it is important to understand how people are using these services. The following two subsections explore the responses of people who have used ridehailing services, considering the purposes for which they use the services, and the impacts on other modes, respectively.

5.3.1. Purpose of Use

Table 5-7 shows the distributions of purposes for engaging in ridehailing or shared ridehailing, among people who have used each service. Social/recreational purposes were major reasons for using ridehailing and shared ridehailing services (57.5% and 57.1%, respectively). More than 40 percent of ridehailing users in each category have used the service for eating/drinking or accessing/egressing the airport. As shown by the raw counts, unshared ridehailing was employed more than the shared form for each purpose measured. With respect to shares, there are few clear differences between the ridehailing and shared ridehailing purpose distributions, but the shared form was used relatively less often for work-related, airport, and other trips. We speculate that such trips are more often time-sensitive or require more privacy.

As in the previous section, the adoption and use frequency of ridehailing services differ by population segment, especially geographically. The reasons people have used such services are also asymmetric. Figure 5-9 and Figure 5-10 show that Atlanta area residents and urban area residents have distinctively higher fractions of ridehailing use for work/school-related, eating/drinking, and airport access purposes. In particular, more than 50 percent of ridehailing users in the Atlanta region have used these services for airport access, whereas less than 30 percent of ridehailing users in other areas have done so.

TABLE 5-7

Purpose of Ridehailing Services ("check all that apply")

Purpose	Ridehailing (N=1,270)		Shared ridehailing (N=408)	
	Count	*Share (%)*	*Count*	*Share (%)*
Work/school related	423	33.3	119	29.2
Shopping	142	11.2	40	9.8
Eating/drinking	552	43.5	174	42.7
Social/recreational	730	57.5	233	57.1
Airport	623	49.1	169	41.4
Other (e.g., medical)	146	11.5	28	6.8

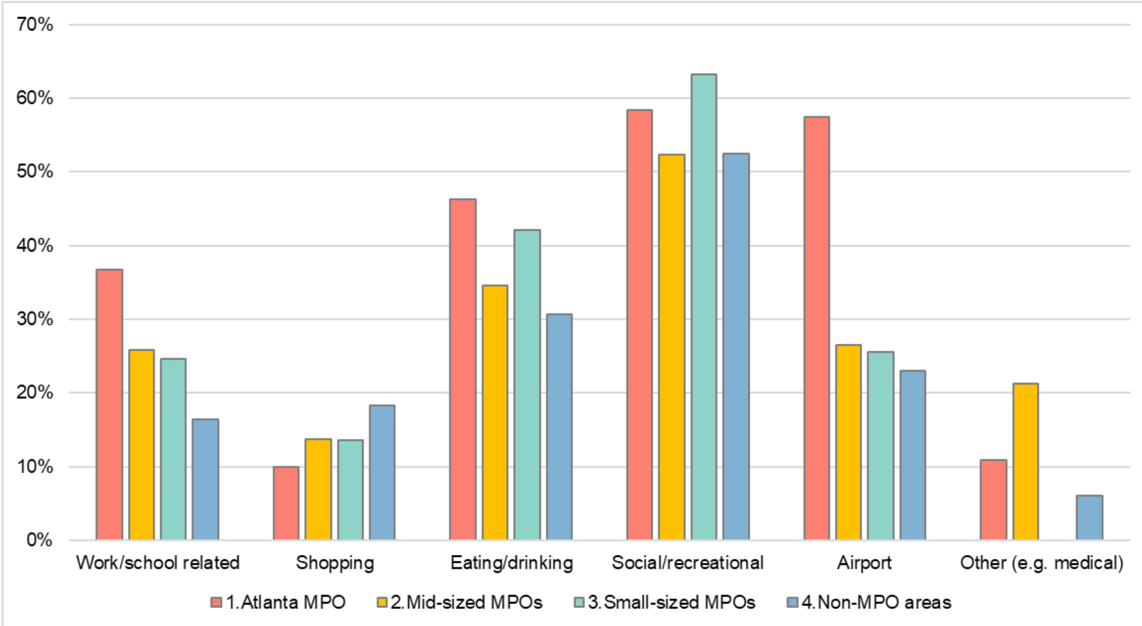


FIGURE 5-9

Purposes for Using Regular Ridehailing Services (by MPO size) (among people who have used; "check all that apply") (N=1,270)

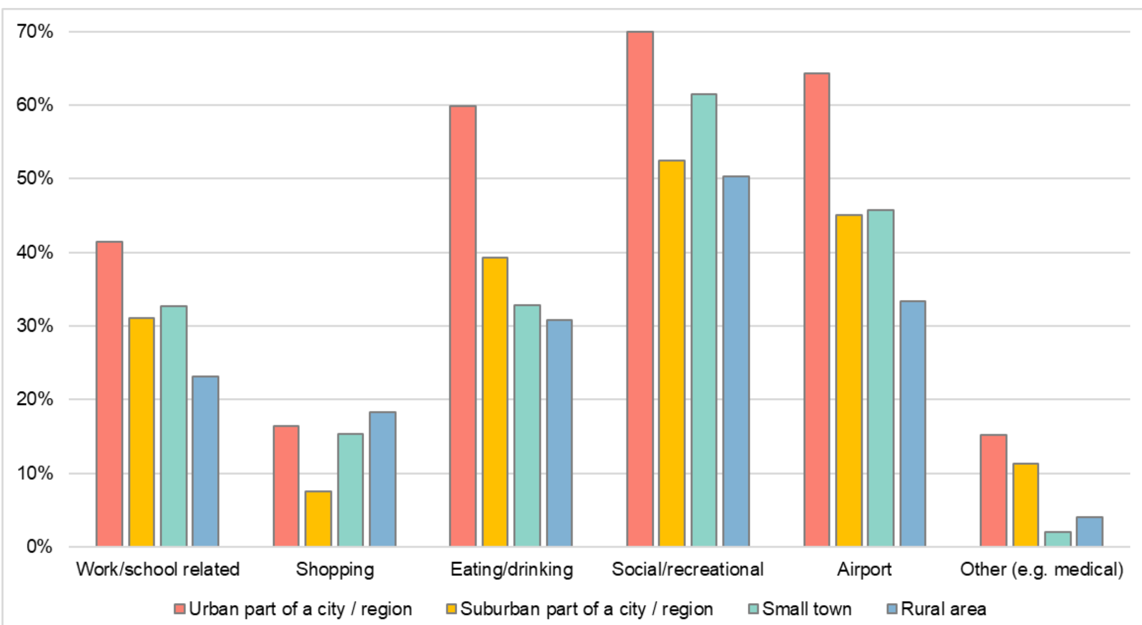


FIGURE 5-10

Purposes for Using Regular Ridehailing Services by Neighborhood Type (among people who have used; "check all that apply") (N=1,257)

5.3.2. Impact of Ridehailing Services on Other Modes

A major interest related to ridehailing services is how they affect other modes. Such services have the potential to complement existing trips currently made by other modes, substitute for those other modes, or generate a new trip altogether. Effects on other modes can differ from trip to trip and by context, and accordingly, it is not easy to capture those effects. In the survey, we tried to capture general effects by asking about the most recent trip by Uber/Lyft rather than detailing the context. Since there could be multiple effects, we allowed respondents to give all answers that applied. Figure 5-11 exhibits how people think their Uber/Lyft use affected the use of other modes for the most recent trip.

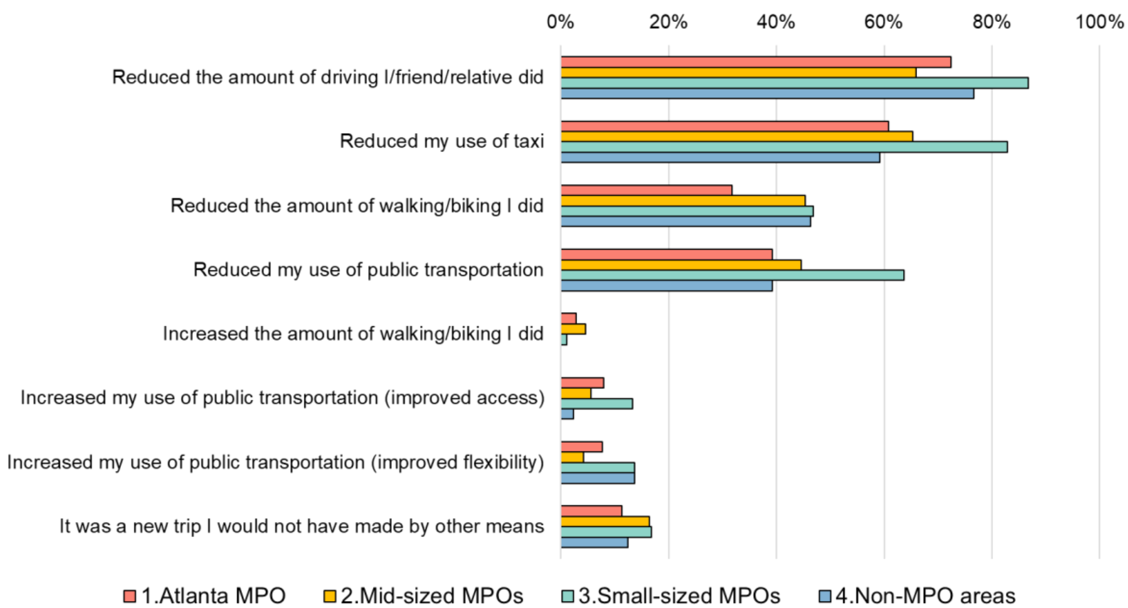


FIGURE 5-11

Impact of Uber/Lyft Use on Other Modes for the Most Recent Trip (N=1,217)

Consistent with several other studies (e.g. Clewlow and Mishra, 2017; Circella, Alemi, et al., 2018; though the issue is still under debate; see Hall et al., 2018), overall, ridehailing services seem to have more substitution effects than complementarity and generation effects. Often, the substitution is of another's car for one's personal car: about 70–80 percent of people reported that use of Uber/Lyft reduced the amount of driving (either by themselves or other friends/relatives), but the net effect after accounting for the ridehailing driver's travel is unclear. In general, ridehailing appears to have reduced trips by active modes and public transit more than it increased them. Compared to residents of larger MPO areas, a higher fraction of residents of small-sized MPO areas reported that use of Uber/Lyft reduced their use of public transportation. The latter effect may reflect the lower level of service in small-sized MPO areas compared to other MPO areas. On the other hand, the smaller fraction reporting such a reduction in rural areas probably reflects the fact that transit may not exist at all in many of those areas. Finally, a small but non-trivial (12% for the overall sample) share of ridehailing trips constitute new vehicular travel.

For all of these statistics, however, it is important to keep in mind that we are looking only at the *most recent* ridehailing trip for each user, not a representative sample of *all* their trips. The most recent trip will tend to be much longer ago for infrequent ridehailers than for frequent ones, and the distributions of these responses could be quite different on a *trip* basis than it is on a *tripmaker* basis. Since it is the distribution across *trips* that is pertinent to fully understanding impacts on other modes, these statistics can only be taken as suggestive, not definitive.

6. FUTURE TRANSPORTATION: AUTONOMOUS VEHICLES

Undoubtedly, autonomous vehicles (AVs) are expected to reshape the landscape of daily life, transportation, and land use; hence, understanding (or predicting) how AVs will impact that landscape is of keen interest for planning. Because fully automated technologies (say, level 5 [42]) have not been realized yet, exploration of such impacts is necessarily limited. Among the various approaches being used to do so, our survey provided a textual and pictorial description of AVs, and invited participants to offer their perceptions (Section 6.1) and envision their future behavioral responses (Section 6.2). Although any such reactions offered now must be considered rather volatile, it is not too soon to begin assessing responses to an all-AV future—both for what those responses can tell us about future impacts, and also to establish a benchmark against which ongoing shifts in opinion can be measured.

6.1. How Do People Perceive Autonomous Vehicles?

6.1.1. Familiarity with Autonomous Vehicles and Expectation for Realization

To set the stage, we begin with a description of respondents' familiarity with the AV concept, and their expectations concerning the ubiquitous realization of level 5 AVs. Table 6-1 shows that only 7.7 percent of the sample has never heard of AVs (i.e., about 92.3% has heard of AVs). In the literature, Schoettle and Sivak (2014) reported that 70.9 percent of 501 adults in the U.S. had heard of AVs; Bansal and Kockelman (2018) and Zmud, Sener, and Wagner (2016) reported that 80 percent of Austin, Texas, residents in 2014 were aware of AVs. Perhaps most relevant to the present study, the Atlanta Regional Commission (ARC, 2015) reported that 90 percent of its 2015 sample (6,300 residents in 26 counties of the Atlanta metro region) had heard of AVs. We should

[42] The levels of automation described by the Society of Automotive Engineers have been widely used in both academia and industry. Level 5 constitutes full automation, which allows vehicles to perform all driving functions under any conditions. (Source: https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety, accessed on May 16, 2019)

be cautious when comparing those statistics with the results in this study, in that each study has its own context, including different sampling methods. However, taken at face value, there was an increase in the awareness of AVs from 2015 to 2017–2018; in particular, 95 percent of the Atlanta-area residents in this study had heard of AVs, as shown in Figure 6-1. Almost half of the respondents expressed some level of familiarity with AVs.

Figure 6-1 and Figure 6-2 exhibit the familiarity with AVs by segment (MPO size and age cohort). As expected, on average, Atlanta-area residents are more familiar with AVs than residents in other areas. Although *awareness* is similar across all age groups, younger people are more *familiar* with AVs, as would be expected. Still, even among those 65 or older, 43 percent report being somewhat or very familiar with the concept of a self-driving car.

The survey also asked how long it would take "for **all cars** to be ***fully*** self-driving", with the five response options shown in Table 6-1. Nearly half of the respondents (48.7%) envisioned that all cars will become fully self-driving within 20 years. About 15 percent of people thought that fully-automated self-driving for the entire fleet will never be realized. This expectation could serve as a proxy for general belief in AV technologies.

TABLE 6-1
Familiarity with AVs and Expected Timing of Full Fleet Automation

Question	Category	Count	Share (%)
Familiarity with AVs	I've never heard of it	247	7.7
	I've heard of it but am not familiar with it	1144	35.6
	I've heard of it and am somewhat familiar with it	1412	44.0
	I've heard of it and am very familiar with it	408	12.7
	Total	3211	100.0
Expected timing of full fleet automation	10 years or less	559	17.8
	11–20 years	971	30.9
	21–30 years	648	20.6
	More than 30 years	498	15.9
	Never	466	14.8
	Total	3141	100.0

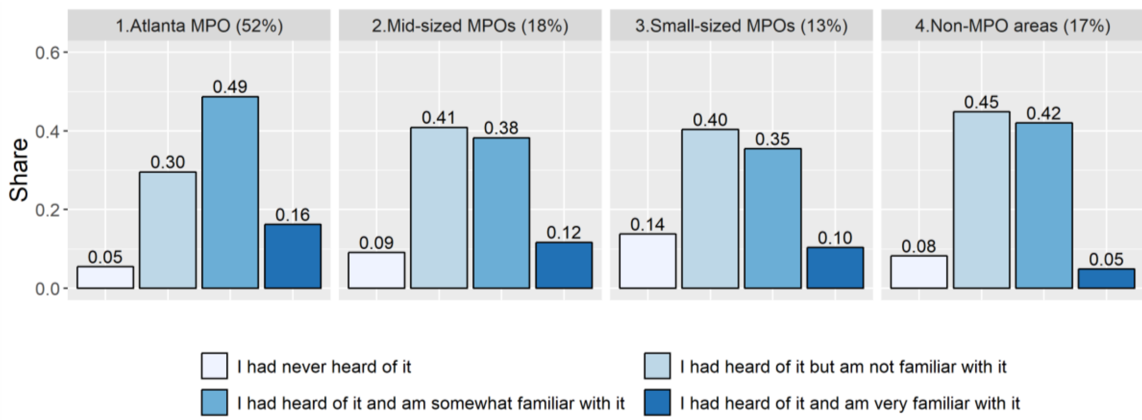


FIGURE 6-1

Familiarity with AVs (by MPO size) (N=3,211)

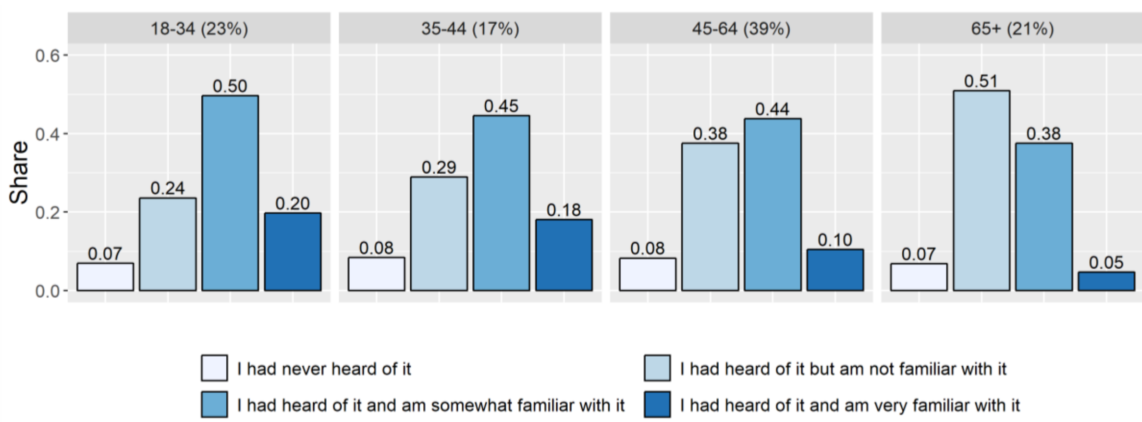


FIGURE 6-2

Familiarity with AVs (by age cohort) (N=3,211)

6.1.2. Opinions on the Advantages and Disadvantages of AVs

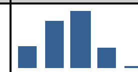
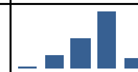
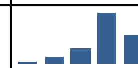
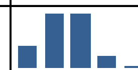
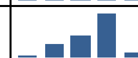
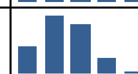
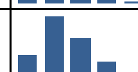
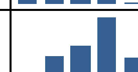
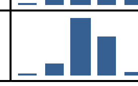
There are multiple aspects of AVs that can trigger behavioral changes. In particular, perceptions of the advantages and disadvantages of AVs could influence the decision to change or not. After investigating the literature, we selected some important dimensions to measure and designed 12 statements (five-point Likert-type response scale, from “strongly disagree” to “strongly agree”) to tap those dimensions. Table 6-2 exhibits the descriptive statistics and distribution of responses.

The responses capture some ambivalence—or perhaps, a balanced opinion—about AVs. On average, people think:

- Self-driving cars will not, in general, be faster than driving oneself.
- On the other hand, people can gain useful time by sending an empty (zero-occupant) vehicle on errands.
- They will miss the joy of driving and the feeling of being in control.
- At the same time, AVs can introduce fun in various respects, and increase comfort.

One interesting result is that there seems to be a split in the opinion on multitasking in AVs and time use (as shown by the two peaks in the distribution of responses to the statement "Even if I could do other activities in the car while it drove itself, I would not gain that much useful time"). Some studies have started to investigate time use or the value of travel time in the era of AVs, and this simple statistic implies that there could be two distinct groups of people in terms of the perceived usefulness of the time while "being-driven."

TABLE 6-2
Opinions on Advantages and Disadvantages of AVs

Statement	Mean	Std. Deviation	Distribution
A self-driving car would enable me to get to places faster than if I had to drive myself.	2.69	1.14	
I would gain a lot of useful time by sending my vehicle to do certain things (e.g. pick up dry cleaning) without me.	3.21	1.27	
I would miss the joy of driving and the feeling of being in control.	3.64	1.19	
I am concerned that the self-driving car would lead to spending less time with family or friends (e.g. because of having more work trips).	2.51	1.02	
I would more often travel even when I am tired or sleepy.	3.25	1.17	
A self-driving car would reduce by too much the exercise I get through walking or biking.	2.50	1.08	
A self-driving car would enable me to enjoy traveling more (e.g. watching the scenery).	3.55	1.16	
Even if I could do other activities in the car while it drove itself, I would not gain that much useful time.	2.96	1.15	
I would be able to travel more often when under the influence of alcohol or medicines.	3.00	1.31	
I am concerned that the self-driving car would lead to me using a car too much.	2.47	1.02	
Having the vehicle drive itself would allow me to be more comfortable on trips.	3.27	1.25	
I would reduce my parking costs because my self-driving car could drive itself to a cheaper parking space.	3.17	1.08	

* Note: The last column depicts the distributions of the responses to the five-point Likert-type scale. The leftmost and the rightmost bars indicate "strongly disagree" and "strongly agree", respectively.

As described in Chapter 4, exploratory factor analysis is a good way to capture underlying constructs that are represented by multiple attitudinal statements. For details about EFA, please refer to Section 4.2. Here, we employ principal axis factoring with oblique rotation (oblimin, with delta=0). In terms of quantitative criteria, the 2-factor solution is preferred by the eigenvalue-greater-than-one rule, while the 3-factor solution is preferred by the elbow rule. After further exploration, we decided to adopt the 2-factor solution, which is more logically interpretable. Table 6-3 exhibits the pattern factor loadings for each AV perception.

The first construct is oriented toward the advantages or benefits offered by AVs. For example, agreeing with being more comfortable while taking an AV, or with gaining more time by sending an AV for errands, would contribute to a higher score on this factor, and, thus, we label it as "AV pros". The second construct is oriented toward a somewhat negative perspective, which raises the question of how it is distinguished from the negative direction of the first factor. However, the two constructs have a correlation of only −0.2, and the second factor is specifically related to negative outcomes due to the *excessive* use of AVs (e.g., reducing exercise or time with family/friends because of AVs) rather than the use of AVs intrinsically; thus, we label it as "AV overuse cons".

TABLE 6-3
Pattern Factor Loadings for AV Perceptions

Dimension	Statement	*AV pros*	*AV overuse cons*
Comfort	Having the vehicle drive itself would allow me to be more comfortable on trips.	0.751	
Fun	A self-driving car would enable me to enjoy traveling more (e.g., watching the scenery).	0.732	
Productivity	I would gain a lot of useful time by sending my vehicle to do certain things (e.g., pick up dry cleaning) without me.	0.704	
Impaired driving	I would more often travel even when I am tired or sleepy.	0.677	
Parking	I would reduce my parking costs because my self-driving car could drive itself to a cheaper parking space.	0.646	
Mobility	A self-driving car would enable me to get to places faster than if I had to drive myself.	0.588	
Impaired driving	I would be able to travel more often when under the influence of alcohol or medicines.	0.505	
Productivity	Even if I could do other activities in the car while it drove itself, I would not gain that much useful time.	-0.424	0.345
Time/money use	A self-driving car would reduce by too much the exercise I get through walking or biking.		0.662
Relationship	I am concerned that the self-driving car would lead to spending less time with family or friends (e.g., because of having more work trips).		0.652
Time/money use	I am concerned that the self-driving car would lead to me using a car too much.		0.602
Fun	I would miss the joy of driving and the feeling of being in control.		0.339

Scores on each factor were created for each person, as (standardized) weighted linear combinations of their responses on each of the perceptions (where the weights are roughly proportional to the factor loadings of Table 6-3). For example, an AV pros score of 0.5 signifies a "pro" perception that is 0.5 standard deviation units more positive than the overall average. Figure 6-3 shows how the average standardized scores on these perception constructs differ by population segments (i.e., MPO size, income, age cohort). The results are consistent with expectation: residents of the more urbanized/bigger MPO areas, higher-income people, and younger people perceive/expect more potential benefits from AVs. Although (as mentioned) the correlation of the two constructs is only −0.2 (which can be considered low), the AV overuse cons scores also tell a similar story: residents of the more urbanized/bigger MPO areas, higher-income people, and younger people perceive/expect *fewer* potential negative outcomes due to the excessive use of AVs (i.e., the scores show the opposite pattern to those of the AV pros factor).

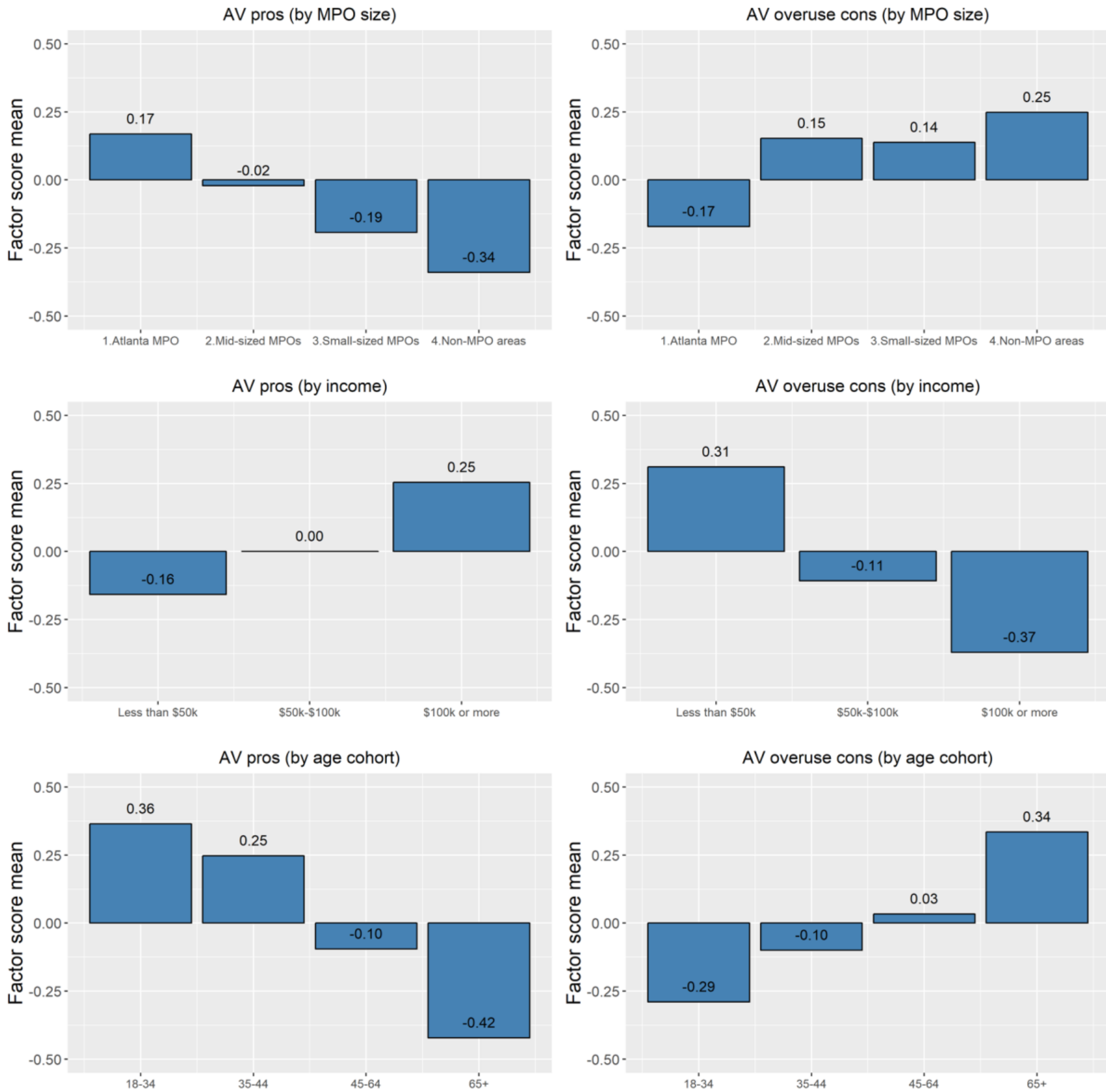


FIGURE 6-3

Segment-specific Factor Score Means for Two AV Perception Constructs (N=3,263)

6.2. How Will AVs Affect Travel-related Choices/Decisions?

Autonomous vehicles can spark different types of behavioral change because of the (perceived) benefits / side effects of the AVs. In the survey, we touched on key behavioral changes with respect to several time scales, namely short-, middle-, and long-term decisions. In general, we used response scales incorporating degrees of inclination (e.g., Likert-type scales) rather than a dichotomous scale (i.e., yes or no), to allow for some degree of uncertainty on the part of respondents about how they will react in the future.

6.2.1. Short-term Decisions: Mode-use Propensity

In the short term, one direct effect of AVs would be on mode use. This includes both how people use AVs and how people choose alternatives for travel. With respect to the former, the survey asked about the willingness to use three different (non-exclusive) AV configurations (related to level of privacy). In the era of AVs, people can defer owning a private vehicle since they can use shared AVs. In addition, people can use shared AVs alone or with others they know, or they can use shared AVs with strangers. These two shared options are similar, but different in that the former is *sequential* (i.e., not sharing a vehicle at the same time, like a typical Uber/Lyft ride, but it is also different from current Uber/Lyft because it is driverless), whereas the latter is *simultaneous* (i.e., sharing a vehicle with an unrelated passenger at the same time, such as with an UberPOOL or Lyft Line ride, or a conventional airport or hotel shuttle).

On average, there are clear differences in willingness to use by the level of privacy (Table 6-4). The more private the vehicle, the more willing the respondent. On average, half of respondents (51%) said they are likely or very likely to own a self-driving car, whereas 27 percent and 12 percent of respondents are likely or very likely to use a driverless taxi alone/with others and with strangers, respectively. When investigating these responses by population segments, there are notable differences:

- ***By MPO size*** (Figure 6-4): Residents in bigger MPO areas will be more likely than others both to own AVs and to use shared AV options. More differences across MPO levels are observed in the shared options. One plausible reason might come from familiarity with or experience with shared mobility options. Ridehailing companies provide major cities with diverse options of shared riding (e.g., UberPOOL, Lyft Line), whereas in less heavily populated areas they do not provide services at all, or provide only basic options (e.g., UberX, which does not entail sharing with others).

- ***By income*** (Figure 6-5): Higher-income people will be more likely than others both to own AVs and use shared AV options. In particular, higher-income people have a higher likelihood of using their own AVs than lower- and middle-income people do. For example, 36 percent of higher-income people said they were "very likely" to own an AV, whereas 26 percent of middle-income people and 20 percent of lower-income people did. On the other hand, it is interesting that even among higher-income respondents, about a third of them were lukewarm or cool toward the prospect of AV ownership.

  Another observation is that although all groups are less positive about sharing AVs than about owning them, higher-income people are more inclined to use the shared options than lower-income people are. This could reflect the multifaceted effects of various factors rather than solely an income effect. Higher-income people tend to be more tech-savvy and, thus, more favorable toward new travel options. In addition, some lower-income people may perceive paying by the ride to be a more costly option than ownership, on the whole.

- ***By age cohort*** (Figure 6-6): In general, as expected, younger people will be more likely both to own AVs, and to use shared AV options. Interestingly, the profile of the millennial respondents (ages 18–34) is rather similar to that of Generation X (ages 35–44). This might be attributable to some compound effects. For example, millennials (18–34) might be generally more tech-savvy and friendly to AVs, but Generation X (35–44) might be better able to afford to own vehicles and might have greater travel needs for which they could see the value of AVs. Both groups differ distinctively from the two older groups, with the latter cohorts showing profiles that are similar to each other, but with AV reluctance magnified among the senior group.

TABLE 6-4
Overall Willingness to Use/Own an AV by AV Configuration

Question	Category	Count	Share (%)
I would own a self-driving car.	Very unlikely	568	17.4
	Unlikely	349	10.7
	Somewhat likely	661	20.2
	Likely	851	26.0
	Very likely	844	25.8
	Total	3273	100.0
I would use a driverless taxi alone or with others I know.	Very unlikely	851	26.1
	Unlikely	750	23.0
	Somewhat likely	767	23.5
	Likely	607	18.6
	Very likely	284	8.7
	Total	3259	100.0
I would use a driverless taxi with other passengers who are strangers to me (like UberPOOL).	Very unlikely	1199	36.7
	Unlikely	1090	33.4
	Somewhat likely	587	18.0
	Likely	295	9.0
	Very likely	95	2.9
	Total	3266	100.0

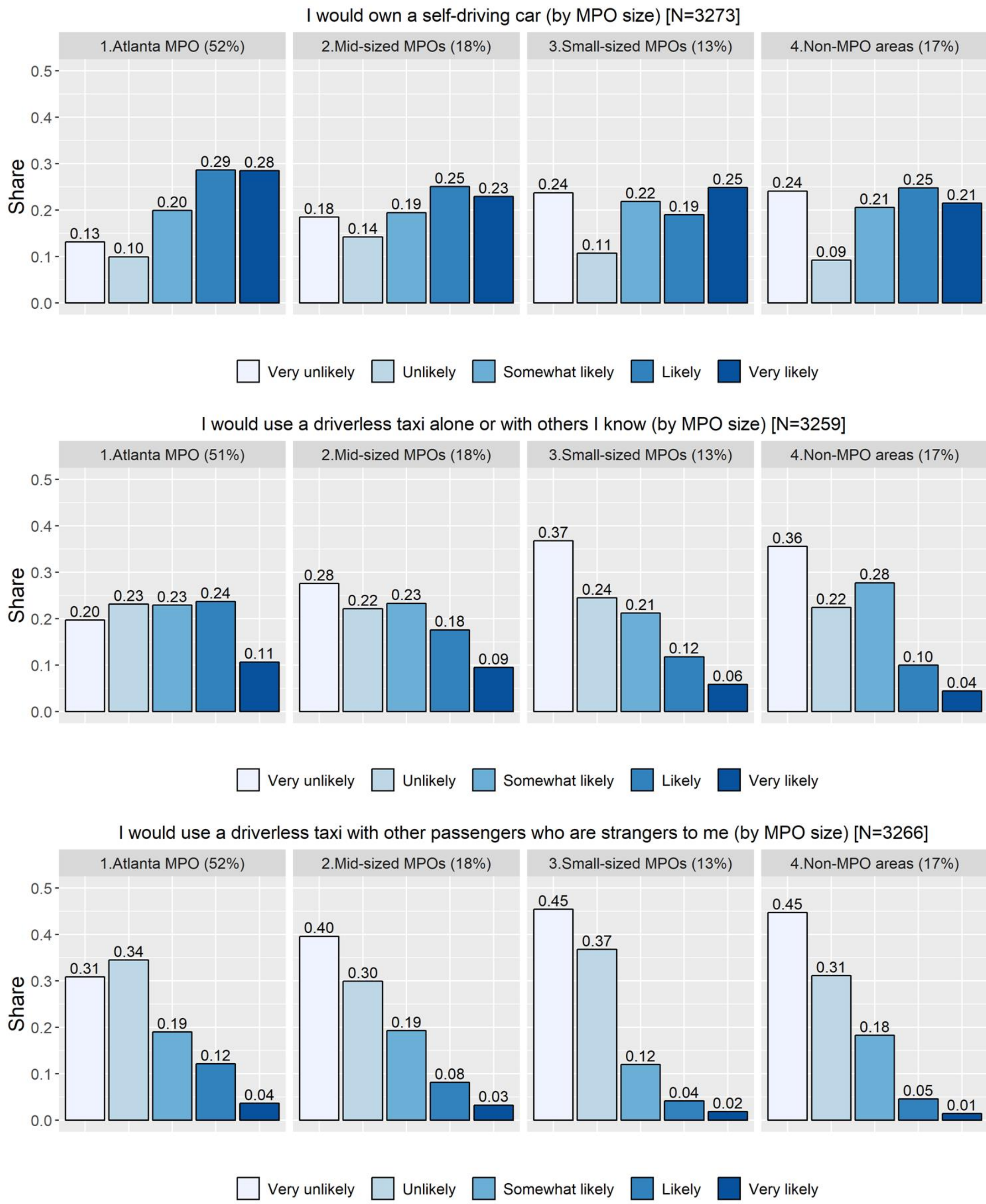


FIGURE 6-4

Willingness to Use AVs by Configuration (by MPO size)

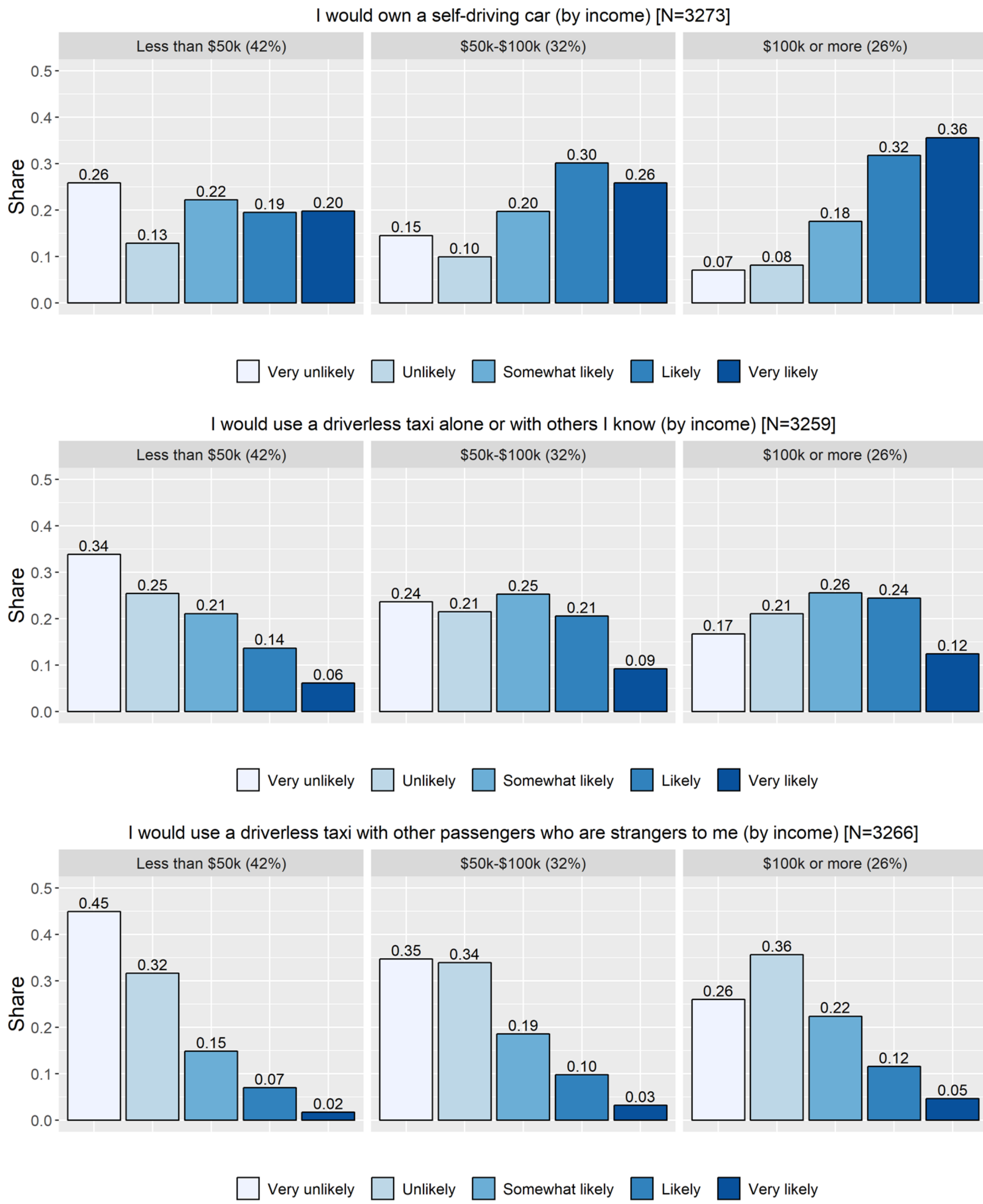


FIGURE 6-5

Willingness to Use AVs by Configuration (by income)

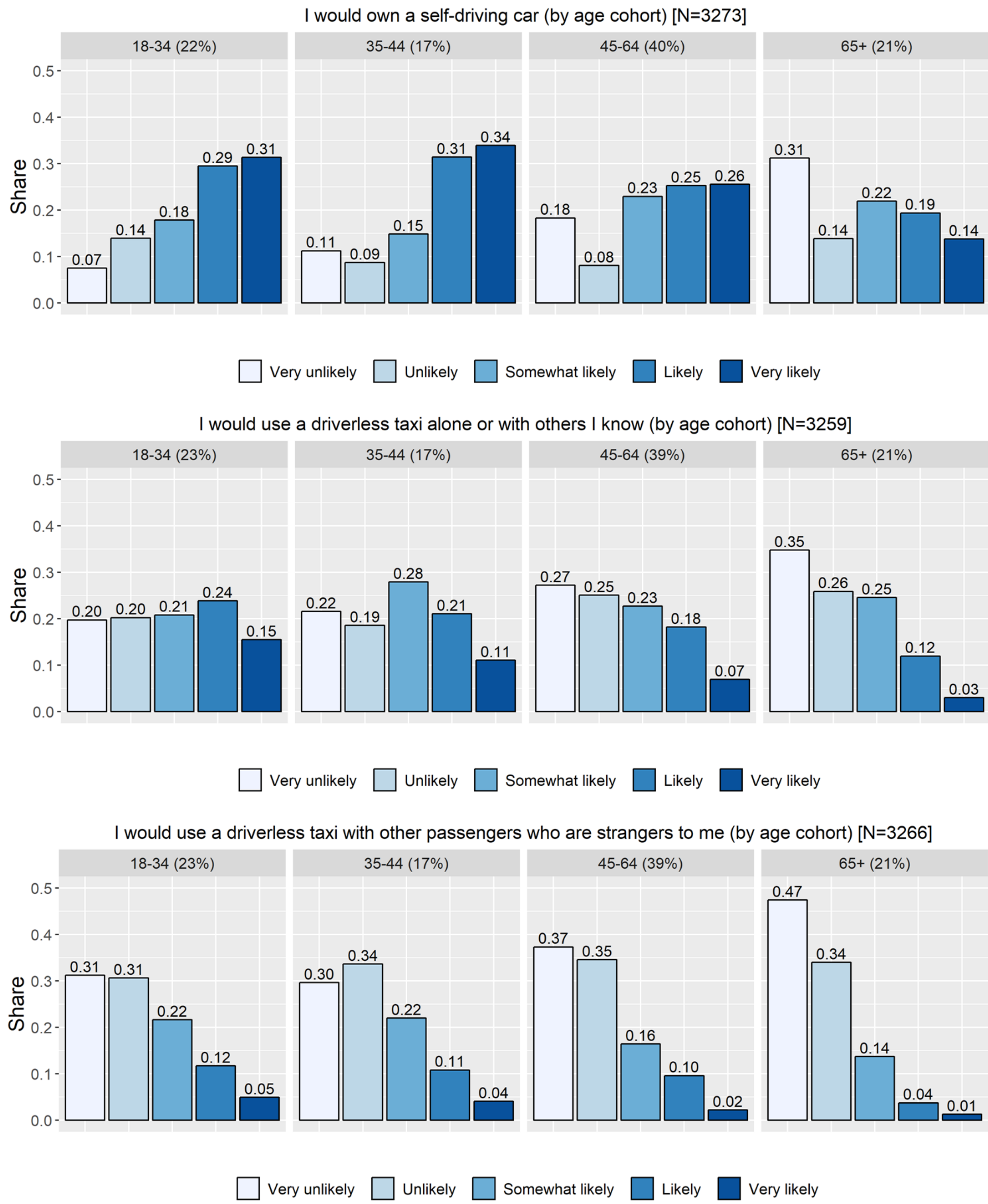


FIGURE 6-6

Willingness to Use AVs by Configuration (by age cohort)

In addition to the questions about respondents' general intention to own or use AVs, we obtained another glimpse of their inclinations by presenting them with a series of forced choices between using an AV or an alternative mode in several common settings. We wanted to see whether respondents would avoid using AVs if at all possible, or whether they would embrace the new technology completely, or only selectively. Rather than using a typical stated preference format, we intentionally tried to capture general inclinations, because respondents may not be able to be sensitive to differences in attributes (e.g., time, cost) given that AVs have not yet been realized. Specifically, the survey includes a block of 12 items, each presenting a brief hypothetical transportation "need", and offering an AV-based alternative for meeting that need, versus an alternative involving another appropriate mode (such as walk/bike, bus/train, and plane). Respondents were asked to indicate, on a continuous/ordinal scale anchored at each end by the AV and non-AV alternatives, where their inclination fell. To further condense these items into a smaller number of mode-use propensity dimensions, we applied factor analysis (see the discussion of this method in Chapter 4). Based on qualitative and quantitative criteria, we chose the 4-factor solution, labeling the factors *AV over walk/bike*, *zero-occupant vehicle (ZOV) over occupied vehicle (OV)*, *AV over flight*, and *AV over transit* (Table 6-5). A high score on one of these dimensions signifies a general preference for the first mode of the factor label over the second mode.

TABLE 6-5
Pattern Factor Loadings for Mode-Use Propensities

	AV over walk/bike	*ZOV over OV*	*AV over flight*	*AV over transit**
Walk/bike for 20 minutes to get to work/school vs. Take a **self-driving car** to get to work/school	0.953			
Walk/bike for 20 minutes to get to a transit station vs. Take a **self-driving car** to get to a transit station	0.869			
Walk/bike for 20 mins to social activities or to do personal business vs. Take a **self-driving car** to social activities or to do personal business	0.776			
Walk/bike for 20 mins to go shopping vs. **Take a self-driving car** to go shopping	0.715			
Go with the car to bring other people who are not able to drive vs. **Send an empty self-driving car** to bring others who are not able to drive		0.892		
Go with the car to pick up meals vs. **Send an empty self-driving** car to pick up meals		0.589		
Go with the car to bring my child vs. **Send an empty self-driving car** to bring my child		0.529		
Fly to a vacation in a distant state vs. **Take a self-driving car** to a vacation in a distant state			0.862	
For a one-day trip, **fly** for 3 hours each way (including access/wait time) vs. For a one-day trip, **take a self-driving car** for 6 hours each way			0.590	
Take a bus or train to go shopping vs. **Take a self-driving car** to go shopping				0.912
Take a bus or train to social activities or to do personal business vs. **Take a self-driving car** to social activities or to do personal business				0.874
Take a bus or train to get to work/school vs. **Take a self-driving car** to get to work/school	0.318			0.525

Note: Factor loadings under 0.3 are suppressed for clarity.
* To simplify interpretation, we reversed the directionality of this scale by multiplying the original loadings and factor scores by (−1).

AV over walk/bike captures a general inclination toward using AVs rather than walking or bicycling for several types of short trips. All types of short-trip purposes tested load strongly on this factor (from 0.953 to 0.715). ***ZOV over OV*** is about a new type of mode choice in the AV era. AVs will offer a new option: “let the AV go for errands.” Thus, this construct is capturing a general preference between deploying an empty AV versus taking an AV in person for errands. Sending an empty car to pick up other people who cannot drive loads especially highly (0.892). Picking up “my child” with an empty AV is a similar situation but it loads least strongly among the three items associated with this factor (0.529)—probably because of the particular vulnerabilities of the young. ***AV over flight*** is related to long-distance mode choice between an automated ground vehicle and flight. A statement related to “a distant state” loads highly (0.862) and a statement involving travel time is comparatively less strongly loaded (0.590). ***AV over transit*** measures a general inclination toward AVs over transit. In particular, compared to a commuting situation (0.525), items associated with non-commuting situations load more heavily (0.912 and 0.874). Here are some observations based on the average scores by population segments (Table 6-6):

1. Although each population segment has a statistically different "AV over walk" score, this factor exhibits the smallest differences across population segments compared to differences in other mode-use propensities. In other words, with respect to the mode-use propensity between AV and walk, there is little heterogeneity in response across population segments.
2. On average, Atlanta area residents, those age 35–44, and higher-income people are more inclined to employ ZOV rather than OV. It is natural that people with high values of time, high household trip-making needs, and high exposure to congestion see the value in having some of their errands performed without having to be "along for the ride".
3. Non-MPO residents, older people, and lower-income people are more inclined to take an AV than flight for long distance travel. Atlanta area residents probably see less benefit in taking an AV because they are close to a major airport (Hartsfield–Jackson International Airport). Higher-income people have a greater monetary value of time and would, thus, tend to want to take the fastest mode possible. Younger people may be more time-pressured and, thus, have a similar inclination.
4. Residents of smaller MPO areas, older people, and lower-income people are more inclined to use transit than AV. This could indicate a greater distrust of new technologies among these groups, and, at least for the latter two groups, perhaps a greater familiarity with transit.

TABLE 6-6
Factor Score Means for Four Mode-Use Propensities (by population segment)

MPO Size					**ANOVA test**	
Mode-use propensity	Atlanta MPO area	Mid-sized MPO areas	Small-sized MPO areas	Non-MPO areas	F-value	Sig.
AV over walk	0.05	−0.06	−0.03	−0.08	3.42	0.017
ZOV over OV	0.11	−0.07	−0.15	−0.15	14.85	0.000
AV over flight	−0.08	0.05	0.02	0.18	8.63	0.000
AV over transit	0.12	−0.07	−0.19	−0.15	16.60	0.000
Income					**ANOVA test**	
Mode-use propensity	Less than $50,000	$50,000–$99,999	$100,000 or more	-	F-value	Sig.
AV over walk	−0.11	0.06	0.08	-	11.84	0.000
ZOV over OV	−0.11	−0.01	0.19	-	22.86	0.000
AV over flight	0.10	0.01	−0.16	-	16.90	0.000
AV over transit	−0.22	0.07	0.24	-	53.78	0.000
Age Cohort					**ANOVA test**	
Mode-use propensity	18–34	35–44	45–64	65+	F-value	Sig.
AV over walk	−0.04	0.10	0.05	−0.14	6.98	0.000
ZOV over OV	−0.05	0.19	0.02	−0.16	12.20	0.000
AV over flight	−0.14	−0.05	0.07	0.06	7.05	0.000
AV over transit	0.08	−0.03	0.08	−0.24	14.97	0.000

* Note: Positive mean scores indicate more positive inclinations toward AV options

6.2.2. Medium-term Decisions: Activity Pattern Changes

The direct and more short-term effects of introducing AVs might occur when people choose a means of travel, as described in the previous section. As the benefits of AVs become more cogent, we can expect some intermediate-term changes in activity patterns and time use. For example, because people do not need to drive themselves, they might be more willing to travel more frequently and/or farther. This section aims to capture people's general inclination toward changing their activities. Even if their actual behavior eventually differs from what they think now, this exploration can give us some insight into initial reactions. We asked respondents how likely they would be (on a five-point ordinal scale) to change their behavior in each of 16 ways, touching on dimensions of trip frequency, distance traveled, and time use. To condense these specific changes into a smaller number of dimensions, we implemented factor analysis on the 16 statements (see the discussion of this method in Chapter 4). Based on qualitative and quantitative criteria, we selected the 4-factor solution (Table 6-7).

The first two factors capture two different dimensions of travel quantity, largely (but not exclusively) with respect to local travel. ***Distance*** represents a general inclination toward traveling longer distances. People who have a higher score on this factor are more willing to go to *farther-away* restaurants, places where they can socialize with others, shopping malls, and leisure destinations. ***Frequency*** captures a general inclination toward traveling more frequently. Those with a higher score on this factor think they will likely go shopping, to restaurants, and leisure destinations *more often*. ***Time flexibility*** reflects a general inclination toward modifying one's time use. The first three items loading heavily on this factor relate to time freed up by bringing formerly "outside-the-trip" activities inside the trip; the fifth item suggests freeing up "within-trip" time by spending less time in congestion; and the fourth item relates to ways in which the newly freed time (whether formerly within-trip or outside-the-trip) can be spent (Mokhtarian, 2018). Lastly, the ***long-distance/leisure*** factor represents a general inclination toward making specifically long-distance and leisure trips more often. Even the item representing the "eliminat[ion of] some overnight trips because it would be easier to come back the same day" might actually indicate the facilitation of more long-distance travel due to the added convenience and time savings of not spending the night away from home.

Figure 6-7 exhibits the factor score means for the four activity pattern change dimensions by population segment (MPO size and age cohort). For all dimensions, younger people are more likely to change how they travel or allocate their time (i.e., more likely to travel more frequently and farther, use their time more flexibly, and make more long-distance trips). In terms of MPO size, people living in larger MPO areas are more likely to have activity changes. One notable pattern is that, on average, residents of mid-sized MPO areas have higher time flexibility and, especially, frequency scores than those of Atlanta area residents. We are unsure of the explanation for this departure from the monotonic MPO-size-based trends for other variables, but consider it an intriguing subject for further exploration.

TABLE 6-7
Factor Loadings for Activity Pattern Changes

Statement	Distance	Frequency	Time flexibility	Long-distance/ leisure travel
Go to more distant restaurants.	0.666			
Socialize with people who live farther away.	0.654			
Go to more distant grocery stores or shopping malls.	0.630			
Travel to more distant locations for leisure.	0.504			
Go to grocery stores or shopping malls more often.		0.822		
Eat out in restaurants more often.		0.782		
Travel to social/leisure activities more often.	0.375	0.452		
Sleep less time at home and more time in the car, to be more efficient.			0.817	
More often eat meals in a self-driving car instead of at home or in a restaurant.			0.687	
Reduce my time at the regular workplace and work more in the self-driving car.			0.614	
Cultivate new hobbies or skills with the time I saved.			0.463	
Go to work/school at a different time to avoid traffic jams, since I can sleep/work in the car.			0.428	0.335
Make more overnight trips by car because it would be less burdensome to travel long distances.				0.789
Eliminate some overnight trips because it would be easier to come back the same day.				0.652
Take part in more leisure activities after dark, because I wouldn't need to drive myself.				0.457
Take vacations more often.				0.417

Note: Factor loadings under 0.3 are suppressed for clarity.

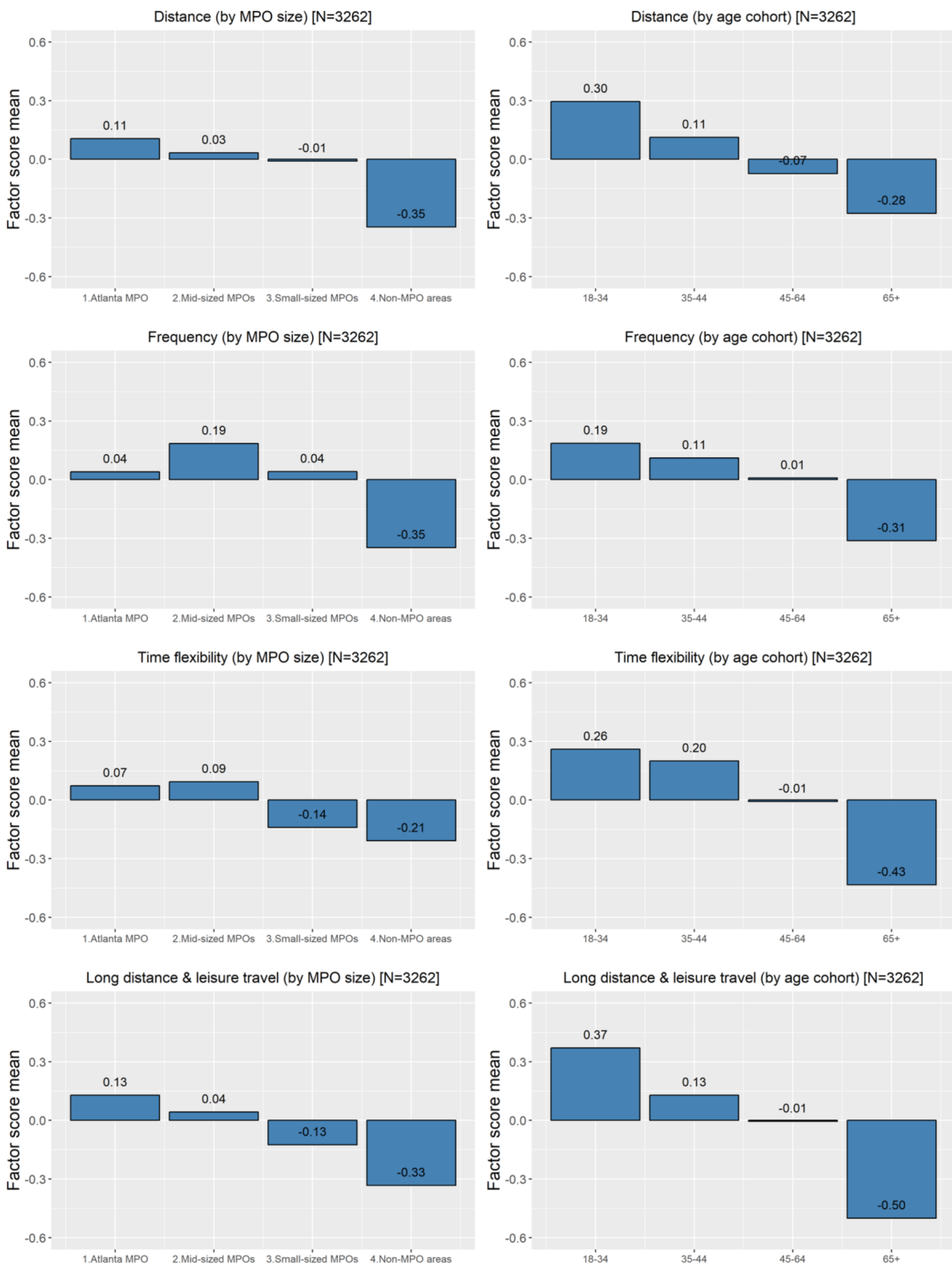


FIGURE 6-7

Factor Score Means for Four Activity Pattern Changes (by population segment)

6.2.3. Long-term Decisions: Vehicle Ownership and Residential Location

Over time, AVs can bring behavioral shifts with respect to long-term decisions. Long-term decisions indicate lifestyle-related decisions that are more fundamental and influence everyday activity participation and the long-term ability to travel (Miller, 2005; Katoshevski et al., 2015). Vehicle ownership and residential location choice are major long-term decisions. For vehicle ownership, the survey provided five categories, indicating whether respondents would very likely or likely own fewer cars, most likely own the same number of cars, or likely or very likely own more cars if AVs were the only cars available, compared to the current number of vehicles. For residential location choice, respondents were asked where they would "prefer to live, if self-driving cars were available", with three response options: (1) "I would like to move closer to the locations I travel to most often (e.g., workplace or school)"; (2) "Having a self-driving car would not influence me to move somewhere else"; and (3) "I would like to move to a more attractive location, even if it means being farther from the locations I travel to most often".

Table 6-8 and Table 6-9 show the overall preferences with respect to vehicle ownership and residential location. More than half of the respondents (57%) expect to own the same number of cars as today and 38 percent expect to shed cars, whereas 5 percent of respondents expect to increase their household fleet size. In terms of residential location, more than three quarters of the sample (77%) expect that AVs would not influence their residential location choice. Figure 6-8 and Figure 6-9 present differences in the expectation of vehicle ownership in the fully-AV era by important segments. On average, a higher share of lower income people (40%) are expecting to shed vehicles than in other income groups. With respect to current vehicle ownership, 41 percent of people having two or more vehicles expect to shed vehicles, whereas only 28 percent of people having one vehicle expect to do so. Ninety-six percent of those in zero-vehicle-households expect to remain carless.[43] In a nutshell, more than half the people in each population segment expect to

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[43] In Figure 6-8, 66 percent of people having zero vehicles answered 'likely to own fewer cars' or 'Very likely to own fewer cars'. Strictly speaking, this is illogical because one cannot own fewer than zero vehicles.

own the same number of vehicles, but there are sizable minorities, especially among car-rich households, who may shed a vehicle when all cars are fully automated.

TABLE 6-8
Overall Expectation Regarding Vehicle Ownership in the Fully-AV Era (N=3,242)

Category	Count	Share (%)
Very likely to own fewer cars	668	20.62
Somewhat likely to own fewer cars	562	17.34
Most likely to own the same number of cars	1854	57.20
Somewhat likely to own more cars	84	2.60
Very likely to own more cars	72	2.23

TABLE 6-9
Overall Residential Location Preference if AVs Were Available (N=3,226)

Category	Count	Share (%)
I would like to move closer to the locations I travel to most often (e.g., workplace or school).	377	11.68
Having a self-driving car would not influence me to move somewhere else.	2502	77.56
I would like to move to a more attractive location, even if it means being farther from the locations I travel to most often.	347	10.76

Figure 6-10 and Figure 6-11 exhibit the residential location preferences by population segment. On average, residents of the three MPO tiers have similar fractions (around 75%) of people who do not expect AVs to affect their residential location choice, while that fraction is even larger for rural residents (87%). In terms of current neighborhood type, in general, the more urban the current area of residence, the more inclined respondents are to move (whether closer to the locations they visit most often or to more attractive/distant locations). It is not clear whether AVs are *increasing* the inclination to move—after all, in general, residential location processes are

However, this is a common response pattern under such circumstances (see, e.g., Choo et al. [2005]), and we interpret it to mean "we will continue not to own a vehicle". However, we intentionally did not recode them into "most likely to own the same number of cars", to show their answers as they are.

already more dynamic in urban areas (where there are higher concentrations of renters, more single adults, and more households with no children). But these results suggest that the *geographic unpredictability* of those choices may increase over time, since many more locations will become feasible once AVs facilitate the more productive use of travel time, and possibly higher speeds.

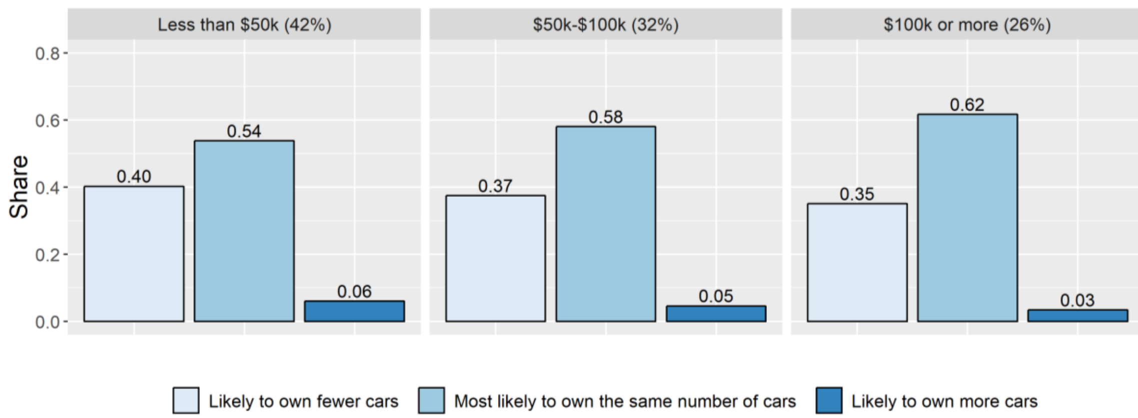
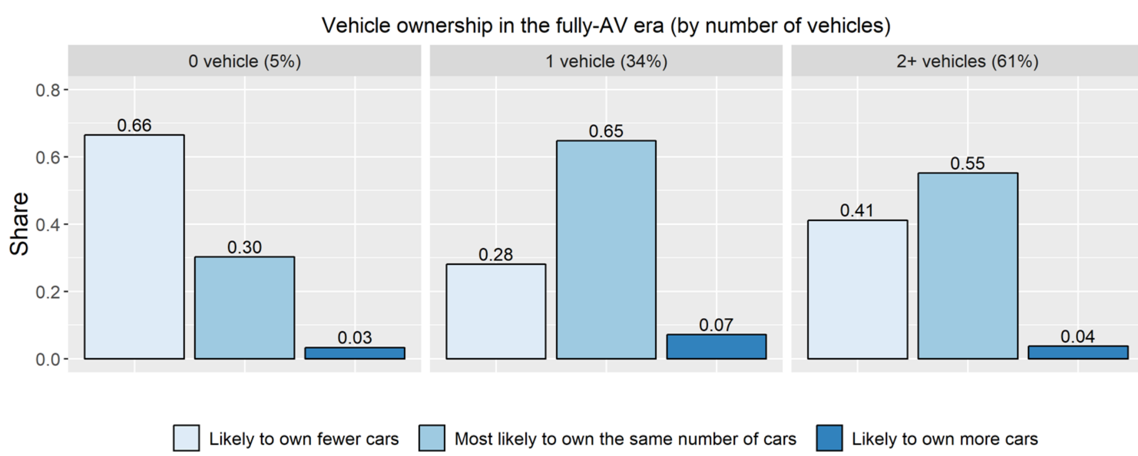


FIGURE 6-8

Expectation Regarding Vehicle Ownership in the Fully-AV Era (by income) (N=3,242)



Note: See footnote 43 regarding the zero-vehicle owners reporting being "likely to own fewer cars".

FIGURE 6-9

Expectation Regarding Vehicle Ownership in the Fully-AV Era (by current vehicle ownership) (N=3,242)

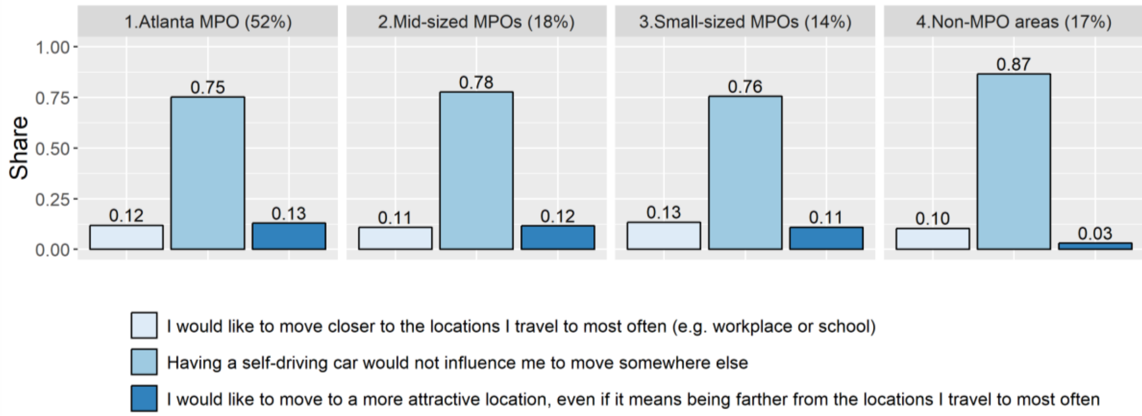


FIGURE 6-10

Residential Location Preference if AVs Were Available (by MPO size) (N=3,226)

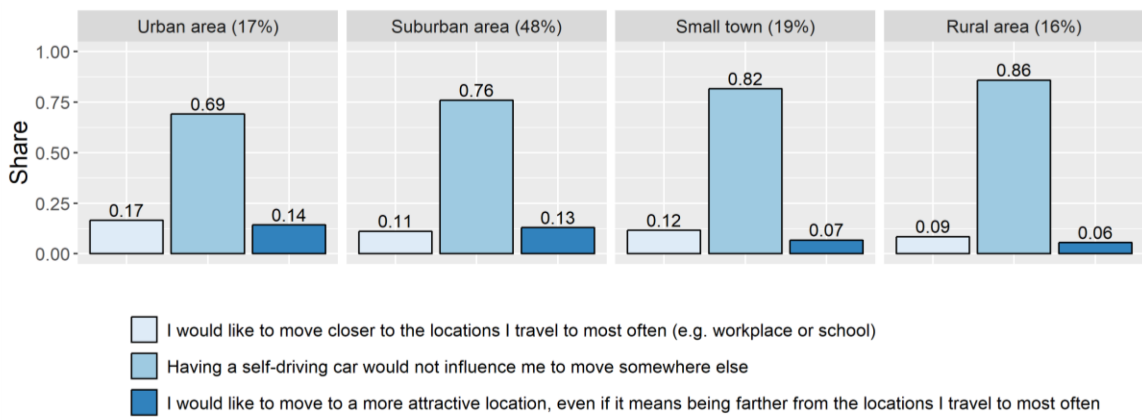


FIGURE 6-11

Residential Location Preference if AVs Were Available (by neighborhood type) (N=3,151)

7. CONCLUSIONS AND RECOMMENDATIONS

This study explored the landscape of transportation-related attitudes and behaviors in Georgia, using data collected from a statewide survey designed by the research team and fielded in 2017–2018. Some of the key findings of the analysis, together with some planning/policy implications, are listed in the Executive Summary for Part 2; we do not repeat all of them here for the sake of brevity. The survey is distinctive both in its topical breadth and its geographic scope. With respect to the former distinction, the survey provides both a snapshot of current attitudes and behavior, and a glimpse of the future *from the traveler's perspective*—specifically, measures of perceptions and intentions regarding an array of new and emerging transportation products and services. With respect to the latter distinction, it is typical for such surveys to focus on specialized demographic (e.g., millennials) and/or geographic (e.g., metro area) populations, but far less common to take the statewide viewpoint of the present study. Our goal in so doing was to support the statewide mission of GDOT's policy and planning role, by providing a wealth of fresh knowledge regarding a number of pertinent issues. In all of the major themes explored, we found notable differences across population segments in how people travel and how they think. In particular, segmentations into four tiers based on the size of the applicable MPO area offers useful geographic nuance to the findings.

Among the numerous findings of this study, several implementation possibilities present themselves. For example:

- The current data obtained by this study can be used to develop a disaggregate vehicle ownership model that can be stratified by any desired demographic or geographic variable. Such a model, or suite of models, can provide useful input to the GSTDM and MPO models supported by GDOT. Although the actual vehicle ownership models incorporated into the GSTDM and the MPO models will most likely be aggregate models, it will be important to have a disaggregate benchmark against which to validate the aggregate ones.

- The high level of interest in alternative-fuel vehicles suggests considerable receptivity to policies promoting their adoption. Accordingly, GDOT could consider supporting a reinstatement of the tax credit for purchasing such vehicles, or other price-lowering instruments; increased density of charging stations to ameliorate range anxiety; and research and development of technologies that would increase range and/or lower cost.
- At present, some 42% of Georgia workers can telecommute (their jobs and supervisors apparently allow it), but only 5% do. In the interests of helping to reduce peak-period congestion, improving air quality, and achieving other societal benefits (such as workforce attraction and retention), GDOT could consider supporting the promotion of telecommuting through policy instruments and other means.
- The increasing adoption of ridehailing, though expanding the mobility options for many and allowing some to forgo vehicle ownership (while still relying on *others'* personal vehicles) is not altogether benign, in view of the impacts on transit, active transportation, and trip generation identified by this study. The data collected in this study could be used to develop models of ridehailing adoption and frequency that could potentially be integrated into the GSTDM and MPO models supported by GDOT. However, ridehailing is still a rapidly expanding/developing phenomenon, and thus it is important to maintain up-to-date information about its status. We recommend that, via traveler surveys as well as data obtained from the service providers, GDOT aggressively monitor the progression of ridehailing (and related services) statewide, together with its impacts on travel behavior, traffic flow, and urban design. We further recommend that GDOT partner with local governments in developing policies to promote the benefits of ridehailing while mitigating its disbenefits.

As noted in the Introduction, our survey prioritized breadth over depth. As a consequence, the granularity of our findings is somewhat coarse, and many questions cannot be answered by such an approach. Of course, there is always more to learn about human attitudes and behavior, but in the present climate of technological and social ferment, it is more imperative than ever to update our understanding of travelers' behavior, intentions, constraints, perceptions, and opinions on a regular basis. The current analysis suggests some follow-on studies that would allow a finer-grained exploration of several important topics; we sketch a few ideas below.

- In view of the volatility of the present times, it would be valuable to conduct a broad-brush statewide survey on a regular basis (e.g., bi- or triennially). It need not be comprehensive, but certain variables (e.g., vehicle ownership, key attitudes, use of ridehailing and other new mobility options, AVs) are of particular current and ongoing interest. Such a series would allow GDOT, MPOs, and other relevant agencies to monitor how these attitudes and behaviors evolve as current services mature and new ones emerge, providing a more solid basis for projecting into the future.
- In addition to periodic administration of a general-purpose transportation survey, several topics call for a more in-depth investigation requiring a survey dedicated to each subject.
- There is a clear need for more data on shared mobility behavior. Between the time we designed the present survey (2017) and now (2019), Uber and Lyft have further penetrated the market; more companies are providing bikesharing (e.g., JUMP); and new types of "micromobility" (i.e., e-scooter, e-bike) have emerged. The extent to which, and ways in which, these services are being used is unclear: are they addressing the first/last mile (transit access/egress) problem? Are they replacing more active means of travel? Do they replace short car trips?
- The disparity in driver's licensing identified by this study, between workers and non-workers and higher versus lower incomes, is striking, and the direction of causality is not clear. However, research has shown (Blumenberg and Pierce, 2014; 2017) that lack of access to a car restricts access to employment opportunities. Accordingly, additional

investigation into the causes of lower licensing rates for non-workers and lower-income people may identify barriers amenable to policy intervention.

- It is important to better understand the evolving attitudes and behavior of Generations Y (millennials) and Z: Are millennials who marry and have children living and traveling much like previous generations at that lifecycle stage? But how are marriage and childbearing rates evolving over time? Are they eventually obtaining driver's licenses, and with what delay, compared to previous generations? How does an increased sensitivity to environmental issues (and, thus, a desire to reduce one's carbon footprint) balance out against a desire for novel experiences, which tend to involve air travel (which greatly contributes to carbon emissions)?
- Fewer decisions are more central to one's travel patterns than vehicle ownership. How will vehicle ownership evolve as options for purchasing travel by the trip (i.e., carsharing, ridehailing, micromobility, AVs) continue to emerge and grow? Will there continue to be a strong predilection for ownership, or will this weaken in the generations now growing up? How will the shares of voluntarily "carfree" and "carlite" (retaining one vehicle, but shedding at least one) households change over time? What are the attitudinal and technological barriers to adopting alternative-fuel vehicles, and how can those be mitigated?
- What is the potential for telecommuting to help mitigate peak-period congestion and improve work–life balance? To what extent do job suitability, management willingness, and employee interest, respectively, constitute barriers to increased adoption?
- Certain issues raise the need for specialized surveys addressing the traveler's sensitivity to key policy variables. For example, how does the willingness to buy an electric vehicle change with given levels of financial subsidy? What kinds of incentives will induce a sizable number of people to switch to shared mobility? These kinds of questions will probably call for surveys built around a stated preference choice experiment.

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