Title

Barriers to Reducing the Carbon Footprint of Transportation Part 2: Investigating Evolving Travel Behaviors in the Post-Pandemic Period in California

Authors
Ozbilen, Basar
Gulhare, Siddhartha
Makino, Keita
et al.

Publication Date
2024-05-01

Barriers to Reducing the Carbon Footprint of Transportation Part 2: Investigating Evolving Travel Behaviors in the Post-Pandemic Period in California

May 2024

Prepared for: California Air Resources Board
Barriers to Reducing the Carbon Footprint of Transportation
Agreement No. 19STC006 (Part 2)

Prepared by: 3 Revolutions Future Mobility Program (3RFM)
Institute of Transportation Studies, University of California, Davis

Authors:

Basar Ozbilen, PhD, Institute of Transportation Studies, University of California, Davis

Siddhartha Gulhare, PhD, Institute of Transportation Studies, University of California, Davis

Keita Makino, Institute of Transportation Studies, University of California, Davis

Aurojeet Jena, Institute of Transportation Studies, University of California, Davis

Xiatian Iogansen, Institute of Transportation Studies, University of California, Davis

Patrick Loa, PhD, Institute of Transportation Studies, University of California, Davis

Yongsung Lee, PhD, Institute of Transportation Studies, University of California, Davis

Jai Malik, PhD, The World Bank

Giovanni Circella, PhD, Institute of Transportation Studies, University of California, Davis, and Department of Geography, Ghent University

UCDAVIS
3 Revolutions
Future Mobility
Institute of Transportation Studies

CALIFORNIA
AIR RESOURCES BOARD

TECHNICAL REPORT DOCUMENTATION PAGE

<table>
<tr><td colspan="2">1. Report No.
UCD-ITS-RR-24-25</td><td colspan="2">2. Government Accession No.
N/A</td><td colspan="2">3. Recipient's Catalog No.
N/A</td></tr>
<tr><td colspan="4" rowspan="2">4. Title and Subtitle
Barriers to Reducing the Carbon Footprint of Transportation Part 2: Investigating Evolving Travel Behaviors in the Post-Pandemic Period in California</td><td colspan="2">5. Report Date
May 2024</td></tr>
<tr><td colspan="2">6. Performing Organization Code
N/A</td></tr>
<tr><td colspan="4" rowspan="2">7. Author(s)
Basar Ozbilen, Ph.D., https://orcid.org/0000-0001-9419-4341
Siddhartha Gulhare, Ph.D., https://orcid.org/0000-0003-2377-5717
Keita Makino, https://orcid.org/0000-0001-5080-2843
Aurojeet Jena, https://orcid.org/0000-0003-3113-520X
Xiatian Iogansen, https://orcid.org/0000-0002-4851-1323
Patrick Loa, Ph.D., https://orcid.org/0000-0002-8606-6283
Yongsung Lee, Ph.D., https://orcid.org/0000-0002-1980-1225
Jai Malik, Ph.D., https://orcid.org/0000-0002-7137-7302
Giovanni Circella, Ph.D., https://orcid.org/0000-0003-1832-396X</td><td colspan="2">8. Performing Organization Report No.
UCD-ITS-RR-24-25
UC-ITS-2021-05b
NCST-UCD-RR-24-08</td></tr>
<tr><td colspan="2">10. Work Unit No.
N/A</td></tr>
<tr><td colspan="4">9. Performing Organization Name and Address
University of California, Davis
Institute of Transportation Studies
1605 Tilia Street, Suite 100, Davis, CA 95616</td><td colspan="2">11. Contract or Grant No.
CARB Contract No. 19STC006, Task 2
UC-ITS-2021-05
USDOT Grant 69A3551747114</td></tr>
<tr><td colspan="4" rowspan="2">12. Sponsoring Agency Name and Address
California Air Resources Board, Research Division, 1001 I Street, Sacramento, CA 95814
The University of California Institute of Transportation Studies, www.ucits.org
U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology, 1200 New Jersey Avenue, SE, Washington, DC 20590</td><td colspan="2">13. Type of Report & Period Covered
Final Research Report (July 2020 – May 2024)</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code
CARB, UC ITS, USDOT OST-R</td></tr>
<tr><td colspan="6">15. Supplementary Notes
N/A</td></tr>
<tr><td colspan="6">16. Abstract
During the early months of the pandemic, stay-at-home orders and concerns about infection catalyzed a shift toward online activities, such as remote work and e-shopping, resulting in a significant decrease in conventional travel. However, as the effects of the pandemic diminished, the pandemic-induced online activities began to subside, and conventional travel started to rebound. The challenge among transportation planners and policymakers is to determine the lasting effects of the pandemic and adjust the policies accordingly. In the same efforts to understand the evolving travel-related activities and inform policymaking, the 3 Revolutions Future Mobility Program at the University of California, Davis, conducted four waves of mobility surveys between Spring 2020 and Fall 2023. Key findings from the analysis of these data reveal that remote work and a combination of remote work and physical commuting (i.e., hybrid work) emerge as an enduring outcome of the pandemic. The pandemic accelerated the rise of e-shopping, both for grocery and non-grocery purchases, with findings demonstrating the critical influence of socio-demographic factors, including age, gender, and income, on e-shopping adoption and frequency. The findings show that socio-demographic factors such as work status, income level, and work arrangements are associated with household vehicle ownership changes and individual vehicle miles traveled (VMT). In particular, an increase in commute frequency reduces the likelihood of vehicle shedding, while amplifying the likelihood of vehicle acquisition. In the meantime, remote workers exhibit lower commuting VMT but higher non-commuting VMT compared to hybrid workers. The findings demonstrate a similarity between the percentage of respondents who used public transit, bikes, e-bikes, and e-scooters for commuting and non-commuting trips to some degree between 2019 and 2023. These insights underscore that adapting to shifting activity and transportation patterns is crucial for policymakers and planners to build a sustainable and inclusive post-pandemic future.</td></tr>
<tr><td colspan="4">17. Key Words
Travel Behavior, COVID-19 Pandemic, Remote Work, Hybrid Work, Online Shopping, Shared Mobility, Vehicle Ownership, Vehicle Miles Traveled, Longitudinal Data</td><td colspan="2">18. Distribution Statement
No restrictions</td></tr>
<tr><td colspan="2">19. Security Classif. (of this report)
Unclassified</td><td colspan="2">20. Security Classif. (of this page)
Unclassified</td><td>21. No. of Pages
123</td><td>22. Price
N/A</td></tr>
</table>

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

About the UC Davis Institute of Transportation Studies

The Institute of Transportation Studies at UC Davis (ITS-Davis) is the leading university center in the world on sustainable transportation, hosting the National Center on Sustainable Transportation since 2013 (awarded by the U.S. Department of Transportation) and managing large research initiatives on energy, environmental, and social issues. It is home to more than 60 affiliated faculty and researchers, and more than 120 graduate students, and, with its affiliated centers, a budget of more than $20 million. ITS-Davis has a strong commitment not just to research, but interdisciplinary education and engagement with government, industry, and non-governmental organizations.

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the California Air Resources Board, and through funding received by the University of California Institute of Transportation Studies from the State of California through the Road Repair and Accountability Act of 2017 (Senate Bill 1). However, the State of California assumes no liability for the contents or use thereof. Nor does the content necessarily reflect the official views or policies of the State of California. This report does not constitute a standard, specification, or regulation.

The statements and conclusions in this report are those of the contractor and not necessarily those of the California Air Resources Board nor the State of California. The mention of commercial products, their source, or their use in connection with material reported herein is not to be construed as an actual or implied endorsement of such products.

Acknowledgments

This report was prepared as part of a project that was funded by a research grant provided by the California Air Resources Board (CARB). This study was also supported by the National Center for Sustainable Transportation (NCST), a U.S. Department of Transportation (USDOT) University Transportation Center. Additional funding for the project was provided by the University of California Institute of Transportation Studies from the State of California through the Road Repair and Accountability Act of 2017 (Senate Bill 1), and by the 3 Revolutions Future Mobility (3RFM) Program of the University of California, Davis. The authors would like to thank CARB, the NCST, the USDOT, the State of California and 3RFM for their continued support of university-based research, and especially for the support provided for this project. The authors would also like to thank the Southern California Association of Governments for their additional support in the data collection process.

Additionally, the authors would like to thank Grant Matson, Bailey Affolter, Tak Chun Marcus Chan, Mikayla Elder, Sean McElroy, Jamie Soza Parra, Junia Compostella, Mischa Young, Dillon Fitch, Susan Handy, Patricia Mokhtarian and other colleagues at the University of California, Davis and other institutions who contributed to the design and administration of the survey. However, the contents of this report are the sole responsibility of the authors, who are responsible for the accuracy of the information that has been presented. The findings presented in this report do not necessarily reflect the official findings, views, or policies of the State of California, CARB, or any of the other funding or partner agencies that supported the study.

This report was submitted in partial fulfillment of CARB contract 19STC006 Task 2 by the University of California, Davis under the partial sponsorship of the California Air Resources Board. Work was completed as of May 6, 2024.

TABLE OF CONTENTS

List of Tables

List of Figures

Executive Summary

The COVID-19 pandemic broadly disrupted society in many ways starting in the first quarter of 2020. In the early months of the pandemic, curfews and stay-at-home orders restricted people from making trips outside their homes. This effect was critical for the transportation industry. Among other impacts, commuting trips and on-site work were replaced with work-from-home, shopping trips were replaced with e-shopping, and air travel for work purposes was replaced with online meetings. These effects were, in some sense, positive for lowering vehicle miles traveled (VMT) and reducing air pollution, at least temporarily, and promoting active modes of travel, including walking and bicycling. On the other hand, the use of public transit and shared mobility options drastically decreased due to the fear of exposure to the disease. The use of private vehicles and air travel have quickly recovered as the unique public health threat subsides, while transit ridership and the use of shared mobility options are still lower than in the pre-pandemic era. Further, the disruption of the COVID-19 pandemic might have not positively impacted the sustainability of transportation (e.g. through a reduction in VMT) in the long term, as at some point it seemed to be the case.

There have been some long-term effects of the pandemic that remain in society, which may support better, efficient, or sustainable transportation in the future. For instance, remote and hybrid work practices have been widely accepted over the world since the early stages of the pandemic. Thanks to the efforts of tech companies and local administrators, digital devices and online videoconferencing have become a tool not only for younger generations in the tech industry but also for relatively older generations or those who work in more traditional industries. As a result, workers now make fewer commuting trips per week, on average, lowering their commute-related VMT by sometimes (or mostly) working from home.

The pandemic has significantly changed the way people purchase various items. A sharp increase in e-shopping activities was observed in earlier phases of the pandemic. Lockdowns and social distancing measures made it challenging for people to purchase in person, and thus, an increasing number of people started to utilize e-commerce to meet their demands for most items, if not all, from non-essential items to groceries. The exposure to e-shopping, especially among those who had no experience in the pre-pandemic period, resulted in an increasing popularity as many people have discovered unique merits of shopping online. Consequently, the elevated level of e-shopping adoption largely persisted in the post-pandemic period.

Aside from remote work and online shopping, the pandemic might also have a long-term impact on transportation preferences. Although the use of public transit and shared mobility options has rebounded from the initial impacts of the pandemic, there is evidence that the use of these modes (and public transit in particular) remains below pre-pandemic levels. As a result, efforts to reduce VMT and emissions associated with passenger travel may need to include measures to overcome the long-term impacts of the pandemic (e.g., shift away from shared transportation options).

To identify these long-term effects and legacies of the COVID-19 pandemic, the research team in the 3 Revolutions Future Mobility Program at University of California, Davis (referred to as the research team henceforth) has been conducting a series of travel surveys since Spring 2020. In Fall 2023, the research team administered the latest survey of the series as a sequel of the preceding surveys, which included the waves of surveys from the California Mobility Panel Study in 2018 and the Pulse of the Nation on 3 Revolutions Study in 2019, and the COVID-specific surveys carried out as part of this study in three pandemic phases: Spring 2020, Fall 2020, and Summer 2021. The latest wave in 2023 was mostly designed to follow the prior waves to support longitudinal analyses, but also was updated in its content and structure to capture some evolving travel behavior and preferences in society, as the first survey to be administered in a truly post-pandemic era. The content from all surveys included questions about individual attitudes toward various transportation-related topics, socio-demographic characteristics, household compositions, employment status, work and study activities, daily travel patterns by travel purposes and by travel modes, and the use of new mobilities such as ride-hailing or e-scooters. Meanwhile, in the 2023 wave, the research team especially focused on three major topics: the temporal and spatial arrangement of work activities, the various components of VMT by distinct trip purposes, and the changes in daily travel patterns in response to the changes in fuel prices.

To capture a wide range of opinions from diverse subjects, the research team adopted five different distribution channels: longitudinal panel, opinion panel, convenience sampling, mail-out-mail-back, and mail-out-to-online. The first channel re-recruited all the former survey participants (who agreed to be re-contacted) via an email invitation. The opinion panel channel reached out to a panel of self-registered survey takers, maintained by a market research firm, Qualtrics. The convenience sampling channel then relied on distributing invitations through various professional networks and through Facebook social media advertisements. The last two channels were specifically designed to achieve better coverage of target population segments, reaching out to California residents by a physical mail invitation (mail-out-mail-back channel with the survey questionnaire, and mail-out-to-online with an invitation letter containing the link to the online version of the survey). After thorough data quality check, the research team built four-wave longitudinal data with 13,658, 8,029, 13,953, and 6,469 valid responses in Spring 2020, Fall 2020, Summer 2021, and Fall 2023, respectively.

In this report, with the latest survey dataset collected in Fall 2023, the research team provides several key insights of usefulness for policymakers, transit operators, planners and investigators of various practices of the *new normal*, such as alternative fuel vehicles, adoption of remote and hybrid workstyles, or changes in VMT in society.

Key findings reveal that remote work arrangements and hybrid work arrangements – a combination of remote work and traditional commuting – appear to be emerging as an enduring outcome of the pandemic. The analysis of the data collected in Fall 2023 indicates that a large proportion of paid workers in California have embraced some degree of remote/hybrid work, a trend anticipated to persist into 2024 and beyond. The research team, using a newly developed question about one’s detailed work arrangements, looked at a finer level of one’s work arrangement – where and what time of day people work at the primary or alternative workplace, temporary location, or home – for each of the two-hour time windows. As a result, a non-trivial portion of workers are found to work at two or more workplaces on the same day, at least once a week. This share also varies across the occupations of the survey takers, with a higher share among those who work in social services, construction, or management/legal industries, for instance. While the nature of some job types might require working at multiple locations in a day even before the pandemic, the work arrangements and remote work practices among workers in management, finance, or computer industries could be largely affected by the disruption of the COVID-19 pandemic.

Even before the onset of the COVID-19 pandemic, e-shopping frequency was on rise, a trend that accelerated for both grocery and non-grocery purchases throughout the pandemic period. The analyses showed a decline in the proportion of respondents reporting almost never shopping online throughout the pandemic, which is particularly evident in grocery e-shopping (the proportion of those who have never shopped online for groceries decreased from 77.1% to 54% between 2019 and 2023). When this is evaluated together with the increase in the proportion of frequent e-shoppers, it could indicate that the trend towards increased online shopping persists. This persistence suggests potential longer-term implications of the pandemic on individuals' shopping behavior. Socio-demographic factors play a crucial role in e-shopping habits: younger individuals and those with higher income levels reported higher rates of e-shopping, a pattern observed across various time periods. An interesting finding is that gender differences in e-shopping tendencies shifted during the pandemic. Women who were more likely to report almost never shopping online in the pre-pandemic period, reported a higher frequency for e-shopping both for grocery items and non-grocery items than men with the start of the pandemic. As e-shopping continues to evolve, understanding these socio-demographic nuances is essential for policymakers and businesses seeking to adapt to changing consumer behaviors and develop targeted strategies by reflecting on new shopping patterns of different groups in society. The increased adoption of e-shopping requires novel policy implications related to transportation and the environment. First, local governments should appropriately invest in last-mile delivery infrastructure, such as road networks, curbside space, and parking facilities, to accommodate the shift from physical shopping to e-shopping. Second, promoting electrification for last-mile delivery is crucial for reducing greenhouse gas (GHG) emissions associated with e-commerce. In this sense, efficient solutions like electric delivery vans and cargo e-bikes can enhance transportation efficiency and help reduce net-zero emissions if supported by government incentives and widely available charging infrastructure. Third, understanding the behavioral shifts in travel demand due to the increased e-shopping patterns is imperative. Policymakers should integrate e-commerce trends into transportation planning models to optimize funding allocation and make more accurate predictions. Accounting for these policy implications will allow policymakers to create sustainable and equitable transportation systems that adapt to changing consumer behaviors.

As part of the analyses presented in this report, the potential long-term impacts of the pandemic on travel mode preferences are explored. The analysis consisted of an examination into changes in the percentage of respondents using various modes of travel and a comparison of attitudes towards travel. One of the more encouraging findings was the similarity between the *percentage* of respondents who "used (at least, less than once a month)" public transit, bikes, e-bikes, and e-scooters for commuting and non-commuting trips in Fall 2023 and that of Fall 2019. Moreover, the results suggest that the prevalence of public transit, bike, e-bike, and e-scooter use have continued to evolve following the disruptive impacts of the pandemic. However, additional work is needed to understand how these modes are used compared to before the pandemic. In contrast, walking was less common for commuting and non-commuting trips in Fall 2023 compared to Fall 2019, despite relatively positive attitudes towards walking. While this could stem from differences in the attributes of the trips being made during the two time periods, further work will be needed to explore the determinants of this shift. Finally, attitudes towards travel appeared to remain relatively consistent between Fall 2020, Summer 2021, and Fall 2023. Initiatives aiming to reduce VMT can include continuing to provide financial support to transit agencies, expanding the coverage of pedestrian and cycling facilities, implementing transit priority measures along high-ridership corridors, promoting the use of shared micromobility services, and integrating shared micromobility services with public transit.

In the report, the factors influencing changes in household vehicle ownership, including additions, removals, and replacements, both in the past (from Spring 2020 to Fall 2023) and expected future (from Fall 2023 to Fall 2026) are investigated. Notably, pro-driving, novelty-seeking and younger individuals are more likely to consider increasing or replacing their vehicle in the future. It is crucial to formulate policies that divert them away from increasing vehicle ownership or incentivize them to transition to cleaner vehicles. Households with children, and those experiencing an increase in the number of children or adults demonstrate an elevated likelihood of acquiring or replacing vehicles, likely in response to evolving travel demand needs in their household. Additionally, transitions into the workforce and increases in household income correlate with an increased probability of vehicle acquisition. Furthermore, an uptick in commute frequency is associated with a lower likelihood of having shed vehicles in the recent past, while amplifying the likelihood of vehicle acquisition in the future. The impact of commute frequency on vehicle count appears more pronounced during the pandemic compared to the post-pandemic period, potentially due to the largely rebounded demand for non-commuting trips. Governments should support companies in formulating tailored remote/hybrid work policies and travel demand management policies aimed at reducing commute trips for different worker groups. Lastly, the study highlights that COVID health concerns led to a smaller chance of vehicle shedding during the pandemic, though that was largely a temporary impact.

Last but importantly, this report presents the unique challenges and adjustments of low-income respondents during and after the pandemic across multiple domains. Across three time points, Fall 2020, Summer 2021, and Fall 2023, low-income participants reported economic hardship more than their middle-/high-income counterparts: a larger proportion of them were unemployed or underemployed during the early phase of the pandemic and have continued searching for employment since then. The nature of jobs taken by many low-income individuals did not allow them to work remotely even during the heightened risk of virus contraction during the pandemic. In association with this pattern, a larger share of low-income workers expressed that remote work was not feasible for various reasons (e.g., lack of office devices and distractions from family members). Although they needed reliable transportation more than others in the sample, low-income respondents had lower access to private vehicles, which left them relying more on public transit and other travel options. It is noteworthy that, while low-income individuals in the sample tended to use public transit more often, they were not more positive toward this mode of travel than their middle-/high-income counterparts. That is, their use of public transit appears to be driven by necessity, not preference. Not surprisingly, low-income participants tended to experience difficulties in meeting their basic needs (e.g., paying bills on time) and reported lower life satisfaction in the years 2020-2023.

The research team compared VMT among different socio-demographic groups. Not surprisingly, students or workers (compared to non-students and non-workers) and individuals living in high-income households (earning $100,000 or more annually) generate more VMT. After all, student/work status and income level typically positively correlate with economic opportunities, demand for travel, and resources for mobile lifestyles. Commuters (who commute at least once a week while working remotely less than once a week) exhibit the highest VMT for commuting, non-commuting, and long-distance trips. Conversely, remote workers (who work remotely at least once a week while commuting less than once a week), generate the lowest commuting VMT, but have higher non-commuting VMT compared to hybrid workers (who both commute and remote work at least once a week). These descriptive analyses inspire the research team to further explore the causal effect of work arrangements on VMT and the interrelationships among trips between different trip proposes (e.g., substitution effect between commute trips and leisure trips), which will be carried out as part of future research steps building on the analysis of the rich datasets collected in the study. Expected results can provide valuable policy recommendations aimed at decreasing vehicle ownership, reducing commute trips, and effectively managing remote and hybrid work arrangements.

1 Introduction

In early 2020, the world faced widespread disruption caused by the COVID-19 pandemic. Several restrictions such as stay-at-home orders, curfews, or capacity restrictions significantly disrupted the social activities and travel behaviors of individuals all over the world (Liu et al., 2021; Wilder-Smith & Freedman, 2020). Due to the stay-at-home orders, in the U.S., the number of people staying home was 55% higher in April 2020, compared to that in the previous year (Bureau of Transportation Statistics, 2022). Many industries and academic institutions quickly adopted remote work/study practices to reduce exposure to the virus. People also started to refrain from shopping in physical stores and did more online shopping. These changes in daily activity patterns resulted in a decline in VMT of up to 60% (Bureau of Transportation Statistics, 2020). However, as new vaccines for the disease became widely available, VMT started to rebound in early 2021. Meanwhile, transit ridership has shown slower recovery, potentially due to the concerns about being exposed to the virus (De Vos, 2020). For the U.S., statistics indicate that the annual nationwide transit ridership is still at the same level as that of the year 2020 (Bureau of Transportation Statistics, 2022).

The situation surrounding the transportation sector quickly evolved in response to changes in orders/restrictions and vaccination status. The current literature addresses the short- and long-term effects of the pandemic on transit ridership (Shimamoto & Kusubaru, 2023) or street space usage (Kutela et al., 2022). As a typical yet significant example of the short-term effects, commuting trips declined by 75% in the early stages of the pandemic Wang et al. (2024a). Also, e-shopping has become one of the major options not only among younger generations but also among elderly or retired people (Unnikrishnan & Figliozzi, 2021). Moreover, vehicle ownership increased and transit ridership declined during the pandemic (Manville et al., 2023). It is important to note that studies about the longer-term effects of the pandemic indicated that these trends might not be permanent. It is indicated that remote/hybrid work practices could return close to pre-pandemic levels among California workers, with only a 4.2% net gain in the ratio of remote/hybrid workers to the entire worker population (Islam & Saphores, 2023). Essential consideration should also be given to transportation justice and equity. For example, while individuals from lower-income households (with an annual household income of less than $50,000) use ride-hailing services more frequently than the population as a whole, the reason not to use the services varies across those with and without a car, where a higher rate of concerns about COVID-19 is observed among those with a car (Brown et al., 2022).

Understanding the evolving behaviors and latest trends in transportation is essential for the California Air Resources Board (CARB), which is committed to promoting zero-emission vehicles (ZEVs), developing regulations for reduced emissions, and addressing air pollution across the state of California. To provide vital information and rich insights to the organization, the 3 Revolution Future Mobility (3RFM) Program started to conduct the COVID-19 Mobility Study in Spring 2020. By leveraging two prior projects (the California Mobility Panel Study and The Pulse of the Nation on 3 Revolutions), the research team has launched four new waves of public surveys to build both cross-sectional data about the latest situations in travel behavior and longitudinal data about the evolving trends. These waves include Fall 2020 (sample size: 5,521), Summer 2021 (sample size: 6,400), and Fall 2023 (sample size: 6,110). The latest dataset obtained in 2023 contains 3,609 respondents who have joined the longitudinal panel channel of the survey. The questionnaires used in each survey waves covered similar topics, such as individual attitudes toward various transportation-related topics (e.g., environmental friendliness, tech savviness), use of digital devices and applications, employment/student status, dwelling status, household composition, daily travel patterns with various modes, use of new mobilities (e.g., car-sharing), or preference for alternative fuel vehicles. In the Fall 2023 wave, the research team focused specifically on three topics: one's work arrangement, disaggregate level VMT, and choices and behaviors in response to high motor fuel prices. Questions regarding these topics were designed to understand how the public is shifting from the era of the COVID-19 pandemic to the "new normal" with a disruption of increased fuel costs. The details of the data collection and cleaning/weighting process are described in Chapter 3 and Chapter 4.

After presenting the overview of the construction of the dataset, Chapter 5 to Chapter 9 of this report introduce key findings with different areas of interest: remote/hybrid workstyles, e-shopping, travel behavior, access/use of private vehicles, and unique challenges that low-income households have faced. Research findings presented in these sections will (1) explain how the travel behaviors and preferences on transportation have changed during and after the COVID-19 pandemic and whether those are evolving into a new normalcy unique to the post-pandemic era, (2) identify the social cohorts with atypical travel patterns from the general public, and (3) provide policy implications that inform planning and policy for sustainable and equitable transportation, e.g., via lower commuting rates (and associated reduction in VMT) and promotion of greener choices over private vehicles.

While the dataset of the 2023 survey wave contains some respondents from non-California regions (i.e., some returning participants from the previous survey waves conducted across the U.S. and Canada), this report mainly focuses on California residents. However, each study presented in Chapter 5 to Chapter 9, may use a dataset slightly different from each other due to their internal validation and filtering process.

The report summarizes the key findings in Chapter 10 and then concludes in Chapter 11 with policy implications, limitations, and expected future work. Although some findings and implications presented in this report will merely confirm the trends or behaviors that society empirically understands, this report adopts rigorous analytical methods with numerous cross-sectional and longitudinal observations that prior studies have not achieved.

There are several limitations that have the potential to affect the reliability of the results presented in this report. First, reliance on self-reported information collected through surveys might introduce potential biases related to recall and response accuracy, particularly in capturing activity schedules and travel patterns without a comprehensive travel diary. Second, inherent limitations of data collection methods, including possible sampling biases and challenges in generalizing results to broader populations or analyzing smaller sub-groups, were evident. Third, variations in sampling and recruitment methods across the three data collection rounds may affect the ability to compare results across waves. Despite efforts to include underrepresented populations, such as people of color and rural residents, low response rates led to relatively small sample sizes among these socio-demographic groups. Although weights were developed to help improve the extent to which the samples represented the target population, some discrepancies in the distributions of socio-demographic attributes remain.

Lastly, while repeated cross-sectional analysis offers larger sample sizes, it compares different samples over time, potentially limiting internal validity. Conversely, longitudinal datasets maintain strong internal validity but may suffer from smaller sample sizes and issues of self-selection, impacting generalizability. Moreover, the samples are not comprised of the exact same set of respondents (although many respondents participated in multiple surveys). This creates the potential for differences between samples to stem from differences in the respondents included in each sample. While the analysis of weighted responses can help mitigate the impacts of these differences, it cannot eliminate them. Hence, readers should interpret the findings cautiously, keeping these limitations in mind.

2 Literature Review

2.1 Commuting and Teleworking

Commuting trips make up a significant portion (28.07%) of the total VMT in the United States, with 87.5% of workers using private vehicles for their commutes (McGuckin & Fucci, 2018). Recent studies show that average commute duration in the U.S. has increased from 25.1 to 26.9 minutes between 2005 and 2017, and commuting has become more reliant on private vehicles, despite the commuting distances remaining roughly unchanged (Islam & Saphores, 2022; Mitra & Saphores, 2019). This suggests that commuting trips play a significant role in traffic congestion, and by extension, air pollution (Su et al., 2021).

However, the onset of the COVID-19 pandemic brought about significant changes in work arrangements worldwide, including in the U.S. The enforcement of stay-at-home and social distancing measures nationwide resulted in a 75% decrease in commuting trips by March 2020 Wang et al. (2024). A survey-based study found that from February to March 2020, over one-third of the U.S. labor force had transitioned from in-person work to remote work, increasing the proportion of remote workers to approximately 50% of the nation's workforce (Brynjolfsson et al., 2020). A separate study indicated that teleworking reduced workplace visits and non-work-related activities, but this reduction was primarily due to a decrease in non-work activities that were related to work (Rafiq et al., 2022). Working from home (WFH), also known as teleworking, can be defined as a work arrangement where workers spend some or all portion of their employment hours working from home (Mokhtarian, 1991).

But why is it essential to understand the travel behavior of teleworkers? Su et al. (2021) reveal that 20% of teleworkers stay home throughout a typical workday in contrast to 8% of commuters. However, the authors also found that teleworkers who make at least one trip during their workday tend to accumulate more VMT compared to their commuting counterparts. Furthermore, a study conducted in the San Francisco Bay Area and California's Central Valley revealed that while vaccination efforts led to some recovery in morning peak hour and home-based traffic, the volume remained below pre-pandemic levels. The prevalence of telework has also highlighted disparities in commute burdens, with essential economic sectors and lower-income workers experiencing the smallest declines in commute traffic and quickest recoveries (Wang et al., 2024). Another reason to be concerned about commuting in California's Central Valley region is the phenomenon of supercommuting, where individuals commute long distances, attributed to rising housing costs and household migration (Boarnet et al., 2021). Moreover, an additional 4.2% of California workers, compared to the current number, expect to participate in some form of telecommuting after the pandemic. Workers with higher education levels increased their teleworking during the pandemic, a trend that is expected to continue. However, full-time work status and household size have a negative impact on teleworking frequency both during and after the pandemic (Islam & Saphores, 2023). A recent news article published in January 2024 used five-year data provided by Caltrans to reveal that commuting traffic has almost recovered to pre-pandemic (2019) levels in California's Bay Area and Central Valley region (Cano, 2024). Finally, the need to study teleworking and commuting behavior has intensified due to significant findings by Asmussen et al, (2023). Transitioning from 100% in-person work to 100% telework from home increases the average commute distance by 64.8%. However, working from a third workplace for any part of a month reduces commute lengths compared to exclusively home-based teleworking. Surprisingly, the author found that infrequent teleworking (e.g., working from home less than once per week) can increase overall monthly commute VMT. Significant reductions in monthly VMT are only noticeable at around 30-40% teleworking per worker (approximately 2 days of telework per week for full-time workers with 22 workdays per month). In conclusion, understanding the dynamics of teleworking is crucial as it sheds light on its influence on travel behavior, including trip frequency and distance traveled. This comprehension holds significant implications for transportation planning and policy, and the lasting effects of the pandemic on commuting patterns and mobility.

2.2 Online Shopping and Home Delivery

In their study exploring the 2009 and 2017 National Household Travel Surveys, Saphores & Xu (2021) discovered a gradual increase in online shopping even prior to the COVID-19 pandemic. This trend persists despite Americans being 24 times more likely to opt for in-store grocery shopping over online shopping. Yet another study on delivery preferences in the Greater Los Angeles region shows that e-commerce has expanded to include all types of shopping, a trend that was accelerated by the COVID-19 pandemic, reaching older age groups and a wider range of products. However, the use of automated parcel lockers (APL) for e-commerce deliveries is still uncommon, as most people prefer individual residence deliveries for their convenience (Giuliano et al., 2022). The study also suggests that using APLs for clustered deliveries could reduce delivery truck VMT while only slightly increasing passenger VMT.

The COVID-19 pandemic gave a boost to e-commerce deliveries and the adoption of online shopping due to travel restrictions and possibility of health hazards (Luo et al., 2023; Unnikrishnan & Figliozzi, 2021). Unnikrishnan & Figliozzi (2021) conducted a study in the

Portland-Vancouver-Hillsboro Metropolitan region during the pandemic, which revealed a substantial rise in home deliveries. The study also noted an increased likelihood of online shopping among households with elderly or retired individuals, those with disability, and single workers due to health concerns. This result is also supported by Xu & Saphores (2022), who documented similar trends in California. However, Young et al. (2022) discovered from a longitudinal study that while the pandemic caused a five-fold increase in e-shopping and home deliveries, this trend might be temporary and restricted to specific groups in the post-pandemic. In particular, e-shopping was expected to be more popular among tech-savvy individuals and younger generations after the pandemic. Additionally, households that ordered more than three deliveries per month before the COVID-19 pandemic are expected to return to their pre-pandemic ordering habits, while households that made less than three deliveries per month before the pandemic were more likely to state that they would order online more often post-pandemic (Unnikrishnan & Figliozzi, 2021). Ultimately, pre-pandemic exposure to online shopping, delivery rates, and subscription accessibility will dictate trends in e-commerce deliveries post-pandemic (Unnikrishnan & Figliozzi, 2021; Young et al., 2022). A news article from November 2023 delves into the evolving landscape of online shopping post-pandemic. It notes that while online shopping decreased compared to the COVID-19 era as physical stores reopened and consumers reverted to their previous shopping routines, the enduring impact of COVID-19 continued to maintain the e-commerce share of retail sales well beyond pre-pandemic levels (Desilver, 2023). Given the VMT and emissions associated with home deliveries, it will be important to understand the factors influencing online shopping post-pandemic.

2.3 Use of Various Transportation Options

COVID-19 disrupted mobility trends across the globe, including deep impacts on mobility in the United States. The adoption of telecommuting, more frequent online shopping, and an increase in walking for leisure have collectively reduced overall trip numbers (Matson et al., 2023). Matson et al. (2023), analyzing data from 2018/2019 and 2020, also indicates that lower-income and blue-collar workers faced greater negative impacts from the pandemic's transportation effects. Supporting these claims, Brown & Williams (2023), in their California-based study, report significant decreases in ride-hailing and transit trips during the initial stages of the pandemic. However, these effects varied across the population, with higher-income areas and areas with more transit commuters and zero-car households experiencing sharper declines in trip rates. Conversely, neighborhoods with a higher proportion of older residents (aged 45+) and a greater percentage of Black, Hispanic/Latinx, and Asian residents continued to rely more on ride-hailing during the pandemic compared to other areas. Another study by Parker et al. (2021) found that the pandemic had a greater impact on the travel patterns of transit users compared to non-riders, as indicated by changes in weekly trip rates and travel distance before and during the pandemic. The study also noted that 75% of respondents reported using transit less since the start of the pandemic, likely due to transit service changes and concerns about infection risk. Fewer than 10% of transit riders in the sample indicated that they felt comfortable using transit despite the infection risk and were unaffected by service reductions. Transit riders were also more likely to change their travel behavior, such as increasing walking. However, lower-income transit riders had a smaller reduction in trips and distance traveled, suggesting they had less flexibility in their travel during the pandemic. In a post-pandemic environment, it is anticipated that there will be fewer auto and transit commuters (decreasing by 9% and 31%, respectively) due to widespread adoption of hybrid work and increased e-shopping. Additionally, 41% of pre-pandemic business travelers expect to engage in lesser air travel after the pandemic, while only 8% anticipate an increase compared to pre-pandemic levels (Javadinasr et al., 2022). According to a study conducted in December 2020, 15% of transit riders are comfortable using transit (Parker et al., 2021). A more recent report from the American Public Transport Association (APTA) published in December 2023 reveals that after declining to 20% of pre-pandemic levels in April 2020, public transit ridership has rebounded to 79% of pre-pandemic levels (American Public Transportation Association, 2024a, 2024b). California, on the other hand, was successful in restoring 91% of its pre-pandemic transit service and 65% of its ridership (California Transit Association, 2023). A press release from the San Francisco Municipal Transportation Agency (SFMTA) in February 2024 stated that transit in the city has regained 71% of its pre-pandemic (2019) ridership. The release also notes that weekday ridership is at 68% of pre-pandemic levels, while weekend ridership is at 86% (SFMTA, 2024).

2.4 Access and Use of Private Vehicles

Private vehicle access and ownership are crucial factors in travel demand forecasting. Vehicle ownership models help identify factors affecting VMT, allowing for targeted solutions to energy consumption, air pollution, and traffic congestion issues (Sabouri et al., 2021). Studies conducted before the pandemic indicate that vehicle ownership was positively correlated with household income, household size, and the number of workers and licensed drivers in a household. Conversely, it was negative correlated with the use of ride-hailing services, online shopping, and reliance on technology-enabled activities (Blumenberg et al., 2021; Ma et al., 2022; Sabouri et al., 2021). Supporting the findings, Schouten (2022) confirms that low-income households and urban-to-suburban movers are more likely to become car owners, while those moving from suburban to urban neighborhoods are more likely to become car-less. Similar trends are observed among higher-income households with more significant effects. Another study by Hoogland et al. (2022) focusing on battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs) reveals that a higher electric range is linked to a higher likelihood of purchasing BEVs but a lower likelihood for PHEVs. Socio-demographic factors such as living in a single-family home, homeownership, and having at-home solar panels are also associated with purchases. An increase in the perceived importance of high-occupancy vehicle/carpool lane access is linked to leasing, while a higher importance placed on state rebates is linked to purchasing.

The COVID-19 pandemic brought in concerns of health risk related to using public transport and ride-hailing, thus increasing private vehicle ownership. Zheng et al. (2023) studied the Boston area during the gradual return to pre-pandemic activities in Fall 2021. They found that increased car ownership led to a sharp decline in public transport and ride-hailing use due to the perceived lower infection risk of using a car. The study also showed that car ownership is linked to increased on-site work. Surprisingly, higher-income individuals were more likely to commute to work using active modes rather than by car, a trend that became more pronounced in Fall 2021. This is likely because higher-income individuals value the benefits of active commuting, such as environmental sustainability, improved health, and reduced COVID-19 risk. In support, a study by Manville et al. (2023) in Southern California and the Los Angeles region revealed that the decline in transit ridership and the rise in vehicle ownership during the pandemic are closely linked to decreased prices of used cars, fluctuations in gasoline prices, and changes in transit services. They propose that since it became easier for previous transit riders and low-income households to purchase and use private vehicles, they could attain similar access and mobility as car-dependent individuals in California. The study suggests that this sudden increase in vehicle ownership could lead to a prolonged decline in transit ridership.

The COVID-19 pandemic significantly impacted daily VMT due to travel restrictions and health concerns. Despite this, studies indicate a quick recovery in Summer 2020 and steady increases in VMT since then. By Spring 2023, the VMT had rebounded to the pre-pandemic level (U.S. Federal Highway Administration, 2024). In contrast, the recovery of bus and rail ridership has not yet returned to pre-pandemic levels (Abdelfattah & Bahramipanah, 2021; Concas et al., 2022).

2.5 Low-income Communities

Historically and presently, low-income communities in the United States have experienced transportation inequities due to unequal treatment in urban planning, development, decision-making, and societal institutions (Barajas, 2021). In particular, these disparities restricted mobility access for African Americans, Indigenous peoples, and people of color. Therefore, according to Wang et al. (2022), individuals residing in low-income communities with limited transit access are more inclined to use shared modes of transportation and mobility-on-demand (MOD) services. However, those facing technological barriers to access MOD services inevitably have to use fixed-route transit. Further, African Americans use bicycles less than their Caucasian counterparts due to lack of infrastructure and insufficient street lighting. This is unfortunate given that cycling is often motivated by a desire for a reduction in financial burden of travel (Sadeghvaziri et al., 2023b). The cycling literature reports that neighborhoods with inadequate cycling infrastructure are primarily those predominantly with African Americans, Hispanics, Asians, low-wage workers, individuals with less education, and older adults (Sadeghvaziri et al., 2023a).

The COVID-19 pandemic significantly altered the transportation landscape, particularly impacting low-income households that heavily relied on public transportation. Changes in public transport services, lack of transit access and health risks forced low-income communities including African Americans, Hispanics, Asians, and older individuals to shift towards private vehicles or ride-hailing services (Brown et al., 2022; Brown & Williams, 2023; Manville et al., 2023). A study found that lower-income travelers, especially those without personal vehicles, use ride-hailing services differently from the rest of the population. Individuals without cars are more inclined to use ride-hailing services more frequently than those with cars, especially to bridge gaps in public transit service and to access medical care and grocery stores. However, the costs and unpredictability of pricing remain significant barriers limiting the use of ride-hailing services (Brown et al., 2022).

The pandemic led to a significant increase in vehicle ownership among low-income communities, which is closely connected to the decline in transit ridership. According to Manville et al. (2023), this decline in transit ridership and the increase in vehicle ownership during the pandemic are linked to lower prices of used cars, changes in gasoline prices, and modifications in transit services. They suggest that because it became easier for previous transit riders and low-income households to buy and use private vehicles, they could achieve similar access and mobility as those who rely on cars in California. The study implies that this sudden rise in vehicle ownership could result in a lasting decrease in transit ridership. To curb the increase in vehicle ownership among low-income communities, particularly among individuals who previously relied on transit, cities should prioritize investing in transit, biking, and walking infrastructure to provide viable alternatives to car ownership in the post-pandemic era. These investments, though, require time. In the interim, cities and agencies could consider subsidizing ride-hail trips to fill gaps in the current transportation systems (Brown et al., 2022; Sadeghvaziri et al., 2023b). Additionally, investing in public transit in the post-pandemic era is crucial because it caters to low-income populations in key California areas like Los Angeles and the San Francisco Bay Area. These individuals are less likely to be able to work from home and depend on public transit for their daily commutes (Karlamangla, 2023).

3 Data Collection

3.1 Overview

The research team has collected six waves of survey data for the Mobility Panel project from 2018 to 2023. Building on the 2018 California mobility survey and 2019 "8 cities" travel survey, which were acquired as part of existing research efforts by the research team, four additional survey waves were administered to explore the short-term and long-term impacts of the COVID-19 pandemic on activity and travel behavior of individuals. While the entire data collection included six waves, this report particularly focuses on the analysis of the latest three datasets collected during and after the pandemic, namely Fall 2020, Summer 2021, and Fall 2023. Figure 3-1 describes our sampling and recruitment approaches that consist of re-contacting previous respondents and recruiting new respondents who had not participated in the previous rounds of data collection. For the latter approach, mailing channels expanded the coverage of various segments of the population and enabled the collection of responses from sections considered traditionally challenging to reach online.

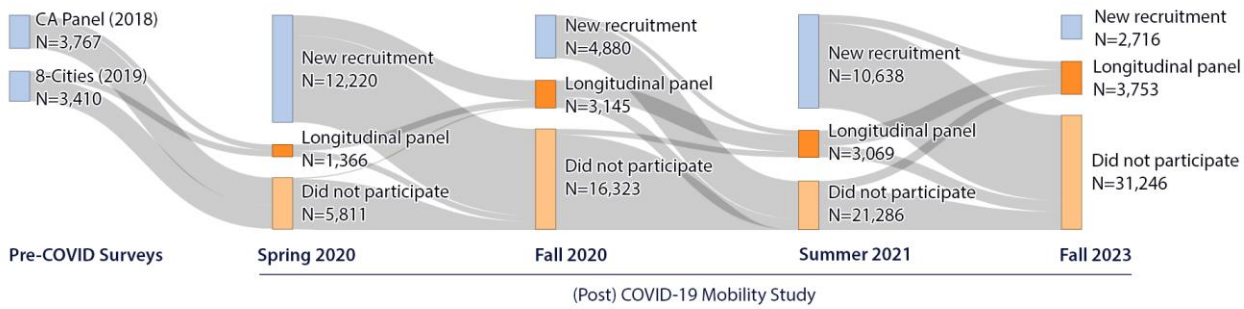


Figure 3-1. Repeated cross-sectional survey data collection
Notes: The light orange cells representing for "Did not participate" category are not proportional to the actual sample size.

The team employed multi-channel sampling and recruitment approaches to collect robust samples. Table 3-1 provides an overview of the sampling and recruitment strategies used during the administration of surveys in Fall 2020, Summer 2021, and Fall 2023, along with other details of data collection. While the data collection process remained largely consistent across three surveys from 2020 to 2023, the later waves incorporated valuable insights gained during the collection and analysis of the early waves of surveys. As part of broader data collection efforts in the State of California and the United States, the research team partnered with the Southern California Association of Governments (SCAG) to conduct dedicated data collections targeting residents in Southern California in Fall 2020 and Summer 2021 surveys. This collaborative effort aimed to evaluate the changing travel behavior and resulting impacts of the pandemic on equity and the environment, in support of the goals of SCAG within their region encompassing six counties, namely Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura. As a result, the datasets in Fall 2020 and Summer 2021 oversampled those in the SCAG region. In the 2023 wave, the data collection was conducted differently, and the research team built a state-wide representative sample and avoided the oversampling of the SCAG region. For all three waves, survey weights were applied by the research team to enhance the representativeness of the samples in each dataset by mirroring the socio-demographic characteristics of California residents.

For the three rounds of data collection used in this report, the research team used multiple sampling methods, including (1) new participant recruitment through a commercial online opinion panel; (2) recontacting respondents who participated in previous waves conducted by the research team in the state (i.e., a longitudinal panel that spans from 2018 to 2023); (3) convenience sampling through close collaboration with community-based organizations that were based in the Bay Area and in Los Angeles County. In the last two waves, which were conducted in the Summer of 2021 and Fall of 2023, the research team also collected a (4) stratified random sample of households in California by mailing a one-page invitation to an online survey. Separately, printed questionnaires with pre-paid return envelopes were sent to another set of randomly selected households in both Summer 2021 and Fall 2023. These approaches enabled the research team to mitigate the shortcomings of each method to the extent possible. As an example, opinion panels tend to recruit respondents with unique characteristics (e.g., tech-savvy individuals, individuals who have more time available and are more likely to subscribe to an online opinion panel), and thus it is considered a nonprobabilistic sampling method (also known as convenience sampling). For this reason, the sampling frame of an online opinion panel remains largely unknown, as it relies heavily on the ability of the commercial provider to recruit and keep participants in their panel. On the other hand, stratified random sampling through mailed surveys allows reaching out to different population segments that could not be recruited through a commercial online opinion channel. Additionally, stratified random sampling-based data collection relies on probabilistic sampling, and thus, it eliminates the sampling biases that could be introduced by relying solely on an online opinion channel. In Fall 2023, the research team emphasized reaching out to the individuals in equity priority (disadvantaged) communities via mail and therefore, oversampled addresses from these equity priority census tracts. While stratified random sampling has clear positive aspects as compared to the online opinion panel, it is much more resource intensive, in terms of the resources required to prepare, print and mail out the surveys, the time required to collect the responses, and the need to digitize the data from the printed questionnaires.

Table 3-1. Summary information for the Fall 2020, Summer 2021, and Fall 2023 data collections in the State of California

	Fall 2020 Survey	Summer 2021 Survey	Fall 2023 Survey
Sampling Methods	Recall of previous survey participants + online opinion panel + convenience sample	Recall of previous survey participants + online opinion panel + convenience sample + stratified random sample	Recall of previous survey participants + online opinion panel + convenience sample + stratified random sample
Recruitment Methods	Direct email + advertisements and posts via listservs and social media	Direct email + advertisements and posts via listservs and social media + mailing out of printed survey invitations and questionnaires	Direct email + mailing out of printed survey invitations and questionnaires + advertisements with community-based organizations
Number of Cleaned Responses within California[1]	4,969	5,194	4,369
Survey Administration	December 2020 – January 2021	August 2021– October 2021	August 2023 – November 2023[2]
Survey Time Period(s)	Nov/Dec 2019 (retrospective), Nov/Dec 2020	Before March 2020 (retrospective), June/July 2021, June/July 2022 (future expectations)	July/August 2023, July/August 2024 (future expectations) + For CBO surveys: January/February 2024, January/ February 2025 (future expectations)
Language	English, Spanish	English, Spanish	English, Spanish

1. The cleaning procedure is explained later in chapter 4 - section 1.
2. The data collection via Community Based Organizations (CBO) was still ongoing as of February 2024

The research team utilized the Qualtrics online survey platform to administer the online versions of (1) the Fall 2020 survey from December 2020 to January 2021; (2) the Summer 2021 survey from August to October 2021; and (3) the Fall 2023 survey from August 2023 to February 2024. The printed survey was distributed starting from July 19, 2021, as part of the Summer 2021 data collection process, and from the week of September 25, 2023, as part of the Fall 2023 data collection process. The respondents from the mailing channels had the option to complete the survey either online or by returning the printed questionnaires via mail. Those who received the invitation letters to participate online were given the option to request for the printed questionnaire. To ensure maximum participation, follow-up postcards were dispatched during the week of August 9, 2021 for the Summer 2021 survey, and in the week of October 25, 2023 for the Fall 2023 survey, to all the addresses. Subsequent sub-sections will provide additional details regarding each sampling and recruitment method employed for this project.

3.2 Online Opinion Panel Survey Dataset

The research team employed a quota sampling approach for the online opinion panel recruitment. This approach establishes quotas for various socio-demographic groups in the sample based on their representation in the population according to the American Community Survey (ACS) 5-year estimates. During the data collection for the Fall 2020 and Summer 2021 surveys, geographic quota estimates were derived from the distribution of respondents across six regions spanning the State of California, with an emphasis on the SCAG region. The research team used population targets by region, neighborhood type, age, gender, race and ethnicity, employment status, and annual household income derived from the ACS 2020 5-year estimates. The population targets used in Fall 2023 data collection included age, gender, ethnicity, employment status and annual household income that were derived from the ACS 2022 5-year dataset. In the Fall 2023 data collection, the research team under sampled the SCAG region, which contains 46% households of the state, and oversampled from other regions, except MTC. Figure 3-2 demonstrates the six regions that are used to build the geographic quotas based on the distribution of the respondents.

a) **San Francisco Bay Area** corresponding to the boundaries of the Metropolitan Transportation Commission (MTC),

b) **Los Angeles/Southern California** corresponding to the boundaries of the Southern California Council of Governments (SCAG),

c) **Sacramento region** corresponding to the boundaries of the Sacramento Area Council of Governments (SACOG),

d) **San Diego** corresponding to the boundaries of the San Diego Association of Governments (SANDAG),

e) **Central Valley** corresponding to the eight counties in the central San Joaquin Valley,

f) **Northern California and Others** which includes the rest of State not included in the previous regions.

Figure 3-2. Six Regions in California used for Quota Sampling

3.3 Longitudinal Survey Dataset

The second channel used for the three data collections involved the longitudinal panel. This panel has been built on previous surveys administered for a larger research project at UC Davis and it included previous data collections carried out by the research team: 2018 California Mobility (Circella et al., 2019), the 2019 8-Cities Study, and the COVID-19 Mobility Study (which started with the Spring 2020 wave and continues with the three additional waves that were used for this project report). The three initial waves (i.e., 2018, 2019, and Spring 2020) provided a rich database of previous respondents from California (and other states in the US that are excluded from this report) who agreed to be re-contacted to participate in new transportation studies that will be organized by the research team. For the deployment, an email containing a unique link for each respondent was generated and then shared with previous respondents through the official study email address at UC Davis (mobilitystudy@ucdavis.edu). The email invited the previous respondents to take the online survey to share their insights during-COVID (Fall 2020 and Summer 2021) and post-COVID (Fall 2023). A $10 incentive was offered in the Fall of 2020, and a $5 incentive was offered in the Summer of 2021 and Fall of 2023 to encourage the completion of the survey. After the initial invitation emails, the research team sent two reminders to those who had not submitted their surveys by the date of each reminder email. Through this mechanism, the research team was able to establish a rich dataset that allows us to analyze the evolving activity/travel behavior of the same individuals.

3.4 Mail-based Survey Dataset – MM/MO

Both in the Summer 2021 and Fall 2023 data collections, the research team employed additional methods to improve the representativeness of the sample and address challenges encountered in previous waves (e.g., the difficulty of recruiting individuals from disadvantaged households). Mail-based data collection, the primary method used for this purpose, consisted of (1) mailing a one-page invitation letter to a group of randomly selected residents in California with the link to the online survey platform and (2) mailing a printed questionnaire with a pre-paid return envelope to a similar, but separate group of residents in the state. The printed questionnaire also included an invitation letter offering the residents the option to complete the survey online. To incentivize participation, the respondents were offered the chance to enter a randomized drawing, with prizes including 10 $100 gift cards and 500 $10 gift cards upon survey completion.

The research team drew a stratified random sample based on the six regions that were described in Section 3.2 both in 2021 and 2023. In the Summer 2021 survey, there was an emphasis on the SCAG region counties based on the partnership between the research team and SCAG. In the Fall 2023 survey, the SCAG region was under sampled to avoid the domination of Southern California counties in the mail-based survey dataset.

In the Fall 2023 survey, 30,000 households were selected to receive postcard invitations containing access codes and online survey links, and 10,000 households were selected to receive printed questionnaires (i.e., survey booklets) with pre-paid return envelopes to return the completed questionnaire via USPS. The research team applied higher sampling rates for equity priority or disadvantaged areas (census tracts), which are often underrepresented in similar studies. The invitations were bilingual (English and Spanish) and sent through the United States Postal Service (USPS) to the household addresses. The letter informed the reader that the survey should be completed by an adult (18 years old or older) member of the household. The readers were also informed that they could complete the survey in their language of choice (English or Spanish) using the online link. All mailed packages contained instructions to complete the survey and the link to the online as an alternative for those who preferred.

Previously, the research team oversampled the Hispanic and low-income households during the Summer 2021 survey after identifying the census tracts with high proportions of Spanish-speaking households. The households in these census tracts received Spanish versions of the questionnaire. Despite targeted efforts to recruit respondents from Hispanic and low-income households in 2021, response rates were lower than expected. While the research team was able to collect a higher number of responses from Hispanic populations in 2021 as compared to previous waves, there were notable limitations in geographic and socio-demographic sampling, particularly in rural counties. Considering the relatively limited impact and lower efficiency of sending Spanish questionnaires directly in 2021, all recipients in the Fall 2023 survey were sent a printed questionnaire in English, with a bilingual cover page. Then, the recipients were informed that they could request a printed questionnaire in Spanish if they returned the cover page the English questionnaire to the research team.

3.5 Convenience Sample Survey Dataset

The research team has also employed an additional method to recruit additional respondents, to increase the participation of groups that tend to be underrepresented in the online opinion panel sampling frames.

In addition to sharing the invitation to complete the survey across multiple professional networks and through Facebook advertisements in the various survey waves, in the Fall 2023 data collection, two community-based Organizations (CBOs) were also contacted and closely engaged with the team to recruit individuals from disadvantaged households in the northern and southern regions of the State of California. These two CBOs were based in Los Angeles (serving disadvantaged households in Los Angeles County) and Sacramento (serving disadvantaged households in the Bay Area), respectively. The convenience sample data collection included a mix of mailing printed questionnaires (which also offer residents the option to complete the questionnaire online) and direct access to the online questionnaire through emails. To incentivize their participation, the research team offered respondents $10 gift cards upon survey completion.

4 Data Handling and Processing

4.1 Data Cleaning

When the dataset of each of the waves is collected on Qualtrics, the team performed thorough data cleaning tasks to filter out those cases with low attention to the survey or those who intentionally provided unreliable responses. The former category includes a mistake in attention-check questions (e.g., not following a direction of the survey to select a particular option in a question to confirm their attention) or a misunderstanding of the survey direction (e.g., excluding themselves from counting the household members while the survey direction explicitly not to do so). The latter category includes making gibberish or non-sensical responses in text-entry question, reporting unrealistically high/low numbers to certain questions (e.g., 100 or more working hours per week), or completing a section or the survey in extremely short time.

During the cleaning of the 2023 wave, several four-level flags among the responses were identified, which are denoted in the following subsections. Each level of the flags represents:

- Level 4: Crucial issue. A response with a level-4 flag was immediately dropped from the dataset.
- Level 3: Extremely bad issue. If combined with other level 2+ flags, the responses should be dropped. If not, the research team took a closer look at the response to determine if it needs to be dropped.
- Level 2: Moderately bad issue. A response with multiple level-2 flags might receive further investigation of the research team for the decision to be dropped.
- Level 1: Minor issue. This level of flags can be used as supporting rationale in the manual investigation of the research team.

4.1.1 Speeding

The research team identified bad survey takers who completed the survey in an unreasonably short time. A threshold $T = MD - C \times SD$ was defined, where MD is the median survey completion time among those who completed it within 2 hours (i.e., excluding those who took more than 2 hours, which might be because they paused taking the survey and resumed it later), C is a constant, and SD is the standard deviation of the completion time among the survey takers. The research team applied a different level of the flag to different C ($C = 2.5 \Rightarrow$ level 4, $C = 2 \Rightarrow$ level 3).

4.1.2 Individual characteristics

Several individual characteristics were investigated to examine if a survey taker made inconsistent or invalid responses about their social demographics. Some examples include: selection all options for the race/ethnicity question (level 1), an incomprehensible response about gender (level 1), and inconsistent number of household members (level 1). These flags are not high-level ones but would be used as supporting material to determine the integrity of a response.

4.1.3 Attitudinal Questions

Questions about one's level of agreement with various transportation-related statements were placed at the very beginning of the survey, consisting of 28 statements and two attention-check questions. If the survey taker is on the Qualtrics platform, the 30 sub-questions were then split into three pages. The two “trap” questions there asked them to select a certain option (e.g., "To confirm you're really reading this, please select "Somewhat agree" here."). Survey takers who had failed to follow these directions would soon be terminated early from the survey. Additionally, the research team investigated the response time spent on each of the three web pages. A level-2 flag was applied to those with time less than the number of statements in seconds (e.g., nine seconds for the page with nine statements). Moreover, a level-2 flag was applied to a complete flatline on their response on each page, excluding the trap questions (e.g., selecting "Somewhat agree" for all statements in one page). If these level-2 flags were combined in one of the three pages, a level-3 flag was applied instead of two level-2 flags. Lastly, those who made an almost flatline over the 28 statements, which resulted in a variance less than 0.25, received a level-2 flag.

4.1.4 Work Arrangement

Analyzing one's work arrangement was one of the most important emphases of the research team during this survey wave. Hence, flags regarding one's work status were applied with several criteria, including: 100 or more work hours in a week (level 3), a high discrepancy between the reported work hours in two questions (level 2, one asked the average work hours over the last two months and the other asked the detailed work hours in each day of the last week), and inconsistent response about remote work status (level 2).

4.1.5 Usual Travel Behavior

Also, one's usual travel behavior was another important topic that the research team investigated carefully. The survey asked respondents to report the average frequency of travel for nine purposes, such as going to non-work meetings, visiting relatives/friends, or traveling to/from the airport. A level-1 flag was applied to speeding (i.e., completing the question in less than nine seconds) and a flatline (i.e., selecting a certain option for all travel purposes). A level-2 flag was applied to the responses with both of the level-1 flags. Next, the survey asked the average frequency of travel by 10 travel means (e.g., private mode, public bus, ride-hailing), for work and leisure purposes separately. A flatline in each of the travel purpose received a level-2 or level-3 flags, depending on the selected option (i.e., reporting the use of every mode for “5 or more times a week” was more severe than that for “1-2 times a week”). Also, if survey takers select unreasonably high travel frequency with all modes combined, they received a level-2 or level-3 flag (more than 60 trips per month ⇒ level 3, 46-60 ⇒ level 2).

4.1.6 Settlement

After compiling the flags described above with additional ones (e.g., high frequency of online shopping, flatlining for the last attitudinal statement section in the survey), the research team selected a threshold to determine unreliable responses. Then, those responses close to but below the threshold were reviewed individually for the final call. Ultimately, the research team identified 359 cases (~5.5%) to be dropped from the dataset.

4.2 Weighting

This report uses data from multiple waves of repeated cross-sectional surveys to understand changes in out-of-home activity participation and travel behavior during and after the COVID-19 pandemic in California. An important consideration when comparing responses from different surveys is the extent to which the sample represents the target population (Solon et al., 2015). If the sampling procedure is purely random, and the sample size is large enough to mitigate sampling errors, then the sample should be reasonably representative of the population. However, the representativeness of the sample can be affected by factors such as sampling bias, response bias, non-response bias, and the use of non-probability-based sampling and recruitment methods. To help mitigate the impacts of these factors, a weighting procedure was developed and applied to help improve the extent to which each wave represents the socio-economic attributes and geographic distribution of California residents.

The attributes that were considered in the weighting process, as well as their distributions in the target population, unweighted datasets, and weighted datasets, are presented in Table 14-1, Table 14-2, Table 14-3 in the Appendix. The application of the weighting procedure helped improve the extent to which the three samples represented the population of California. The following sections provide a detailed summary of the weighting procedure.

4.2.1 Variable Selection for Weighting

The variables considered in the weighting process were selected based on a review of prior studies and the procedure used to develop weights for the National Household Travel Survey (NHTS). A total of seven socio-demographic attributes were considered in the weighting process: age, gender, race, ethnicity, education, household income, and employment at the time of the survey. The target distribution of these attributes among the population of California were obtained from the American Community Survey (ACS) 5-year estimates. These seven attributes were used as target variables to develop weights for each of the three waves of the survey.

In addition to socio-demographic attributes, telework status both before and during the pandemic were also considered in the weighting process. These attributes were included in the weighting process due to: 1) the shift to online activities that occurred at the onset of the pandemic, and 2) the potential for teleworkers to be over-represented in the samples due to the use of a web-based survey instrument to collect data (International Monetary Fund, 2021; Wang et al., 2023). In the weighting process, telework status before and during the pandemic were only considered for respondents who were employed before and during the pandemic, respectively. Based on the work of Wang et al. (2023), three categories of telework status were defined:

- Non-teleworkers: do not work from home
- Non-usual teleworkers: work from home less than 3 days per week
- Usual teleworkers: work from home at least 3 days per week

The target distributions of pre-pandemic (i.e., before the pandemic) and pandemic (i.e., during the pandemic) telework status among California residents were obtained from the 2017 and 2022 NHTS, respectively. The distribution of pre-pandemic telework status was determined based on the responses to questions regarding whether the respondent had the option to work from home and the number of days that the respondent worked from home in a typical month before the pandemic. In contrast, the distribution of pandemic telework status during the pandemic was based on the responses to the question regarding the number of days that the respondent works from home per week at the time of the survey.

In the Fall 2020 and Summer 2021 surveys, respondents were asked to report their employment status at two points in time: before the pandemic (retrospective) and at the time of the survey. Respondents who indicated that they were employed were then asked to report how often they typically worked from home at each point in time. The responses to these questions were used to determine the telework status of each respondent before and during the pandemic. However, the Fall 2023 survey only asked respondents about their employment at the time of the survey. Consequently, the pre-pandemic telework status of Fall 2023 respondents could not be determined, and this attribute was subsequently omitted from the weighting process for the Fall 2023 sample.

Due to the nature of weighting procedures, weights cannot be developed for individuals whose attributes do not correspond to the categories used in the reference distributions. Consequently, respondents whose attributes did not correspond to the categories used in the ACS were omitted from the weighting process. The number of respondents used in the weighting process for each wave of the survey is presented in Table 4-1 below.

Table 4-1. Number of respondents used to develop weights, by survey

Survey wave	Number of respondents
Fall 2020	4,624
Summer 2021	5,103
Fall 2023	4,159

4.2.2 Weighting Process

A similar process was used to develop weights for each wave of survey (the process used to develop weights for the Fall 2020 and Summer 2021 samples is shown in Figure 14-1 in the Appendix). However, this process had to be slightly adjusted for the Fall 2023 survey due to the absence of information regarding telework frequency before the pandemic. The weighting process was implemented at the region level, with California being divided into two regions – SCAG and non-SCAG.

The weighting process was based on an eight-step procedure to help improve the extent to which each sample represents the population of California. In each step of the procedure, iterative proportional fitting (IPF) was applied to help reduce discrepancies between the distributions of one or two target variables in the sample and the population distribution. The weights produced in each step of this procedure were used as the seed (i.e., input) values for the next step of the procedure. As part of this process, IPF was applied using the mipfp package in R (Barthélemy et al., 2018). The order of the steps in this procedure was determined based on the work of Wang et al. (2023). The procedure was repeated until the difference between the weights produced by successive iterations of the procedure was negligible. Once the procedure was completed, the presence of extreme weights was addressed based on guidelines from the literature. Finally, the discrepancy in the geographic distribution of respondents in California was corrected through the application of a correction factor.

4.3 Descriptive Statistics

The distributions of the target variables in the Fall 2020, Summer 2021, and Fall 2023 samples are summarized and compared to the population distribution in Table 4-2. Overall, the weighted sample distributions are reasonably consistent with the population distribution. Notably, the weighting process helped improve the extent to which the samples represented both pre-pandemic and pandemic teleworkers. Moreover, the distributions of the target variables are relatively consistent across the three samples, which helps enable comparisons of out-of-home activity participation and travel behavior between waves.

The weighting process also helped reduce discrepancies between the population and sample distributions of the target variables. Specifically, the root mean square error corresponding to the weighted dataset is lower than that of the unweighted dataset for the Fall 2020 (0.0588 vs. 0.0986), Summer 2021 (0.0639 vs. 0.1621), and Fall 2023 surveys (0.0279 vs. 0.1196). This result is consistent with the values presented in Table 14-1, Table 14-2, Table 14-3.

Table 4-2. Descriptive statistics of the weighted Fall 2020, Summer 2021, and Fall 2023 datasets

Target variable	Sub-category	Population percentage (2020)	Fall 2020	Summer 2021	Fall 2023
Age	18 to 34	32.0%	29.3%	29.2%	29.8%
	35 to 64	49.4%	54.1%	52.4%	50.2%
	65+	18.6%	16.6%	18.5%	20.0%
Gender	Male	49.7%	51.1%	46.2%	49.9%
	Female	50.3%	48.9%	53.8%	50.1%
Ethnicity	Hispanic	39.1%	35.4%	31.8%	37.5%
	Non-Hispanic	60.9%	64.6%	68.2%	62.5%
Race	White	56.1%	56.6%	61.9%	50.0%
	Black	5.7%	5.4%	5.5%	5.8%
	Other	38.2%	38.0%	32.6%	44.2%
Education	High school or less	36.4%	24.7%	20.8%	32.9%
	Some college	28.8%	31.6%	32.0%	29.3%
	Bachelor's or higher	34.7%	43.6%	47.2%	37.7%
Household income	Less than $50,000	32.6%	28.0%	28.5%	28.8%
	$50,000 to $99,999	27.7%	29.7%	29.6%	25.9%
	$100,000 or higher	39.7%	42.3%	41.9%	45.3%
Employment status	Employed	65.6%	80.8%	78.6%	73.1%
	Not employed	34.4%	19.2%	21.4%	26.9%
Pre-pandemic telework status	Non-teleworker	84.3%	81.1%	74.8%	---
	Non-usual teleworker	14.4%	17.3%	23.0%	---
	Usual teleworker	1.3%	1.7%	2.3%	---
Pandemic telework status	Non-teleworker	53.5%	49.7%	60.7%	51.9%
	Non-usual teleworker	12.5%	12.5%	10.4%	13.3%
	Usual teleworker	34.0%	37.8%	28.9%	34.7%

Note: "---" denotes a variable that was not included in the survey.

5 The Impact of COVID-19 on Remote/Hybrid Work

This chapter includes two related studies. The first study investigates the evolution of the work arrangement (remote work and hybrid work) during and after the pandemic in California. It also investigates the variations in adoption among different socio-demographic groups. The second study further explores the post-pandemic/current work arrangement in detail. More specifically, this chapter attempted to answer the following questions:

1) Evolution of Remote Work and Hybrid Work - How did the share of remote and hybrid workers vary during and after the pandemic? How did the adoption of remote work and hybrid work culture vary across socio-demographics? To what extent does the remote work and hybrid work culture induced by the pandemic persist in the current/post-pandemic era?
2) Exploration of post-pandemic work arrangement patterns - How does the post-pandemic/current new normal work arrangement look? How do these patterns vary across socio-demographic characteristics?

The first study utilizes the repeated cross-sectional data encompassing two survey waves (collected in Summer 2021 and Fall 2023) to monitor the changes in work arrangement among California residents across five timepoints: before the pandemic (retrospective question, asked in Summer 2021), Summer 2021, Summer 2022 (near-future expectation from the 2021 survey timepoint), Fall 2023, and Fall 2024 (near-future expectation from the 2023 survey timepoint). To answer the second question, the research team designed a new question to capture the detailed post-pandemic work arrangement during the Fall 2023 survey. The details of the questions and the results are presented later in the chapter.

5.1 Evolution of Remote Work and Hybrid Work

5.1.1 Introduction

Before the pandemic, most of the workforce used to commute to their workplaces at designated hours, and it was hard to imagine that this traditional work arrangement could be altered. However, the stay-home-orders and fear of getting infected during the early phase of the pandemic disrupted the traditional work arrangement that had been in place for decades. Information and Communication Technology (ICT) development facilitated many to work from home and remotely collaborate with their colleagues via apps such as Zoom and Microsoft 365. While a section of the workforce could comfortably work from home, avoiding the risk of infection, other sections, especially blue-collar workers, continued to commute to the workplace throughout the pandemic.

As pandemic restrictions eased and widespread vaccination drives were conducted, employers began inviting employees back to the offices, at least for a few days a week, leading to an era of hybrid work culture. A blend of in-office and remote work has emerged as an optimal middle ground for employers and employees. It allows workers to choose an optimal mix of working from office and home while enabling employers to reduce infrastructure liability by shedding the seating capacity. The degree of flexibility in the hybrid arrangement largely depends on the occupation and the discretion of the employers.

Understanding post pandemic work arrangements – when and where people work – is crucial. Workplace related choices directly influence travel decisions such as trip rates and VMT and impact long term decision making such as residential relocation. Knowledge of post-pandemic work arrangements is essential for policymakers to tailor the policies effectively to addresses travel related challenges.

5.1.2 Data and Method

5.1.2.1 Classifying Different Types of Work Arrangements

The first study utilizes the repeated cross-sectional data encompassing two survey waves (collected in Summer 2021 and Fall 2023) to monitor the changes in work arrangement among residents in California across five time points: before the pandemic (retrospectively asked in the 2021 survey), Summer 2021, Summer 2022 (i.e., near-future expectation from the 2021 survey timepoint), Fall 2023, and Fall 2024 (near-future expectation from the 2023 survey timepoint).

It is generally difficult to capture work patterns due to its high flexibility. Traditionally, the respondents are asked to self-report their frequency of working from home and workplace. This study developed a quantitative and systematic way to classify different types of work arrangements based on how frequently workers engage in work activities in all alternatives of work location and working hours. The categories of workers, based on individuals' self-reported working patterns are defined in Table 5-1 and are also described below:

1) Check the report frequency of commuting and that of remote work.
2) If both are "Never", the person is classified into the "non-worker" category.
3) If both are one of "1-2 days a week", "3-4 days a week", or "5 or more days a week", the person is classified into the "hybrid worker" category.
4) If the commuting frequency is one of "1-2 days a week", "3-4 days a week", or "5 or more days a week" and the remote-work frequency is one of "Never", "Less than a month", or "1-3 days a month", then the person is classified into the "commuter" category.
5) If the remote-work frequency is one of "1-2 days a week", "3-4 days a week", or "5 or more days a week" and the commuting frequency is one of "Never", "Less than a month", or "1-3 days a month", then the person is classified into the "remote worker" category.

Table 5-1. Definition of commuting status in the Fall 2023 survey

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="6">Commuting frequency</td></tr>
<tr><td>Never</td><td>Less than once a month</td><td>1-3 days a month</td><td>1-2 days a week</td><td>3-4 days a week</td><td>5 or more days a week</td></tr>
<tr><td rowspan="6">Remote working frequency</td><td>Never</td><td colspan="3" rowspan="3">Excluded from the analysis</td><td colspan="3" rowspan="3">Commuter</td></tr>
<tr><td>Less than once a month</td></tr>
<tr><td>1-3 days a month</td></tr>
<tr><td>1-2 days a week</td><td colspan="3" rowspan="3">Remote worker</td><td colspan="3" rowspan="3">Hybrid worker</td></tr>
<tr><td>3-4 days a week</td></tr>
<tr><td>5 or more days a week</td></tr>
</table>

In Fall 2023, the respondents were asked how often they generally work in the following places, with the categories including (1) primary workplace/school location, (2) other workplace/school location, (3) home, (4) temporary location such as coffee shops, parks, and public library. The following categories measured the frequency: never, less than once a month, 1-3 days a month, 1-2 days a week, 3-4 days a week, or 5 or more days a week. There was a minor difference in the language of the frequencies between the Summer 2021 and Fall 2023 surveys. The Summer 2021 survey asked frequencies in terms of “times,” and the Fall 2023 survey asked frequencies in terms of “days”. The research team assumed that this minor change would not alter the meaning.

The respondents who reported being paid workers (full-time, part-time, self-employed, and those with multiple jobs) were only considered for further analysis. There were 3,231 workers in the Summer 2021 survey and 2,798 workers in the Fall 2023 survey after the weighing process.

5.1.2.2 Transition in Work Arrangements and Commuting Patterns

Figure 5-1 shows two Sankey diagrams, representing the overall transition of work status (commuter, hybrid worker, or remote worker) from (1-1) pre-pandemic period (retrospective) to 2021 (concurrent), (1-2) 2021 (concurrent) to 2022 (expectation), and (2) 2023 (concurrent) to 2024 (expectation). Firstly, the unprecedented disruption caused by the COVID-19 pandemic resulted in a large shift from commuting to remote or hybrid work, losing about 40 percentage points (pp) of commuters in the pre-pandemic period in 2021. At that point, many remote workers, as of 2021, considered adopting a hybrid workstyle in 2022. However, although there is a gap of one year, the figure implies that the anticipated outcome failed to materialize as the second diagram showed a higher adoption rate of remote work as of 2023 compared to the expected share in 2022. One important indication in this figure is that the expected work arrangement in 2024 does not differ from the concurrent work arrangement in 2023 as much as the comparison between 2021 and 2022 does. This result suggests that the turbulence in the working patterns is almost over, and the new normal work arrangement has a higher share of remote and hybrid workers.

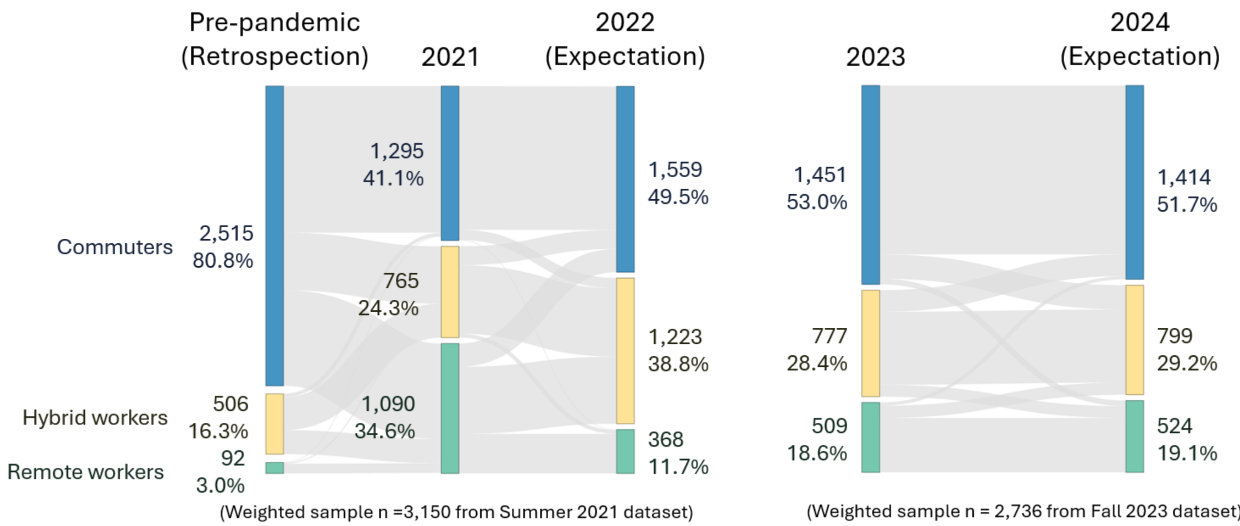


Figure 5-1. Transition of commuting status in the CA state (weighted repeated cross-sectional data)

5.1.2.3 Socio-demographic Characteristics of Remote and Hybrid Workers

Table 14-6 shows the socio-demographic characteristics of remote/hybrid workers in five different timeframes: pre-pandemic (retrospective), 2021 (concurrent), 2022 (expectation), 2023 (concurrent), and 2024 (expectation). Note that only two timeframes (2021 and 2023) reflect the survey takers' concurrent behavior, with the former three timeframes are included in the 2021 survey wave, and the latter two are in the 2023 survey wave. Also, this table summarizes only the ratios of paid workers. As suggested by prior studies, or even empirically known, the ratio of remote/hybrid workers largely increased from the pre-pandemic period to 2021. While only 19.3% of workers adopted remote/hybrid work practices (3.0% remote + 16.3% hybrid) in the pre-pandemic period, the ratio increased to 58.9% (34.6% remote + 24.3% hybrid) in 2021, accounting for about three out of five workers adopting remote practices to some degree. On the other hand, many remote workers in 2021 thought that they would eventually settle into a good balance between remote work and on-site work as only 11.7% (-22.9pp vs. 2021) of workers answered that they would be remote working in 2022, one year later after the 2021 survey, while 38.8% (+14.5pp vs. 2021) workers answered that a hybrid workstyle was what they would do at that time.

Two years later, in the 2023 survey wave, however, it turned out that 18.6% (+5.9pp vs. 2022, -16.0pp vs. 2021) of workers were doing remote work, and 28.4% (-10.4pp vs. 2022, +4.1pp vs. 2021) of them were doing hybrid work. This result suggests that, although its overall share decreased from what the population's workstyle in 2021, the remote workstyle has been accepted more than the public initially thought in 2021. Instead, the hybrid workstyle did not spread as much as people expected. Considering that the sum of remote and hybrid workers has slightly decreased from 2022 to 2023 (2022: 50.5% = 11.7% remote + 38.8% hybrid, 2023: 47.0% = 18.6% remote + 28.4% hybrid), it is inferred that some people had to return to full-on-site work as the pandemic ended. Another important finding is provided by the expectation about their workstyles in 2024. 19.1% (+0.5pp vs. 2023) of workers foresaw their future as a remote worker and 29.2% (+0.8pp vs. 2023) did as a hybrid worker. These results strongly indicate that the public now considers that their work arrangement converged in the new normal era after the pandemic.

There are some additional insights that the detailed tabulation between different social classes vs. remote/hybrid workstyles provides. Some examples are:

- Except for the pre-pandemic period, women have always been slightly more remote-work oriented than men (up to +3.5pp) while they are slightly less hybrid-work oriented, except for the year 2022.
- The younger group (age 18 to 34) already had a higher adoption rate of remote/hybrid workstyles than the mid-age (age 35 to 64) and older (age 65 or older) groups even in the pre-pandemic period (remote work: + 2.2pp vs. mid-age, +1.4pp vs. older, hybrid work: +3.7pp vs. mid-age, +5.7pp vs. older). This trend continues after the pandemic arrived (in 2021 and 2023). However, the younger group exhibited less expectation for remote workstyle in 2022 and 2024, compared to the mid-age group. This indicates that younger workers could be less willing to adopt remote-work-oriented lifestyles than workers in their mid-age.
- Regarding the Hispanic and Latinx status, more non-Hispanic/Latinx adopted remote work in 2021 (+9.7pp vs. Hispanic/Latinx) and 2023 (+5.7pp vs. Hispanic/Latinx). They showed a weaker orientation to hybrid work in 2021 (-4.2pp vs. Hispanic/Latinx) but stronger in 2023 (+4.4pp vs. Hispanic/Latinx). More non-Hispanic/Latinx workers expected to shift to the hybrid workstyle in 2022 while fewer of them to remote work at that time. Meanwhile, the expectation about their workstyle in 2024 is stable compared to that in 2023 for each of the two groups (i.e., Hispanic vs non-Hispanic/Latinx).
- Income is one of the most important factors to account for the remote/hybrid workstyles. The high-income cohort (with $100,000 or more annual income) showed the highest adoption rate of remote and hybrid workstyles since 2021, except for the reported concurrent behavior of hybrid work in 2021 and the expectation of doing remote work in 2022.
- Education showed a clear discrepancy between the low-education (with a high school diploma or less) and high-education (with a bachelor's degree or higher) workers. The high-education workers always showed a higher adoption rate to remote and hybrid workstyles

since 2021, regardless of the concurrent behavior (up to +19.7pp vs low-education workers) or future expectation (up to +15.6pp vs low-education workers).

- Employment type is another key to understanding the variation of remote/hybrid workstyles among workers. As one can expect, self-employed workers have always shown the largest ratio of remote/hybrid workstyles since the pre-pandemic era. Comparing full-time workers and part-time workers, the former type of workers showed a higher adoption rate of remote (+5.6pp vs. part-time workers) and hybrid (+7.3pp vs. part-time workers) workstyles in 2021. Although a larger ratio of full-time workers considered themselves doing hybrid work in 2022 (+18.5pp vs. part-time workers) rather than remote work (-0.8pp vs. part-time workers), their concurrent behavior reported as of 2023 was oriented to remote work (+6.1pp vs. part-time workers) than hybrid work (-6.0pp vs. part-time workers). The expectation for the year 2024 shows that, however, full-time workers will again have a higher adoption rate of hybrid work. This result may indicate that full-time workers may always be likely to desire a hybrid workstyle rather than heavily remote or on-site one.

5.2 Exploration of post-pandemic work arrangement patterns

5.2.1 Introduction

Surveys traditionally inquire about the frequency to work from home on a weekly or monthly basis, assuming that an individual would either work from home or office on a given day. However, this dichotomous perspective may not necessarily hold in the post-pandemic work environment, where an individual can work from multiple locations on the same day and the work patterns can vary across workdays in a week based on their flexibility or job requirement. For example, an individual can attend work meetings from home or work from a café in the morning to avoid peak AM traffic and later commute to the workplace. The spatial and temporal flexibility along with day-to-day variation in work routine cannot be easily captured through traditional questions in the travel survey. Therefore, the research team designed a new question to measure more detailed work arrangement using the work matrix in the latest Fall 2023 survey. The details are presented in the section.

5.2.2 Data and Method

The research team designed a new question for the Fall 2023 survey to capture respondents' detailed work patterns for the past week. Each day was divided into nine two-hour timeslots (from 6 AM to 12 AM) and one six-hour slot (from 12 AM to 6 AM). There were also three options for the location: primary or secondary location (e.g., office), temporary location (e.g., café), and home. The respondent was requested to fill their work patterns (time and location) for all the seven days. The question enabled us to capture not only the workplace(s) where an individual worked on a day but also captured their temporal distribution (e.g., when they started/ended working in a day). It also recorded the variations in work patterns across days of the week.

To effectively analyze this complex response, compared to traditional responses to a survey, the research team focused on several important metrics for this report. First, the research team compiled the number of work hours spent in each workplace: primary or alternative workplace, temporary location, or home. Knowing the time allocation of the various segments in the population provides a clear illustration of the new normal work arrangement in the post-pandemic era. Second, the research team introduced a simple metric called “episodes” which represents the number of work experiences at different workplaces on a given day. For example, an individual reported to work from home between 8 AM and 10 AM and from the primary work location between 10 AM and 2 PM, and then again from home between 2 PM and 4 PM. The number of episodes would be counted as three. However, if an individual reported working at primary location between 8 AM and 12 PM and then again from same location 2 PM to 6 PM and did not report working between 12 PM and 2 PM, then the number of episodes would be one because it is considered that their work experience is continuous with an intermediate break between. This metric allows for measuring the need to travel/commute during a workday.

5.2.3 Time allocation for different workplaces

Figure 5-2 shows the share of the weekly working hours at the three different workplaces for distinct occupations in Fall 2023. Some occupations have a higher share of work hours at home or at a temporary location. Occupations with a high share of work-from-home hours include: “Arts, Design, Entertainment, Sports, and Media”, “Computer and Mathematical, Architecture and Engineering, Life, Physical, and Social Science”, or “Business and Financial Operations”. On the other hand, occupations such as “Food Preparation and Serving Related” or "Protective Service, Building and Grounds Cleaning and Maintenance” show a relatively low share of work-from-home hours. At this point, this figure tells more nuanced differences across occupation groups than what a conventional question (e.g., “How many days do you work from home?”) would reveal. Regarding household income, workers from high-income households ($100K or more) spend more time working from home (41.7% of weighted work hours), while those from low-income are more likely to work on-site (20.7% work hours at home for workers with less than $50K, 21.5% work hours at home for workers with $50K to $100K). These results imply a discrepancy between the workstyles of the white-collar workers and blue-collar workers.

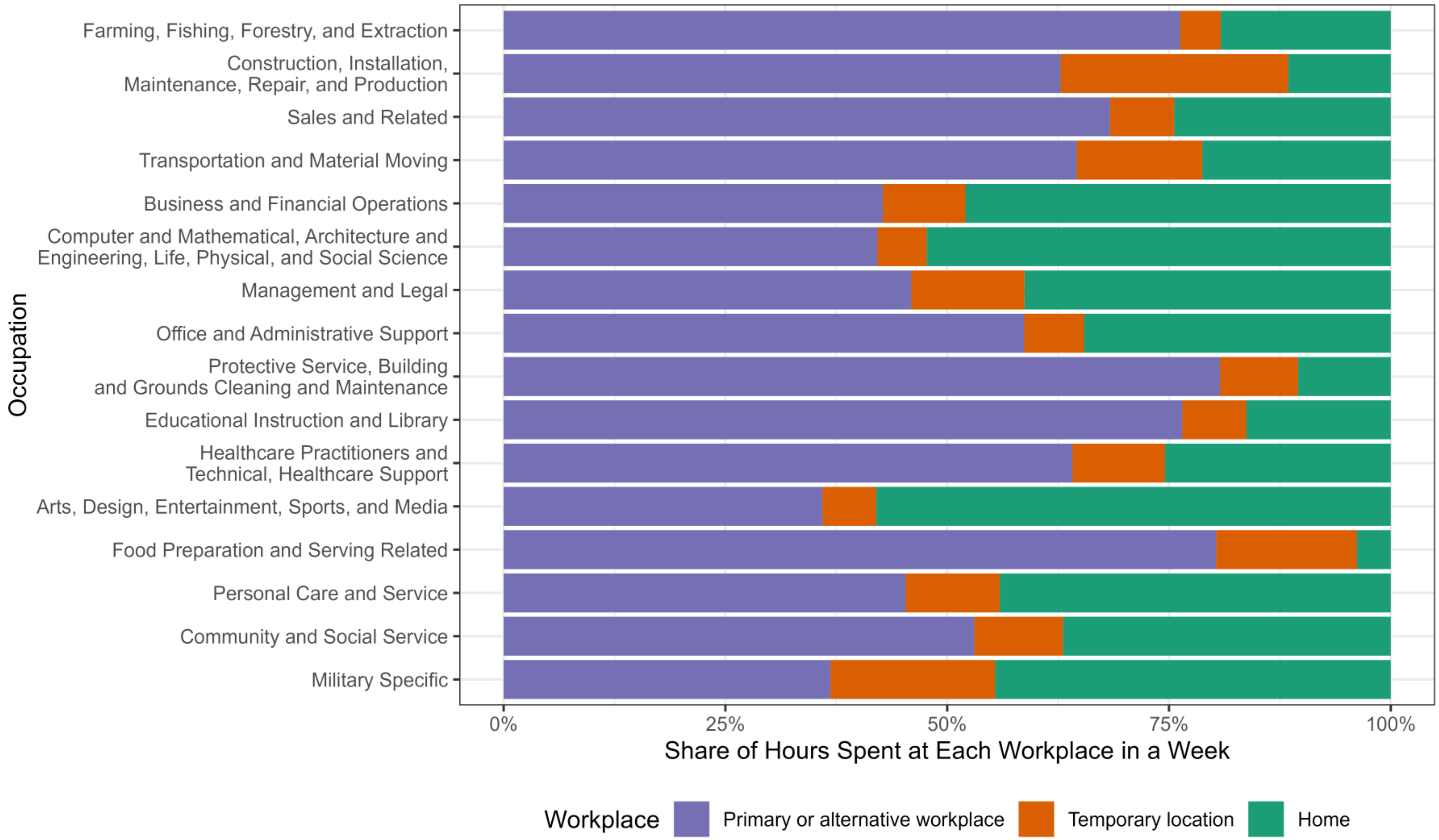


Figure 5-2. Share of Work Hours at Three Workplaces in a Week against Occupation

5.2.4 Episodes in a day

To further investigate the variation of workplaces in detail, the research team counted the number of workplaces (referred to as "episodes" hereafter) that a worker continuously experiences in a day. Given the definition, out of 2,484 weighted sample observations, 411 observations (16.5%) have two or more episodes for at least a day in the week, and 2,073 observations (83.5%) of workers had one episode each day during the entire week. The presence of multiple episodes suggests that 16.5% workers worked from multiple location on a given day and this illustrates the effectiveness of the new question to capture such details in the post pandemic work arrangement, which otherwise could not be captured through conventional survey questions.

The 'maximum episodes in a day' during the week by occupation types are shown in Table 5-2. When compared with Figure 5-2 for the work hours spent at each of the workplaces, a higher share of work-from-home hours does not necessarily lead to a higher share of two or more episodes in a day (e.g., "Arts, Design, Entertainment, Sports, and Media" occupation has the highest share of work-from-home hours but their share of workers with two or more maximum episodes are not very high among the 16 occupation types).

Some occupations including "Community and Social Service" or "Construction, Installation, Maintenance, Repair, and Production" have a relatively high share of workers with two or more maximum episodes during the week. Note that these occupation types often require workers to work from multiple locations in a day. Some other occupations, such as "Management and Legal" or "Business and Financial Operations" have a higher share of multiple episodes and working hours from home. It is possible that this rise is attributed to the pandemic-induced hybrid work culture. A small portion of workers have multiple episodes including working from home and these workers are likely partial-day-teleworkers. A closer look should be given to the work arrangement of these specific types of workers in future studies to reveal the underlying causes and their implication on travel decision makings.

Table 5-2. Share of Workers with Different Maximum Episodes during the Past Week against Occupation

Occupation	Share of workers with maximum *episodes* on a day during the week	
	1	2 or more
Farming, Fishing, Forestry, and Extraction	81.0%	19.0%
Construction, Installation, Maintenance, Repair, and Production	70.0%	30.0%
Sales and Related	88.8%	11.2%
Transportation and Material Moving	84.4%	15.6%
Business and Financial Operations	79.1%	20.9%
Computer and Mathematical, Architecture and Engineering, Life, Physical, and Social Science	82.9%	17.1%
Management and Legal	73.6%	26.4%
Office and Administrative Support	90.8%	9.2%
Protective Service, Building and Grounds Cleaning and Maintenance	95.1%	4.9%
Educational Instruction and Library	88.8%	11.2%
Healthcare Practitioners and Technical, Healthcare Support	86.9%	13.1%
Arts, Design, Entertainment, Sports, and Media	81.2%	18.8%
Food Preparation and Serving Related	92.0%	8.0%
Personal Care and Service	81.3%	18.7%
Community and Social Service	65.6%	34.4%
Military Specific	77.3%	22.7%

Further, Table 5-3 illustrates the share of days with different numbers of episodes among workers. Overall, the patterns are similar to the results shown in the previous table. However, some noticeable differences exist in the results from the two tables. For instance, occupations "Computer and Mathematical, Architecture and Engineering, Life, Physical, and Social Science" and "Arts, Design, Entertainment, Sports, and Media" have comparable shares of workers with at maximum, two or more episodes a day in the past week (17.1% and 18.8% in Table 5-2); however, the former have much fewer workdays with three or more episodes than the latter (1.5% vs 5.6% in Table 5-3). That is, while those in the tech industry may work at multiple workplaces in a day as frequently as those in the creative industry, they work either from home or at the office, but not more than those two sites. By contrast, for instance, a worker in the media industry may need to start their workday by working from home, commute to the office, and then visit another place for an interview, resulting in three episodes in a day. The difference in workstyles across occupations or industries could not be well captured by conventional surveys that assign a “single” work location to each day, supporting the effectiveness the new format that the research team introduced in the 2023 survey wave.

Table 5-3. Share of Workdays with Different Numbers of Episodes against Occupation

Occupation	Number of *episodes* on a workday		
	1	2	3 or more
Farming, Fishing, Forestry, and Extraction	87.6%	4.9%	7.5%
Construction, Installation, Maintenance, Repair, and Production	80.3%	11.0%	8.7%
Sales and Related	94.4%	4.1%	1.6%
Transportation and Material Moving	90.1%	6.7%	3.2%
Business and Financial Operations	91.3%	6.2%	2.5%
Computer and Mathematical, Architecture and Engineering, Life, Physical, and Social Science	92.5%	6.0%	1.5%
Management and Legal	88.3%	6.8%	4.9%
Office and Administrative Support	96.6%	2.3%	1.2%
Protective Service, Building and Grounds Cleaning and Maintenance	98.1%	1.3%	0.6%
Educational Instruction and Library	94.7%	4.5%	0.8%
Healthcare Practitioners and Technical, Healthcare Support	95.2%	4.0%	0.8%
Arts, Design, Entertainment, Sports, and Media	88.1%	6.3%	5.6%
Food Preparation and Serving Related	94.8%	3.3%	1.8%
Personal Care and Service	90.3%	7.8%	1.9%
Community and Social Service	80.9%	7.4%	11.8%
Military Specific	85.0%	12.7%	2.3%

6 The Impact of COVID-19 on e-Shopping/Home Delivery

6.1 Introduction

With the increasing adoption of internet-based services, smartphone and tablet use, and the changing lifestyles associated with these changes, e-shopping has shown a gradual increase between the early 2000s and the COVID-19 pandemic (Ozbilen et al., 2021; Saphores & Xu, 2021). The share of e-commerce increased from 2.8% in 2006 to 10% in 2019 (Bucchioni et al., 2015; U.S. Department of Commerce, 2024). The pandemic has had significant implications for the e-shopping frequency of individuals. During the early phases of the pandemic, lockdown measures considerably limited in-person shopping opportunities. This resulted in a significant increase in the adoption of virtual alternatives for shopping and increased the frequency of shopping online compared to pre-pandemic trends (Saphores & Xu, 2021; Unnikrishnan & Figliozzi, 2021). In particular, low-frequency e-shoppers in the pre-pandemic period, such as older adults and less wealthy individuals, increased their e-shopping frequency due to the restrictions imposed by the pandemic.

The rise of e-commerce has brought the attention of policymakers and transportation scholars to the association between e-shopping and the activity/travel behavior of individuals. Researchers conducted studies worldwide to assess the facilitators and deterrents of online shopping behavior during the pandemic and its broader social, economic, and behavioral impacts on communities (Luo et al., 2023; Unnikrishnan & Figliozzi, 2021). Studies showed that the growth in e-shopping could have implications on residents' housing location decisions and their frequency of shopping-related trips. Researchers highlighted that the ease of shopping online could impact the relocation decision, in particular among wealthier, well-educated individuals who have a higher likelihood of working from home (Matson et al., 2023). One major question pertains to whether the emerging online shopping practices developed during the pandemic will persist in the post-COVID era. While some newly acquired online shopping habits may revert to traditional in-person shopping, others may endure, especially among more tech-savvy people or those with disabilities and mobility limitations (e.g., older adults experiencing driving cessation due to aging).

Understanding the determinants of shifts in grocery and non-grocery shopping behaviors due to COVID-19 is imperative for transportation scholars and government agencies to better navigate in the post-pandemic period. This section of the report will present two analyses aimed at addressing the following inquiries: (1) How has e-shopping behavior changed from pre-pandemic to post-pandemic? (2) What are the differences across different socio-demographic groups in terms of e-shopping behavior? The design of the 2021 and 2023 surveys allows the research team to analyze e-shopping behavior from 2019 to 2023 comprehensively. The detailed information about various types of e-shopping (i.e., grocery and non-grocery) allows the analysis of different e-commerce alternatives and provides valuable insights into the adoption of e-shopping among California households.

6.2 Data and Methods

While there are three waves that were included in this report (Fall 2020, Summer 2021, and Fall 2023), only the 2021 and 2023 surveys are used in this section on online shopping. This is mainly because the structure of the shopping patterns section changed significantly from Fall 2020 to Summer 2021 based on the lessons learned during the data cleaning and analysis phases in 2020. As a result, starting in 2021, the research team collected e-shopping frequency in terms of the number of purchases (i.e., enter “3” as a monthly frequency) rather than the frequency category that was used before (e.g., select “less than once a week”). This provided the collection of more precise responses about the e-shopping frequency of individuals. Additionally, the 2021 survey asked e-shopping frequencies for the pre-pandemic (retrospective), pandemic, and post-pandemic (expectation) periods, which allows a comparison of behaviors at three timepoints for the same individual. The 2023 survey responses are considered as actual post-pandemic e-shopping behavior of respondents that allow the analysis of whether shopping behaviors during the COVID-19 period persist among California residents.

The analyses were conducted on repeated cross-sectional data (which includes both previous respondents who were re-contacted and additional respondents who were added to the sample in the corresponding wave for the very first time). Following the removal of entries with missing values and/or non-responses for the shopping behavior questions in the 2021 and 2023 waves, the complete responses with weights are used for the analysis. For ease of interpretation, the counts of shopping frequency associated with different items were categorized under five main categories, namely almost never, 1-3 times a month, 1-2 times per week, 3-4 times per week, and 5 or more times per week. Table 6-1 demonstrates the conversion values used for the categorization. It is important to note that since the respondents’ answers were continuous numbers, the research team included slightly higher/lower values to certain categories to classify each answer under one of these categories.

Table 6-1. Conversion values from shopping frequency count values

Respondents answer (X)	Classification category
0 <= X < 1	Almost never (less than once a month or never)
1 <= X < 4	1-3 times a month
4 <= X < 11	1-2 times per week (4 to 10 times per month)
11 <= X < 18	3-4 times per week (11 to 17 times per month)
18 <= X	5 or more times per week (18 times or more per month)

While the shopping pattern questions included more detailed information, the research team aggregated responses to each question under two main categories for brevity, namely online grocery shopping and online non-grocery shopping. The grocery shopping category includes (1) ordering grocery items online with premium/express home delivery, (2) ordering grocery items online with regular home delivery, and (3) ordering grocery items online with curbside or local store pick-up. The non-grocery shopping category includes (1) ordering non-grocery items (e.g., clothing, books, etc.) online with premium/express home delivery, (2) ordering non-grocery items (e.g., clothing, books, etc.) online with home delivery, (3) ordering non-grocery items (e.g., clothing, books, etc.) online with curbside or local store pick-up, and (4) ordering non-grocery items (e.g., clothing, books, etc.) online with alternative delivery locations (e.g., Amazon Locker, PO Box). For ease of analysis and interpretation, the research team summed up the value of the responses to each statement under online grocery shopping and online non-grocery shopping accordingly and converted the final counts to the classification categories in Table 6-1 for interpretation.

6.3 Results

6.3.1 The increase in e-shopping during and after the COVID-19 pandemic

The first part of the results section uncovers the shorter- and longer-term impacts of the pandemic on individuals' e-shopping behavior by comparing the frequency of e-shopping for grocery items and non-grocery items in the Summer 2021 and Fall 2023 waves. Since the Summer 2021 wave asked respondents about their pre-pandemic e-shopping behavior and their expectations about their future behavior in 2022, the results include e-shopping frequencies from the pre-pandemic (retrospectively), during pandemic (Summer 2021), expected post-pandemic, and actual post-pandemic periods. A summary of respondents' e-shopping frequency per time period is presented in Table 6-2.

The results reveal that online shopping has increased both for non-grocery and grocery items from the pre-pandemic to the post-pandemic period. The proportion of respondents who almost never shopped online decreased from 77.1% to 54% for grocery items and from 30.7% to 26.8% for non-grocery items from pre-pandemic to Fall 2023. Looking at this trend more closely, a non-linear change both for grocery and non-grocery items can be observed. As can be seen in Table 6-2, there was a sharp decrease in the proportion of those who almost never shopped online for both item types in 2021 (57.3% for grocery items and 23.5% for non-grocery items) as compared to pre-pandemic values. One interesting finding is that while 65.3% of respondents expected almost never to shop online for grocery items and 27.9% of respondents expected almost never to shop online for non-grocery items in the post-pandemic period, there were lower proportions of people who were categorized in almost never category in Fall 2023 (54% for grocery items and 26.8% for non-grocery items). In other words, while the expectation of some respondents was that their e-shopping to go back to pre-pandemic levels, the actual post-pandemic behavior shows otherwise (in particular for grocery items). This might be interpreted as the implications of the pandemic on e-shopping might persist in the longer term.

The results demonstrate that the proportion of those who shopped online at least once a week increased significantly both for grocery and non-grocery items. For grocery shopping, the proportion of respondents who shopped online at least once a week (hereafter used interchangeably with frequent e-shoppers) has increased nearly two-fold between 2019/pre-pandemic (10.8%) and 2021/during-pandemic periods (22.6%). While the 2021 respondents expected this to diminish to as low as 17.1% in 2022 (post-pandemic period), the 2023 survey results showed that the proportion of those who shopped online at least once a week for grocery items consisted of 22.7% of all respondents in the actual post-pandemic period. This shows the persistence of frequent e-shopping behavior in the post-COVID era.

Furthermore, for non-grocery shopping, the proportion of respondents who shop online at least once a week has increased from 33.3% in 2019/pre-pandemic to 45% in 2021/during-pandemic periods. While the 2021 respondents expected this to slightly decrease to 40.8% in 2022 (post-pandemic period), the proportion of respondents who shopped online for non-grocery items at least once a week reduced only to 43.2% in 2023/actual post-pandemic period. The results show a considerably higher share of relatively frequent e-shoppers for non-grocery items in the post-pandemic as compared to the pre-pandemic, which suggests that the impacts on non-grocery shopping activity might endure in the longer term.

E-shopping behavior, both for grocery and non-grocery items, has shown considerable persistence in the post-pandemic era. While some of the surge in e-shopping may have been temporary, there has been a noticeable decline in the proportion of respondents who indicate they almost never shop online from 2019 to 2023. This trend is particularly pronounced in online grocery shopping, which was less prevalent in the pre-pandemic era. Thus, it can be inferred that the pandemic has significantly influenced grocery shopping behavior through online alternatives. While the effect on non-grocery e-shopping is less pronounced (since many people were already used to ordering non-grocery items online even before the pandemic), the results reveal that there is a significant increase in the proportion of frequent e-shoppers for non-grocery items. While there are varying impacts on grocery and non-grocery items, it would be plausible to expect that the increased overall e-shopping frequency will continue in the longer term.

6.3.2 The change in e-shopping based on socio-demographics throughout the pandemic

Table 6-3 and Table 6-4 present the socio-demographic characteristics of the respondents and how their e-shopping frequencies change per time period in the dataset. For brevity and ease of understanding, the tables include time periods for the pre-pandemic (F19), during the pandemic (S21), and post-pandemic periods (F23). In parallel with previous studies, the results show that those who are younger and have higher income were more likely to shop online both for grocery and non-grocery items even before the pandemic. For example, in the pre-pandemic period, while 71.4% of young adults (18-34) indicated that they have almost never shopped online for grocery items, the share of mid-age adults (35-64) and older adults (65+) who almost never shopped online for grocery items was 75.8% and 89.2%, respectively.

Table 6-2. Online shopping frequency per timepoint

Time Period	Pre-pandemic (retrospective)	Pre-pandemic (retrospective)	2021	2021	2022 (Expectation)	2022 (Expectation)	2023	2023
Category	Online grocery	Online non-grocery	Online grocery	Online non-grocery	Online grocery	Online non-grocery	Online grocery	Online non-grocery
Almost never (less than once a month or never)	77.1%	30.7%	57.3%	23.5%	65.3%	27.9%	54.0%	26.8%
1-3 times per month	12.1%	36.1%	20.1%	31.6%	17.8%	31.3%	23.3%	30.1%
1-2 times per week	9.2%	25.2%	18.6%	31.0%	14.1%	28.7%	17.4%	32.0%
3-4 times per week	0.9%	5.5%	2.3%	7.4%	1.7%	6.7%	4.0%	7.2%
5 or more times per week	0.7%	2.6%	1.7%	6.6%	1.3%	5.4%	1.3%	4.0%
TOTAL	100%	100%	100%	100%	100%	100%	100%	100%

Notes: (1) The 'Pre-pandemic (retrospective)' and '2022 (Expectation)' columns are created based on the 2021 wave dataset.
(2) While the 'almost never' category includes answers that are less than 1 (0 or a value between 0 and 1), only less than 1% of respondents provided a number that was less than 1 for the e-shopping frequency.

Similarly, for non-grocery items, while 24.6% of young adults (18-34) indicated that they have almost never shopped online, 30.2% of mid-age adults (35-64) and 41% of older adults (65+) reported the same in the pre-pandemic period. Similar trends are also observed for different household income levels. Those who have never shopped online for grocery and non-grocery items were 79.8% and 41.4% in low-income households, 77.7% and 30% in middle income households, and 75% and 24.5% in high income households. Surprisingly, the adoption rate of e-shopping post-pandemic was much higher for lower income households as compared to their middle- and high-income counterparts. In the Fall 2023 wave, the proportion of those who have shopped online at least once a week for grocery items was 24.7% for low-income households, 21.3% for middle income households, and 21.9% for high income households. However, this trend is not observed for non-grocery items. The share of those who shopped online at least once a week for non-grocery items was 31.2% for low-income households, 40.9% for middle income households, and 52.1% for high income households in 2023. Such changes are not observed in the adoption rate of weekly e-shopping behavior of different age groups, meaning that those who are younger have a higher percentage for online shopping throughout (except for those aged 35-64, having a slightly higher percentage for non-grocery e-shopping in 2023 than those aged 18-34).

In the pre-pandemic period, the research team found that men were more likely to shop online for grocery items (73.7% of men and 80.1% of women have almost never shopped online for grocery items), while women were more likely to shop online for non-grocery items (33.9% of men and 27.7% of women have almost never shopped online for non-grocery). Nevertheless, this trend starts to reverse with the start of the pandemic and men become considerably more likely to report almost never shopping online for both grocery items and non-grocery items. In the post-pandemic period, women were more likely to shop online for grocery items (56.7% of men and 51.4% of women have almost never shopped online for grocery items) and non-grocery items (28.2% of men and 25.3% of women have almost never shopped online for non-grocery). This trend is observed for those who shop at least once a week during the 2021 and 2023 time periods: women are more likely to be frequent e-shoppers (i.e., shop at least once a week) both for grocery and non-grocery items.

The findings demonstrate interesting trends about the adoption of e-shopping across individuals with different educational attainment levels. As consistent with previous studies, for those with lower educational attainment, almost never shopping online for non-grocery items was more common before, during, and after the pandemic. However, for grocery shopping, the trend is the exact opposite for the pre- and post-pandemic periods, meaning that online grocery shopping was less common among those with higher educational attainment. When it comes to frequent e-shoppers, the findings show that the share of those who shop online for grocery and non-grocery items at least once a week was higher for respondents with lower educational attainment as compared to their counterparts with at least a bachelor's degree (except for the e-shopping associated with non-grocery items in the Fall 2023 wave). This finding contradicts findings in recent studies (i.e., positive associations between educational attainment and e-shopping adoption), and it warrants a further analysis that controls for various confounding factors.

Table 6-3. Distribution of socio-demographic characteristics among study participants, in each of three study periods, according to their frequency of online shopping for grocery items (all values shown are percentages)

Online grocery shopping		Almost never (less than once a month or never)**			1-3 times a month			1-2 times per week			3-4 times per week			5 or more times per week		
Time period		**F19***	**S21**	**F23**	**F19***	**S21**	**F23**	**F19***	**S21**	**F23**	**F19***	**S21**	**F23**	**F19***	**S21**	**F23**
Gender	Female	80.1	55	51.4	10.4	21.3	24.3	8.6	20.3	18.7	0.4	1.9	4.1	0.5	1.5	1.5
	Male	73.7	59.8	56.7	14	18.8	22.4	9.9	16.7	16	1.4	2.8	3.9	0.9	2	1.1
Age	18-34	71.4	49.4	48.2	14.8	21.1	26.7	11.2	24.3	20.3	1.7	3.3	5.4	1	1.9	1.1
	35-64	75.8	55.3	50.8	12.5	21.6	24.5	10.5	18.9	18.9	0.8	2.4	4.1	0.4	1.8	1.7
	65+	89.2	74.9	71	7	14.4	18.2	2.6	8.9	9.1	0	0.7	1.3	1.1	1.1	0.4
Income	Low Income	79.8	62.2	53.5	11.9	16.9	21.7	7.7	17.2	20.4	0.2	2.2	3	0.4	1.5	1.3
	Middle Income	77.7	58.7	51.1	11.2	16.6	27.5	9	21.8	16.9	1.4	1.2	2.9	0.7	1.8	1.5
	High Income	75	53.3	56	12.9	24.5	22	10.3	17.2	15.6	0.9	3.2	5.2	0.8	1.8	1.1
Education	High school or less	75.3	57.8	52.9	13.3	18.3	23.4	9.9	20.6	18.3	0.9	1.8	3.8	0.7	1.4	1.6
	Bachelor's or higher	78.9	56.7	55.9	11	21.9	23.3	8.6	16.4	15.8	0.9	2.9	4.3	0.6	2	0.7

Notes: * Fall 2019 refers to the retrospective question in the 2021 wave that asks for the ‘pre-pandemic’ behavior of respondents.
** While the ‘almost never’ category includes answers that are less than 1 (0 or a value between 0 and 1), only less than 1% of respondents provided a number that was less than 1 for the e-shopping frequency.

Table 6-4. Distribution of socio-demographic characteristics among study participants, in each of three study periods, according to their frequency of online shopping for non-grocery items (all values shown are percentages)

Online non-grocery shopping		Almost never (less than once a month or never)**			1-3 times a month			1-2 times per week			3-4 times per week			5 or more times per week		
Time period		**F19***	**S21**	**F23**	**F19***	**S21**	**F23**	**F19***	**S21**	**F23**	**F19***	**S21**	**F23**	**F19***	**S21**	**F23**
Gender	Female	27.7	19.7	25.3	37.9	30.7	30.2	27.5	34.6	33.4	4.1	7.7	7.2	2.8	7.3	3.9
	Male	33.9	27.8	28.2	34.2	32.6	30	22.6	26.9	30.6	7	7	7.1	2.4	5.8	4.1
Age	18-34	24.6	19.1	29.5	36.9	30.6	26.7	26.9	32.4	30.5	7.1	9.8	8.8	4.5	8.2	4.5
	35-64	30.2	23	25.5	35.2	31.1	28.6	26.6	31.7	33.6	5.9	7.7	7.7	2	6.6	4.7
	65+	41	31.8	26	37.3	34.4	39	18.4	26.8	30.2	2.2	3	3.3	1.1	4	1.5
Income	Low Income	41.4	31.6	36.7	29.7	26.6	32	21.6	29.2	23.9	5.5	7.1	3.8	1.8	5.5	3.5
	Middle Income	30	23.2	29.2	38.2	34.2	30	24.1	29.4	30.7	3.7	6.6	5.8	4	6.7	4.4
	High Income	24.5	18.8	19	38.6	33	28.9	28.1	33.1	37.9	6.7	8.1	10.1	2.2	7.1	4.1
Education	High school or less	34.5	27.9	32.3	28.6	25.5	29.4	28.4	31	28.3	5.1	8.3	6	3.3	7.2	4
	Bachelor's or higher	26.8	19.1	17.7	43.6	37.7	31.2	21.9	30.9	37.9	5.9	6.5	9.1	1.9	5.9	4

Notes: * Fall 2019 refers to the retrospective question in the 2021 wave that asks for the ‘pre-pandemic’ behavior of respondents.
** While the ‘almost never’ category includes answers that are less than 1 (0 or a value between 0 and 1), only less than 1% of respondents provided a number that was less than 1 for the e-shopping frequency.

7 Impacts of the COVID-19 Pandemic on Travel Behavior

7.1 Introduction

The COVID-19 pandemic significantly impacted activity-travel behavior in cities around the world. In particular, the onset of the pandemic resulted in a decline in the use of public transit, an increased preference for travel by private vehicles and active modes, and a decline in out-of-home activity participation (Habib et al., 2021; Monahan & Lamb, 2022; Shamshiripour et al., 2020). These shifts can be attributed to several factors, including the temporary closure of certain businesses, the shift to teleworking, and the perceived infection risk associated with different modes of travel (Aaditya & Rahul, 2021; Parady et al., 2020; Zhao & Gao, 2022). Given its impacts on activity-travel behavior, it is important to explore the potential long-term impacts of the pandemic.

Studies on changes in travel mode preferences during the pandemic suggest that the use of private vehicles and active modes has approached (and in some cases, exceeded) pre-pandemic levels, while public transit and ride-hailing use have remained below pre-pandemic levels (Beck & Hensher, 2022; Molloy, 2021). Continuing to explore changes in travel mode preferences can offer insights into whether the impacts of the pandemic will persist into the post-pandemic period. Understanding the potential long-term impacts of the pandemic is crucial, given that travel mode preferences have important implications for both VMT and emissions. Additionally, exploring changes in attitudes could also shed light on the potential long-term impacts of the pandemic, given their impacts on travel behavior during the pandemic (de Haas et al., 2020; Oum & Wang, 2020).

This section presents the results of an examination of changes in travel behavior among different segments of California residents during the COVID-19 pandemic. The analysis focused on two aspects of travel behavior: 1) the modes used for commuting and non-commuting trips, and 2) attitudes towards travel. To examine how these aspects of travel behavior have changed during the pandemic, data from three waves of a repeated cross-sectional survey are compared. The results shed light on how these aspects of travel behavior have evolved following the disruptive impacts of the pandemic and its potential long-term impacts.

7.2 Data and methods

The analysis presented in this section utilized data from three waves of a repeated cross-sectional sectional survey conducted in Fall 2020 (F2020), Summer 2021 (S2021), and Fall 2023 (F2023). Additionally, retrospective information regarding travel behavior in Fall 2019 (F2019) that was collected in the Fall 2020 wave of the survey was used as a benchmark of pre-pandemic behavior. The designs of questions related to the use of travel modes and attitudes were consistent across the three waves, which facilitated the comparison of the responses to said questions. In the analysis, the use of various modes of travel for commuting and non-commuting trips were compared across socio-demographic groups.

7.2.1 Modes used for commuting and non-commuting trips

In each wave of the survey, respondents were asked to indicate how often they used various travel modes for commuting (i.e., trips to work or school) and non-commuting (i.e., leisure, social, and shopping trips) trips during a given period of time. Respondents were presented with seven response options: 1) not available, 2) available but I did not use it, 3) less than a day per month, 4) 1 – 3 days per month, 5) 1 – 2 days per week, 6) 3 – 4 days per week, and 7) 5 or more days per week. Respondents who selected either of the first two options were classified as non-users of a given mode, while all other respondents were classified as users.

Seven modes were considered for commuting trips: 1) private vehicle (both alone and with others), 2) public bus, 3) subway or train (including commuter rail and light rail), 4) ride-hailing, 5) personal bike, e-bike, or e-scooter, 6) shared bike, e-bike, or e-scooter, and 7) walk. The analysis of modes used for non-commuting trips considered car-sharing in addition to the same seven modes considered for commuting trips. In this analysis, the percentage of respondents using these modes in each wave of the survey was compared among different segments of respondents based on factors such as age, gender, race, ethnicity, and household income. These values were also compared to the values corresponding to Fall 2019 to explore differences in mode use during the pre-pandemic and pandemic periods.

7.2.2 Attitudes towards travel

Each wave of the survey asked respondents to complete a series of attitudinal questions in which they were asked to indicate their level of agreement (or disagreement) with each statement using a five-point Likert scale. In the following analysis, three categories were defined based on the responses to these questions: 1) disagree, 2) neither agree nor disagree, and 3) agree.

The responses to seven attitudinal questions were considered as part of this analysis: 1) I like walking, 2) I like driving a car, 3) I like riding a bike, 4) I definitely want to own a car, 5) I prefer to live in a spacious home, even if it is farther from public transit and many places I go, 6) I prefer to be a driver rather than a passenger, and 7) I like the idea of public transit as a means of transportation for me. The percentage of respondents who agreed and disagreed with each statement were compared between the three waves of the survey.

7.3 Results

7.3.1 Changes in modes used for commuting trips

The percentage of respondents in each income group that used each mode for commuting trips is summarized in Figure 7-1. Across all three income groups, the percentage of respondents who used the public bus, subway or train, ride-hailing, and walk modes for commuting trips was lower in Fall 2020 and Summer 2021 compared to Fall 2019. However, the discrepancy between the percentage of respondents using public transit (i.e., the public bus and subway or train modes) and ride-hailing in Fall 2019 and Summer 2021 is smaller among individuals from households earning over $50,000 annually compared to those from households earning less than $50,000 annually. In contrast, among individuals from households earning less than $100,000 annually, the percentage of respondents who used the personal bike, e-bike, or e-scooter mode was higher in Summer 2021 compared to Fall 2019. This trend could be influenced by the implementation of programs that temporarily allocated road space to active mode users in the early stages of the pandemic (such as the Slow Streets program in Oakland (National Association of City Transportation Officials, 2020)).

Interestingly, changes in the use of the shared bike, e-bike, and e-scooter mode differed among the income groups. Specifically, the use of this mode was more common in Summer 2021 compared to Fall 2019 among those from households earning over $50,000 annually; however, the opposite was observed for individuals from households earning less than $50,000 annually. This could be cost associated with the use of shared micromobility (i.e., bikes, e-bikes, and e-scooters) services (Brown & Howell, 2024) or the placement of docking stations. Notably, the percentage of respondents who used a private vehicle for commuting trips was higher in Fall 2020 and lower in Summer 2021 compared to Fall 2019 across all income groups.

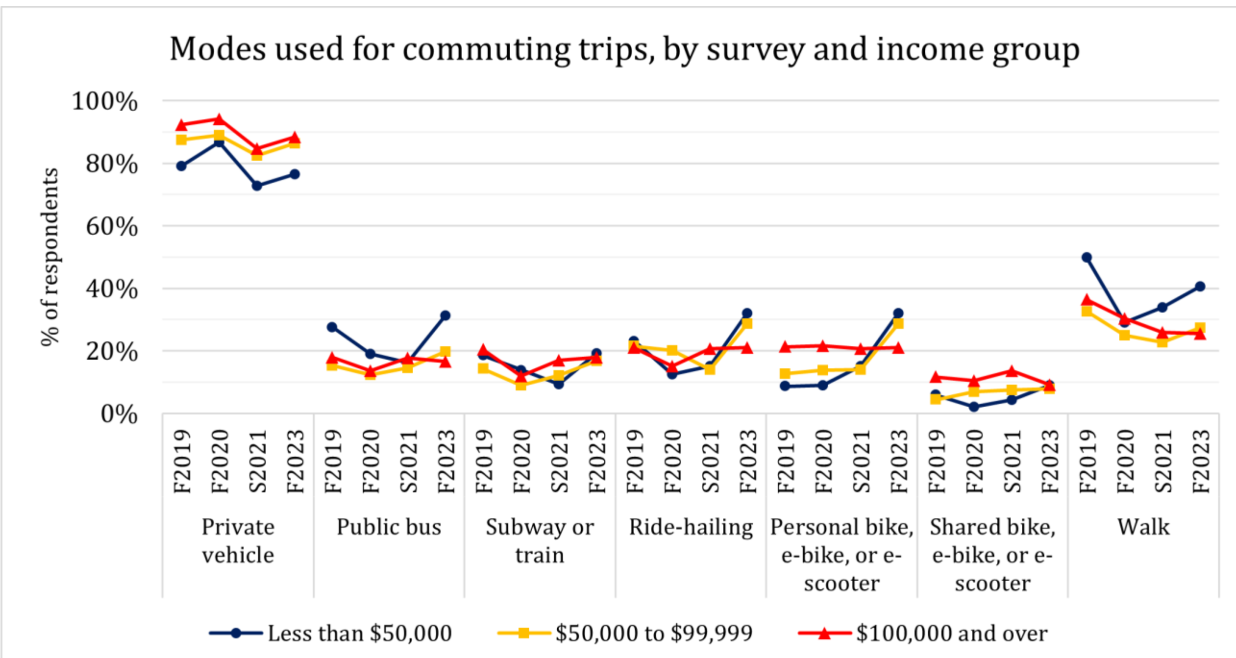


Figure 7-1. Use of modes for commuting trips, by survey

The results also shed light on the differences in the use of each mode for commuting trips in Fall 2023 and Fall 2019. Among individuals from households earning less than $100,000 annually, the percentage of respondents using the public transit modes was higher in Fall 2023 compared to Fall 2019. While this is an encouraging sign, an important caveat is that these values do not reflect how often these modes were used during the two periods. Conversely, the percentage of respondents who use public transit for commuting trips in Fall 2023 was lower than in Fall 2019 among individuals from households earning over $100,000 annually. Besides, the percentage of respondents from households earning less than $100,000 annually who use the ride-hailing, personal bike, e-bike, and e-scooter, and shared bike, e-bike, and e-scooter modes to commute was higher in Fall 2023 compared to Fall 2019. This trend may suggest that the use of ride-hailing, bicycles, and e-scooters could be more prevalent among this segment of the population during the post-pandemic period compared to the pre-pandemic period.

The use of these modes for commuting trips is compared among different socio-demographic groups in Table 14-8 and Table 14-9 of the Appendix. The key findings of the comparison suggest that:

- Respondents below the age of 35 and over the age of 64 were slightly more likely to report that they used the private vehicle mode in Fall 2023 compared to Fall 2019. Female respondents were less likely to have used a private vehicle in Fall 2023 compared to Fall 2019, while the opposite was true for male respondents. Similarly, respondents who identified as Hispanic, Black, or Native American were less likely to have used a private vehicle for commuting trips in Fall 2023 compared to Fall 2019.
- Respondents below the age of 65 were less likely to have used public transit for commuting trips in Fall 2023 compared to Fall 2019. Conversely, respondents over the age of 64 were more likely to indicate that they used the public bus mode. Female respondents were more likely to indicate that they used the public bus mode in Fall 2023 compared to Fall 2019, while male respondents were slightly less likely to have used the subway or train mode. Respondents who identified as Hispanic or Native American were more likely to have used public transit in Fall 2023 compared to Fall 2019. Respondents who identified as Black were more likely to have used the public bus mode in Fall 2023 compared to Fall 2019 and less likely to have used the subway or train mode.
- Across all age groups, respondents were more likely to have reported using ride-hailing in Fall 2023 compared to Fall 2019. Female respondents were slightly more likely than male respondents to report using ride-hailing in Fall 2023, which is the opposite of what was observed in Fall 2019. Respondents who identified as Hispanic, Asian, White, or Native American were more likely to indicate that they used ride-hailing in Fall 2023 compared to Fall 2019. Conversely, respondents who identified as Black were slightly less likely to report that they used ride-hailing.
- Regardless of age group, respondents were more likely to indicate that they used a personal bike, e-bike, or e-scooter in Fall 2023 compared to Fall 2019. However, respondents below the age of 35 were the only age group that was more likely to report that they used shared micromobility options in Fall 2023 compared to Fall 2019. Female respondents were more likely to report using both personal and shared bikes, e-bikes, and e-scooters, while male respondents were more likely to have used a personal bike, e-bike, or e-scooter. Respondents who identified as Hispanic were more likely to have used both personal and shared bikes, e-bikes, and e-scooters. Similarly, respondents who identified as White were more likely to have used the shared bikes, e-bikes, and e-scooters in Fall 2023 compared to Fall 2019, while the opposite was observed for respondents identifying as Asian, Black, or Native American.

- Overall, respondents were less likely to have made commuting trips on foot in Fall 2023 compared to Fall 2019. However, respondents who identified as Hispanic or Native American were more likely to indicate that they walked for said trips.

Overall, the results underscore the extent to which changes in the use of modes for commuting trips vary across different segments of the population. The results also shed light on the use of modes for commuting trips in the post-pandemic period. In particular, public transit and ride-hailing were more likely to be used by younger individuals, those who belong to lower-income households, and individuals who identify as Black, Native American, or Hispanic. Consequently, the needs of these individuals should be considered when planning public transit services.

7.3.2 Changes in modes used for non-commuting trips

The percentage of respondents that reported using each mode for non-commuting trips is outlined in Figure 7-2. Similar to the results regarding commuting trips, the percentage of respondents using public transit and ride-hailing was lower in Fall 2020 and Summer 2021 compared to Fall 2019 regardless of income group. Moreover, the use of car-sharing services declined from Fall 2019 to Summer 2021, with the exception of respondents from households earning over $100,000 annually (14.6% in Summer 2021 vs. 14.2% in Fall 2019). A similar trend was observed regarding the use of personal and shared bikes, e-bikes, and e-scooters, but only for individuals from households earning over $50,000 annually. Respondents from households earning less than $50,000 annually were more likely to have used these modes in Fall 2020 and Summer 2021 compared to Fall 2019.

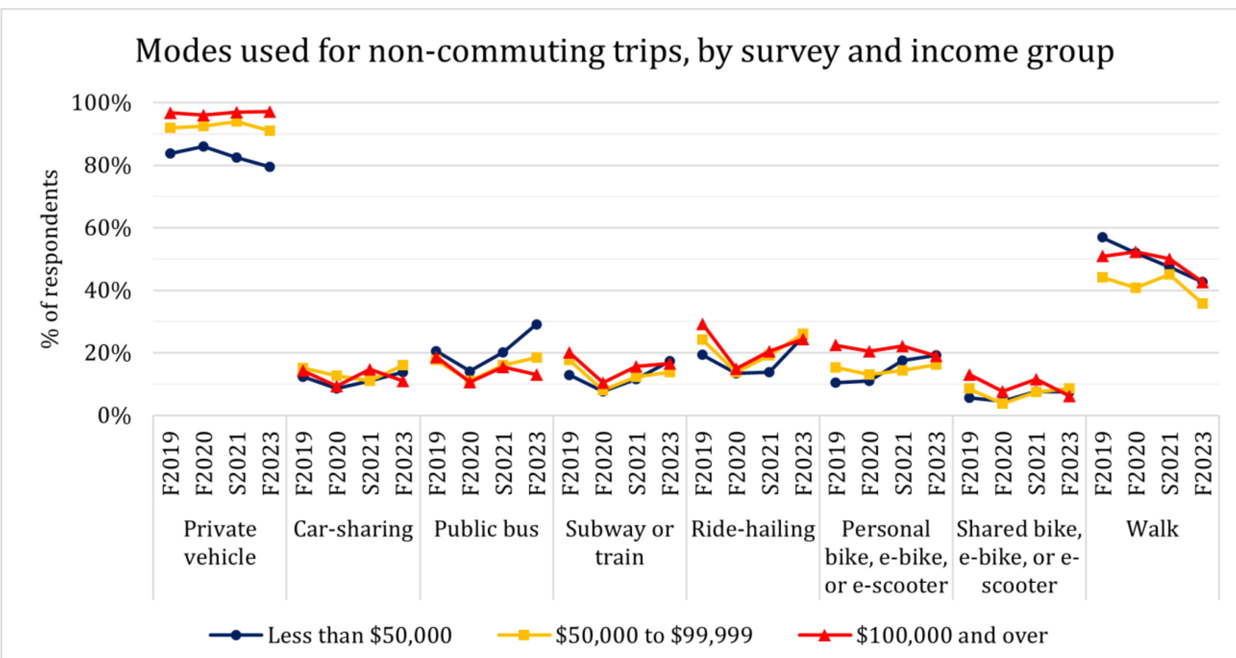


Figure 7-2. Use of modes for non-commuting trips, by survey

Interestingly, the percentage of respondents indicating that they walked declined from Fall 2019 to Summer 2021 among individuals from households earning less than $50,000 annually.

Conversely, the percentage of respondents who reported walking was lower in Fall 2020 compared to Fall 2019 but approached the pre-pandemic percentage in Summer 2021. These findings are somewhat counterintuitive given the reports of increases in the prevalence of travel using active modes in the early stages of the pandemic (Budd & Ison, 2020; Molloy, 2021). One possible explanation is that respondents did not report their undirected trips (Hook et al., 2021) when responding to these questions due to the examples of non-commuting trips that were provided in the questionnaires.

The differences in the percentage of respondents using a given mode in Fall 2023 and Fall 2019 vary across income groups. For example, respondents from households earning less than $50,000 annually were more likely to have used public transit in Fall 2023 compared to Fall 2019. The opposite was observed for individuals from households earning over $50,000 annually; however, respondents from households earning between $50,000 and $99,999 annually were more likely to have used the public bus mode in Fall 2023. A similar trend was observed for the car-sharing, ride-hailing, personal bike, e-bike, and e-scooter, and the shared bike, e-bike, and e-scooter modes. Specifically, respondents from households earning less than $100,000 annually were more likely to use these modes in Fall 2023 and Fall 2019. In contrast, respondents from households earning over $50,000 annually were roughly as likely to have used a private vehicle in Fall 2023 compared to Fall 2019, whereas respondents from households earning less than $50,000 annually were less likely to have used a private vehicle.

The use of these modes for non-commuting trips is compared for different socio-demographic groups in Table 14-10 and Table 14-11 of the Appendix. The results of the comparison suggest that:

- Respondents between the ages of 18 and 34 were more likely to have used a private vehicle in Fall 2023 compared to Fall 2019 (83.5% vs. 79.6%); however, older respondents were still more likely to have used a private vehicle. Female respondents were less likely to have used a private vehicle in Fall 2023 compared to Fall 2019, while the opposite was observed for male respondents. Respondents who identified as Hispanic, Black, or Native American were less likely to have used a private vehicle in Fall 2023 compared to Fall 2019.
- Those over the age of 64 were more likely to have used car-sharing in Fall 2023 compared to Fall 2019. Respondents who identified as Hispanic or Asian were more likely to have used car-sharing in Fall 2023 compared to Fall 2019, while the opposite was observed for respondents who identified as Black or Native American.
- Younger respondents (below the age of 65) were less likely to have used public transit in Fall 2023 compared to Fall 2019; however, the opposite was observed for older respondents. Female respondents were more likely to have used the public bus mode in Fall 2023 compared to Fall 2019, whereas male respondents were less likely to have used public transit. Respondents who identified as Hispanic, Asian, or Native American were more likely to have used public transit in Fall 2023 compared to Fall 2019. However, respondents who identified as Black were more likely to have used the public

bus mode and less likely to have used the subway or train mode in Fall 2023 compared to Fall 2019.

- Respondents between the ages of 35 and 64 were less likely to have used ride-hailing in Fall 2023 compared to Fall 2019, while the opposite was observed for respondents in other age groups. Male respondents were less likely to have used ride-hailing in Fall 2023 compared to Fall 2019, while female respondents were more likely to have used this mode. Respondents who identified as Hispanic, Native American, or White were more likely to have used ride-hailing in Fall 2023 compared to Fall 2019, whereas respondents who identified as Asian or Black were less likely to have used this mode.
- Regardless of age group, respondents were more likely to have used the private bike, e-bike, and e-scooter mode in Fall 2023 compared to Fall 2019. The opposite trend was observed for the shared bike, e-bike, and e-scooter mode, with the exception of respondents over the age of 64. Female respondents were more likely to have used the personal bike, e-bike, and e-scooter mode and less likely to have used the shared bike, e-bike, and e-scooter mode in Fall 2023 compared to Fall 2019. Conversely, male respondents were less likely to have used both the personal and shared bike, e-bike, and e-scooter modes in Fall 2023 compared to Fall 2019. Respondents who identified as Hispanic or Black were more likely to have used the personal bike, e-bike, and e-scooter mode in Fall 2023 compared to Fall 2019. Conversely, respondents were less likely to have used the shared bike, e-bike, or e-scooter mode in Fall 2023 compared to Fall 2019.
- Overall, respondents were less likely to have walked in Fall 2023 compared to Fall 2019.

The results of this analysis offer insights into differences between the use of modes for non-commuting trips in Fall 2023 and Fall 2019, and how these differences can vary across different segments of the population. For example, the results suggest adults under the age of 35 were most likely to indicate that they used public transit for non-commuting trips. However, these individuals were less likely to indicate that they used public transit in Fall 2023 compared to Fall 2019, and more likely to have used private vehicles. Conversely, respondents who identify as Hispanic or Black were more likely to have used public transit and less likely to have used a private vehicle in Fall 2023 compared to Fall 2019. Moreover, respondents over the age of 64 were more likely to have used public transit in Fall 2023 compared to Fall 2019. Additional work will be needed to understand the factors influencing these shifts in the use of private vehicles and public transit more comprehensively.

7.3.3 Changes in attitudes towards travel

The responses to the attitudinal questions are summarized in Table 7-1. Overall, the responses are indicative of positive attitudes towards walking and driving and reflect the desire to own a car. However, despite these results, respondents were less likely to agree that they preferred to be a driver instead of a passenger than they were to agree that they liked driving. This discrepancy could stem from the relative convenience of being a passenger compared to being the driver. Mixed results were observed for the questions pertaining to the enjoyment of riding a bike and the desire to live in a spacious home even if it is further away from public transit and the places that one visits. Approximately half of the respondents expressed their agreement with these statements, while one-quarter expressed their disagreement. Notably, respondents were least likely to agree (and most likely to disagree) with the statement “I like the idea of public transit as a means of transportation for me”. This result may partially be attributed to the service cuts (Barbour et al., 2023) and changes in the perceived risk associated with using transit (de Haas et al., 2020) due to the pandemic.

Table 7-1. Responses to attitudinal questions, by survey

Statement	Wave	Response		
		Disagree	Neither agree nor disagree	Agree
I like walking	Fall 2020	6.9%	13.4%	79.7%
	Summer 2021	8.7%	12.6%	78.7%
	Fall 2023	9.3%	12.4%	78.4%
I like riding a bike	Fall 2020	24.7%	20.9%	54.3%
	Summer 2021	29.2%	19.4%	51.4%
	Fall 2023	30.1%	21.9%	48.0%
I like driving a car	Fall 2020	7.3%	11.5%	81.2%
	Summer 2021	10.8%	13.9%	75.3%
	Fall 2023	9.7%	12.3%	78.0%
I definitely want to own a car	Fall 2020	5.4%	10.0%	84.5%
	Summer 2021	7.0%	11.8%	81.2%
	Fall 2023	6.3%	9.6%	84.1%
I prefer to live in a spacious home, even if it is far from public transit and many places I go	Fall 2020	26.6%	23.0%	50.4%
	Summer 2021	28.0%	23.0%	48.9%
	Fall 2023	28.4%	21.9%	49.7%
I prefer to be a driver rather than a passenger	Fall 2020	21.9%	20.5%	57.6%
	Summer 2021	23.2%	22.6%	54.2%
	Fall 2023	25.5%	22.2%	52.2%
I like the idea of public transit as a means of transportation for me	Fall 2020	35.7%	25.1%	39.2%
	Summer 2021	35.1%	22.4%	42.6%
	Fall 2023	33.2%	24.7%	42.0%

Comparing responses to the attitudinal questions across different waves of the survey also offers insights into the evolution of attitudes during the pandemic. Notably, the percentage of respondents who agreed that they liked the idea of public transit as a means of transportation was slightly higher in Fall 2023 compared to Fall 2020; however, this sentiment was expressed by only 42.0% of individuals. Moreover, respondents were less likely to agree that they like riding a bike in Fall 2023 compared to Fall 2019. This shift could be influenced by changes in biking over the course of the pandemic, the removal of temporary cycling infrastructure that was implemented in the early stages of the pandemic, or the decline in undirected travel over the course of the pandemic (Hook et al., 2023). Interestingly, attitudes towards living in a spacious home that is far from public transit and the places that one visits were fairly consistent across the three survey waves. This result could be reflective of residential self-selection among respondents, or it may be influenced by factors such as housing prices and the ability to telework. Similarly, sentiments towards walking also remained relatively consistent across the three waves.

8 Impacts of the COVID-19 Pandemic on Access and Use of Private Vehicles

8.1 The Change in vehicle ownership during and after the COVID-19

8.1.1 Introduction

The demand for cars remained strong during the pandemic (Krolikowski & Naggert, 2021). According to a national survey (Auto Remarketing, 2021), 60% of car buyers said that the pandemic affected their decision to purchase a vehicle, and over 50% of these buyers reported purchasing a car sooner than originally planned. Some of the former non-car owners may have been compelled to buy or lease one to avoid mass transportation. However, the automotive industry struggled to meet the heightened demand. Most auto manufactures faced disruptions due to business shutdown, international logistics chain interruptions, and shortage of raw materials amid the pandemic, resulting in a substantial decline in vehicle production and delivery (Krolikowski & Naggert, 2021). This resulted in a decline in new automotive sales in the United States (Marina et al., 2022), while contributed to the boom in used car sales during the pandemic (Rosenbaum, 2020). Such market uncertainty and economic downturn may have also spared certain consumers from unnecessary hassles and expenses associated with purchasing or replacing cars (de Palma et al., 2022).

Policymakers, government officials, auto manufacturers, and related businesses all seek to understand the ways that the pandemic has affected consumer behavior regarding vehicle ownership and the unique characteristics of the “new normal”. However, serious gaps exist in the knowledge about these topics. First, although vehicle ownership has been well-studied before the pandemic, limited research has been focused on any temporary and longer-term changes during and after the pandemic in the U.S. Second, many studies employ cross-sectional data (Klein & Smart, 2017) or pseudo panel data (Anowar et al., 2016), which do not allow the examination of changes that the same households undergo over time. In addition, those data tend not to capture the impacts of life events (e.g., relocating to a new area, starting or leaving a job), which are critical to understanding the underlying reasons behind key decisions behind vehicle ownership. Third, to the best of the authors’ knowledge, no prior study has simultaneously modeled both recent-past and expected-near-future changes in vehicle ownership. Modeling these two changes in a single framework enables the estimation of the effects of various factors, observed and unobserved, whose nature may have shifted over time. For example, households that experienced economic changes during the pandemic may have postponed vehicle purchases in the past; however, such delays in vehicle acquisition or replacement may influence their near-future decisions in the opposite direction.

To address these research gaps, this study employs a two-wave panel dataset, collected in the U.S., to simultaneously investigate individuals' changes in vehicle ownership in two time periods: actual changes in the recent past from March 2020 (i.e., pre-pandemic period) to July/August 2023 (i.e., Fall 2023), and expected changes during the next three years from July/August 2023 to July/August 2026 (i.e., Fall 2026). In doing so, the research team looks at four types of changes: (1) increase in the number of vehicles, (2) decrease in the number of vehicles, (3) keep the same total but replace one (or more) vehicle(s), and (4) make no change. With an integrated choice and latent variable (ICLV) model, factors affecting changes in vehicle ownership are identified, with a focus on attitudes (e.g., tech-savviness), socio-demographic characteristics, life events (e.g., starting a job), work arrangement (e.g., adopting remote work schedule), and COVID health concerns.

8.1.2 Data and Method

The present study focuses on a cohort of 1,612 longitudinal respondents who participated in both the Spring 2020 and Fall 2023 surveys in the U.S, as part of the Mobility Study. To better capture changes during and after the pandemic, some questions in the surveys elicited responses for the present (i.e., at the time of data collection), the past (via retrospective recall), and the future (via expectation) situations.

The analyses center on two dependent variables collected from the Fall 2023 survey: (1) past changes in vehicle count from the beginning of the pandemic (i.e., Spring 2020) up to Fall 2023, and (2) expected future changes in vehicle count over the next three year (from Fall 2023 to Fall 2026). As depicted in Figure 8-1, between the pandemic's onset and Fall 2023, 7.3%, 7.4% and 23.6% of respondents reported to have added, shed, or replaced their vehicles, respectively. Looking three years ahead, 7.8%, 4.2% and 32.8% of respondents expected to increase, decrease, or replace their vehicles, respectively. Notably, the proportion of individuals replacing vehicles was and is also expected to be much higher than those adding or shedding their cars. While past trends show nearly equal proportion of individuals increasing or decreasing their vehicle, a larger share of respondents expected to increase their vehicle count in the future (7.8%) compared to those anticipating a decrease (4.2%). It is hypothesize that certain instances of vehicle ownership changes may be directly linked to household dynamics, such as individuals moving in or out and bringing or taking their vehicles with them. To address this potential confounding factor, Figure 8-2 presents the trends while controlling for household composition. Specifically, it only includes households that maintain a consistent total number of children and adults in the household. Unsurprisingly, the proportion of individuals who altered their vehicle count (including increases, decreases and replacements) reduced.

An ICLV model was used to jointly estimate two dependent variables (i.e., past changes and expected future changes in vehicle count). Each part combines two sub-models: a latent variable model and a discrete choice model (Abou-Zeid & Ben-Akiva, 2014). The latent variable model addresses the relationships between observable features of individuals (such as socioeconomic, demographic and neighborhood characteristics, as well as COVID-19 health concerns) and underlying psychometric factors. The discrete choice model estimates the utility from the four types of vehicle count changes, accounted for by explanatory factors such as life events and latent factors. Figure 8-3 depicts the modeling framework in this study.

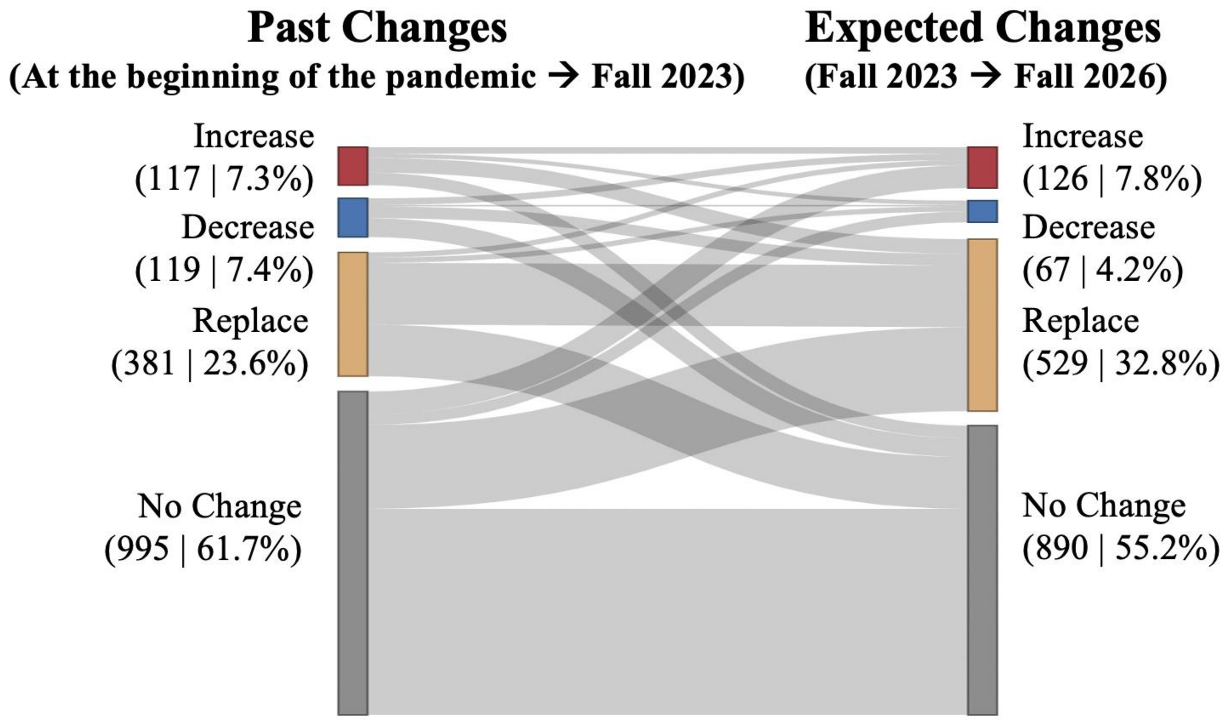


Figure 8-1. Past and Expected Future Changes in Vehicles (N=1,612)

Notes: This figure includes entire sample.

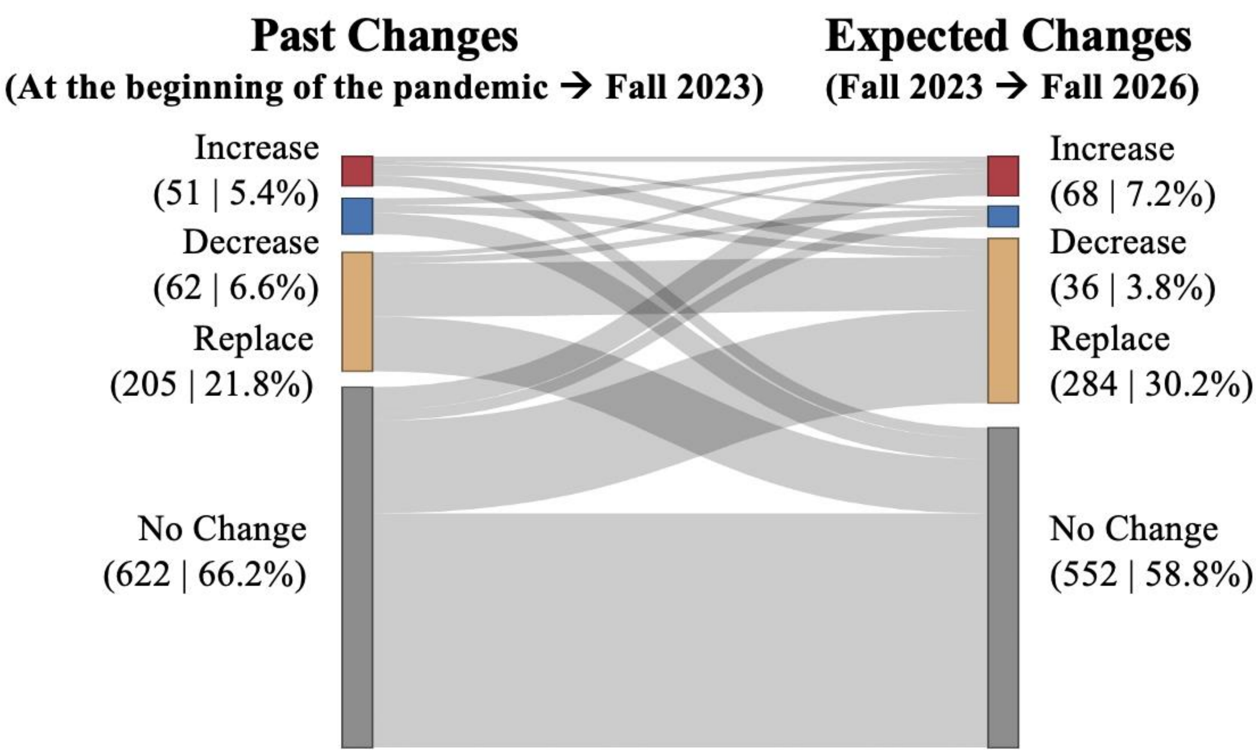


Figure 8-2. Past and Expected Future Changes in Vehicles (N=940)

Note: This figure includes only those cases without any changes in household composition

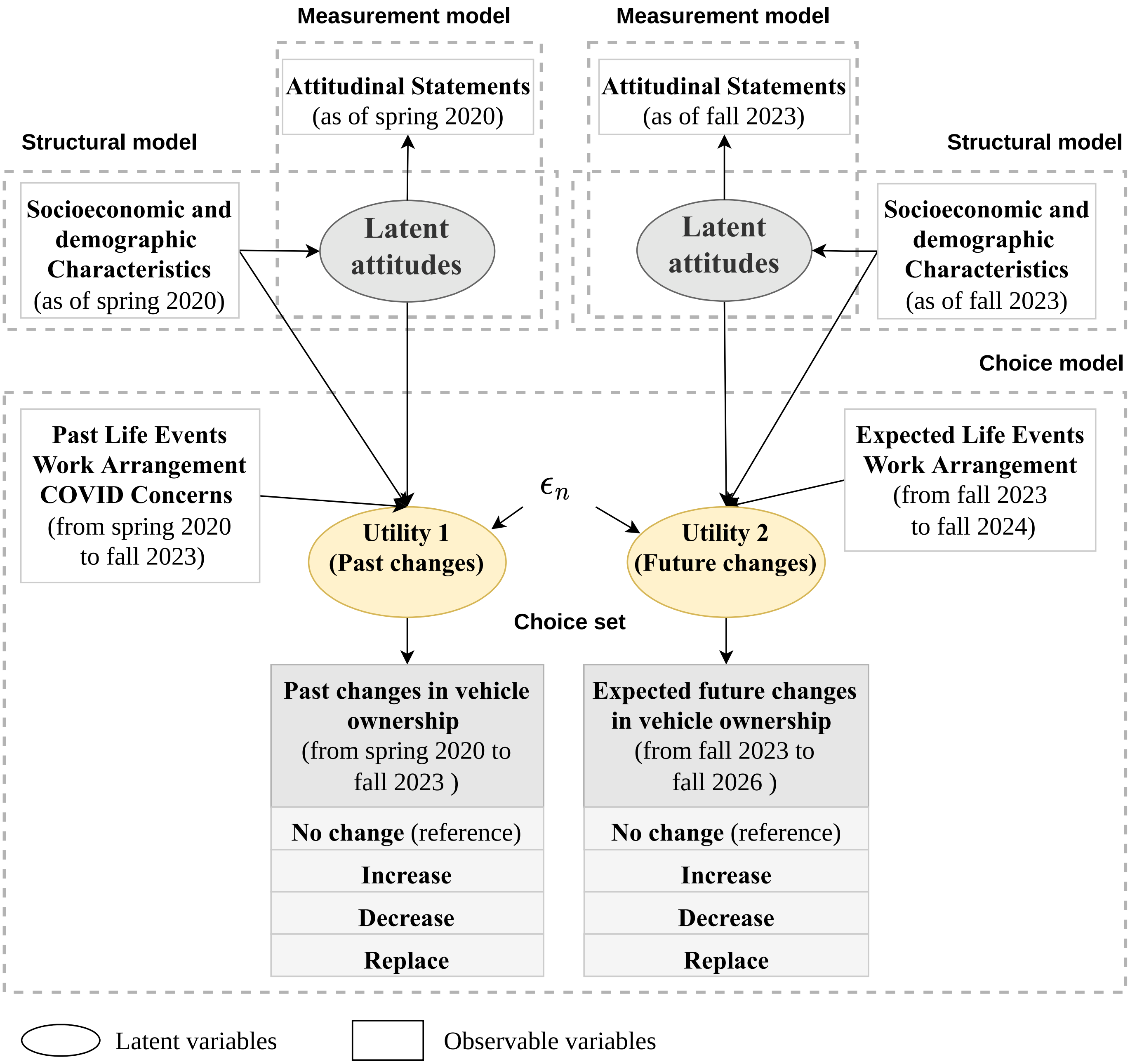


Figure 8-3. Modeling Framework of the ICLV Model

Table 8-1. Results of the Choice Model (N=1,612)

Variables	Categories	Past changes in vehicle count (Spring 2020 → Fall 2023, "no change" as the reference)			Expected future changes in vehicle count (Fall 2023→ Fall 2026, "no change" as the reference)		
		Increase	Decrease	Replace	Increase	Decrease	Replace
Attitudes (Past: as of Spring 2020; Expected: as of Fall 2023)							
Pro-environment				-0.13*			
Pro-driving					0.22***		
Pro-active				0.21**			
Novelty-seeking					0.33**	0.40**	0.26***
Socio-demographic Characteristics (Past: as of Spring 2020; Expected: as of Fall 2023)							
Age cohort (ref[1]: Millennials or younger)	Generation X				-0.59***		
	Baby Boomers or older	-1.21***			-0.68***		
Gender (ref: non-female)	Female	-0.43**					
Race (ref: not white only)	White only				-0.54**		
Educational attainment (ref: lower than bachelor)	Bachelor's degree or higher						0.38**
Household size (ref: one member)	Two members		1.33***	0.69***			0.69***
	Three or more members		1.34***	1.05***			0.76***
Presence of a child(ren) (ref: no)	Yes	1.12***			1.42***		
Annual household income (ref: less than $50,000)	$50,000 - $99,999						0.72***
	$100,000 or more	0.55**					0.74***
Past (Spring 2020-- Fall 2023) and Expected (Fall 2023-- Fall 2026) Life Events							
Employment status (ref: no change)	Worker→ non-worker					1.16**	
	Non-worker → worker				1.21***		
Household income (ref: no change)	Increased	0.90***		0.37**	---	---	---
Number of kids (<18) (ref: no change)	Increased	0.91**		0.70**	---	---	---
Number of adults (18-64) (ref: no change)	Increased	0.76***		1.05***	---	---	---

Variables	Categories	Past changes in vehicle count (Spring 2020 → Fall 2023, "no change" as the reference)			Expected future changes in vehicle count (Fall 2023→ Fall 2026, "no change" as the reference)		
		Increase	Decrease	Replace	Increase	Decrease	Replace
Past (Spring 2020 --Fall 2023) and Expected (Fall 2023--Fall 2026) Work Arrangement							
Monthly commute frequency			-0.03**		0.02*		0.01*
Change in commute			-0.04***	-0.02**			
Change in remote							0.02**
COVID Health Concerns (Past changes: as of Spring 2020)							
Level of concerns (ref: not concerned or neutral)	Somewhat concerned		-0.95***		---	---	---
	Strongly concerned		-0.96***		---	---	---

Notes:

1. Ref refers to the reference category for a given variable, for which coefficients for the other categories are listed here, indicating differences in probabilities for distinct types of vehicle changes.
2. Statistics in the table represent coefficients and significance level (*10%, **5%, ***1%).
3. Blank cells indicate variables that are tested in the model but not statistically significant, whereas cells with "---" indicate variables that are not tested in the model due to lack of information.

8.1.3 Results

Table 8-1 lists variables that have statistically significant impacts on the past and expected future changes in vehicle count. Overall, the significance level and magnitude of these variables' impact varied across two timepoints (Anowar et al., 2016).

8.1.3.1 Attitudes

The measurement model[1] revealed four significant latent variables: *pro-environment*, *pro-driving*, *pro-active* and *novelty-seeking*.

The *pro-environment* factor encompasses individuals' attitude towards environmental protection. In both timepoints, *pro-environment* attitudes were more pronounced among those with higher education (Dietz et al., 2002) and urban residents (Ambrosius & Gilderbloom, 2015). The younger cohort is found to be more pro-environment as of Spring 2020 (Yamane & Kaneko, 2021). The *pro-driving* latent factor indicates people's strong preference to own a vehicle and their enjoyment from driving. Females and those with higher education were less *pro-driving,* while those with a driver's license were the opposite. Homeowners are found to be more *pro-driving* in Spring 2020, while suburban or rural residents are found to be more *pro-driving* in Fall 2023. Unsurprisingly, older individuals were less *pro-driving* potentially due to their physical constraints. The *pro-active* factor pertains to people's value on active lifestyle through regular walking and exercising. Preferences for active lifestyles were more prevalent among younger individuals, those with higher education and high household incomes and urban residents in both timepoints. Those with children and those without driver's license are also more *pro-active* in Spring 2020, but this is not the case in Fall 2023. The *novelty-seeking* factor reflects an individual's familiarity and proficiency with new technologies, as well as their inclination and openness to new things and experience. Younger individuals, of Hispanic, Latino or Spanish origin, with higher household incomes, living with a child(ren) in the household, and urban residents are more novelty-seeking.

Between Spring 2020 and Fall 2023, individuals with a stronger *pro-environment* stance were less likely to have replaced vehicles, whereas those with a greater proclivity for active lifestyles were more likely to do so. Regarding expectations, *pro-driving* individuals are more likely to increase their vehicle count. Unsurprisingly, individuals characterized by a propensity for *novelty-seeking* have higher chances of altering their vehicle count. More precisely, they are more likely to acquire new vehicles, dispose of their current ones, or replace existing one(s) with different models.

8.1.3.2 Socioeconomic and Demographic Characteristics, Life Events, Work Arrangements and COVID Concerns

Younger generations demonstrated a higher propensity to increase vehicle count compared to older cohorts. This trend is attributed to the dynamic nature of their life, which has a greater

[1] Coefficients from the measurement models were omitted in this report for the sake of conciseness.

need for additional vehicles to accommodate commuting obligations and household responsibilities. A similar pattern emerges when comparing Millennials to Gen X regarding the expected vehicle ownership change in the coming three years.

Furthermore, gender disparities are evident, with females exhibiting a lesser inclination towards augmenting their vehicle ownership. This aligns with existing research highlighting lower car dependence among women compared to men (den Braver et al., 2020; Guan & Wang, 2019). Additionally, within multi-member households, females may exert lesser influence over vehicle ownership decisions, especially if they are not employed.

Households with children are more predisposed to have increased or expect to increase their vehicle count. A positive correlation between the increase in the number of children/adults and the rise in household vehicles during the pandemic is observed, corroborating findings from prior research (Goodwill, 1993; Lee & Goulias, 2018). Households with children have more intricate travel needs, including school drop-offs, extracurricular activities, and medical appointments, which may necessitate vehicle usage.

Moreover, higher educational attainment as of Fall 2023 is associated with a greater likelihood of vehicle replacement in subsequent years. Those with higher income levels are also more likely to have increased their vehicle count in the past and expect vehicle replacement in the future. Additionally, households with increased income in the past tended to have added or replaced a vehicle(s) compared to those without changes in income. After all, education and income level typically positively correlate with economic opportunities, demand for travel, and resources for mobile lifestyles.

Work status also plays a significant role in changes in vehicle count. Individuals expected to start or resume work by Fall 2024 are more likely to increase their vehicle count in the future, while those anticipating a pause or termination in employment are more likely to shed their vehicle(s). Regarding work arrangement, a higher monthly commuting frequency is associated with a decreased likelihood of vehicle reduction in the past, and an increased likelihood of vehicle addition or replacement in the future. Additionally, an increase in commuting frequency between Spring 2020 and Fall 2023 was negatively associated with vehicle-shedding in the past, while an expected increase in remote working frequency between Fall 2023 and Fall 2024 is positively associated with vehicle replacement in the future.

Finally, individuals who expressed concerns about the health impact of the coronavirus in Spring 2020 were less inclined to decrease their vehicle ownership in the past. This trend reflects shifts towards private means of travel (e.g., driving) during the pandemic due to lingering health concerns about the pandemic (Loa et al., 2021; Zhang et al., 2021).

8.2 VMT by Population Groups and Trip Purposes

8.2.1 Introduction

Vehicle travel, measured as VMT, experienced a sharp decline following the implementation of “stay-at-home” orders issued by the state and counties in response to the pandemic. As depicted in Figure 8-4, there was a notable decrease in VMT during the initial stages of the pandemic (U.S. Federal Highway Administration, 2024). In April 2020, during the first peak of the outbreak, daily VMT nationwide in the U.S. were as low as 40% of the value expected had there been no pandemic (Bureau of Transportation Statistics, 2020). This reduced travel activity also led to a noticeable decrease in air pollution across cities in the U.S., with Brodeur et al. (2021) documenting a 25% reduction of PM2.5. The changes resulting from the stay-in-place orders represent an opportunity for fundamental shift in travel behavior within the state. However, VMT quickly rebounded along with economic recovery and had fully returned to pre-pandemic levels by Fall 2023.

As VMT generation continues to evolve, it is essential to investigate what factors influence VMT and the impacts vary among different demographic groups. For instance, the impact of remote work on VMT warrants examination. Pre-pandemic research has presented conflicting findings, with some studies suggesting a decrease (Koenig et al., 1996; Ory & Mokhtarian, 2006), while others indicate an increase (Ravalet & Rérat, 2019) in individual travel due to remote work. A recent study in Chicago revealed that a rise in flexible work hours from the baseline of 12% to 50% could reduce system-VMT by up to 2%, translating to about 0.71% and 1.14% reductions in greenhouse gas (GHG) and particulate matter emissions, respectively (Shabanpour et al., 2018). Additionally, Brodeur et al. observed that counties with younger populations and a higher share of remote-work capable jobs experienced more substantial declines in air pollution (Brodeur et al., 2021). Further investigation is necessary to validate the effects of remote work on VMT. This information is valuable for policymakers in identifying opportunities for VMT and GHG emission reduction from transportation in the post- COVID-19 era.

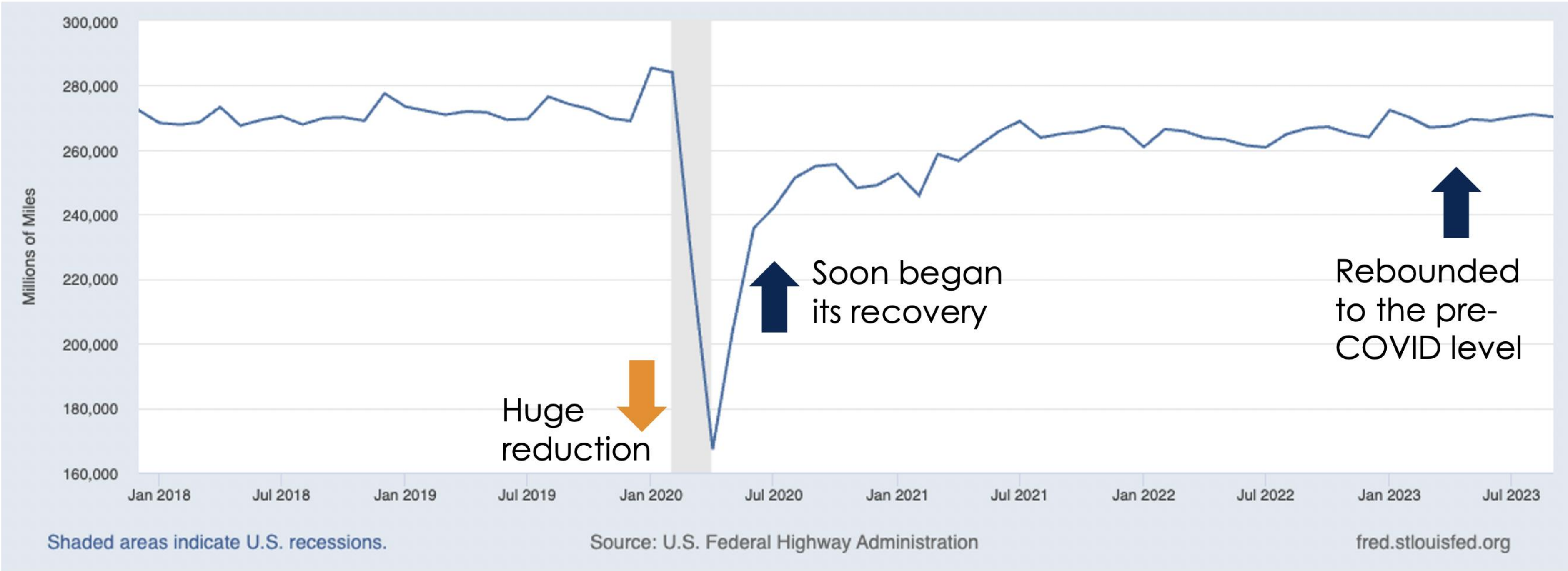


Figure 8-4. Seasonally Adjusted monthly VMT in the US

8.2.2 Data and Method

Measuring VMT accurately is crucial for planning purposes, yet traditional methods often rely on GPS tracking devices, which are costly, require intense post processing of raw data, and challenging to administer due to errors and issues on the participant side. In this regard, in the Fall 2023 survey, the team devised an innovative approach, breaking down VMT into three categories (illustrated in Figure 8-5), which enhances respondents' ability to recall each part with greater accuracy and precision. For commute related VMT, the research team multiply the respondents' self-reported commute distance with the frequency of driving (as detailed in Section 7.2.1). Non-commute related VMT encompasses trips for work but not commutes, and include leisure, shopping, and other purposes. Additionally, long-distance trips exceeding 50 miles one way are reported separately, with respondents given the option to report either monthly or yearly VMT depending on how frequent they have those trips. Furthermore, participants were able to over-write the estimated commute and non-commute VMT if they recognized inaccuracies. Questions concerning commute and work-related trips were only asked among students and workers as of Fall 2023 (n=1,965), while questions related to all other trips were presented to all 4,067 California residents.

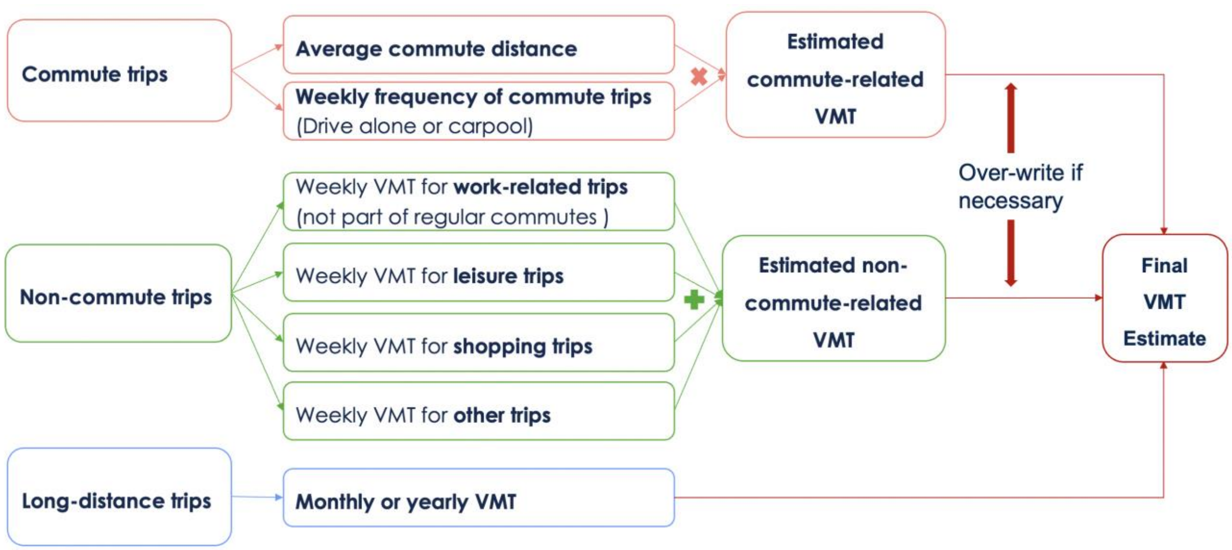
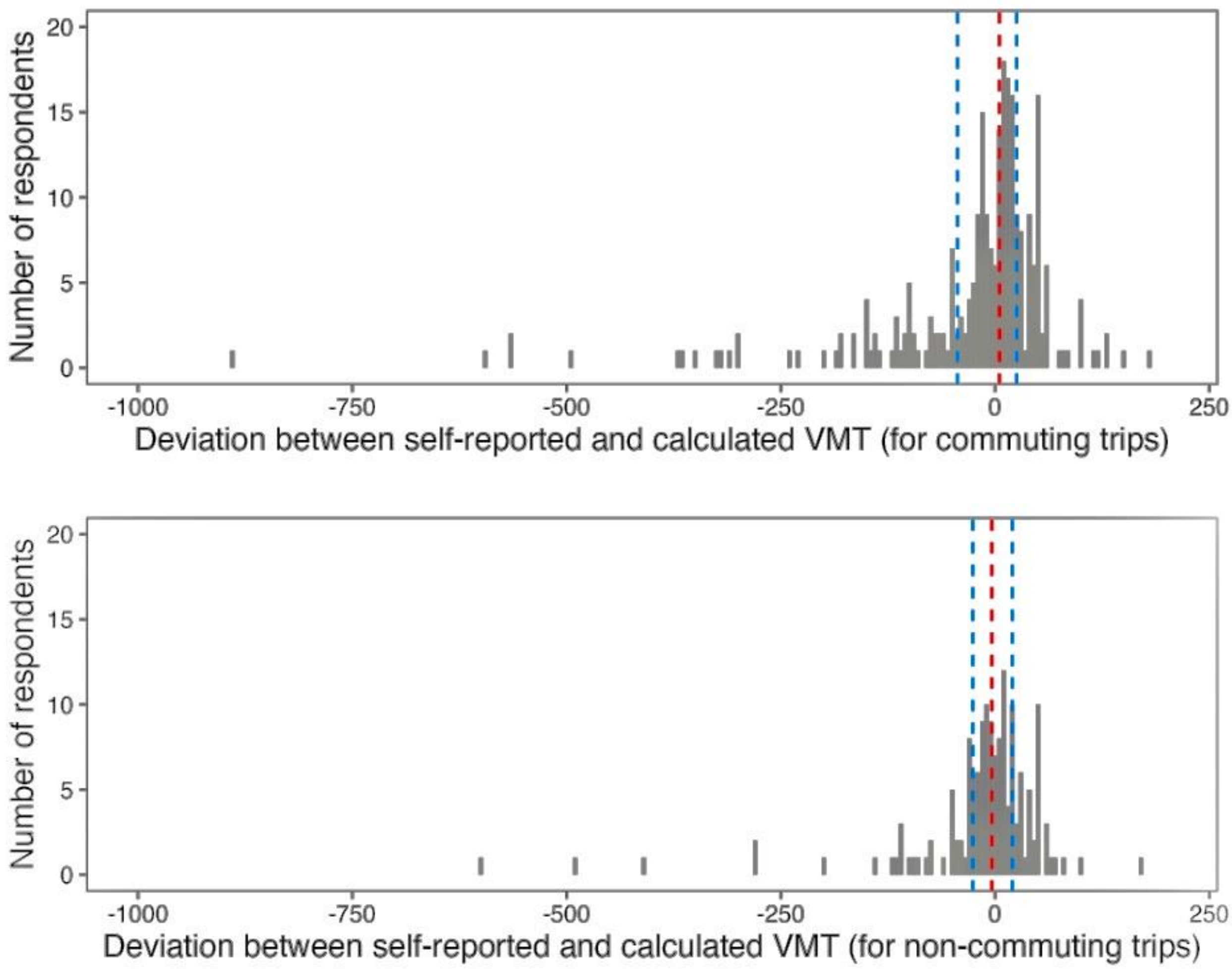


Figure 8-5. **VMT question set in the** Fall **2023 survey**

In total, 261 and 153 respondents over-wrote the calculated VMT with their self-reported VMT for commuting trips and non-commuting trips, respectively. As depicted in Figure 8-6, the average deviations between these self-reported and calculated VMT are not dramatic, with 75% of those made adjustments Falling into a narrow range. For those who updated their estimates for non-commuting trips, it is important to note that their breakdowns can no longer be used for further analyses.



Note: colored dash lines from left to right represent 25, 50 and 75 percentiles.

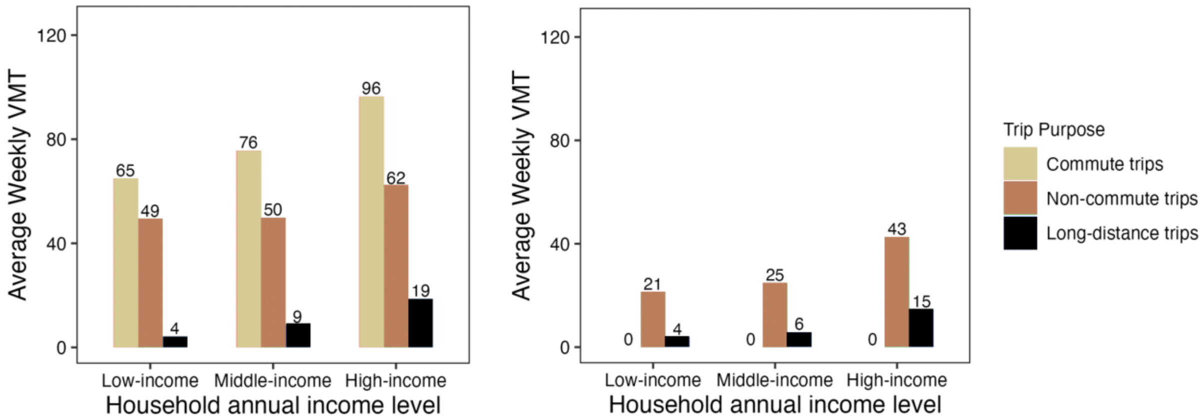
Figure 8-6. Deviation between self-reported and calculated VMT for commuting and non-commuting trips

8.2.3 Results

The VMT patterns are presented separately for students/workers and the rest of population, as two distinct behaviors are expected.

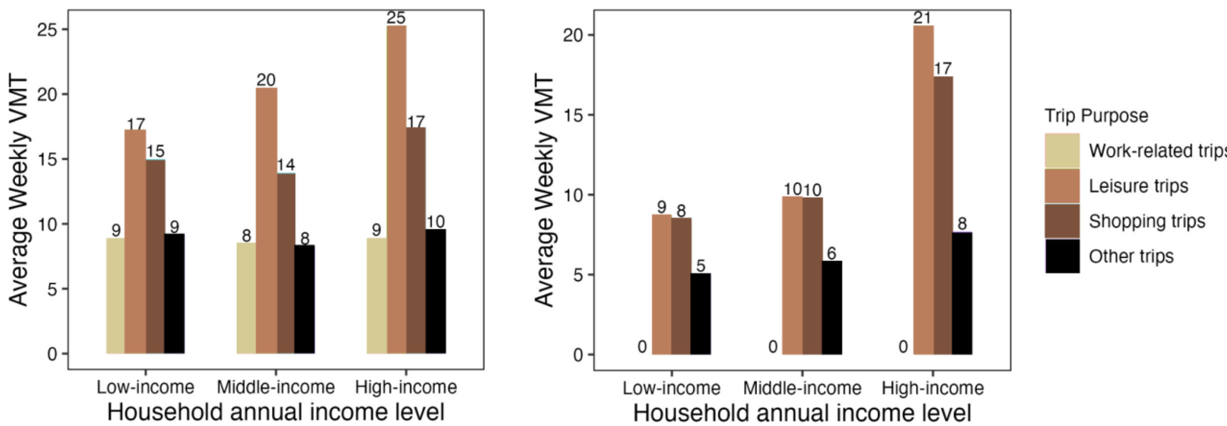
Figure 8-7 shows the average weekly VMT by different trip purpose across three income groups. Across the board, individuals living in high-income households (earning $100,000 or more annually) generate the highest VMT for all purposes, regardless of their student or work status. Moreover, students and workers tend to engage in more non-commute and long-distance trips compared to their counterparts.

Figure 8-8Figure 8-8 delves deeper into non-commute trips. While there are no disparities in work-related, shopping, and other trips across different income levels, the most prominent differences across groups manifest in leisure trips.



(Students or workers, n=1,965) (Non-students and non-workers, n=1,253)

Figure 8-7. Estimated average weekly VMT by trip purposes and household income levels



(Students or workers who did not overwrite the calculated VMT, n=1,965) (Non-students and non-workers who did not overwrite the calculated VMT, n=1,106)

Figure 8-8. Estimated average weekly VMT for non-commuting trips by trip purposes and household income levels

Figure 8-9 and Figure 8-10 present comparisons among individuals with different work arrangements. As expected, commuters exhibit the highest VMT pertaining to their commute. Interestingly, they also have the highest VMT for non-commuting and long-distance trips. Conversely, remote workers, who predominantly avoid commuting, generate lower commuting VMT compared to hybrid workers. However, they have higher non-commuting VMT compared to hybrid workers.

Regarding the four non-commuting trip categories, commuters consistently generate the highest VMT in every category. Remote workers surpass hybrid workers in VMT for leisure, shopping, and other trips.

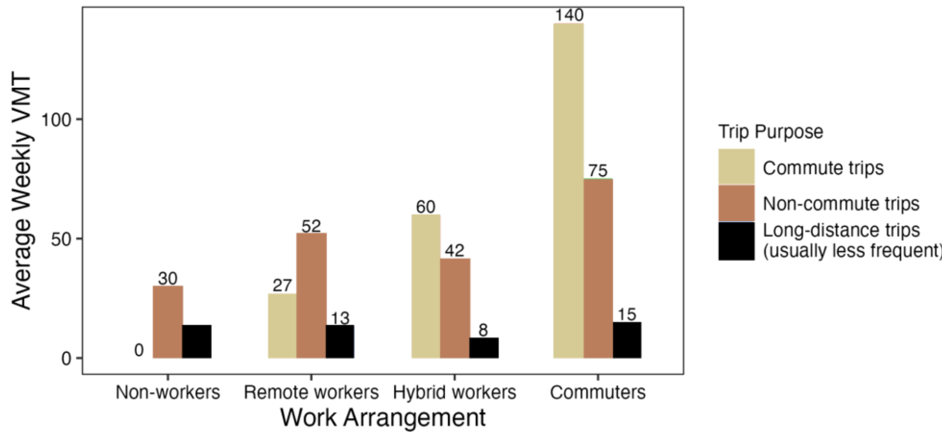


Figure 8-9. Estimated average weekly VMT by trip purposes and work arrangements (n=3,218)

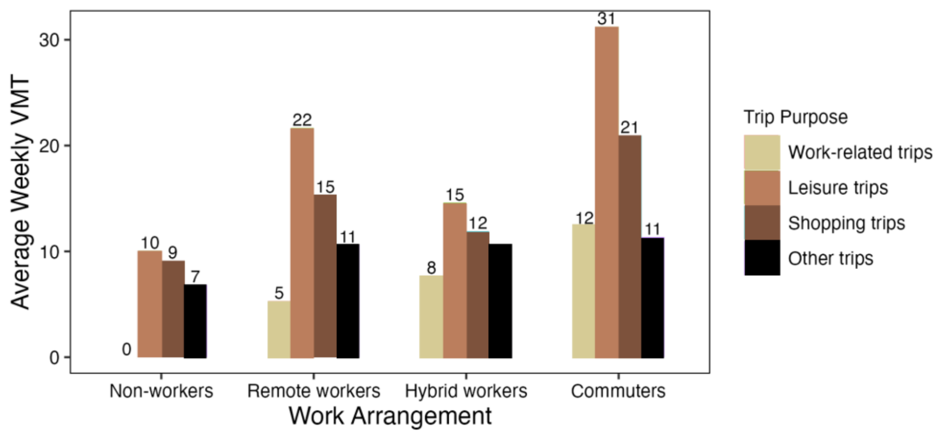


Figure 8-10. Estimated average weekly VMT for non-commuting trips by trip purposes and household income levels (N=3,071, among those who did not overwrite the calculated VMT)

It is crucial to note that the statistics presented above offer comparisons based solely on descriptive statistics and should not be interpreted as causality. For example, factors such as income may influence the likelihood of being a remote worker and VMT levels. Therefore, conclusions regarding the impact of teleworking on VMT cannot be drawn solely from these observations. While these simple statistics serve to generate hypotheses, uncovering deeper nuances necessitates advanced modeling. The research team aims to further explore the causal effect of work arrangements on VMT and the interrelationships among trips between different trip proposes (e.g., substitution effect between commute trips and leisure trips). Expected results could provide valuable policy recommendations aimed at decreasing vehicle ownership, reducing commute trips, and effectively managing remote and hybrid work arrangements.

9 Unique Challenges and Adjustments of Low-Income Households During the Pandemic

This chapter presents descriptive analysis on three survey waves – Fall 2020, Summer 2021, and Fall 2023 – regarding low-income respondents' various challenges across multiple domains during and after the pandemic. In doing so, it takes a basic approach to identifying low-income individuals in the survey data, i.e., those who reported before-tax household income as below $50,000. Each survey wave was then split into two income groups, low income and middle/high-income groups, and key personal and household attributes are computed and compared to each other and tested for statistically significant differences (e.g., chi-square test for categorical variables and t test for continuous variables). Key findings and implications are presented below and associated summary tables are in the appendix.

9.1 Worker Status, Nature of Work, and Perceptions of Remote Work

9.1.1 Worker status

In Fall 2020, larger shares of low-income respondents reported the following cases: "*I was let go from my job during the COVID-19 pandemic.*", "*My place of employment went out of business during the COVID-19 pandemic.*", and "*I am now working fewer hours than I did before the COVID-19 pandemic.*" After all, low-skilled low-earning workers often find jobs in the retail and service sectors, in which well-performing in-person interactions is a key to the success of businesses and job stability of employees. In addition, in Summer of 2021 and even in Fall of 2023, a greater proportion of low-income workers were looking for employment than non-low-income workers. That is, pandemic-caused work-related hardships (e.g., a loss of jobs, periods of un/under-employment, and disruptions in one's career development) may have left long-lasting impacts, especially on low-income workers.

9.1.2 Nature of job

The mobility panel includes a few related but different questions regarding the telework-ability of one's job, and across all those questions, low-income workers answered that their jobs were less feasible for remote work (see Figure 9-1). In Fall of 2020, about half of low-income workers indicated that the nature of their job did not allow them to work from home. A similar portion of them strongly agreed that they had to "*physically go do work even* [for periods with high risk of infections] *during the pandemic*". In Summer 2021, about half of low-income workers selected "*Never*" to two questions, "*What is the maximum frequency that the nature of your job would allow you to telework?*" and "*What is the maximum frequency that your supervisor would let you telework?*". In Fall 2023, similar patterns persist, suggesting that low-income workers continue working at jobs for which in-person performance is critical (or the only mode), or those jobs could not be transformed during the pandemic to accommodate alternative modes of work.

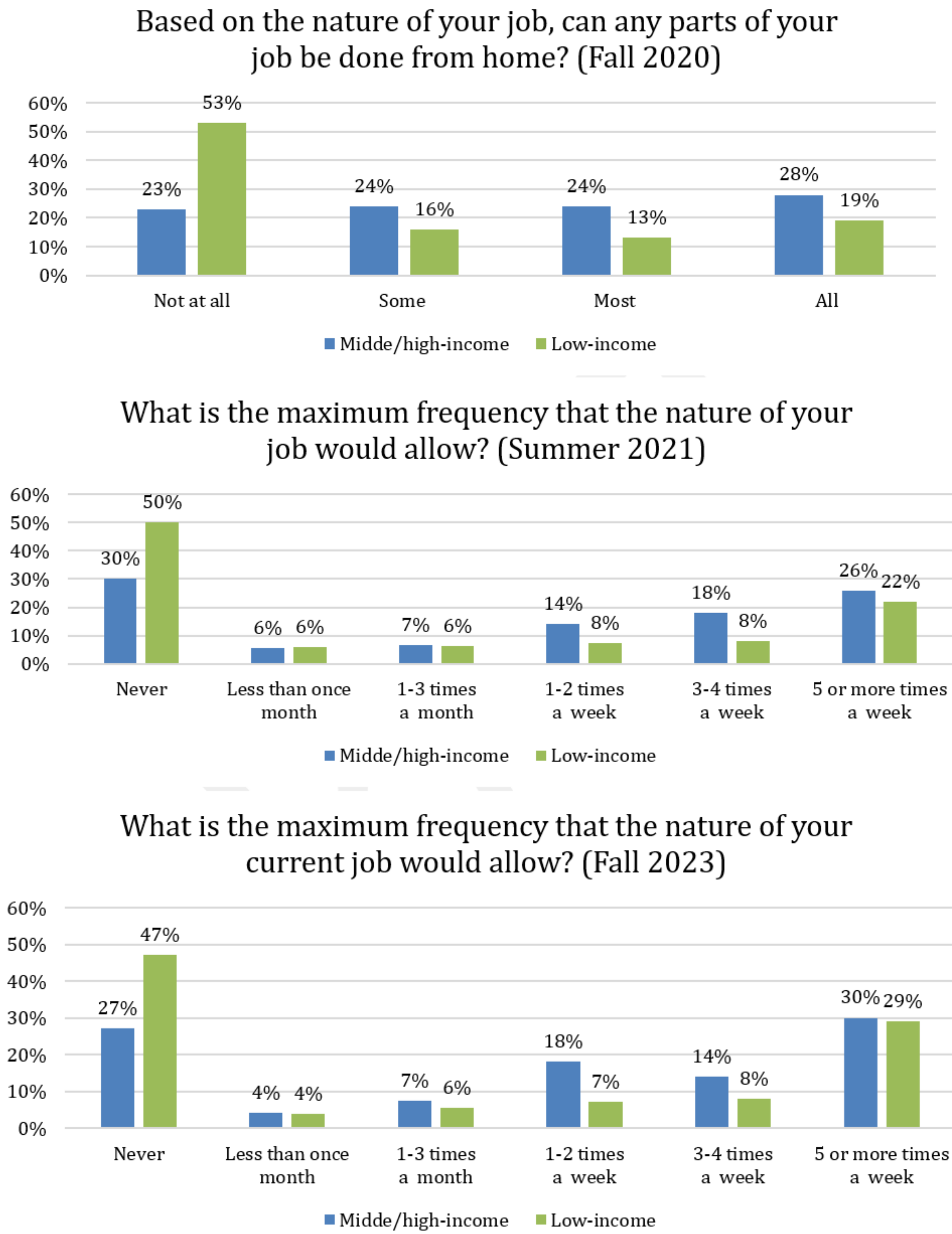


Figure 9-1. Feasibility of Remote Work

9.1.3 Perception about remote work and technology

Regarding their evaluation of teleworking experience, smaller shares of low-income workers did not reject the idea that "*Working from home is not practical (e.g., due to lack of office devices, distractions from family members).*" Their response patterns are consistent across Fall 2020, Summer 2021, and Fall 2023. A possible reason for low-income workers to struggle while working remotely (more so than their non-low-income counterparts) may be because of their lack of access to digital devices or less familiarity with information communication technology in general. In fact, low-income individuals (not only low-income workers) tend not to have laptops and desktop computers at home, consistent across three survey waves (e.g., 14-24% point lower). In addition, in response to an attitudinal statement "*I like to be among the first people to have the latest technology*.", intended to measure individuals' familiarity with the latest technology and savviness, low-income individuals (not only low-income workers) tend not to agree as strongly as their non-low-income counterparts. After all, early adoption often requires non-trivial economic and financial resources, which low-income individuals are lacking while meeting essential needs met.

9.2 Access to Private Vehicles and Attitudes about Transportation Options

9.2.1 Access to private vehicles

Not surprisingly, low-income households have less access to private vehicles (see Figure 9-2). The differences between the two income groups in terms of owning a private vehicle are consistent at about 20% in all three survey waves: in Fall 2020, 68% and 87%; in Summer 2021, 66% and 86%; and in Fall 2023, 67% and 81% for low-income households and the others, respectively. In addition, a larger share of low-income households have no regular access to private vehicles (via other channels such as via job or borrowing from friends and relatives): Fall9.6% vs 1.5% in Fall 2022, Summer, 13% vs 2.4% in Summer 2022, and Fall18% vs 2.9% in Fall 2023 for low-income households compared to others respectively. These patterns point to low-income households' unique challenges in meeting their routine travel demand, both during and after the pandemic. Low-income workers had to work in-person during the pandemic, during which public transit services were cut severely and considered not safe, and low-income individuals now make daily trips with a combination of private vehicles and public transit, whose supply has not yet recovered to pre-pandemic levels.

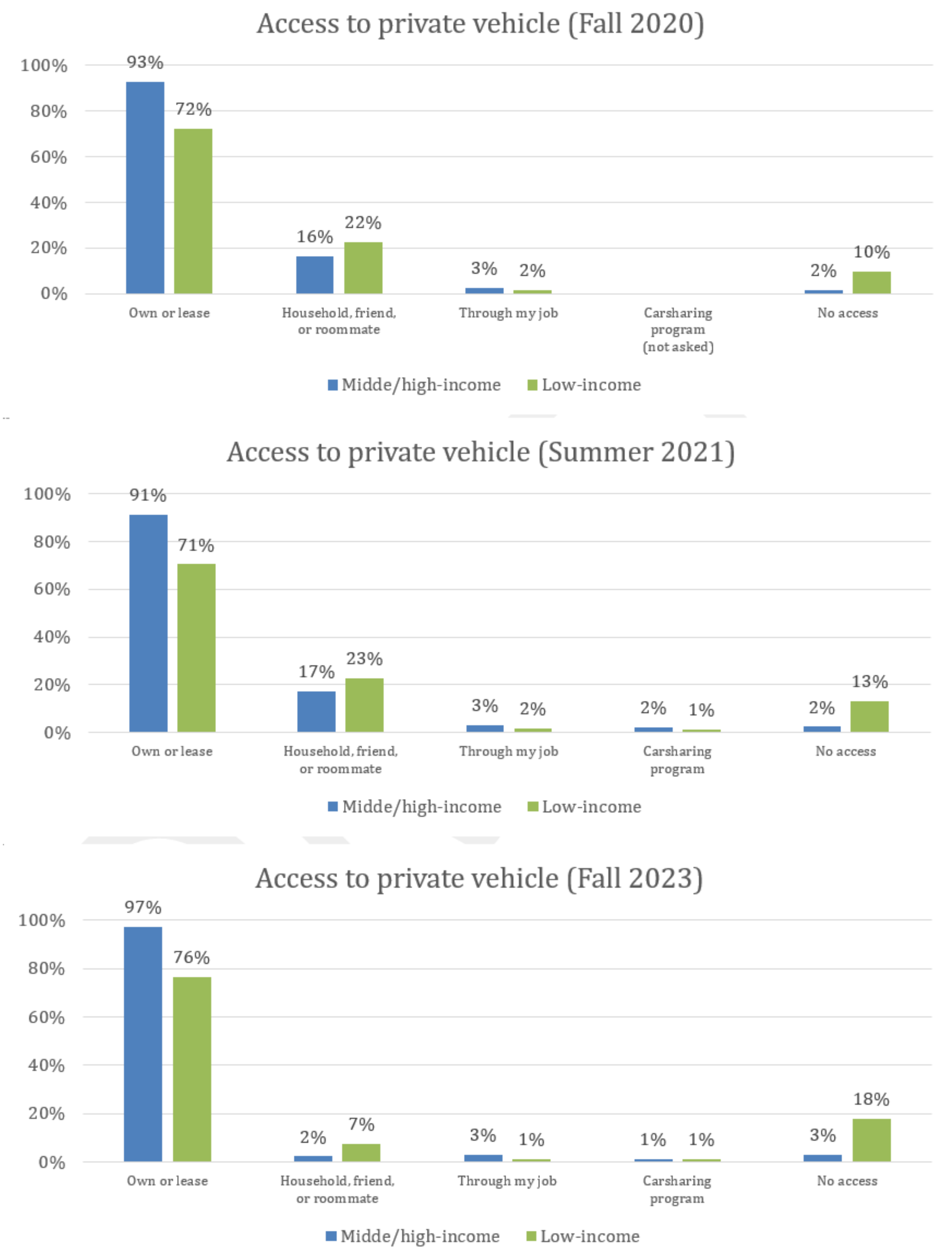


Figure 9-2. Access to Private Vehicles

9.2.2 Perceptions and preferences about transportation options

To understand attitudes towards transportation options and their changes over time, the three surveys included several attitudinal statements, asked on a five-point Likert scale from "*Strongly disagree"* to "*Strongly agree*", some of which appeared repeatedly across multiple waves of the survey.

- *"To me, a car is just a way to get from place to place."* (all three waves)
- *"I like the idea of public transit as a means of transportation for me."* (all three waves)
- *"My schedule makes it hard or impossible for me to use public transportation."* (all three waves)
- *"We should raise the price (or cost) of gasoline (or driving) to provide funding for better public transportation."* (all three waves)
- *"I will feel uncomfortable using public transportation due to concerns about pathogens (e.g., COVID-19 or other)."* (Fall 2020, Summer 2021)
- *"My local transit agency's efforts to minimize COVID exposure to passengers is sufficient to make me comfortable using transit."* (Fall 2020)
- *"I am generally satisfied with my transportation options."* (Summer 2021)

As expected, low-income respondents tend to value a car's practical aspect (as a means for transporting passengers) more than non-low-income respondents. By contrast, differences in perception regarding public transit are nuanced. First, regarding their affection towards public transit, the two income groups are not statistically different in two waves out of three. Even in Summer 2021, where differences between the two income groups are statistically significant (at $p < 0.05$), low-income respondents appeared to like public transit less, not more, than the others. That is, more frequent use of public transit by low-income individuals seems to be by necessity or constraint, not by choice based on preferences. In addition, across all three survey waves, low-income respondents reported schedule conflicts to be less of an issue when it comes to public transit use, compared to respondents from the other income groups. Since the former rides public transit more than the latter, they seem to have realistic knowledge about transit schedules and coverage, which the latter may have a vague or biased understanding. Interestingly, middle/high-income groups are more likely to support policy that raises the cost of driving to support public transit. After all, low-income individuals also drive (although not as much as their middle/high-income counterparts), and these individuals may prefer more public spending on social services, but not on public transit. As for discomfort in riding public transit out of health concerns in Fall 2020, the two income groups were marginally different (at $p<0.05$) especially for "*Somewhat agree*" (i.e., somewhat concerned; 30% among the middle/high-income groups vs. 25% among the low-income group). In Summer 2021, the differences between the two income groups were not statistically significant. That is, transit riders and non-riders (i.e. frequent and occasional) are not very different in terms of hygienic concerns. However, while the latter had the luxury of choosing other transportation options, the former may not have had that luxury.

9.3 Economic Hardship and Life Satisfaction

Not surprisingly, low-income households reported struggles in meeting basic needs during and after the pandemic (see Figure 9-3). To be specific, the proportion of individuals in the lower-income groups with issues paying bills are larger than those among middle/high-income groups. Response patterns have not changed much across the three survey periods, implying that post-pandemic economic recovery has been limited to certain segments in the population, while not relieving much of financial burdens on low-income households. With all hardships and struggles, low-income households may well report overall less satisfaction with their life than those in the other income groups. While large shares of higher income households reported positive responses (78% in Fall 2020, 83% in Summer 2021, and 84% in Fall 2023 for "*Somewhat agree*" and *"Strongly agree"* combined), the lower-income households are left quite behind (44% in Fall 2020, 62% in Summer 2021, and 64% in Fall 2023).

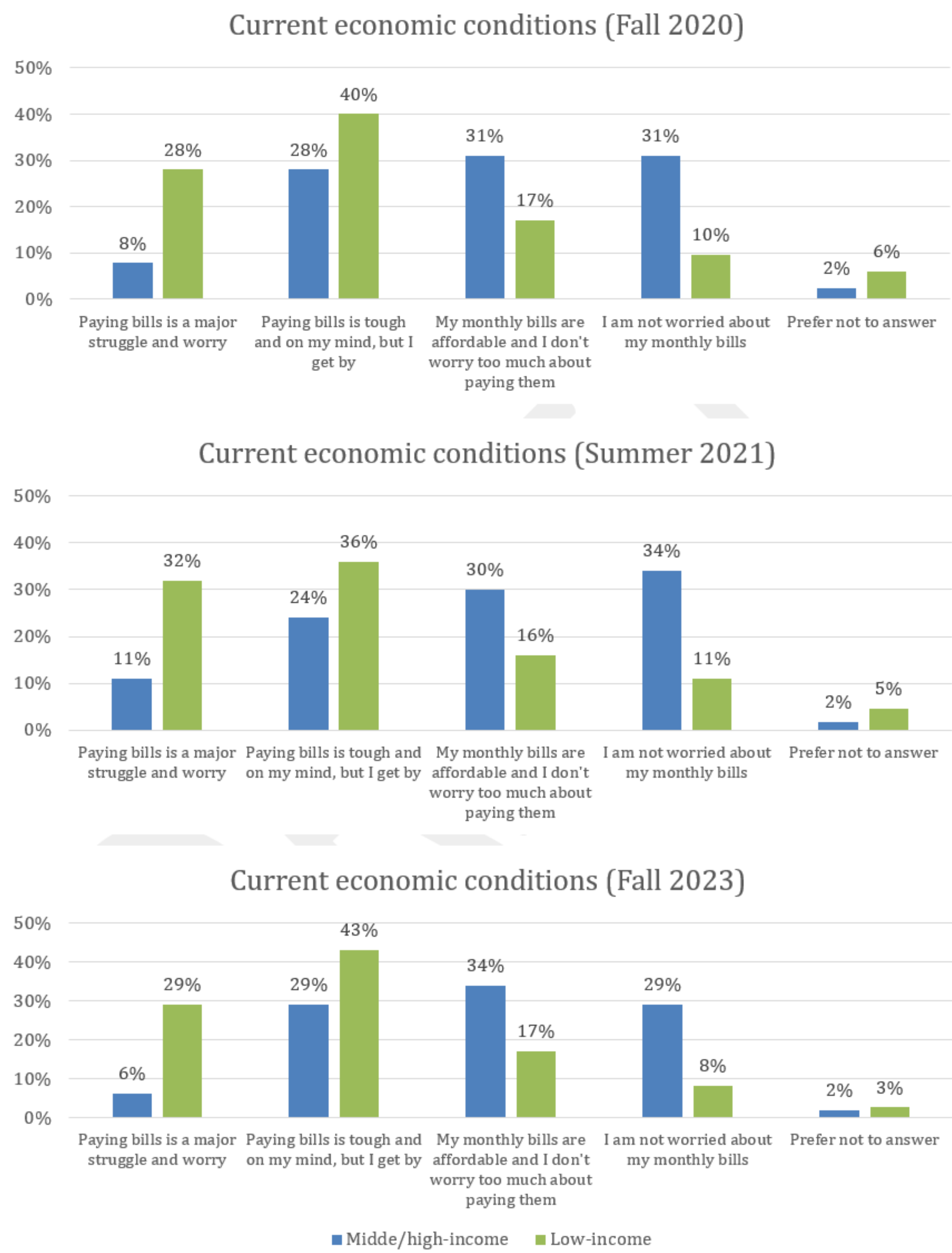


Figure 9-3. Current Economic Conditions

10 Key Findings and Discussion

10.1 The evolution of Remote work and Hybrid Forms of Work

Remote/hybrid work practices were largely accelerated by the pandemic since early 2020 to reduce the exposure to COVID-19 infection. With wide-spread use of online communication tools, about 60% of workers adopted remote or hybrid workstyles as of 2021. At that time, many workers anticipated to finally embrace the hybrid work practices in 2022, for a good balance between the on-site work and work-from-home. However, the new survey dataset collected in Fall 2023 illustrated that the share of remote work practices is even higher than what people expected for 2022.

Some additional findings have been provided through looking at the remote/hybrid work practices over different social cohorts. For example, when it comes to the tendencies among different generations, the younger group were more used to remote-work practices since the pre-pandemic period. However, they seem to be less willing to the remote-work-oriented workstyle in the future compared to older groups. Also, a small discrepancy exists between the non-Hispanic/Latinx group and Hispanic/Latinx group, indicating that the former group would be more likely to adopt remote/hybrid work practices as of 2023 and would still be in 2024.

Workers in the 2023 survey dataset now report a somehow stable workstyle as the expectation in 2024. This implies that the work arrangements of society are overall now converging to the new normal in the post-pandemic era. Therefore, it is an emergent task of researchers to identify the profile of people's workstyles and to explain the underlying motivations/challenges that encourage/discourage workers to/from adopting work-from-home practices.

To satisfy this need, the research team developed a new question in the 2023 survey, revealing the work arrangements in the two-hour granularity. The result showed that 16.5% of the weighted sample workers experienced two or more work *episodes* (i.e., the number of continuous work experience at one location in a day) at least once in a week, supporting the importance of the detailed question. Future studies will explore variations in episodes across occupations and individual characteristics, aiming to promote remote/hybrid work practices.

10.2 The evolution of E-Shopping throughout the COVID-19 pandemic

The pandemic has significantly impacted e-shopping trends by boosting existing patterns and introducing significant shifts for some population groups. In the pre-pandemic period, there was already a growing reliance on e-shopping solutions. This trend intensified during and after the pandemic. This study shows that the proportion of respondents who shopped online at least once a week increased from 10.8% to 22.6% for grocery items, and from 33.3% to 45% for non-grocery items, between 2019 (pre-pandemic) and 2021 (during the pandemic). When comparing the shares during the pandemic with their post-pandemic counterparts, the new e-shopping behavior persisted in the post-pandemic period, with the proportion of respondents who shopped online at least once per week at 22.7% for grocery items and 43.2% for non-grocery items in the Fall 2023 period. This shows that the impacts of the COVID-19 pandemic on e-shopping may be long-lived, which could be explored further through new data collections in the upcoming years.

In the analysis of changes in e-shopping based on socio-demographics throughout the pandemic, younger age and higher household income continue to be positively correlated with e-shopping frequency. Those who were young adults and come from higher income households were more likely to shop online for non-grocery items prior, during, and after the pandemic. However, it is important to note that those with higher income levels shopped more for groceries pre-pandemic, but in the post-pandemic period, they have shifted away from online grocery shopping, which is a trend that should be investigated further. Regarding the association between e-shopping and age, it is crucial to underline that the increase in e-shopping frequency was most visible for older adults, who were traditionally less inclined to shop online. Notably, individuals with lower educational attainment, who were previously more inclined to shop online for non-grocery items, no longer exhibit a higher likelihood to do so in the post-pandemic period. This shift may be attributed to the universal impact of COVID-19 on less skilled workers, prompting disadvantaged individuals with lower educational attainment to limit their shopping frequency in general.

Initially, a gender disparity in e-shopping habits was found, with men showing a higher likelihood to shop online for non-grocery items and women for grocery items. However, the onset of the pandemic led to the change of this trend, with men increasingly reporting less frequent online shopping than women for all types of items. Conversely, women exhibited a higher likelihood of frequent online shopping (i.e., shopping at least once a week) during and after the pandemic period. This shift highlighted the significant impact of the pandemic on women's increased engagement in e-commerce activities.

The findings demonstrate that those who are unable to transition to e-shopping may face economic challenges as frequent and experienced e-shoppers increase their purchases and more individuals adopt e-commerce activities. This shift in consumer behavior may prompt vendors to relocate away from central parts of the cities, potentially reducing shopping options for those who prefer the traditional methods. This might eventually lead to a significant decrease in purchasing costs for in-person stores, further challenging the survival of small shops in downtown areas and impacting the vibrancy and diversity of urban life. Additionally, as e-shopping frequency increases, travel demand will undergo a significant shift, with individuals making fewer shopping trips but increasingly relying on online orders, consequently leading to a higher frequency of last-mile delivery trips. This will have impacts on increased GHG emissions associated with e-shopping and increased traffic related to logistics purposes in urban and rural areas. Potentially, the decrease in shopping trips could result in decreased VMT for shopping purposes for passenger travel, though e-shopping research has shown that individuals who reduce in-person shopping activities often continue to travel for social or entertainment purposes (e.g., meeting with friends or family, or going out for food or beverages, even if not shopping in person in stores). Overall, the increase in delivery-related VMT could at least in part cancel out the reduction in shopping VMT due to the surge in online orders.

10.3 Shifts in mode usage for commuting and non-commuting trips

The results of the analysis highlight similarities in the percentage of respondents travelling by private vehicle for commuting and non-commuting trips in Fall 2019 and Fall 2023. Moreover, there are certain segments of the population (such as people under the age of 35, those from households earning over $100,000 annually, and individuals who identify as Asian) who were more likely to have travelled by private vehicle in Fall 2023 compared to Fall 2019. In light of the continued use of private vehicles for travel, policies that aim to encourage carpooling and increase the VMT produced by zero-emissions vehicles can help mitigate the emissions produced by private vehicles. In the near-term, examples of such policies include incentivizing the purchase of hybrid and electric vehicles and encouraging employers to adopt transportation demand management strategies (U.S. Federal Highway Administration, 2023). Additionally, long-term strategies such as investments in public transit service, investments in walking and cycling facilities, and the adoption of land use and zoning policies that allow residents to travel shorter distances in their daily lives could help reduce the VMT produced by private vehicles.

The results suggest that respondents from households earning less than $100,000 annually and those who identify as Hispanic or Black were more likely to have travelled by bus in Fall 2023 compared to Fall 2019. Additionally, respondents from households earning less than $50,000 annually and respondents who identify as Hispanic were more likely to have travelled by subway or train. While this is encouraging, there are many segments of the population who were less likely to have used public transit in Fall 2023 compared to Fall 2019. However, additional work is needed to determine whether the frequency with which these modes were used in Fall 2023 is similar to that of Fall 2019. Given that transit ridership in the third quarter of 2023 among metropolitan areas in California with at least 500,000 residents remained below 2019 levels (Fitzpatrick & Beheraj, 2023), it is unlikely that transit was used as often in Fall 2023 as it was in Fall 2019. Efforts to reduce the VMT and emissions produced by private vehicles should aim to increase the use of public transit, which will likely require financial support from the state and federal government given the tendency for transit agencies to rely on fares to fun operating costs (Barbour et al., 2023; Vuchic, 2005). These initiatives could include increases in the frequency of existing transit routes, the span of transit service, and accessibility to public transit, with a focus on routes that serve communities where residents are more likely to use or to rely on public transit.

Similarly, measures could be implemented to encourage the use of bikes, e-bikes, and e-scooters. For example, prior studies have found that the decision to use bicycles and e-scooters can be influenced by perceptions of safety (Badia & Jenelius, 2023; Mitra & Hess, 2021; Teixeira et al., 2023). Moreover, cycling infrastructure tends to be “positively associated with cycling for transport” (Handy et al., 2014). Consequently, improving the quality and coverage of cycling facilities could help encourage the use of bikes and e-scooters. Additionally, offering promotions that provide the opportunity to try out shared bikes and e-scooters, either for free or at a discounted rate, could help encourage the use of shared bikes and e-scooters. These promotions could target college and university students, given that younger individuals are more likely to use shared bikes and e-scooters (Fishman, 2016; Yang et al., 2023). More broadly, these initiatives could target areas with a greater percentage of households earning less than

$100,000 annually and residents who identify as Hispanic or Black, as respondents belonging to these segments of the population were more likely to have used personal bikes, e-bikes, or e-scooters in Fall 2023 compared to the population as a whole. Besides, integrating shared bike and e-scooter services with public transit could also help encourage the use of these modes, particularly for commuting (Espinoza et al., 2019; Wang et al., 2023).

Notably, the percentage of respondents who reported walking was lower in Fall 2023 compared to Fall 2019 for both commuting and non-commuting trips. However, Fall 2023 respondents expressed relatively positive sentiments towards walking. This may suggest that the decline in the percentage of respondents who reported walking is due to differences in the attributes of trips made in Fall 2019 and Fall 2023. However, additional work will be needed to examine the factors influencing this decline, which can help inform efforts to make walking a more feasible alternative.

10.4 Changing Trends in Household Vehicle Ownership and VMT

Our study found that individuals who are *pro-driving* and *novelty-seeking* are more likely to consider increasing or replacing their vehicle in the future. Younger people have a higher likelihood in increasing vehicle count compared to their older counterparts. This can be attributed to their more dynamic household composition, financial condition, and student/work status. It is crucial to formulate policies that divert younger individuals away from increasing vehicle ownership, especially among those who are currently non-vehicle owners, while promoting alternative modes of travel. Moreover, higher educational attainment and income levels positively associate with vehicle addition and replacement. High-income individuals also associate with high VMT for all trip purposes (i.e., commute trips, non-commute trips and long-distance trips). After all, education and income level typically positively correlate with economic opportunities, demand for travel, and resources for mobile lifestyles. Furthermore, the presence of children is positively associated with increased vehicle ownership and an increase in the number of children and adults in the household is linked to an increase in vehicle ownership.

In terms of work status, those who expected a transition to employment in the near future also expect increased personal mobility needs, rendering increased vehicle ownership more desirable for them. Moreover, commuting is positively associated with a lower likelihood of shedding vehicles during the pandemic and a higher likelihood of purchasing/replacing vehicles in the future. However, significant impacts of remote work on vehicle count in the past were not observed. This may indicate that the effect of remote work on vehicle count depends on its influence on commute frequency. For instance, if workers opt for a flexible work arrangement where they split their working time between the worksite and remote work (e.g., working at the worksite for half the day and remotely for the other), the increase in remote work may not necessarily reduce travel needs. In fact, it could potentially lead to increased vehicle usage and more intricate trip chaining, especially if workers choose to work from third-party locations such as libraries or coffee shops instead of working at home. As remote workers reached an equilibrium point as of Fall 2023, remote working practice encourages vehicle replacement to fulfill newly established travel needs.

The research team calculated the Average Treatment Effort (ATE) of commuting frequency (Heckman & Vytlacil, 2000). For example, if the model indicates that work arrangement (e.g., commuting and remote work frequency) significantly influences a particular outcome, such as reducing vehicle count, then implementing policies aimed at altering work arrangements such as commute trip reduction and remote working policies, could be effective in reducing the number of overall vehicles. To estimate the treatment effect of work arrangement, workers in the sample are assumed to be in four distinct states S1- S4 (see Figure 10-1 for their definitions), relative to the actual self-reported commute frequency (S0). Then, the estimated ICLV model can be utilized to compute the probability of each alternative within the choice set at the observation level for each state (S0-S4). Finally, the ATE is determined as the difference between the average predicted probability for state S1- S4 and that of state S0.

Figure 10-1 presents *changes* in the average predicted probability of past and expected changes in vehicle count (in percentage points or p.p.). This analysis allows for an assessment of the ATE across four distinctive states (S1 to S4) and two time points (past versus future). Key findings indicate that reducing commute trips during the pandemic led to a greater increase in probability of vehicle-shedding, compared to post-pandemic period (e.g., a 3.16 p.p. increase for individuals with zero commutes in the past versus a 0.31 p.p. increase in the future). This can be attributed to the fact that non-commuting trips were largely restricted during the pandemic. With reduced commuting trips at the same time, household vehicles were underutilized, thereby encouraging vehicle shedding. In contrast, by Fall 2023, the demand for non-commuting trips had largely rebounded. Even if workers continue to avoid commute trips, household vehicles are now frequently utilized, reducing the probability of vehicle shedding. Nevertheless, it is still expected that reducing commute trips will decrease the likelihood of increasing household vehicles (e.g., a 1.11 p.p. decrease for individuals with zero commutes).

State	Interventions in work arrangement status as of spring 2020 and fall 2023	Past Changes (Among workers as of spring 2020 and fall 2023, n=799)			
		Increase	Decrease	Replace	No change
S1	Fully commute (commute 20 days/month)	0.43%	-1.70%	-1.04%	2.30%
S2	Reducing a quarter of current commute frequency	0.00%	0.63%	-0.47%	-0.15%
S3	Reducing half of current commute frequency	-0.02%	1.35%	-0.96%	-0.38%
S4	No commute (commute 0 days/month)	-0.09%	3.16%	-1.98%	-1.09%

State	Interventions in work arrangement status as of fall 2023 and fall 2024	Expected Changes (Among workers as of fall 2023 and fall 2024, n=961)			
		Increase	Decrease	Replace	No change
S1	Fully commute (commute 20 days/month)	0.70%	-0.21%	1.78%	-2.27%
S2	Reducing a quarter of current commute frequency	-0.29%	0.08%	-0.64%	0.85%
S3	Reducing half of current commute frequency	-0.57%	0.16%	-1.29%	1.71%
S4	No commute (commute 0 days/month)	-1.11%	0.31%	-2.59%	3.39%

Figure 10-1. Average Treatment Effect of Work Arrangements

Notes:

1. State S1 to S4 were established by updating the values in two variables, “monthly commute frequency” and “change in commute”, as listed in Table 8-1.
2. Respondents who already commute more than 20 days/month maintain their current commute frequency in the S1 state.
3. The values in the table are changes in the average predicted probability of past and expected changes in vehicle count (in percentage points or p.p.).

This study also shows that the health concerns of the COVID-19 have been identified as a factor preventing individuals from reducing their vehicle ownership, potentially due to the fear of virus transmission in public and shared travel modes. As the effects of the pandemic fade away, transportation agencies and mobility providers should continue to work at increasing the attractiveness of modes alternative to the use of private cars.

11 Conclusions, Policy Implications, Future Works, and Limitations

11.1 The New Normal of Work Arrangements

This study helps understand the temporary vs. longer-term impacts brought by the COVID-19 pandemic on transportation, and the way in which individuals are adjusting their lives in the post-pandemic society, with important implications on the future of mobility. In Chapter 5, two distinct aspects of the evolution of remote/hybrid work practices have been discussed. Thanks to the widespread use of digital devices and online communication apps such as video conferencing, the share of workers who adopt either the remote or hybrid workstyle reached 60% as of the 2021 survey wave. Also, the new 2023 survey dataset implies that people's expectations about the future workstyle are somehow stable from what they do in 2023. These results indicate that the pandemic-induced turbulence in the work arrangement might have come to an end. However, the new normal of work arrangements seems rather different from the pre-pandemic society, with increased adoption of remote/hybrid work in the post-pandemic society. It is therefore important to analyze the detailed profile of the current work practices of society and understand the underlying motivations and challenges related to the adoption of remote/hybrid work practices to work towards curbing the growth of, and hopefully reducing, future VMT.

To address this concern, the research team introduced a new question dedicated to the work arrangement in the 2023 survey. The series of seven matrix questions revealed not only how many days a survey taker works at their primary or alternative workplace, a temporary location, or from home, but also during what time on each day of the previous week they work at those locations, with the granularity of down to two hours. The analysis of the responses about the detailed work arrangement suggested that most individuals work from one location on a given day. However, nearly 15% of respondents reported working from multiple work locations during the day. This means that a portion of typical commuting, in the morning peak and evening peak, seems to have shifted to another time of day.

This leads to an implication about the effect of people's travel-decision making. For example, the reduction of morning commute trips has a direct impact in lowering travel demand and traffic volumes in the morning peak. On the other hand, the hybrid workstyle that reduces the number of commuting days per week could result in a long-term choice, such as relocation into neighborhoods that are more affordable, but more remotely located from the workplace. Consequently, it is, at this point, unclear whether this type of shift to a hybrid workstyle will eventually lead to a longer-term reduction in VMT. If the distance between one's home and workplace increases, the total VMT for commuting may increase instead. Moreover, adopting a more remote-oriented workstyle often leads to an increase in home-based non-work trips, such as shopping or visiting recreational activities. These additional events may add up to extra VMT that would not have existed before the pandemic. Therefore, a future study will not only focus on the work arrangement itself but also on its long-term effects, combined with individual preferences and long-term lifestyles.

11.2 Seize the Window of Opportunity for the Transition toward Sustainable Mobility

This study finds that *pro-driving*, *novelty-seeking* and younger individuals tend to increase or replace their vehicle in the future. Interestingly, individuals with these characteristics were also more inclined to embrace new vehicle technologies, such as electric vehicles (Iogansen et al., 2023), autonomous vehicles (Wang & Akar, 2019), as well as shared mobility services, such as ride-hailing (Lavieri & Bhat, 2019), carsharing (Mueller et al., 2015) and micromobility (Mahmoud et al., 2021). Therefore, policies aimed at incentivizing these individuals to transition to cleaner vehicles or promoting mode shift away from private vehicles altogether, could be viable and have significant impacts on reducing carbon emissions. Policies that promote the use of shared micromobility services could begin by targeting younger adults, as the habits built in the early stages of adulthood can influence future travel behavior (De Vos et al., 2022).

This research suggests that understanding household characteristics is crucial when analyzing vehicle ownership patterns. In particular, a deeper understanding of how vehicles are shared and utilized among family numbers, and how daily trip chaining patterns are structured will be crucial to help policymakers develop transportation policies that meet the diverse household needs.

Increased commute frequency was found to be positively associated with a lower likelihood of shedding vehicles during the pandemic and a higher likelihood of purchasing/replacing vehicles in the future. At the same time, commuters exhibit the highest VMT pertaining to their commute, as well as non-commuting and long-distance trips. Even though remote workers have much lower VMT for commuting and work-related trip purposes than hybrid workers, they are found to have higher non-commuting VMT than hybrid workers, potentially due to more flexibility in travel throughout the day. Governments should support companies in formulating policies aimed at reducing commute trips and effectively managing remote and hybrid work arrangements. This can assist workers in adapting to their evolving travel needs and requirements for vehicles. However, the impact of such policies can vary depending on the level of flexibility offered. For instance, companies may need to discourage partial-day hybrid work as it would offset the trip reduction benefits from full-day working from home (though still providing some beneficial effects on reducing traffic congestion during peak time).

Planning agencies will also need to customize policies for different population segments. For individuals who have the option to work remotely entirely, usually full-time workers, may choose to reduce the number of vehicles they own. However, for those who still need to commute, vehicle ownership may be seen as necessary to access jobs and opportunities. Nevertheless, this can lead to tremendous financial burdens for those who are not in good economic status, as our study showed that those in the highest income category or those who experienced an increase in income during the pandemic had much more likelihood to acquire or replace vehicles compared to low-income individuals. Therefore, it is crucial to provide more travel alternatives for this group. Governments and employers should consider policies to encourage commuting by bike, e-scooter, and walking. This includes expanding infrastructure for cyclists and pedestrians and providing secure storage facilities for bikes and e-scooters. Additionally, governments could provide subsidies for ride-hailing and shared micromobility services with proper safety measures in place. Moreover, governments should further support transit agencies to help improve the frequency and span of service for transit routes that serve lower-income and other transportation-disadvantaged communities.

Reducing barriers to the use of cleaner vehicles and alternative modes of transportation will be an important component of reducing the carbon emissions associated with passenger travel. Policies aiming to reduce barriers to the use of cleaner vehicles could include offering funding to expand vehicle charging infrastructure and subsidizing the purchase of vehicles and at-home charging systems to members of lower-income communities. For public transit, such policies could include offering financial support to transit agencies, offering subsidized transit passes, and implementing transit priority measures in heavily congested areas. Moreover, expanding the coverage of pedestrian-friendly streets could both improve access to public transit and encourage people to walk more frequently. Finally, access to bicycles and e-scooters could be improved by expanding the coverage of cycling facilities, offering subsidized passes for shared bike and e-scooter services, and partnering with micromobility companies to increase the supply of bikes and e-scooters.

11.3 Accommodate and Drive the Growth of E-commerce

The COVID-19 pandemic has caused a significant surge in e-shopping, which persisted beyond pre-pandemic levels. This transition to the virtual means of shopping has profound implications for urban planning and transportation strategies, particularly as it also overlaps with the increasing adoption of remote work practice. As individuals increasingly opt for online purchases, the appeal of living in cheaper and larger houses that are distant from city centers grows, especially among well-educated and more affluent white-collar workers, who are more likely to work remotely and engage in frequent e-shopping. Consequently, city officials may face challenges associated with urban sprawl and decreased pedestrian activities in commercial areas, necessitating policy interventions to retain central businesses effectively. Moreover, the move to remote areas could amplify the already-high VMT for non-commuting trips due to the longer distances. The rapid increase in e-shopping could further result in a decrease in activities in the urban centers. Thus, developing a better understanding of post-pandemic e-shopping behavior is critical. For this reason, policymakers should remain alerted in monitoring these shifts and utilize evidence-based approaches to address evolving consumer behaviors related to online shopping.

The pandemic has reshaped purchasing habits and the persistence of e-shopping behavior demonstrates that the changing habits will be the new shopping patterns in the future. While most of the online shopping activity comes from more experienced shoppers, groups which are less likely to shop online also increased their e-shopping frequency significantly (as it could be seen from the case of older adults). As consumers keep experiencing the advantages of streamlined shopping experiences, there will be a steady shift from physical shopping to virtual counterparts. This shift will require adjustments to road networks, curbside access, and parking facilities for delivery drivers to accommodate the increase in online order deliveries. As a result, primary attention should be given to the infrastructure supporting goods delivery to avoid the overwhelming impacts of freight systems while handling the increased demand. Since the rise in e-commerce is expected to have implications for GHG emissions and energy consumption, the electrification of delivery fleets will be an increasingly important topic for public authorities that aim to reduce transportation related emissions. State agencies and local governments should pro-actively promote solutions to complement the delivery of goods through electrified and lighter vehicles, e.g., cargo e-bikes and light micromobility vehicles in urban areas. Policymakers could encourage the electrification of delivery vehicles such as vans or bikes by providing incentives for electric delivery vehicle adoption for businesses, prioritizing charging infrastructure expansions, promoting rightsizing of delivery vehicles in urban areas (including the use of two- three- and light four-wheelers) and introducing fleet electrification programs. It is important to note that the promotion of alternative delivery methods, such as bike couriers or cargo e-bikes, has the potential to considerably reduce GHG emissions and traffic congestion in urban areas.

Even if the focus of this report has primarily been on consumer behavior related to e-shopping, it is essential to recognize that increased e-shopping frequency may lead to considerable changes in travel demand and other associated travel patterns. As more people shop online, there may be a reduction in physical trips for grocery and non-grocery purposes, reducing VMT for shopping trips. If multiple purchases made by different consumers could be consolidated, the need for multiple individual trips for shopping various items could be eliminated. Conversely, the increase in online deliveries may result in higher VMT for delivery purposes, particularly in urban areas with dense populations of e-shoppers. Additionally, commercial VMT could increase while retailers try to meet the rising demand for online orders through transporting goods between warehouses and distribution centers more frequently. This could result in changes in freight transportation patterns and potentially increase overall VMT, particularly on highways and major corridors. Overall, as society navigates the post-pandemic era, careful consideration of e-shopping related findings will be critical in shaping resilient urban environments and inclusive economic systems.

11.4 Limitations

There are several important limitations of the datasets and analyses presented in this report, which are worth mentioning. First, despite efforts to produce a sample that is reasonably representative of the population of California, self-selection and non-response biases are always a concern. Consequently, the attributes of those who chose to participate in the survey could systematically differ from both the population as a whole and those who chose not to participate in the survey. Second, the lack of a comprehensive sampling frame of California residents creates the potential that certain residents were omitted from the sampling process. For example, members of groups that are traditionally harder to reach (such as BIPOC, non-

English speakers, and residents of rural areas) were under-represented in the survey samples. While sample weights were developed to help improve the extent to which the samples represented the population of California, future studies should explore alternative methods of recruitment, data collection, and incentives to help improve the representativeness of the members of harder-to-reach populations.

Another important limitation is that the data were primarily collected using a web-based survey interface. Consequently, the survey respondents may be more technologically savvy compared to the population of California as a whole. This discrepancy would have important implications in particular for the findings pertaining to remote and hybrid work arrangements, online shopping, and the use of shared mobility services presented in this paper. Additionally, the use of online and paper questionnaires to collect information from respondents introduced the potential for errors related to recall and response accuracy. To help address this issue, a rigorous data cleaning process was applied to help identify and remove lower-quality responses. The analyses presented in this report used multiple samples; however, the exact same respondents are not included in each and every sample (although numerous respondents are included in multiple sub-samples). As a result, differences in activity-travel behavior between samples could be due to both changes in the pandemic context as well as differences in the attributes of the respondents in each sub-sample. While the use of weighted data can help mitigate the impacts of the latter, it is still possible that these differences somewhat affected the results of certain analyses.

Finally, while the report aims to offer insights into the evolving activity-travel behavior of California residents, it is important to acknowledge that results may vary significantly across the state. In particular, differences in contextual factors including land use attributes, the structure of the transportation network, employment opportunities, and economic conditions could affect the extent to which the results can be applied to specific areas. This underscores the importance of accounting for local needs and contextual factors when developing policies.

It is also important to note that the results presented in this study refer to patterns that might further change in the future. Accordingly, the research team will continue to study the changing situation with subsequent rounds of data collection (not included in the current project). Furthermore, additional analyses are being conducted by the research team using additional data collection methods, such as in-depth interviews or focus groups, which offer a more qualitative perspective. These methods can help shed light in particular into the behaviors and preferences of specific groups (including hard-to-reach population segments). Overall, the mixed-methods approach will provide deeper insights into our findings, presenting a comprehensive understanding of human behavior during and after emergency situations like the recent pandemic.

12 References

Aaditya, Bh., & Rahul, T. M. (2021). Psychological impacts of COVID-19 pandemic on the mode choice behaviour: A hybrid choice modelling approach. Transport Policy, 108, 47–58. https://doi.org/10.1016/j.tranpol.2021.05.003

Abdelfattah, N., & Bahramipanah, M. (2021, September 7). Impact of COVID-19 on Mobility and traffic Volume trends in Montana and California. 2021 IEEE International Smart Cities Conference, ISC2 2021. https://doi.org/10.1109/ISC253183.2021.9562956

Abou-Zeid, M., & Ben-Akiva, M. (2014). Hybrid choice models. In Handbook of Choice Modelling (pp. 383–412). Edward Elgar Publishing. https://doi.org/10.4337/9781781003152.00025

Ambrosius, J. D., & Gilderbloom, J. I. (2015). Who's greener? Comparing urban and suburban residents' environmental behaviour and concern. Local Environment, 20(7), 836–849. https://doi.org/10.1080/13549839.2014.926870

American Public Transportation Association. (2024a). APTA Public Transportation Ridership Update. https://www.apta.com/wp-content/uploads/APTA-POLICY-BRIEF-Transit-Ridership-04.01.2024.pdf

American Public Transportation Association. (2024b). Public Trnasportation Ridership Report: Fourth Quarter 2023. https://www.apta.com/wp-content/uploads/2023-Q4-Ridership-APTA.pdf

Anowar, S., Eluru, N., & Miranda-Moreno, L. F. (2016). Analysis of vehicle ownership evolution in Montreal, Canada using pseudo panel analysis. Transportation, 43(3), 531–548. https://doi.org/10.1007/s11116-015-9588-z

Asmussen, K. E., Mondal, A., & Bhat, C. R. (2023). The Interplay between Teleworking Choice and Commute Distance.

Auto Remarketing. (2021). One year into pandemic, Americans prioritize car ownership.

Badia, H., & Jenelius, E. (2023). Shared e-scooter micromobility: review of use patterns, perceptions and environmental impacts. Transport Reviews, 43(5), 811–837. https://doi.org/10.1080/01441647.2023.2171500

Barajas, J. M. (2021). The roots of racialized travel behavior. In Advances in Transport Policy and Planning (Vol. 8, pp. 1–31). Elsevier B.V. https://doi.org/10.1016/bs.atpp.2021.06.007

Barbour, E., Gradjura, S., Sun, R., Circella, G., Barajas, J. M., Jaller, M., D'Agostino, M., & Handy, S. (2023). Post-Covid Transportation Scenarios: Evaluating the Impact of Policies. https://ww2.arb.ca.gov/sites/default/files/2023-08/V.1%20-%20DFR%20-%2021STC008%20UCD.pdf

Barthélemy, J., Suesse, T., & Namazi-Rad, M. (2018). mipfp: An R Package for Multidimensional Array Fitting and Simulating Multivariate Bernoulli Distributions. Journal of Statistical Software, 86(2), 1–20. https://doi.org/10.18637/jss.v086.c02

Beck, M. J., & Hensher, D. A. (2022). Australia 6 months after COVID-19 restrictions- part 1: Changes to travel activity and attitude to measures. Transport Policy, 128, 286–298. https://doi.org/10.1016/j.tranpol.2021.06.006

Blumenberg, E., Paul, J., & Pierce, G. (2021). Travel in the digital age: Vehicle ownership and technology-facilitated accessibility. Transport Policy, 103, 86–94. https://doi.org/10.1016/j.tranpol.2021.01.014

Boarnet, M., Rodnyansky, S., Wang, B., & Comandon, A. (2021). Displacement and Commuting in the San Displacement and Commuting in the San Francisco Bay Area and Beyond: An Analysis of the Relationship Between the Housing Crisis, Displacement, and Long Commutes December 2021 A Research Report from the Pacific Southwest Region University Transportation Center Displacement and Commuting in the San. https://sites.usc.edu/ca-regional-impact/

Brodeur, A., Cook, N., & Wright, T. (2021). On the effects of COVID-19 safer-at-home policies on social distancing, car crashes and pollution. Journal of Environmental Economics and Management, 106, 102427. https://doi.org/10.1016/j.jeem.2021.102427

Brown, A., & Howell, A. (2024). Mobility for the people: Equity requirements in US shared micromobility programs. Journal of Cycling and Micromobility Research, 2, 100020. https://doi.org/10.1016/j.jcmr.2024.100020

Brown, A., Klein, N. J., Smart, M. J., & Howell, A. (2022). Buying Access One Trip at a Time: Lower-Income Households and Ride-Hail. Journal of the American Planning Association, 88(4), 495–507. https://doi.org/10.1080/01944363.2022.2027262

Brown, A., & Williams, R. (2023). Equity Implications of Ride-Hail Travel during COVID-19 in California. In Transportation Research Record (Vol. 2677, Issue 4, pp. 1–14). SAGE Publications Ltd. https://doi.org/10.1177/03611981211037246

Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, G., Tuye, H.-Y., & Upwork, A. O. (2020). COVID-19 and Remote Work: An Early Look at US Data.

Bucchioni, P., Liu, X., & Weidenhamer, D. (2015). Quarterly Retail E-Commerce Sales 1st Quarter 2015 [WWW Document]. U.S. Census Bureau. https://www2.census.gov/retail/releases/historical/ecomm/15q1.pdf

Budd, L., & Ison, S. (2020). Responsible Transport: A post-COVID agenda for transport policy and practice. Transportation Research Interdisciplinary Perspectives, 6, 100151. https://doi.org/10.1016/j.trip.2020.100151

Bureau of Transportation Statistics. (2020). Daily Vehicle Travel During the COVID-19 Public Health Emergency. https://www.bts.gov/covid-19/daily-vehicle-travel

Bureau of Transportation Statistics. (2022). This Week in Transportation. https://www.bts.gov/covid-19/week-in-transportation

California Transit Association. (2023). Transit Watch: Public Transit in Crisis. https://caltransit.org/cta/assets/File/Transit%20Watch/Transit%20Watch%203-3-23.pdf

Cano, R. (2024, January 8). These Bay Area commuter highways are approaching 2019 traffic levels. San Francisco Chronicle. https://www.sfchronicle.com/bayarea/article/highway-freeway-traffic-commute-18592029.php

Concas, S., Kourtellis, A., Kummetha, V., Kamrani, M., Rabbani, M., & Dokur, O. (2022). Longitudinal Study of the COVID-19 Pandemic Impact on Activity Travel Using Connected Vehicle Data. Transportation Research Record: Journal of the Transportation Research Board, 036119812211070. https://doi.org/10.1177/03611981221107006

de Haas, M., Faber, R., & Hamersma, M. (2020). How COVID-19 and the Dutch ‘intelligent lockdown’ change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. Transportation Research Interdisciplinary Perspectives, 6, 100150. https://doi.org/10.1016/j.trip.2020.100150

de Palma, A., Vosough, S., & Liao, F. (2022). An overview of effects of COVID-19 on mobility and lifestyle: 18 months since the outbreak. Transportation Research Part A: Policy and Practice, 159(March), 372–397. https://doi.org/10.1016/j.tra.2022.03.024

De Vos, J. (2020). The effect of COVID-19 and subsequent social distancing on travel behavior. Transportation Research Interdisciplinary Perspectives, 5, 100121. https://doi.org/10.1016/j.trip.2020.100121

De Vos, J., Waygood, E. O. D., Letarte, L., & Cao, M. (2022). Do frequent satisfying trips by public transport impact its intended use in later life? Transportation, 49(4), 1245–1263. https://doi.org/10.1007/s11116-021-10209-0

den Braver, N. R., Kok, J. G., Mackenbach, J. D., Rutter, H., Oppert, J.-M., Compernolle, S., Twisk, J. W. R., Brug, J., Beulens, J. W. J., & Lakerveld, J. (2020). Neighbourhood drivability: environmental and individual characteristics associated with car use across Europe. International Journal of Behavioral Nutrition and Physical Activity, 17(1), 8. https://doi.org/10.1186/s12966-019-0906-2

Desilver, D. (2023, November 22). Online shopping has grown rapidly in U.S., but most sales are still in stores. Pew Research Center. https://www.pewresearch.org/short-reads/2023/11/22/online-shopping-has-grown-rapidly-in-u-s-but-most-sales-are-still-in-stores/

Dietz, T., Kalof, L., & Stern, P. C. (2002). Gender, Values, and Environmentalism. Social Science Quarterly, 83(1), 353–364. https://doi.org/10.1111/1540-6237.00088

Espinoza, W., Howard, M., Lane, J., & Van Hentenryck, P. (2019, October 13). Shared E-scooters: Business, Pleasure, or Transit? https://arxiv.org/abs/1910.05807

Fishman, E. (2016). Bikeshare: A Review of Recent Literature. Transport Reviews, 36(1), 92–113. https://doi.org/10.1080/01441647.2015.1033036

Fitzpatrick, A., & Beheraj, K. (2023). Where public transit is recovering — and where it's not. https://www.axios.com/2023/12/14/public-trasnportation-transit-america-recovery-pandemic-covid

Giuliano, G., Fang, J., Binder, R. B., Ha, J., & Holmes, A. (2022). Travel Behavior in E-commerce: Shopping, Purchasing, and Receiving. https://doi.org/10.7922/G2377723

Goodwill, P. B. (1993). Car ownership and public transport use: revisiting the interaction. Transportation, 20, 21–33. https://doi.org/10.1007/BF01099974

Guan, X., & Wang, D. (2019). Residential self-selection in the built environment-travel behavior connection: Whose self-selection? Transportation Research Part D: Transport and Environment, 67, 16–32.

Habib, K. N., Hawkins, J., Shakib, S., Loa, P., Mashrur, Sk. Md., Dianat, A., Wang, K., Hossain, S., & Liu, Y. (2021). Assessing the impacts of COVID-19 on urban passenger travel demand in the greater Toronto area: description of a multi-pronged and multi-staged study with initial results. Transportation Letters, 13(5–6), 353–366. https://doi.org/10.1080/19427867.2021.1899579

Handy, S., van Wee, B., & Kroesen, M. (2014). Promoting Cycling for Transport: Research Needs and Challenges. Transport Reviews, 34(1), 4–24. https://doi.org/10.1080/01441647.2013.860204

Heckman, J. J., & Vytlacil, E. J. (2000). The relationship between treatment parameters within a latent variable framework. Economics Letters, 66(1), 33–39. https://doi.org/10.1016/S0165-1765(99)00181-0

Hoogland, K., Chakraborty, D., & Hardman, S. (2022). To purchase or lease: Investigating the finance decision of plug-in electric vehicle owners in California. Environmental Research Communications, 4(9). https://doi.org/10.1088/2515-7620/ac8397

Hook, H., De Vos, J., Van Acker, V., & Witlox, F. (2021). Does undirected travel compensate for reduced directed travel during lockdown? Transportation Letters, 13(5–6), 414–420. https://doi.org/10.1080/19427867.2021.1892935

Hook, H., De Vos, J., Van Acker, V., & Witlox, F. (2023). Evolutions in undirected travel (satisfaction) during the COVID-19 pandemic. Transportation Research Part F: Traffic Psychology and Behaviour, 94, 99–113. https://doi.org/10.1016/j.trf.2023.01.025

International Monetary Fund. (2021). Policy Responses to COVID-19. https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19

Iogansen, X., Wang, K., Bunch, D., Matson, G., & Circella, G. (2023). Deciphering the factors associated with adoption of alternative fuel vehicles in California: An investigation of latent attitudes, socio-demographics, and neighborhood effects. Transportation Research Part A: Policy and Practice, 168, 103535. https://doi.org/10.1016/j.tra.2022.10.012

Islam, M. R., & Saphores, J. D. M. (2022). An L.A. story: The impact of housing costs on commuting. Journal of Transport Geography, 98. https://doi.org/10.1016/j.jtrangeo.2021.103266

Islam, M. R., & Saphores, J. D. M. (2023). WILL COVID-19 jump-start telecommuting? Evidence from California. Transportation. https://doi.org/10.1007/s11116-023-10424-x

Javadinasr, M., Maggasy, T., Mohammadi, M., Mohammadain, K., Rahimi, E., Salon, D., Conway, M. W., Pendyala, R., & Derrible, S. (2022). The Long-Term effects of COVID-19 on travel behavior in the United States: A panel study on work from home, mode choice, online shopping, and air travel. Transportation Research Part F: Traffic Psychology and Behaviour, 90, 466–484. https://doi.org/10.1016/j.trf.2022.09.019

Karlamangla, S. (2023, June 21). Why California Transit Agencies Are Rebounding at Such Different Rates. The New York Times. https://www.nytimes.com/2023/06/21/us/california-transit-agencies.html

Klein, N. J., & Smart, M. J. (2017). Car today, gone tomorrow: The ephemeral car in low-income, immigrant and minority families. Transportation, 44(3), 495–510. https://doi.org/10.1007/s11116-015-9664-4

Koenig, B. E., Henderson, D. K., & Mokhtarian, P. L. (1996). The travel and emissions impacts of telecommuting for the State of California Telecommuting Pilot Project. Transportation Research Part C: Emerging Technologies, 4(1), 13–32. https://doi.org/10.1016/0968-090X(95)00020-J

Krolikowski, P. M., & Naggert, K. N. (2021). Semiconductor Shortages and Vehicle Production and Prices. 17.

Kutela, B., Combs, T., John Mwekh'iga, R., & Langa, N. (2022). Insights into the long-term effects of COVID-19 responses on transportation facilities. Transportation Research Part D: Transport and Environment, 111, 103463. https://doi.org/10.1016/j.trd.2022.103463

Lavieri, P. S., & Bhat, C. R. (2019). Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. Transportation Research Part C: Emerging Technologies, 105(May 2018), 100–125. https://doi.org/10.1016/j.trc.2019.05.037

Lee, J. H., & Goulias, K. G. (2018). A decade of dynamics of residential location, car ownership, activity, travel and land use in the Seattle metropolitan region. Transportation Research Part A: Policy and Practice, 114, 272–287. https://doi.org/10.1016/j.tra.2018.01.029

Liu, J., Gross, J., & Ha, J. (2021). Is travel behaviour an equity issue? Using GPS location data to assess the effects of income and supermarket availability on travel reduction during the COVID-19 pandemic. International Journal of Urban Sciences, 25(3), 366–385. https://doi.org/10.1080/12265934.2021.1952890

Loa, P., Hossain, S., Mashrur, S. M., Liu, Y., Wang, K., Ong, F., & Habib, K. N. (2021). Exploring the impacts of the COVID-19 pandemic on modality profiles for non-mandatory trips in the Greater Toronto Area. Transport Policy, 110, 71–85. https://doi.org/10.1016/j.tranpol.2021.05.028

Luo, Q., Forscher, T., Shaheen, S., Deakin, E., & Walker, J. L. (2023). Impact of the COVID-19 pandemic and generational heterogeneity on ecommerce shopping styles – A case study of Sacramento, California. Communications in Transportation Research, 3. https://doi.org/10.1016/j.commtr.2023.100091

Ma, T., Aghaabbasi, M., Ali, M., Zainol, R., Jan, A., Mohamed, A. M., & Mohamed, A. (2022). Nonlinear Relationships between Vehicle Ownership and Household Travel Characteristics and Built Environment Attributes in the US Using the XGBT Algorithm. Sustainability (Switzerland), 14(6). https://doi.org/10.3390/su14063395

Mahmoud, A., Chouaki, T., & Puchinger, J. (2021). The Integration of Innovative Mobility into the Urban Transport Network: A Literature Review (pp. 153–166). https://doi.org/10.1007/978-3-030-72976-9_7

Manville, M., Taylor, B. D., Blumenberg, E., & Schouten, A. (2023). Vehicle access and falling transit ridership: evidence from Southern California. Transportation, 50(1), 303–329. https://doi.org/10.1007/s11116-021-10245-w

Marina, D., Pandjaitan, N. K., Hasanah, N., & Cesna, G. P. (2022). Analysis of Lifestyle and Consumer Attitude Towards Intention to Purchase a Personal Car During Pandemic. APTISI Transactions on Management, 7(1), 15–34. https://doi.org/10.33050/atm.v7i1.1806

Matson, G., McElroy, S., Lee, Y., & Circella, G. (2023). Longitudinal Analysis of COVID-19 Impacts on Mobility: An Early Snapshot of the Emerging Changes in Travel Behavior. In Transportation Research Record (Vol. 2677, Issue 4, pp. 298–312). SAGE Publications Ltd. https://doi.org/10.1177/03611981221090241

McGuckin, N., & Fucci, A. (2018). Summary of Travel Trends: 2017 National Household Travel Survey. https://rosap.ntl.bts.gov/view/dot/68751

Mitra, R., & Hess, P. M. (2021). Who are the potential users of shared e-scooters? An examination of socio-demographic, attitudinal and environmental factors. Travel Behaviour and Society, 23, 100–107. https://doi.org/10.1016/j.tbs.2020.12.004

Mitra, S. K., & Saphores, J. D. M. (2019). Why do they live so far from work? Determinants of long-distance commuting in California. Journal of Transport Geography, 80. https://doi.org/10.1016/j.jtrangeo.2019.102489

Mokhtarian, P. L. (1991). Defining Telecommuting. https://escholarship.org/uc/item/35c4q71r

Molloy, J. (2021). MOBIS-COVID19: Results as of 20/11/2021 (Fourth wave). https://ivtmobis.ethz.ch/mobis/covid19/reports/latest

Monahan, T., & Lamb, C. G. (2022). Transit's downward spiral: Assessing the social-justice implications of ride-hailing platforms and COVID-19 for public transportation in the US. Cities, 120, 103438. https://doi.org/10.1016/j.cities.2021.103438

Mueller, J., Schmoeller, S., & Giesel, F. (2015). Identifying Users and Use of (Electric-) Free-Floating Carsharing in Berlin and Munich. 2015 IEEE 18th International Conference on Intelligent Transportation Systems, 2568–2573. https://doi.org/10.1109/ITSC.2015.413

National Association of City Transportation Officials. (2020). Streets for Pandemic Response & Recovery: Slow Streets. https://nacto.org/publication/streets-for-pandemic-response-recovery/emerging-street-strategies/slow-streets/

Ory, D. T., & Mokhtarian, P. L. (2006). Which Came First, the Telecommuting or the Residential Relocation? An Empirical Analysis of Causality. Urban Geography, 27(7), 590–609. https://doi.org/10.2747/0272-3638.27.7.590

Oum, T. H., & Wang, K. (2020). Socially optimal lockdown and travel restrictions for fighting communicable virus including COVID-19. Transport Policy, 96, 94–100. https://doi.org/10.1016/j.tranpol.2020.07.003

Ozbilen, B., Wang, K., & Akar, G. (2021). Revisiting the impacts of virtual mobility on travel behavior: An exploration of daily travel time expenditures. Transportation Research Part A: Policy and Practice, 145, 49–62. https://doi.org/10.1016/j.tra.2021.01.002

Parady, G., Taniguchi, A., & Takami, K. (2020). Travel behavior changes during the COVID-19 pandemic in Japan: Analyzing the effects of risk perception and social influence on going-out self-restriction. Transportation Research Interdisciplinary Perspectives, 7, 100181. https://doi.org/10.1016/j.trip.2020.100181

Parker, M. E. G., Li, M., Bouzaghrane, M. A., Obeid, H., Hayes, D., Frick, K. T., Rodríguez, D. A., Sengupta, R., Walker, J., & Chatman, D. G. (2021). Public transit use in the United States in the era of COVID-19: Transit riders' travel behavior in the COVID-19 impact and recovery period. Transport Policy, 111, 53–62. https://doi.org/10.1016/j.tranpol.2021.07.005

Rafiq, R., McNally, M. G., Sarwar Uddin, Y., & Ahmed, T. (2022). Impact of working from home on activity-travel behavior during the COVID-19 Pandemic: An aggregate structural analysis. Transportation Research Part A: Policy and Practice, 159, 35–54. https://doi.org/10.1016/j.tra.2022.03.003

Ravalet, E., & Rérat, P. (2019). Teleworking: Decreasing mobility or increasing tolerance of commuting distances? Built Environment, 45(4), 582–602. https://doi.org/10.2148/benv.45.4.582

Rosenbaum, E. (2020). The used car boom is one of the hottest, and trickiest, coronavirus markets for consumers. In CNBC.

Sabouri, S., Tian, G., Ewing, R., Park, K., & Greene, W. (2021). The built environment and vehicle ownership modeling: Evidence from 32 diverse regions in the U.S. Journal of Transport Geography, 93. https://doi.org/10.1016/j.jtrangeo.2021.103073

Sadeghvaziri, E., Javid, R., & Jeihani, M. (2023a). Active Transportation for Underrepresented Populations in the United States: A Systematic Review of Literature. Transportation Research Record. https://doi.org/10.1177/03611981231197659

Sadeghvaziri, E., Javid, R., & Jeihani, M. (2023b). Investigating Walking and Biking Activities Among Low-Income African Americans. https://orcid.org/0000-0003-1002-237X

Saphores, J. D., & Xu, L. (2021). E-shopping changes and the state of E-grocery shopping in the US - Evidence from national travel and time use surveys. Research in Transportation Economics, 87. https://doi.org/10.1016/j.retrec.2020.100864

Schouten, A. (2022). Residential relocations and changes in vehicle ownership. Transportation, 49(1), 89–113. https://doi.org/10.1007/s11116-021-10167-7

SFMTA. (2024). Muni Ridership rises 25% in 2023.

Shabanpour, R., Golshani, N., Tayarani, M., Auld, J., & Mohammadian, A. (Kouros). (2018). Analysis of telecommuting behavior and impacts on travel demand and the environment. Transportation Research Part D: Transport and Environment, 62, 563–576. https://doi.org/10.1016/j.trd.2018.04.003

Shamshiripour, A., Rahimi, E., Shabanpour, R., & Mohammadian, A. (Kouros). (2020). How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. Transportation Research Interdisciplinary Perspectives, 7, 100216. https://doi.org/10.1016/j.trip.2020.100216

Shimamoto, H., & Kusubaru, R. (2023). Evaluation of the short- and long-term impacts of the COVID-19 pandemic on bus ridership in Miyazaki City, Japan. Asian Transport Studies, 9, 100098. https://doi.org/10.1016/j.eastsj.2023.100098

Solon, G., Haider, S. J., & Wooldridge, J. M. (2015). What Are We Weighting For? The Journal of Human Resources, 50(2).

Su, R., McBride, E. C., & Goulias, K. G. (2021). Unveiling daily activity pattern differences between telecommuters and commuters using human mobility motifs and sequence analysis. Transportation Research Part A: Policy and Practice, 147, 106–132. https://doi.org/10.1016/j.tra.2021.03.002

Teixeira, J. F., Diogo, V., Bernát, A., Lukasiewicz, A., Vaiciukynaite, E., & Stefania Sanna, V. (2023). Barriers to bike and e-scooter sharing usage: An analysis of non-users from five European capital cities. Case Studies on Transport Policy, 13, 101045. https://doi.org/10.1016/j.cstp.2023.101045

Unnikrishnan, A., & Figliozzi, M. (2021). Exploratory analysis of factors affecting levels of home deliveries before, during, and post- COVID-19. Transportation Research Interdisciplinary Perspectives, 10. https://doi.org/10.1016/j.trip.2021.100402

U.S. Department of Commerce. (2024). Quarterly Retail E-Commerce Sales 4th Quarter 2023 [WWW Document]. U.S. Census Bureau. http://www.census.gov/retail

U.S. Federal Highway Administration. (2023). Transportation Demand Management. https://ops.fhwa.dot.gov/plan4ops/trans_demand.htm

U.S. Federal Highway Administration. (2024, April 26). Vehicle Miles Traveled [TRFVOLUSM227SFWA]. https://fred.stlouisfed.org/series/TRFVOLUSM227SFWA

Vuchic, V. R. (2005). Urban transit: Operations, Planning, and Economics. John Wiley and Sons Inc.

Wang, B. S., Rodnyansky, S., Boarnet, M. G., & Comandon, A. (2024). Measuring the impact of COVID-19 policies on local commute traffic: Evidence from mobile data in Northern California. Travel Behaviour and Society, 34. https://doi.org/10.1016/j.tbs.2023.100660

Wang, K., & Akar, G. (2019). Factors Affecting the Adoption of Autonomous Vehicles for Commute Trips: An Analysis with the 2015 and 2017 Puget Sound Travel Surveys. Transportation Research Record: Journal of the Transportation Research Board, 2673(2), 13–25. https://doi.org/10.1177/0361198118822293

Wang, K., Qian, X., Fitch, D. T., Lee, Y., Malik, J., & Circella, G. (2023). What travel modes do shared e-scooters displace? A review of recent research findings. Transport Reviews, 43(1), 5–31. https://doi.org/10.1080/01441647.2021.2015639

Wang, X., Kim, S. H., & Mokhtarian, P. L. (2023). Teleworking behavior pre-, during, and expected post-COVID: Identification and empirical description of trajectory types. Travel Behaviour and Society, 33, 100628. https://doi.org/10.1016/j.tbs.2023.100628

Wang, X., Yan, X., Zhao, X., & Cao, Z. (2022). Identifying latent shared mobility preference segments in low-income communities: Ride-hailing, fixed-route bus, and mobility-on-demand transit. Travel Behaviour and Society, 26, 134–142. https://doi.org/10.1016/j.tbs.2021.09.011

Wilder-Smith, A., & Freedman, D. O. (2020). Isolation, quarantine, social distancing and community containment: pivotal role for old-style public health measures in the novel coronavirus (2019-nCoV) outbreak. Journal of Travel Medicine, 27(2). https://doi.org/10.1093/jtm/taaa020

Xu, L., & Saphores, J. D. (2022). Grocery shopping in California and COVID-19: Transportation, environmental justice, and policy implications. Transportation Research Part D: Transport and Environment, 113. https://doi.org/10.1016/j.trd.2022.103537

Yamane, T., & Kaneko, S. (2021). Is the younger generation a driving force toward achieving the sustainable development goals? Survey experiments. Journal of Cleaner Production, 292, 125932. https://doi.org/10.1016/j.jclepro.2021.125932

Yang, W., Jafarzadehfadaki, M., Yan, X., Zhao, X., Jin, X., Frolich, D., & Sisiopiku, V. P. (2023). Shared E-Scooter User Characteristics and Usage Patterns across Four U.S. Cities. Transportation Research Record: Journal of the Transportation Research Board. https://doi.org/10.1177/03611981231194626

Young, M., Soza-Parra, J., & Circella, G. (2022). The increase in online shopping during COVID-19: Who is responsible, will it last, and what does it mean for cities? Regional Science Policy and Practice, 14(S1), 162–178. https://doi.org/10.1111/rsp3.12514

Zhang, J., Hayashi, Y., & Frank, L. D. (2021). COVID-19 and transport: Findings from a world-wide expert survey. Transport Policy, 103, 68–85. https://doi.org/10.1016/j.tranpol.2021.01.011

Zhao, P., & Gao, Y. (2022). Public transit travel choice in the post COVID-19 pandemic era: An application of the extended Theory of Planned behavior. Travel Behaviour and Society, 28, 181–195. https://doi.org/10.1016/j.tbs.2022.04.002

Zheng, Y., Caros, N. S., Aloisi, J., & Zhao, J. (2023). Examining the interactions between working from home, travel behavior and change in car ownership due to the impact of COVID-19. Travel Behaviour and Society, 33. https://doi.org/10.1016/j.tbs.2023.100634

13 Data Summary

13.1 Products of Research

As part of the COVID mobility study, the research team has administered multiple rounds of travel surveys in the state of California, other parts of the U.S., and worldwide.

The first COVID survey was conducted in Spring 2020. The research team recontacted respondents, who gave consent to be recontacted, from the previous surveys that were administered by the research team in 2018 and 2019 in California and the U.S. to form a longitudinal sample. They also recruited new respondents through an online opinion panel targeting residents in 15 metropolitan areas in the United States and two regions in Canada (California: Los Angeles, Sacramento, San Diego, and San Francisco; Non-California: Atlanta, Boston, Chicago, Denver, Detroit, Kansas City, New York City, Salt Lake City, Seattle, Tampa, and Washington D.C.; Canada: Toronto, Vancouver). In addition, the team included a convenience sampling method with which they reached out to potential participants through professional email lists and online advertisements (e.g., Facebook Ads), as well as through community outreach with the help of a few community based organizations (CBOs).

The second and third data collection were administered in Fall 2020 and Summer 2021. The research team used similar sampling methods to resample previous respondents while adding new respondents to form a large dataset with a rotating panel structure. The survey administration also included the distribution of a (printed) paper questionnaire to recruit respondents that are conventionally hard to reach.

The fourth wave of survey in this project was administered in Fall 2023. Similar to the third wave, along with recontacting previous respondents and sampling via opinion channel, the research team used mailing channels to recruitment to recruit hard-to-reach respondents, especially those from equity priority (disadvantaged) communities. Additionally, the research team closely collaborated with two CBOs based in Sacramento and Los Angeles to reach out to a convenience sample that consisted of disadvantaged residents of California.

The survey content from all waves was mostly consistent in order to keep track on the longitudinal impacts of the COVID-19 pandemic. All datasets feature a similar structure and contain information on similar topics related to transportation, including personal attitudes and preferences, adoption of mobile devices or social media, household composition, general travel patterns, vehicle ownership, use of new mobility services such as ride-hailing, carsharing, or bikesharing, and household and individual socio-demographics. However, as the COVID-19 pandemic severely disrupted society, some components of the survey were modified accordingly. The latest survey had increased the emphasis on capturing detailed information on post-pandemic work arrangements, VMT at a more disaggregate level, and behaviors in response to changes in fuel prices.

13.2 Data Format and Content

There are three types of data files (.sav file for IBM SPSS system,.xlsx file for Microsoft Office, and .csv file for general purposes), and an .xlsx file for the codebook that describe variables and attributes in the database.

Database: Each row represents a single survey respondent with a unique ID number assigned, and each column corresponds to one variable.

Codebook: The codebook corresponds to the variables in the database. Each row represents a categorical variable, with its level and label. Continuous variables were omitted from this spreadsheet.

13.3 Data Access and Sharing

The final data of this project is subject to the UC Davis Institutional Review Board (IRB) guidelines on the treatment of human subject data and is available upon request from the principal investigator.

13.4 Reuse and Redistribution

The final data of this project is subject to the UC Davis Institutional Review Board (IRB) guidelines on the treatment of human subject data and is available upon request from the principal investigator. For all purposes allowed by the IRB guidelines, there are no restrictions on the use of the data. Data can be reused with credit to this report and the authors of the research.

14 Appendix

Table 14-1. Comparison of the unweighted and weighted sample to the California population in the Fall 2020 dataset

Target variable	Sub-category	Population percentage	Unweighted sample		Weighted sample	
			Sample percentage	Difference	Sample percentage	Difference
Age	18 to 34	32.0%	31.5%	-0.5 p.p	29.3%	-2.7 p.p
	35 to 64	49.4%	51.3%	1.9 p.p	54.1%	4.7 p.p
	65+	18.6%	17.1%	-1.4 p.p	16.6%	-2.0 p.p
Gender	Male	49.7%	41.2%	-8.5 p.p	51.1%	1.4 p.p
	Female	50.3%	58.8%	8.5 p.p	48.9%	-1.4 p.p
Ethnicity	Hispanic	39.1%	22.7%	-16.4 p.p	35.4%	-3.7 p.p
	Non-Hispanic	60.9%	77.3%	16.4 p.p	64.6%	3.7 p.p
Race	White	56.1%	66.5%	10.5 p.p	56.6%	0.5 p.p
	Black	5.7%	5.2%	-0.5 p.p	5.4%	-0.3 p.p
	Other	38.2%	28.3%	-9.9 p.p	38.0%	-0.2 p.p
Education	Highschool or less	36.4%	14.6%	-21.9 p.p	24.7%	-11.7 p.p
	Some college	28.8%	32.2%	3.3 p.p	31.6%	2.8 p.p
	Bachelor’s or higher	34.7%	53.3%	18.6 p.p	43.6%	8.9 p.p
Household income	Less than $50,000	32.6%	36.5%	3.9 p.p	28.0%	-4.6 p.p
	$50,000 to $99,999	27.7%	31.3%	3.6 p.p	29.7%	2.0 p.p
	$100,000 or higher	39.7%	32.2%	-7.5 p.p	42.3%	2.6 p.p
Employment status	Employed	65.6%	59.9%	-5.7 p.p	80.8%	15.2 p.p
	Not employed	34.4%	40.1%	5.7 p.p	19.2%	-15.2 p.p
Pre-pandemic telework	Non-teleworker	84.3%	76.7%	-7.6 p.p	81.1%	-3.3 p.p
	Non-usual teleworker	14.4%	13.6%	-0.8 p.p	17.3%	2.9 p.p
	Usual teleworker	1.3%	9.7%	8.4 p.p	1.7%	0.4 p.p
Pandemic telework	Non-teleworker	53.5%	38.9%	-14.6 p.p	49.7%	-3.8 p.p
	Non-usual teleworker	12.5%	19.3%	6.8 p.p	12.5%	0.1 p.p
	Usual teleworker	34.0%	41.8%	7.8 p.p	37.8%	3.7 p.p

Table 14-2. Comparison of the unweighted and weighted sample to the California population in the Summer 2021 dataset

Target variable	Sub-category	Population percentage	Unweighted sample		Weighted sample	
			Sample percentage	Difference	Sample percentage	Difference
Age	18 to 34	31.3%	33.1%	1.8 p.p	29.2%	-2.1 p.p
	35 to 64	49.5%	43.8%	-5.7 p.p	52.4%	2.9 p.p
	65+	19.3%	23.1%	3.8 p.p	18.5%	-0.8 p.p
Gender	Male	50.2%	39.9%	-10.3 p.p	46.2%	-4.0 p.p
	Female	49.8%	60.1%	10.3 p.p	53.8%	4.0 p.p
Ethnicity	Hispanic	32.5%	30.0%	-2.6 p.p	31.8%	-0.7 p.p
	Non-Hispanic	67.5%	70.0%	2.6 p.p	68.2%	0.7 p.p
Race	White	55.5%	68.6%	13.1 p.p	61.9%	6.4 p.p
	Black	5.0%	5.7%	0.7 p.p	5.5%	0.5 p.p
	Other	39.5%	25.7%	-13.9 p.p	32.6%	-6.9 p.p
Education	Highschool or less	33.2%	17.7%	-15.6 p.p	20.8%	-12.4 p.p
	Some college	29.1%	33.3%	4.2 p.p	32.0%	2.9 p.p
	Bachelor's or higher	37.6%	49.0%	11.4 p.p	47.2%	9.5 p.p
Household income	Less than $50,000	29.1%	38.6%	9.5 p.p	28.5%	-0.6 p.p
	$50,000 to $99,999	26.2%	31.0%	4.9 p.p	29.6%	3.4 p.p
	$100,000 or higher	44.7%	30.4%	-14.3 p.p	41.9%	-2.8 p.p
Employment status	Employed	65.8%	47.6%	-18.2 p.p	78.6%	12.7 p.p
	Not employed	34.2%	52.4%	18.2 p.p	21.4%	-12.7 p.p
Pre-pandemic telework	Non-teleworker	84.3%	36.1%	-48.2 p.p	74.8%	-9.6 p.p
	Non-usual teleworker	14.4%	22.2%	7.9 p.p	23.0%	8.6 p.p
	Usual teleworker	1.3%	41.7%	40.4 p.p	2.3%	1.0 p.p
Pandemic telework	Non-teleworker	53.5%	66.9%	13.4 p.p	60.7%	7.2 p.p
	Non-usual teleworker	12.5%	7.3%	-5.1 p.p	10.4%	-2.1 p.p
	Usual teleworker	34.0%	25.7%	-8.3 p.p	28.9%	-5.1 p.p

Table 14-3. Comparison of the unweighted and weighted sample to the California population in the Fall 2023 dataset

Target variable	Sub-category	Population percentage	Unweighted sample		Weighted sample	
			Sample percentage	Difference	Sample percentage	Difference
Age	18 to 34	31.5%	21.4%	-10.1 p.p	29.8%	-1.7 p.p
	35 to 64	49.4%	51.9%	2.6 p.p	50.2%	0.8 p.p
	65+	19.2%	26.7%	7.5 p.p	20.0%	0.9 p.p
Gender	Male	50.1%	44.5%	-5.6 p.p	49.9%	-0.2 p.p
	Female	49.9%	55.5%	5.6 p.p	50.1%	0.2 p.p
Ethnicity	Hispanic	39.7%	27.0%	-12.7 p.p	37.5%	-2.2 p.p
	Non-Hispanic	60.3%	73.0%	12.7 p.p	62.5%	2.2 p.p
Race	White	48.1%	67.7%	19.6 p.p	50.0%	1.9 p.p
	Black	5.6%	4.8%	-0.8 p.p	5.8%	0.2 p.p
	Other	46.3%	27.5%	-18.8 p.p	44.2%	-2.1 p.p
Education	Highschool or less	36.0%	12.6%	-23.4 p.p	32.9%	-3.1 p.p
	Some college	28.1%	30.6%	2.5 p.p	29.3%	1.2 p.p
	Bachelor's or higher	35.9%	56.8%	20.9 p.p	37.7%	1.9 p.p
Household income	Less than $50,000	27.9%	30.7%	2.8 p.p	28.8%	1.0 p.p
	$50,000 to $99,999	25.7%	31.0%	5.2 p.p	25.9%	0.1 p.p
	$100,000 or higher	46.4%	38.3%	-8.1 p.p	45.3%	-1.1 p.p
Employment status	Employed	65.4%	61.3%	-4.1 p.p	73.1%	7.8 p.p
	Not employed	34.6%	38.7%	4.1 p.p	26.9%	-7.8 p.p
Pandemic telework	Non-teleworker	53.5%	36.8%	-16.7 p.p	51.9%	-1.6 p.p
	Non-usual teleworker	12.5%	30.3%	17.9 p.p	13.3%	0.9 p.p
	Usual teleworker	34.0%	32.8%	-1.2 p.p	34.7%	0.7 p.p

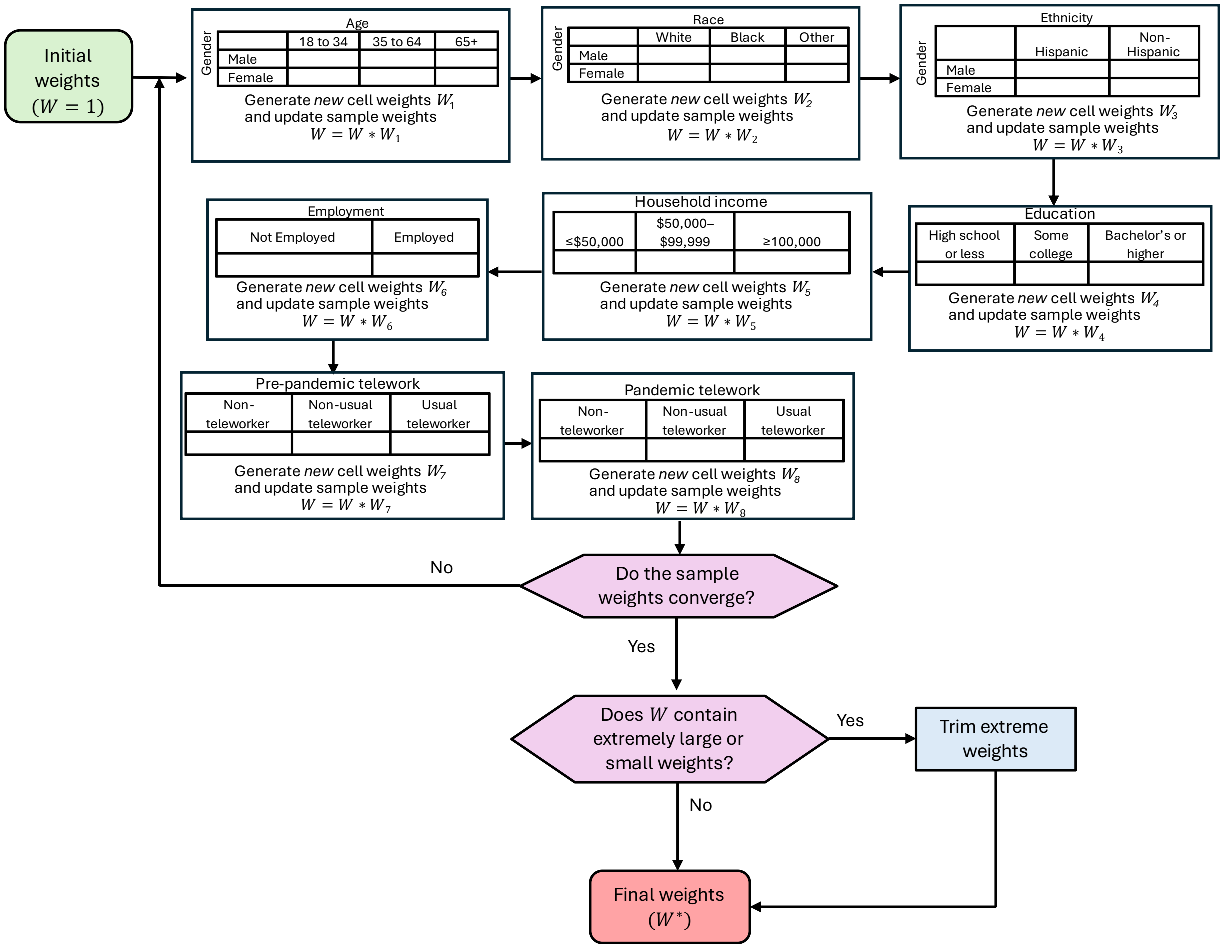


Figure 14-1. The procedure used to develop weights for the Fall 2020 and Summer 2021 samples (adapted from (Wang et al., 2023))

Table 14-4. Summary Statistics for Fall 2020

Variable	Number of valid responses	Household income equal to or more than $50k/year **(N = 2,936)**	Household income below $50k/year **(N = 1,688)**	P value
Worker status				
I work full-time	4,588	1,584 (54%)	336 (20%)	<0.001
I work part-time	4,588	367 (13%)	344 (21%)	<0.001
I have two or more jobs	4,588	76 (2.6%)	51 (3.1%)	0.4
I drive/travel for work (e.g. Taxi/Uber driver, deliveries)	4,588	46 (1.6%)	39 (2.3%)	0.065
I only do unpaid work (e.g. volunteering, unpaid internship)	4,588	30 (1.0%)	29 (1.7%)	0.04
I'm furloughed with pay from my previous job	4,588	10 (0.3%)	7 (0.4%)	0.7
I'm furloughed without pay from my previous job	4,588	61 (2.1%)	51 (3.1%)	0.041
I was let go from my job during the COVID-19 pandemic	4,588	86 (2.9%)	110 (6.6%)	<0.001
My place of employment went out of business during the COVID-19 pandemic	4,588	26 (0.9%)	38 (2.3%)	<0.001
I am now working fewer hours than I did before the COVID-19 pandemic	4,588	189 (6.5%)	138 (8.3%)	0.023
I am now working more hours than I did before the COVID-19 pandemic	4,588	62 (2.1%)	28 (1.7%)	0.3
Nature of work				
Based on the nature of your job, can any parts of your job be done from home?	2,755			<0.001
No, I cannot work from home		470 (23%)	392 (53%)	
Some of my job tasks can be performed from home		491 (24%)	117 (16%)	
Most of my job tasks can be performed from home		491 (24%)	97 (13%)	
All of my job tasks can be performed from home		557 (28%)	140 (19%)	
"The nature of my job requires me to physically go to work even during the pandemic."	2,601			<0.001
Strongly disagree		483 (25%)	107 (16%)	
Somewhat disagree		231 (12%)	52 (7.7%)	
Neither agree nor disagree		238 (12%)	89 (13%)	
Somewhat agree		413 (21%)	124 (18%)	
Strongly agree		559 (29%)	305 (45%)	
"Working from home is not practical (e.g. due to lack of office devices, distractions from family members)."	2,601			<0.001
Strongly disagree		403 (21%)	102 (15%)	
Somewhat disagree		372 (19%)	100 (15%)	
Neither agree nor disagree		429 (22%)	211 (31%)	
Somewhat agree		424 (22%)	158 (23%)	
Strongly agree		296 (15%)	106 (16%)	
Use of technology				
"I like to be among the first people to have the latest technology."	4,624			<0.001
Strongly disagree		390 (13%)	334 (20%)	
Somewhat disagree		654 (22%)	424 (25%)	
Neither agree nor disagree		660 (22%)	466 (28%)	
Somewhat agree		717 (24%)	313 (19%)	
Strongly agree		515 (18%)	151 (8.9%)	
Do you currently own any of the following devices or services?				

Variable	Number of valid responses	Household income equal to or more than $50k/year **(N = 2,936)**	Household income below $50k/year **(N = 1,688)**	P value
Laptop	4,603	2,540 (87%)	1,232 (73%)	<0.001
Desktop computer at home	4,603	1,743 (60%)	666 (40%)	<0.001
Access to private vehicle				
I own a vehicle		2,283 (87%)	929 (68%)	<0.001
I lease a vehicle		152 (5.8%)	57 (4.2%)	0.027
I have regular access to a vehicle for personal use through my job		65 (2.5%)	20 (1.5%)	0.034
Someone else in my household owns/leases a vehicle		420 (16%)	263 (19%)	0.011
There is no vehicle in my household, but I have regular access to one owned by somebody else (e.g. friend, roommate)		11 (0.4%)	46 (3.4%)	<0.001
There is no regular access to a vehicle in my household		38 (1.5%)	132 (9.6%)	<0.001
Perceptions and preferences about transportation options				
"To me, a car is just a way to get from place to place."	4,624			<0.001
Strongly disagree		223 (7.6%)	100 (5.9%)	
Somewhat disagree		525 (18%)	189 (11%)	
Neither agree nor disagree		379 (13%)	282 (17%)	
Somewhat agree		1,097 (37%)	632 (37%)	
Strongly agree		712 (24%)	485 (29%)	
"I like the idea of public transit as a means of transportation for me."	4,624			0.11
Strongly disagree		592 (20%)	353 (21%)	
Somewhat disagree		613 (21%)	357 (21%)	
Neither agree nor disagree		662 (23%)	424 (25%)	
Somewhat agree		704 (24%)	359 (21%)	
Strongly agree		365 (12%)	195 (12%)	
"My schedule makes it hard or impossible for me to use public transportation."	4,624			<0.001
Strongly disagree		464 (16%)	368 (22%)	
Somewhat disagree		490 (17%)	312 (18%)	
Neither agree nor disagree		764 (26%)	505 (30%)	
Somewhat agree		638 (22%)	278 (16%)	
Strongly agree		580 (20%)	225 (13%)	
"We should raise the price of gasoline to provide funding for better public transportation."	4,624			<0.001
Strongly disagree		880 (30%)	594 (35%)	
Somewhat disagree		650 (22%)	359 (21%)	
Neither agree nor disagree		593 (20%)	427 (25%)	
Somewhat agree		537 (18%)	221 (13%)	
Strongly agree		276 (9.4%)	87 (5.2%)	
"I will feel uncomfortable using public transportation due to concerns about pathogens (e.g. COVID-19 or other)."	3,904			0.038
Strongly disagree		290 (11%)	171 (13%)	
Somewhat disagree		238 (9.2%)	121 (9.1%)	
Neither agree nor disagree		384 (15%)	218 (16%)	
Somewhat agree		773 (30%)	338 (25%)	

Variable	Number of valid responses	Household income equal to or more than $50k/year **(N = 2,936)**	Household income below $50k/year **(N = 1,688)**	P value
Strongly agree		892 (35%)	479 (36%)	
"My local transit agency's efforts to minimize COVID exposure to passengers is sufficient to make me comfortable using transit."	3,910			0.8
Strongly disagree		551 (21%)	294 (22%)	
Somewhat disagree		435 (17%)	213 (16%)	
Neither agree nor disagree		991 (38%)	525 (40%)	
Somewhat agree		445 (17%)	213 (16%)	
Strongly agree		161 (6.2%)	82 (6.2%)	
Economic and subjective well-being				
Have you applied for unemployment benefits because of the current economic situation?	4,624	513 (17%)	510 (30%)	<0.001
Which of the following best describes your current economic situation?	4,624			<0.001
Prefer not to answer		70 (2.4%)	100 (5.9%)	
Paying bills is a major struggle and worry		230 (7.8%)	471 (28%)	
Paying bills is tough and on my mind, but I get by		824 (28%)	673 (40%)	
My monthly bills are affordable, and I don't worry too much about paying them		906 (31%)	282 (17%)	
I am not worried about my monthly bills		906 (31%)	162 (9.6%)	
"I am generally satisfied with my life."	4,624			<0.001
Strongly disagree		53 (1.8%)	136 (8.1%)	
Somewhat disagree		217 (7.4%)	238 (14%)	
Neither agree nor disagree		359 (12%)	399 (24%)	
Somewhat agree		1,327 (45%)	657 (39%)	
Strongly agree		980 (33%)	258 (15%)	
Household composition				
Household size	4,327	2.96 (1.42)	2.79 (1.74)	<0.001
Number of people with health risk	4,327	0.529 (0.829)	0.616 (0.902)	0.002
Number of people with the driver's license	4,327	2.02 (0.982)	1.75 (1.2)	<0.001
Number of household vehicles	4,605	1.72 (1.09)	1.19 (1.09)	<0.001

Table 14-5. Summary Statistics for Summer 2021

Variable	Number of valid responses	Household income equal to or more than $50k/year (N = 3,133)	Household income below $50k/year (N = 1,970)	P value
Worker status				
working full-time for pay	4,189	1,150 (43%)	275 (19%)	<0.001
working part-time for pay	4,189	390 (14%)	268 (18%)	0.002
self-employed / an independent contractor for pay	4,189	233 (8.6%)	159 (11%)	0.026
working at two or more paying jobs	4,189	112 (4.1%)	59 (4.0%)	0.8
doing unpaid work In June/July 2021	4,189	113 (4.2%)	105 (7.1%)	<0.001
looking for a job	4,189	186 (6.9%)	258 (17%)	<0.001
Nature of work				
During the COVID-19 pandemic, were you an essential worker that had to physically commute to work?	2,425	819 (47%)	342 (49%)	0.4
Assume there was no pandemic. What is the maximum frequency that the nature of your job would allow you to telework?	2,384			<0.001
Never		510 (30%)	340 (50%)	
Less than once month		96 (5.6%)	40 (5.9%)	
1-3 times a month		114 (6.7%)	42 (6.2%)	
1-2 times a week		242 (14%)	51 (7.5%)	
3-4 times a week		300 (18%)	55 (8.1%)	
5 or more times a week		445 (26%)	149 (22%)	
Assume there was no pandemic. What is the maximum frequency that your supervisor would let you telework?	2,384			<0.001
Never		539 (32%)	343 (51%)	
Less than once month		110 (6.4%)	43 (6.4%)	
1-3 times a month		159 (9.3%)	47 (6.9%)	
1-2 times a week		303 (18%)	60 (8.9%)	
3-4 times a week		271 (16%)	58 (8.6%)	
5 or more times a week		325 (19%)	126 (19%)	
"Working from home is not practical for me (e.g., due to lack of office devices, distractions from family members)."	2,363			0.006
Strongly disagree		429 (25%)	152 (23%)	
Somewhat disagree		280 (17%)	87 (13%)	
Neither agree nor disagree		286 (17%)	153 (23%)	
Somewhat agree		359 (21%)	138 (21%)	
Strongly agree		341 (20%)	138 (21%)	
Use of technology				
"I like to be among the first people to have the latest technology."	5,103			<0.001
Strongly disagree		469 (15%)	400 (20%)	
Somewhat disagree		608 (19%)	436 (22%)	
Neither agree nor disagree		690 (22%)	523 (27%)	
Somewhat agree		753 (24%)	377 (19%)	
Strongly agree		613 (20%)	234 (12%)	
Which of the following devices do you currently own?				
Laptop	5,103	2,441 (78%)	1,222 (62%)	<0.001
Desktop computer at home	5,103	1,700 (54%)	624 (32%)	<0.001
Access to private vehicles				
I own my own vehicle	3,826	2,165 (86%)	870 (66%)	<0.001

Variable	Number of valid responses	Household income equal to or more than $50k/year (N = 3,133)	Household income below $50k/year (N = 1,970)	P value
I lease my own vehicle	3,826	129 (5.2%)	59 (4.5%)	0.3
Someone else in my household owns/leases a vehicle	3,826	392 (16%)	262 (20%)	0.001
I have regular access to a vehicle for personal use through my job	3,826	80 (3.2%)	22 (1.7%)	0.005
I have access to a vehicle through a carsharing/service program (e.g., Zipcar, Turo, GIG Car Share)	3,826	57 (2.3%)	18 (1.4%)	0.052
There is no vehicle in my household, but I have regular access to one owned by somebody else (e.g., friend, roommate)	3,826	30 (1.2%)	38 (2.9%)	<0.001
I have no regular access to a vehicle	3,826	61 (2.4%)	176 (13%)	<0.001
Perceptions and preferences about transportation options				
"To me, a car is just a way to get from place to place."	5,103			0.001
Strongly disagree		224 (7.1%)	113 (5.7%)	
Somewhat disagree		456 (15%)	237 (12%)	
Neither agree nor disagree		457 (15%)	288 (15%)	
Somewhat agree		1,164 (37%)	719 (36%)	
Strongly agree		832 (27%)	613 (31%)	
"I like the idea of public transit as a means of transportation for me."	5,103			0.033
Strongly disagree		570 (18%)	396 (20%)	
Somewhat disagree		541 (17%)	349 (18%)	
Neither agree nor disagree		693 (22%)	472 (24%)	
Somewhat agree		826 (26%)	485 (25%)	
Strongly agree		503 (16%)	268 (14%)	
"My schedule makes it hard or impossible for me to use public transportation."	5,103			<0.001
Strongly disagree		556 (18%)	450 (23%)	
Somewhat disagree		555 (18%)	367 (19%)	
Neither agree nor disagree		740 (24%)	604 (31%)	
Somewhat agree		671 (21%)	295 (15%)	
Strongly agree		611 (20%)	254 (13%)	
"We should raise the price of driving to provide funding for better public transportation."	5,102			<0.001
Strongly disagree		776 (25%)	560 (28%)	
Somewhat disagree		633 (20%)	476 (24%)	
Neither agree nor disagree		663 (21%)	527 (27%)	
Somewhat agree		668 (21%)	295 (15%)	
Strongly agree		392 (13%)	112 (5.7%)	
"I feel uncomfortable using public transportation due to concerns about pathogens (e.g., COVID-19 or other)."	3,778			0.2
Strongly disagree		306 (12%)	189 (14%)	
Somewhat disagree		270 (11%)	127 (9.7%)	
Neither agree nor disagree		437 (18%)	251 (19%)	
Somewhat agree		727 (29%)	365 (28%)	
Strongly agree		728 (29%)	378 (29%)	
"I am generally satisfied with my transportation options."	5,102			<0.001
Strongly disagree		71 (2.3%)	85 (4.3%)	
Somewhat disagree		223 (7.1%)	160 (8.1%)	
Neither agree nor disagree		438 (14%)	354 (18%)	
Somewhat agree		1,423 (45%)	834 (42%)	
Strongly agree		977 (31%)	537 (27%)	

Variable	Number of valid responses	Household income equal to or more than $50k/year (N = 3,133)	Household income below $50k/year (N = 1,970)	P value
Economic and subjective well-being				
Have you applied for unemployment benefits at any time during the COVID-19 pandemic (March 2020-present)?	5,103	759 (24%)	654 (33%)	<0.001
Which of the following best describes your current economic situation?	5,103			<0.001
Prefer not to answer		53 (1.7%)	90 (4.6%)	
Paying bills is a major struggle and worry		344 (11%)	632 (32%)	
Paying bills is tough and on my mind, but I get by		744 (24%)	717 (36%)	
My monthly bills are affordable, and I don't worry too much about paying them		925 (30%)	314 (16%)	
I am not worried about my monthly bills		1,067 (34%)	217 (11%)	
"I live on a tighter budget now than before the pandemic."	4,096			<0.001
Strongly disagree		526 (20%)	131 (9.1%)	
Somewhat disagree		496 (19%)	164 (11%)	
Neither agree nor disagree		544 (21%)	297 (21%)	
Somewhat agree		641 (24%)	381 (26%)	
Strongly agree		445 (17%)	471 (33%)	
"I am generally satisfied with my life."	5,102			<0.001
Strongly disagree		53 (1.7%)	136 (6.9%)	
Somewhat disagree		171 (5.5%)	226 (11%)	
Neither agree nor disagree		311 (9.9%)	382 (19%)	
Somewhat agree		1,254 (40%)	725 (37%)	
Strongly agree		1,343 (43%)	501 (25%)	
Household composition				
Household size	4,071	2.84 (1.44)	2.54 (1.68)	<0.001
Number of people with health risk	4,047	0.51 (0.92)	0.58 (0.90)	<0.001
Number of people with the driver's license	4,050	1.92 (1.05)	1.63 (1.19)	<0.001
Number of household vehicles	3,516	2.04 (1.09)	1.77 (1.08)	<0.001

Table 14-6. Summary Stats for Fall 2023

Variable	Number of valid responses	Household income equal to or more than $50k/year (N = 2,882)	Household income below $50k/year (N = 1,277)	P value
Worker status				
working full-time for pay	4,159	1,471 (51%)	272 (21%)	<0.001
working part-time for pay	4,159	352 (12%)	196 (15%)	0.006
self-employed / an independent contractor for pay	4,159	256 (8.9%)	150 (12%)	0.004
working at two or more paying jobs	4,159	114 (4.0%)	68 (5.3%)	0.046
doing unpaid work	4,159	128 (4.4%)	54 (4.2%)	0.8
Nature of work				
What is the maximum frequency that your current firm/supervisor would let you work remotely?	2,545			<0.001
Never		561 (28%)	285 (50%)	
Less than a day per month		80 (4.1%)	28 (4.9%)	
1-3 days per month		242 (12%)	39 (6.8%)	
1-2 days per week		325 (16%)	39 (6.8%)	
3-4 days per week		294 (15%)	30 (5.3%)	
5 or more days per week		472 (24%)	150 (26%)	
What is the maximum frequency that the nature of your current job would allow you to work remotely?	2,545			<0.001
Never		527 (27%)	267 (47%)	
Less than a day per month		81 (4.1%)	22 (3.9%)	
1-3 days per month		145 (7.3%)	32 (5.6%)	
1-2 days per week		347 (18%)	41 (7.2%)	
3-4 days per week		276 (14%)	45 (7.9%)	
5 or more days per week		598 (30%)	164 (29%)	
"Working from home is not practical for me (e.g., due to lack of office devices, distractions from family members)."	2,545			<0.001
Strongly disagree		703 (36%)	183 (32%)	
Somewhat disagree		339 (17%)	83 (15%)	
Neither agree nor disagree		294 (15%)	116 (20%)	
Somewhat agree		285 (14%)	110 (19%)	
Strongly agree		353 (18%)	79 (14%)	
Use of technology				
"I like to be among the first people to have the latest technology."	4,159			<0.001
Strongly disagree		408 (14%)	260 (20%)	
Somewhat disagree		681 (24%)	314 (25%)	
Neither agree nor disagree		677 (23%)	304 (24%)	
Somewhat agree		759 (26%)	271 (21%)	
Strongly agree		357 (12%)	128 (10%)	
Which of the following devices do you own or have regular access at home?				
Laptop	4,159	2,345 (81%)	854 (67%)	<0.001
Desktop computer at home	4,159	1,429 (50%)	431 (34%)	<0.001
Access to private vehicles				
I/We own or finance a vehicle/vehicles	4,086	2,599 (92%)	905 (72%)	<0.001
I/We lease a vehicle/vehicles	4,086	147 (5.2%)	55 (4.4%)	0.3
I/We borrow a vehicle/vehicles from someone else (including relatives or friends)	4,086	69 (2.4%)	93 (7.4%)	<0.001

Variable	Number of valid respons es	Household income equal to or more than $50k/year (N = 2,882)	Househol d income below $50k/year (N = 1,277)	P value
I/We have access to a vehicle/vehicles through the job (e.g., company car)	4,086	85 (3.0%)	18 (1.4%)	0.003
I have access to a vehicle through a carsharing service/program (e.g., Zipcar, Turo, GIG Car Share)	4,086	40 (1.4%)	15 (1.2%)	0.6
I/We obtained a vehicle/vehicles by other means (please specify):	4,086	8 (0.3%)	9 (0.7%)	0.047
I have no regular access to a vehicle	4,086	83 (2.9%)	225 (18%)	<0.001
Perceptions and preferences about transportation options				
"To me, a car is just a way to get from place to place."	4,159			0.004
Strongly disagree		211 (7.3%)	77 (6.0%)	
Somewhat disagree		431 (15%)	151 (12%)	
Neither agree nor disagree		344 (12%)	159 (12%)	
Somewhat agree		1,099 (38%)	476 (37%)	
Strongly agree		797 (28%)	414 (32%)	
"I like the idea of public transit as a means of transportation for me."	4,159			0.2
Strongly disagree		455 (16%)	204 (16%)	
Somewhat disagree		518 (18%)	214 (17%)	
Neither agree nor disagree		601 (21%)	306 (24%)	
Somewhat agree		816 (28%)	331 (26%)	
Strongly agree		492 (17%)	222 (17%)	
"My schedule makes it hard or impossible for me to use public transportation."	4,159			<0.001
Strongly disagree		452 (16%)	313 (25%)	
Somewhat disagree		586 (20%)	252 (20%)	
Neither agree nor disagree		643 (22%)	326 (26%)	
Somewhat agree		616 (21%)	211 (17%)	
Strongly agree		585 (20%)	175 (14%)	
"We should raise the cost of driving to provide funding for better public transportation."	4,159			<0.001
Strongly disagree		877 (30%)	436 (34%)	
Somewhat disagree		658 (23%)	294 (23%)	
Neither agree nor disagree		522 (18%)	274 (21%)	
Somewhat agree		546 (19%)	195 (15%)	
Strongly agree		279 (9.7%)	78 (6.1%)	
Economic and subjective well-being				
Which of the following best describes your current economic situation?	4,159			<0.001
Prefer not to answer		51 (1.8%)	33 (2.6%)	
Paying bills is a major struggle and worry		177 (6.1%)	370 (29%)	
Paying bills is tough and on my mind, but I get by		847 (29%)	549 (43%)	
My monthly bills are affordable, and I don't worry too much about paying them		982 (34%)	222 (17%)	
I am not worried about my monthly bills		825 (29%)	103 (8.1%)	
"I live on a tighter budget now than before the pandemic."	4,159			<0.001
Strongly disagree		466 (16%)	73 (5.7%)	
Somewhat disagree		525 (18%)	111 (8.7%)	
Neither agree nor disagree		644 (22%)	204 (16%)	
Somewhat agree		688 (24%)	351 (27%)	
Strongly agree		559 (19%)	538 (42%)	

Variable	Number of valid respons es	Household income equal to or more than $50k/year (N = 2,882)	Househol d income below $50k/year (N = 1,277)	P value
"I am generally satisfied with my life."	4,159			<0.001
Strongly disagree		62 (2.2%)	93 (7.3%)	
Somewhat disagree		138 (4.8%)	154 (12%)	
Neither agree nor disagree		251 (8.7%)	210 (16%)	
Somewhat agree		1,221 (42%)	500 (39%)	
Strongly agree		1,210 (42%)	320 (25%)	
Household composition				
Household size	3,329	3.04 (1.25)	3.26 (1.58)	0.013
Number of people with health risk	3,329	0.66 (1.01)	0.67 (1.14)	0.2
Number of people with the driver's license	3,320	2.06 (0.923)	1.91 (1.07)	<0.001
Number of household vehicles	3,764	2.00 (1.05)	1.68 (1.06)	<0.001

Table 14-7. Percentage distribution of remote and hybrid workers for each category of socio-demographic variables at different time points

Socio-Demographic	Category	Remote Workers					Hybrid Workers				
		Pre-pandemic	2021	2022	2023	2024	Pre-pandemic	2021	2022	2023	2024
COUNT		92	1,090	368	509	524	506	765	1,223	777	799
PERCENTAGE		3.0%	34.6%	11.7%	18.6%	19.1%	16.3%	24.3%	38.8%	28.4%	29.2%
GENDER	Woman	2.2%	36.6%	13.7%	20.2%	21.5%	16.2%	22.4%	39.3%	26.7%	28.8%
	Man	3.0%	33.5%	10.3%	17.1%	17.0%	16.3%	26.5%	38.5%	29.9%	29.5%
AGE	18-34	4.1%	39.7%	11.6%	12.4%	15.1%	19.2%	28.3%	46.9%	31.0%	33.4%
	35-64	1.9%	34.9%	13.7%	21.8%	21.3%	15.5%	25.0%	38.0%	27.5%	27.7%
	65+	2.7%	26.5%	4.2%	20.6%	20.2%	13.5%	13.3%	26.5%	24.4%	23.3%
HISPANIC	Not Hispanic or Latinx	2.3%	37.9%	11.0%	20.8%	20.6%	15.0%	23.2%	40.7%	30.1%	30.6%
	Hispanic or Latinx	3.3%	28.2%	14.4%	15.1%	16.8%	19.3%	27.4%	34.5%	25.7%	26.9%
INCOME	Low income (-$49K)	5.0%	22.0%	5.8%	13.7%	14.8%	15.4%	15.8%	30.6%	24.4%	25.5%
	Medium income ($50-99K)	1.8%	32.9%	16.1%	11.2%	13.9%	11.8%	26.8%	37.1%	23.3%	23.9%
	High income ($100K-)	2.3%	40.7%	11.7%	24.7%	23.8%	19.1%	25.7%	42.7%	32.8%	33.6%
EDUCATION	High school or less	3.4%	23.5%	10.2%	15.5%	16.9%	12.6%	17.6%	26.5%	22.7%	22.5%
	Bachelor's degree or higher	2.0%	43.2%	13.3%	22.6%	22.1%	18.8%	29.0%	47.5%	36.0%	38.1%
EMPLOYMENT	Full time Employed	1.8%	36.3%	10.8%	16.5%	17.0%	14.8%	25.6%	41.4%	26.7%	29.7%
	Part time Employed	5.0%	30.7%	11.6%	10.4%	13.2%	18.6%	18.3%	22.9%	32.7%	22.4%
	Self Employed	10.4%	39.8%	24.5%	48.1%	44.5%	34.4%	31.3%	41.7%	34.2%	31.6%

Table 14-8. Comparison of the use of motorized for commuting trips, by survey

Variable	Sub-category	Private vehicle				Public bus				Subway or train				Ride-hailing			
		F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023
Age	18 to 34	76.9%	84.6%	81.6%	79.7%	29.1%	19.5%	26.8%	28.5%	23.8%	17.5%	20.5%	23.5%	30.3%	19.5%	25.8%	32.2%
	35 to 64	90.5%	91.9%	85.2%	87.6%	19.2%	14.7%	15.0%	17.4%	19.4%	11.0%	13.2%	15.9%	22.8%	17.7%	17.0%	24.1%
	65+	86.7%	96.4%	67.1%	88.0%	2.8%	0.4%	5.9%	15.6%	9.7%	0.0%	4.0%	9.6%	5.0%	0.0%	5.7%	12.8%
Gender	Male	83.7%	89.2%	80.0%	85.3%	22.5%	16.1%	19.7%	23.0%	22.2%	13.1%	17.8%	20.5%	23.4%	17.3%	20.3%	25.4%
	Female	89.0%	92.2%	81.4%	84.5%	15.2%	11.6%	13.3%	19.1%	15.2%	8.9%	9.2%	15.2%	19.7%	13.9%	14.2%	26.3%
Ethnicity	Hispanic	88.7%	90.1%	79.7%	79.9%	16.4%	13.5%	20.8%	26.1%	15.8%	11.1%	14.9%	20.1%	20.1%	16.0%	22.6%	33.7%
	Non-Hispanic	85.1%	90.8%	81.2%	88.3%	20.2%	14.3%	14.4%	17.6%	20.4%	11.3%	12.6%	16.4%	22.4%	15.6%	14.7%	20.4%
Race	Asian or Pacific Islander	83.1%	96.2%	79.9%	90.2%	16.4%	7.7%	12.6%	15.0%	19.5%	5.8%	14.0%	15.3%	17.5%	7.9%	9.4%	22.7%
	Black	94.2%	88.8%	85.0%	78.0%	30.7%	29.5%	25.1%	34.9%	34.5%	27.9%	19.7%	29.9%	38.2%	22.7%	36.9%	36.4%
	Native American	96.0%	93.7%	80.2%	86.7%	17.6%	15.2%	21.9%	26.1%	18.7%	16.1%	25.1%	25.6%	19.7%	16.8%	21.6%	36.4%
	White	86.9%	90.0%	82.5%	85.1%	16.5%	13.3%	14.7%	19.7%	17.1%	10.7%	12.3%	16.3%	20.4%	16.7%	15.8%	24.1%
	Other	84.5%	90.5%	64.7%	76.5%	22.4%	11.6%	22.7%	27.3%	16.0%	6.2%	11.6%	19.8%	20.8%	10.9%	21.6%	33.6%

Table 14-9. Comparison of the use of active modes for commuting trips, by survey

Variable	Sub-category	Personal bike, e-bike, or e-scooter				Shared bike, e-bike, or e-scooter				Walk			
		F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023
Age	18 to 34	15.1%	19.6%	25.8%	32.2%	10.2%	10.6%	14.9%	13.5%	49.9%	36.2%	36.6%	37.6%
	35 to 64	15.6%	14.5%	17.0%	24.1%	9.4%	7.0%	9.2%	7.3%	34.6%	23.6%	24.4%	26.6%
	65+	7.1%	9.1%	5.7%	12.8%	0.6%	0.0%	1.1%	0.2%	32.1%	24.8%	21.9%	20.5%
Gender	Male	21.1%	20.4%	20.3%	25.4%	11.5%	10.1%	11.9%	11.2%	40.6%	33.2%	30.2%	31.8%
	Female	6.4%	8.8%	14.2%	26.3%	4.5%	3.3%	6.6%	6.2%	35.5%	20.0%	24.3%	27.8%
Ethnicity	Hispanic	9.3%	16.8%	22.6%	33.7%	6.7%	6.8%	8.6%	10.2%	32.8%	27.4%	29.9%	35.0%
	Non-Hispanic	16.3%	14.2%	14.7%	20.4%	8.8%	7.1%	9.3%	7.7%	40.8%	27.0%	25.9%	26.3%
Race	Asian or Pacific Islander	14.4%	9.2%	9.4%	22.7%	7.2%	2.5%	4.5%	3.4%	35.2%	14.7%	23.4%	23.7%
	Black	11.1%	10.4%	36.9%	36.4%	6.7%	5.6%	19.3%	5.5%	48.5%	26.6%	39.5%	41.0%
	Native American	6.2%	18.7%	21.6%	36.4%	11.8%	2.2%	13.9%	7.9%	36.2%	22.2%	30.5%	40.5%
	White	15.0%	15.8%	15.8%	24.1%	8.8%	8.1%	8.8%	9.7%	37.0%	28.9%	25.0%	30.0%
	Other	10.6%	15.0%	21.6%	33.6%	4.9%	4.6%	5.7%	11.2%	34.5%	21.8%	36.9%	35.1%

Table 14-10. Comparison of the use of private vehicles and transit for non-commuting trips, by survey

Variable	Sub-category	Private vehicle				Car-sharing				Public bus				Subway or train			
		F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023
Age	18 to 34	79.6%	69.1%	87.1%	83.5%	21.8%	13.3%	19.7%	21.1%	28.3%	11.7%	27.4%	28.1%	23.9%	8.5%	22.1%	20.3%
	35 to 64	94.7%	92.7%	94.3%	92.8%	13.8%	9.6%	11.9%	11.5%	18.2%	12.0%	14.4%	17.0%	16.9%	9.4%	12.1%	16.1%
	65+	98.1%	97.9%	93.5%	95.2%	1.0%	1.3%	3.7%	5.2%	5.3%	3.5%	8.1%	10.7%	6.8%	1.3%	4.4%	9.8%
Gender	Male	89.8%	90.1%	90.6%	90.2%	15.6%	12.7%	16.1%	15.0%	20.4%	14.1%	20.8%	18.5%	18.8%	10.8%	16.8%	17.2%
	Female	93.1%	94.6%	93.4%	90.8%	11.4%	7.2%	9.4%	11.2%	16.5%	8.2%	13.5%	19.6%	15.0%	5.7%	10.6%	14.9%
Ethnicity	Hispanic	89.8%	89.6%	88.5%	84.6%	14.0%	12.5%	14.4%	17.5%	16.7%	11.0%	18.3%	26.2%	13.3%	9.6%	13.0%	18.0%
	Non-Hispanic	92.2%	93.6%	93.7%	94.0%	13.4%	8.8%	11.8%	10.4%	19.4%	11.4%	16.3%	14.8%	18.7%	7.7%	13.8%	14.9%
Race	Asian or Pacific Islander	95.9%	96.3%	88.7%	94.3%	8.2%	3.0%	8.1%	10.1%	14.9%	6.3%	16.2%	17.2%	14.5%	1.5%	13.3%	15.8%
	Black	92.3%	92.0%	92.9%	85.6%	22.2%	16.4%	28.7%	13.9%	29.4%	26.0%	27.0%	30.1%	27.7%	21.8%	25.3%	22.3%
	Native American	97.2%	99.0%	97.8%	84.3%	15.2%	10.1%	8.4%	11.9%	13.5%	11.7%	18.8%	28.5%	15.0%	11.0%	15.1%	21.5%
	White	91.3%	93.2%	94.7%	91.3%	13.9%	10.7%	11.8%	12.6%	18.1%	10.5%	14.8%	17.0%	17.2%	8.5%	13.1%	14.9%
	Other	87.1%	83.7%	77.7%	83.7%	11.5%	10.8%	13.6%	16.5%	17.3%	12.0%	25.7%	26.2%	11.1%	8.2%	11.3%	18.8%

Table 14-11. Comparison of ride-hailing and active modes for non-commuting trips, by survey

Variable	Sub-category	Ride-hailing				Personal bike, e-bike, or e-scooter				Shared bike, e-bike, or e-scooter				Walk			
		F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023	F2019	F2020	S2021	F2023
Age	18 to 34	31.1%	13.1%	27.0%	33.1%	19.3%	13.7%	24.3%	20.9%	16.7%	6.7%	14.3%	13.9%	56.9%	40.4%	53.7%	46.1%
	35 to 64	25.7%	15.3%	16.8%	24.2%	17.9%	16.5%	19.2%	19.7%	8.9%	5.5%	9.2%	5.6%	49.0%	47.9%	47.8%	39.9%
	65+	11.3%	3.3%	9.0%	15.2%	9.9%	8.7%	7.8%	10.9%	0.4%	0.4%	1.7%	1.0%	43.3%	45.4%	39.4%	35.3%
Gender	Male	27.2%	17.4%	22.6%	24.9%	23.8%	20.0%	24.4%	22.6%	12.4%	7.2%	12.8%	8.6%	55.3%	51.2%	52.3%	40.9%
	Female	21.7%	9.4%	14.3%	25.2%	9.4%	10.4%	13.2%	13.9%	6.3%	3.4%	6.0%	5.8%	44.4%	45.2%	44.0%	40.8%
Ethnicity	Hispanic	22.6%	14.9%	20.4%	29.9%	14.2%	15.4%	16.5%	17.3%	11.0%	5.6%	9.4%	10.8%	41.7%	43.8%	46.3%	39.8%
	Non-Hispanic	25.5%	12.9%	17.2%	22.2%	18.1%	15.3%	19.4%	18.8%	8.6%	5.3%	9.2%	5.0%	54.2%	50.5%	48.6%	41.4%
Race	Asian or Pacific Islander	26.0%	8.4%	15.5%	22.5%	16.3%	13.8%	15.0%	14.0%	5.8%	2.5%	5.7%	4.2%	57.2%	50.2%	51.1%	39.4%
	Black	41.1%	22.9%	31.3%	36.2%	11.8%	12.6%	27.8%	20.1%	9.3%	5.0%	17.6%	9.0%	62.0%	57.2%	45.3%	52.7%
	Native American	20.5%	16.8%	19.8%	31.5%	17.0%	24.8%	23.7%	15.8%	12.0%	11.0%	14.0%	6.1%	43.8%	63.2%	46.6%	41.6%
	White	23.1%	12.6%	17.6%	23.6%	18.9%	16.5%	18.2%	18.2%	10.5%	6.7%	9.0%	7.0%	48.0%	48.0%	46.5%	40.8%
	Other	22.4%	15.4%	19.0%	31.3%	9.2%	17.2%	17.9%	18.3%	6.0%	1.8%	8.7%	10.9%	44.1%	40.8%	48.8%	44.2%