Title

Investigating the Temporary and Longer-Term Impacts of the COVID-19 Pandemic on Mobility in California

Authors
Circella, Giovanni, PhD
Iogansen, Xiatian
Matson, Grant
et al.

Publication Date
2024-10-01

DOI
10.7922/G2ZW1J90

RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

Investigating the Temporary and Longer-Term Impacts of the COVID-19 Pandemic on Mobility in California

Giovanni Circella, Ph.D., Director of the 3 Revolutions Future Mobility Program[1]
Xiatian Iogansen[1]
Grant Matson[1]
Keita Makino[1]
Jai K. Malik, Ph.D., World Bank
Yongsung Lee, Ph.D., Co-Director of the 3 Revolutions Future Mobility Program[1]

1 Institute of Transportation Studies, University of California, Davis

October 2024

ITS UCDAVIS Institute of Transportation Studies

Report No.: UC-ITS-2021-05 | DOI: 10.7922/G2ZW1J90

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
UC-ITS-2021-05	N/A	N/A

4. Title and Subtitle	5. Report Date
Investigating the Temporary and Longer-Term Impacts of the COVID-19 Pandemic on Mobility in California	October 2024
	6. Performing Organization Code ITS-Davis
7. Author(s) Giovanni Circella, Ph.D., https://orcid.org/0000-0003-1832-396X; Xiatian Iogansen, https://orcid.org/0000-0002-4851-1323; Grant Matson, https://orcid.org/0000-0002-4856-2200; Keita Makino, https://orcid.org/0000-0001-5080-2843; Jai K. Malik, Ph.D., https://orcid.org/0000-0002-7137-7302; Yongsung Lee, Ph.D., https://orcid.org/0000-0002-1980-1225;	**8. Performing Organization Report No.** UCD-ITS-RR-24-29
9. Performing Organization Name and Address Institute of Transportation Studies, Davis 1605 Tilia Street Davis, CA 95616	**10. Work Unit No.** N/A **11. Contract or Grant No.** UC-ITS-2021-05
12. Sponsoring Agency Name and Address The University of California Institute of Transportation Studies www.ucits.org	**13. Type of Report and Period Covered** Final Report (May 2021 – December 2023) **14. Sponsoring Agency Code** UC ITS

15. Supplementary Notes

DOI:10.7922/G2ZW1J90

16. Abstract

This report summarizes the findings from ten sets of analyses that investigated ways the COVID-19 pandemic transformed people's activity-travel patterns. Data were collected through three waves of surveys in Spring 2020, Fall 2020, and Summer 2021 in California and the rest of the US. We found that there was a substantial shift among California workers from physical commuting to exclusive remote work in 2020, followed by a transition to hybrid working schedules by Summer 2021. The adoption of remote work and hybrid work varied significantly among population subgroups, with higher income, more educated individuals, and urban residents showing the greatest shift to these arrangements. In terms of mode use and vehicle ownership, increased concerns about the use of shared modes of travel correlated with an increasing desire to own a car. We observed a major decrease in walking for commuting purposes and a significant increase in walking and biking for non-work trips. The study also found a reduction in the demand for, and/or an elevated aversion to, ridehailing because of the shared nature of the service. Regarding shopping patterns, the study found a nearly five-fold increase in the number of respondents who shopped online at least once per week between Fall 2019 and Spring 2020. However, part of this increase vanished by Fall 2020. Overall, the pandemic brought both temporary changes and longer-term impacts. The study proposes strategies to promote sustainable transportation and social equity among different population groups as communities strive to recover from the pandemic.

17. Key Words	18. Distribution Statement
COVID-19, mobility, travel behavior, activity choices, online shopping, telecommuting, data collection	No restrictions.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	67	N/A

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Acknowledgments

This study was made possible with 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). Additional funding was provided by the National Center for Sustainable Transportation (NCST), supported by the US Department of Transportation (USDOT) and the California Department of Transportation (Caltrans), the California Air Resources Board (CARB), the Southern California Association of Governments (SCAG) and the 3 Revolutions Future Mobility (3RFM) Program of the University of California, Davis. The authors would like to thank the State of California, the USDOT, Caltrans, CARB, SCAG and the 3RFM program for their support of university-based research in transportation, and especially for the funding provided in support of this project. The authors would like to thank Junia Compostella, Mischa Young, Bailey Affolter, Tak Chun Marcus Chan, Mikayla Elder, Sean McElroy, Jaime Soza Parra, Dillon Fitch and several other colleagues at the University of California, Davis and other institutions for their contribution to the activities of this project.

Disclaimer

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Report No.: UC-ITS-2021-05 | DOI: 10.7922/G2ZW1J90

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Executive Summary

1. Executive Summary

The global COVID-19 pandemic significantly disrupted travel behavior and daily activities in communities worldwide. To gain a better understanding of the pandemic's impacts on transportation and society, three rounds of data collection were conducted in California. Data collection periods spanned May to August 2020 (Spring 2020), December 2020 to January 2021 (Fall 2020), and August to October 2021 (Summer 2021). The study was able to generate large repeated cross-sectional datasets, including 3,813 respondents for the Spring 2020 survey, 5,521 respondents for the Fall 2020 survey, and 6,400 respondents for the Summer 2021 survey. A smaller longitudinal sample was derived from 1,092 respondents who completed at least two of the three surveys and 625 respondents who completed all three surveys. Findings of this study and their implications for policy can provide insights for policymakers and stakeholders seeking to understand car ownership and usage in the post-pandemic era.

Surveys collected information from respondents regarding sociodemographic characteristics, attitudes, employment and work/student activities, shopping patterns, travel choices, vehicle ownership, technology use, emerging transportation options, and other topics. We used this information to investigate the evolving behavioral choices and preferences of respondents ranging from Fall 2019 to Summer 2022. The research team aimed to answer the following questions:

- How have commuting and remote work status(es), vehicle ownership, mode use(s), and shopping behaviors changed during the COVID-19 pandemic?
- What factors have influenced these changes, and how do these impacts vary across different time periods, geographical locations, and socio-demographic groups?
- What are the implications of these changes for travel behavior?
- What policies could be implemented to enhance sustainability and equity during the recovery phase after the pandemic?

The study found a significant shift in individuals' work arrangements during the COVID-19 pandemic. Initially, in 2020, there was a substantial transition from physical commuting to exclusive remote work. By Summer 2021, there was a move towards hybrid work schedules, featuring both physical commuting and remote work. The proportion of workers who exclusively or mainly worked remotely during this time increased substantially. However, it decreased slightly by Summer 2021 and further reductions were expected by Summer 2022.

In contrast, the percentage of hybrid workers increased in Fall 2020 and further in Summer 2021. The frequency of remote work among those who had adopted this practice increased during the early phase of the pandemic but declined in the later phase. We observed major differences in socio-demographics and travel patterns between remote work adopters and non-adopters. Hybrid workers predominantly consist of individuals who are younger, highly educated, have a high income, and reside in urban areas. Remote workers were more likely to be living in non-urban locations and have lower vehicle miles traveled (VMT).

Respondents from different survey recruitment channels, such as online opinion panels versus mail-based surveys, exhibited different propensities for adopting hybrid and remote work. Such differences between recruitment channels, often overlooked in previous studies on the impacts of the COVID-19 pandemic on transportation, deserve consideration and has been assessed as part of this study.

In terms of mode preferences and choices, our study found that the desire to own a car increased during the pandemic and that concerns about the use of shared modes of travel were elevated. The mode share for commuting purposes was similar to pre-pandemic levels. Even so, there was an upward trend in vehicle ownership among respondents. The use of public buses decreased somewhat, while the use of rail-based public transportation decreased significantly. We observed a large decrease in walking for commute purposes, and a significant increase in walking and bicycling for non-work trips. While the share of those that have used ridehailing at least once continually increased, the portion of the sample that reported use of a ridehailing service "in the last 30 days" dropped. This highlights the reduction in demand for and/or an aversion to ridehailing, presumably because they perceive shared services as risky in the context of a transmissible disease.

Several factors that significantly influenced changes in vehicle ownership included latent attitudes, sociodemographic characteristics, life events, and concerns related to COVID-19. Tech-savvy and variety-seeking individuals were more likely to increase or replace household vehicles, whereas individuals who are pro-environmental and open to active transportation modes were less likely to do so. Higher levels of education and household income were associated with a greater propensity to acquire a vehicle, while decreases in household size were linked to a reduction in vehicle ownership. Households with multiple family members exhibited more volatility in their vehicle ownership patterns, likely due to their more dynamic travel needs. Furthermore, individuals transitioning from non-students and non-workers into student or worker roles tended to adopt more vehicles. COVID-19 health concerns led some individuals to increase their level of household vehicle ownership, while others embraced a more active lifestyle including walking and cycling.

Regarding travel related to shopping patterns, we found that the number of respondents who shop online (e-shopping) at least once per week increased significantly during the pandemic. However, the proportion of respondents engaging in weekly online shopping started to decrease by Fall 2020. This suggests that the surge in e-shopping observed during the early months of the COVID-19 pandemic may have been temporary (*1*). Although higher-income people increased spending via online shopping more than middle-income people, the latter group increased their online shopping frequency more than the former. Similarly, the pandemic impacted consumers' use of delivery services.

We found three clusters of individuals, each with distinct online shopping behaviors:

(a) Occasional Shoppers who made infrequent purchases and preferred to use fast and standard delivery options,

(b) Non-Shoppers who made few online purchases or did not purchase online and were mainly part of the zero-frequency group in terms of online shopping, and

(c) Super Shoppers who made frequent online purchases or more than three purchases in a month using any delivery option.

Super Shoppers and Occasional Shoppers are more likely to be found among respondents in the age group 35-54, and they are likely to have a bachelor's degree or higher education. Non-Shoppers are more commonly found among respondents of age 55+ and those who do not have a bachelor's degree. Respondents who reported positive attitudes toward technology are mostly Super Shoppers, and those who reported negative attitudes about technology are more likely to be Non-Shoppers. Occasional Shoppers have an almost equal share of respondents who have positive and negative attitudes toward technology. Super Shoppers are more likely to live in urban areas, while Occasional Shoppers and Non-Shoppers are more likely to live in less dense areas.

The analyses conducted in this study provide insights into the changes brought by the pandemic and inform recommendations for policymakers. Major disparities were observed in accessing opportunities to work remotely among workers with different occupations and in different sociodemographic groups. To promote equity and inclusivity, employers could consider ways to promote equitable work options across all types of jobs, including implementing policies that help support flexible work arrangements whenever possible. Such policies can help attract and retain talent while enhancing overall productivity.

Changes in commuting patterns during the pandemic present an opportunity for transportation agencies to reassess their planning, engineering, and investment decisions. Rather than solely focusing on peak-hour demands, agencies can leverage the additional roadway capacity available throughout the day. This approach reduces the immediate need for costly roadway expansions and encourages more efficient use of existing road infrastructure. New patterns of demand might make reorganization of public transit more difficult. Agencies may be challenged to balance peak and non-peak service with demand and to adjust regional and local services for cost-effectiveness.

We also observed an upward trend in vehicle ownership among respondents, with an increasing proportion of individuals owning three or more vehicles and a decreasing proportion of individuals owning two or fewer vehicles by Summer 2021. More individuals increased, rather than decreased, their vehicles in the recent past and in the anticipated future. Those who transitioned from car-owners to non-car-owners during the pandemic may rely on mass transit. However, public transit may not provide service that is as frequent and reliable as it was before the pandemic due to driver shortages, financial uncertainty, and other factors. More transportation alternatives need be provided for this group of workers to increase mobility and accessibility. For instance, increasing support for the use of public transit, active modes, and other shared mobility options can reduce private vehicle use.

In terms of shopping behaviors, it is important to identify the socio-demographics and geographic locations of new online shoppers. The evolving e-commerce sector requires better freight infrastructure, goods delivery services, and curb management. Physical retailers, including grocery stores investigated in this study, must continue to respond to shoppers' evolving behavior and demand volatility. Transportation and city planners must keep pace with the growth in online shopping and the distribution of purchased goods in policy development. Increased online commerce may influence residents' housing location decisions and reduce the frequency of shopping-related trips. Pressure on curbside access and street parking will likely increase due to more frequent deliveries.

Contents

1 Introduction

The COVID-19 pandemic has had a profound impact on the daily activities and travel patterns of individuals worldwide (*2*). Among other changes, virtual activities became a frequently chosen alternative to in-person engagements that required physical travel (*3*, *4*). As a result, many students and employees swiftly transitioned to remote learning and remote work arrangements. Furthermore, the pandemic expedited the widespread adoption of online shopping and food delivery services. Consequently, the volume of passenger VMT in the United States (US) during this period plummeted to 40% of the value projected in the absence of a pandemic (*5*). Although VMT experienced a gradual rebound thereafter, it consistently remained below the pre-pandemic baseline throughout much of 2020 and early 2021. However, this trend shifted in March 2021 as the introduction of new COVID vaccines instilled confidence and transportation providers, such as airlines, implemented stringent sanitization protocols to mitigate exposure risks. As a result, both long-distance air travel and daily passenger vehicle travel bounced back, leading to a surge in VMT. Conversely, transit ridership reached historic lows due to the pandemic, and its recovery has been much slower compared to car travel, as of 2022. By mid-August 2022, nationwide monthly transit ridership remained 36% below the pre-pandemic baseline, exhibiting considerable variations across different transit modes and geographic locations (*6*).

Public transit agencies, planning companies, mobility-service providers, and private businesses have shown a keen interest in the impacts of the pandemic on individuals' activity patterns and travel behaviors. They seek to predict the short- and long-term travel demand as the pandemic evolves (*7*). Nonetheless, the US transportation sector and society remain largely uncertain about the lasting implications of these changes. Concerns among transportation professionals revolve around the potential consequences of reduced demand for public transit and shared modes of travel, coupled with the rise of remote work during the pandemic. There is apprehension that these factors may contribute to further suburbanization and the promotion of car-oriented lifestyles (*8*). However, some cities have taken steps to repurpose existing infrastructure, focusing on promoting walking and cycling. These measures aim to facilitate social distancing and offer an alternative means of transportation amidst the pandemic (*9*). To support positive shifts in travel behaviors and provide insights for transportation policy and infrastructure management, it is imperative to understand the behavioral changes individuals have undergone during this crisis and determine whether these changes are temporary or enduring in nature.

The implications of the pandemic on activity and travel patterns holds particular significance for California. The state is committed to reducing traffic congestion, enhancing transportation efficiency, lowering system-level VMT, and decreasing greenhouse gas emissions. Additionally, California aims to improve access to transportation opportunities, especially for low-income communities and communities of color. To support these goals, three extensive surveys were conducted in California. The first took place from May to August 2020, involving a sample size of 3,813 respondents. The second occurred from December 2020 to January 2021, with a sample size of 5,521 respondents. The third was conducted from August to October 2021, with a sample size of 6,400 respondents. These surveys were part of a larger COVID mobility study and together form a substantial repeated cross-sectional sample. There is a smaller longitudinal sample consisting of 1,092 respondents who completed at least two of the surveys and 625 respondents who completed all three.

The surveys collected a wide range of self-reported information, including individuals' activity patterns and travel choices during and before the pandemic, their use of technology, shopping habits, travel mode preferences, vehicle ownership, and the socio-demographic characteristics of both individuals and households. Respondents' levels of agreement with a series of statements designed to measure latent attitudinal constructs were assessed. These constructs covered environmental issues, preferences for home location, concerns regarding the pandemic, and more. For detailed information on the survey and data collection methodology, please refer to Section 2 of the report.

This report comprises ten studies investigating individuals' changes in work arrangements, mode use and shopping patterns during the pandemic and determining the persistence of these patterns in the post-pandemic period. More specifically, Section 3 includes three studies which examine transformations in physical commute and remote work patterns throughout the pandemic and assess the likelihood of remote work continuing post-pandemic. Section 4 includes four studies which investigate changes in vehicle ownership and mode use that occurred during the pandemic. Section 5 includes three studies which analyze the shifts in online shopping patterns and preferences in delivery options across different timeframes and demographic groups that emerged during the pandemic. Overall, the studies seek to identify mobility barriers and service gaps and provide policy recommendations tailored to diverse population segments to enhance equity, environmental sustainability, and the overall efficiency of the regional transportation system in the future.

Each study uses slightly different datasets. Consequently, we have included explanations in this report regarding the background, data sources, methodology, and results of each of the ten studies. Due to space constraints, this report presents a condensed version of each of the ten studies. For a more in-depth analysis, we refer readers to the full papers, which are referenced accordingly. This report culminates with conclusions and policy implications, a discussion of limitations, and suggestions for future research in Section 6.

2 Data Collection and Handling

2.1 Data Collection

The research team has collected three waves of survey data for the COVID-19 Mobility Study to assess temporary and longer-term impacts of the pandemic. The COVID-19 survey was built on existing research projects, 2018 *California Mobility Survey* (*10*) and the 2019 *Annual Nationwide Mobility* Survey (*11*), that were administered by the research team before the pandemic. Responses were collected in Spring 2020, Fall 2020, and Summer 2021. Data collection targeted 15 regions of the US and two regions in Canada. We attempted to build repeated cross-sectional surveys by contacting respondents from previous surveys (Figure 2-1).

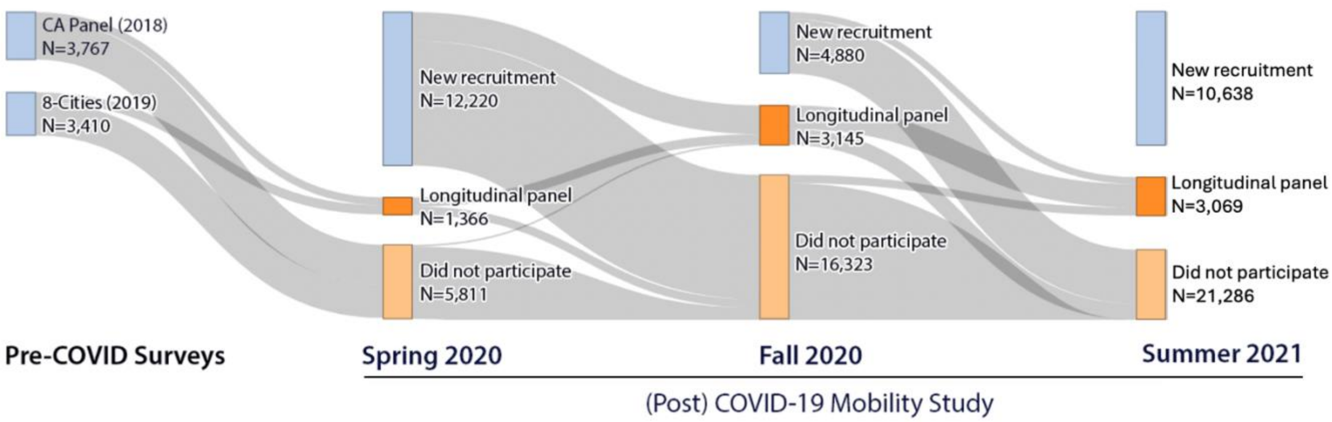

Figure 2-1. Repeated cross-sectional survey data collection

Note: The light orange cells representing for "Did not participate" category are not proportional to the actual sample size.

The team used multi-channel sampling and recruitment methods to generate robust samples (see Table 2-1). For all three rounds of data collection, we used mixed sampling methods, including: (a) new recruitment of participants through a commercial online opinion panel, (b) recontacting previous respondents from other surveys administered by the research team in the state (i.e., use of a longitudinal panel), and (c) convenience sampling through social media, professional email lists, and local listservs from partner agencies. For the third round of data collection in Summer 2021, we also drew a (d) stratified random sample of residents by mailing printed invitations to complete the online survey, sent to the mailing addresses of randomly selected households in the state. In addition, we mailed printed copies of the questionnaire with a pre-paid return envelope to a smaller number of randomly selected households. This mix of approaches allowed for one channel to offset the known shortcomings of other channels. For instance, the sample recruited through an online opinion panel tends to skew toward segments of the population who are tech-savvy internet users, have more time available, and are more likely to subscribe to an online opinion panel. In addition, this sampling method is a type of non-probabilistic quota sampling (thus, convenience sampling) and the sampling frame for an online opinion panel remains largely unknown, as it relies on the ability of the commercial provider to recruit participants for their online opinion panel. The recruitment through stratified random sampling of respondents using a paper survey questionnaire can reach segments of the population that are missing from the online channel. The paper survey option relies on probabilistic sampling and eliminates many of the sampling biases that affect the previous channel but is much more resource intensive. A paper survey requires preparation, printing, and mailing, time to collect responses, and data entry to convert printed questionnaires to a digital format.

The data collection process was similar among these three surveys with a mostly consistent structure and set of questions. However, latter waves of data collection incorporated lessons learned during the former waves of data collection. We introduce weights to increase the representativeness of our sample in each dataset to mirror the socio-demographic characteristics of California residents.

Table 2-1. Summary of sampling and recruitment methods for the Spring 2020, Fall 2020 and Summer 2021 surveys in the state of California

	Spring 2020 Survey	Fall 2020 Survey	Summer 2021 Survey
Sampling Methods	Recall of previous survey participants + online opinion panel + convenience sample	Recall of previous survey participants + online opinion panel + convenience sample	Recall of previous survey participants + online opinion panel + convenience sample + stratified random sample
Recruitment Methods	Direct email+ advertisements and posts on listservs and social media	Direct email+ advertisements and posts on listservs and social media	Direct email+ advertisements and posts in listservs and social media+ mailing out of printed survey invitations and printed questionnaires
Number of Respondents	13,658	7,984	14,084
Survey Administration	May 2020 – August 2020	December 2020 – January 2021	August 2021– October 2021
Survey Time Period(s)	Before March 2020, March-April 2020	Nov/Dec 2019 (retrospective), Nov/Dec 2020	Before March 2020 (retrospective), June/July 2021, June/July 2022 (future expectations)
Language	English	English, Spanish	English, Spanish

We used the Qualtrics online survey platform to administer the online version of the Spring 2020 survey between May 2020 and August 2020, Fall 2020 survey between December 2020 and January 2021, and the Summer 2021 survey between August and October 2021. The printed survey was administered starting on the week of July 19, 2021, as part of Summer 2021 data collection. Respondents from this channel completed the survey either via the online platform or by returning printed questionnaires by mail. Follow-up postcards were sent the week of August 9, 2021, to all respondents that had not already returned a completed survey via the online survey platform or via mail.

2.2 Data Handling

After completing each wave of data collection, the data were cleaned by filtering out incomplete and potentially invalid responses. This process was carried out in a similar way for datasets collected in Spring 2020, Fall 2020, and Summer 2021. Particular attention was given to responses that were severely incomplete or inconsistent, mistakenly-input, had flatlining answers to matrix-type questions, and unintelligible answers to open-ended questions. A series of imputation and recoding tasks were performed to convert the raw data into a format that could be more easily used for analyses. More details are available in a companion report prepared by the research team (*12*).

In the survey, respondents self-reported their current home and regular work locations. "Regular work location" was the primary place, if any, where the person would eventually commute to work in person after any 'work-from-home' requirements were lifted for those working remotely during the pandemic. Home and work locations were recorded through street address or nearest street intersection, city, state, and zip code. Only the zip code field was considered mandatory in the online survey to proceed to the next question. Google geocoding Application Programming Interface (API) was used to convert the address into latitude and longitude. Using these geocodes, the census tract and block group identities of respondents' home locations were appended using the 'CensusAPI' package in R software. Additional built environment variables, such as population density, land use diversity and intersection density, were then incorporated into the dataset.

In addition, efforts were made to recruit respondents from the entire state to represent demographic diversity. However, a major challenge in making comparisons over time is that the samples (i.e., people who responded to surveys) differed between the three surveys. Thus, the internal validity of the analysis might be somewhat compromised. In theory, if both samples were randomly drawn from the population of interest, and the sample sizes for each dataset are large enough to minimize sampling errors, the comparison of results from the analysis of the three samples should be held. However, in practice, this is often not the case due to potential departure from the representativeness of the population in the sampling, eventual sampling and response biases, and the use of non-probability-based sampling and recruitment approaches. To mitigate this issue, a weighting process was developed to make the sample for each wave of data collection more representative of the geographic distribution and socio-economics characteristics of the population.

2.3 Descriptive Statistics

Using the entire sample available for analysis, we summarize sociodemographic characteristics of respondents within the California state for Spring 2020, Fall 2020, and Summer 2021 weighted datasets (Table 2-2). The information includes summary descriptive statistics for the distribution by region, age, race and ethnicity, gender, educational background, student status, employment status, annual household income, household vehicle ownership, household composition, housing tenure and neighborhood type. As shown, the weighting process considerably improved the representativeness of the sample. This approach makes the characteristics of samples from three timepoints reasonably consistent, allowing a cross-comparison.

Table 2-2. Sociodemographic characteristics of respondents

		Spring 2020		Fall 2020		Summer 2021	
		n	**%**	**n**	**%**	**n**	**%**
Region	Central Valley region	340	6.2%	305	8.1%	596	10.0%
	Metropolitan Transportation Commission (MTC) region	1,187	21.5%	762	20.4%	1,186	19.9%
	Northern California and others	322	5.8%	264	7.1%	399	6.7%
	Sacramento Area Council of Governments (SACOG) region	380	6.9%	247	6.6%	387	6.5%
	San Diego Association of Governments (SANDAG) region	498	9.0%	327	8.7%	509	8.5%
	Southern California Association of Governments (SCAG) region	2,794	50.6%	1,839	49.1%	2,887	48.4%
Age	18-34	1,796	32.5%	1,212	32.4%	1,893	31.7%
	35-64	2,704	49.0%	1,850	49.4%	2,890	48.4%
	65 or over	1,021	18.5%	683	18.2%	1,182	19.8%
Ethnicity	Non-Hispanic, Latino, or Spanish origin	3,500	63.4%	2,332	62.3%	3,753	62.9%
	Hispanic, Latino, or Spanish origin	2,021	36.6%	1,413	37.7%	2,212	37.1%
Race	Asian Pacific Islander	1,244	22.5%	709	18.9%	1,234	20.7%
	African American	424	7.7%	211	5.6%	539	9.0%
	Native American	603	10.9%	178	4.7%	496	8.3%
	White	3,068	55.6%	2,036	54.4%	3,131	52.6%
	Other	181	3.3%	612	16.3%	557	9.4%
Gender	Female	2,811	50.9%	1,880	50.2%	2,955	49.6%
	Male	2,710	49.1%	1,865	49.8%	3,006	50.4%
Educational Background	Lower than bachelors	2,476	44.9%	1,604	42.8%	2,641	44.4%
	Bachelor or higher	3,045	55.1%	2,141	57.2%	3,312	55.6%
Student Status	Not a student	4,396	79.6%	2,941	78.5%	4,452	74.6%
	Student	1,125	20.4%	804	21.5%	1,512	25.4%

		Spring 2020		Fall 2020		Summer 2021	
		n	%	n	%	n	%
Employment Status	Non-workers	2,237	40.5%	1,520	40.6%	2,535	42.5%
	Full-time workers	2,306	41.8%	1,445	38.6%	2,222	37.2%
	Part-time workers or other	979	17.7%	780	20.8%	1,208	20.2%
Annual Household Income	Less than $50,000	1,773	32.1%	1,195	31.9%	1,902	32.4%
	$50,000 - $99,999	1,591	28.8%	1,056	28.2%	1,580	26.9%
	$100,000 or over	2,156	39.1%	1,494	39.9%	2,388	40.7%
Household Vehicle Ownership	Zero vehicle household	363	7.3%	22	0.7%	170	3.3%
	Household with vehicle	4,596	92.7%	3,241	99.3%	5,047	96.7%
Household Composition	Live alone	892	16.2%	553	15.4%	1,061	17.8%
	Live with other household members	4,629	83.8%	3,047	84.6%	4,904	82.2%
Housing Tenure	Rent	2,042	39.3%	1,382	38.3%	1,966	33.0%
	Own	2,722	52.4%	1,883	52.1%	3,561	59.7%
	Other	426	8.2%	347	9.6%	438	7.3%
Neighborhood Type	Urban	1,901	35.6%	1,463	40.5%	2,290	38.4%
	Suburban	2,653	49.7%	1,655	45.8%	2,845	47.7%
	Rural	781	14.6%	495	13.7%	829	13.9%

Note: The table shows the descriptive statistics with weighted datasets collected in Spring 2020, Fall 2020, and Summer 2021 in California.

3 The Impact of the Pandemic on Work Arrangement

3.1 Adoption in Hybrid and Remote Work [1]

3.1.1 Introduction

During the COVID-19 pandemic, work from home and homeschooling were widely adopted among workers and students (*13–15*), with up to half of the US workers working from home by April 2020, more than doubling from that in 2017 and 2018 (*16*). While some individuals returned to their pre-pandemic work locations and routine schedules after the initial phase of mandatory lockdown, others continued with remote work and flexible work schedules. A recent news article published in January 2024 revealed that commuting traffic had almost recovered to the pre-pandemic (2019) levels in California's Bay Area and Central Valley region (*17*).

The extent to which the temporary surge in fully remote work and hybrid work induced by the pandemic will persist in the future, and the ways in which this transition will vary across segments in the population, remain uncertain. Few studies have investigated how novel work arrangements impact travel patterns and trip-making. Possible impact to trip frequency, trip distance and mode use will have significant impacts on transportation systems. This information is vital for developing effective managerial and organizational policies. Therefore, this study aims to address the following questions:

- How has the pandemic affected individuals' work arrangements during different phases of the pandemic and, if it has, which population segments have (or have not) adopted remote work and hybrid work?
- How have the adoption and frequency of physical commute and remote work changed across different phases of the pandemic, especially among distinct socio-demographic groups?
- To what extent will the shift to remote and hybrid work persist into the future?

3.1.2 Data and Methods

With repeated cross-sectional datasets collected in Fall 2020 and Summer 2021, we track changes in activity-travel patterns among Southern California residents across four timepoints: Fall 2019 (before the pandemic), Fall 2020 and Summer 2021 (during the pandemic), and Summer 2022 (expectation in a *near future)*. The first wave of the survey was conducted between December 2020 and January 2021 (n=4,606) and the second wave was conducted between August and October 2021 (n=3,258). To address comparability issues between waves,

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[1] The following section is a short version of a paper that is under peer review in Transportation Research Interdisciplinary Transportation Research. Please use the following citation to cite the full paper (*64*): *Iogansen, X., J. K. Malik, Y. Lee, and G. Circella. Change in Work Arrangement during the COVID-19 Pandemic: A Large Shift to Remote and Hybrid Work. Transportation Research Interdisciplinary Perspectives, Vol. 25, 2024, p. 100969. https://doi.org/10.1016/j.trip.2023.100969.*

we developed weights for each survey based on the 2020 American Community Survey (ACS) one-year estimates (*18*). Ultimately, the distribution of demographic characteristics in the two weighted samples was similar and closely reflected population characteristics in the Southern California Association of Governments (SCAG) region. We classified four types of workers and students based on the frequency in which they worked or studied at distinct locations. The first three types include both workers and non-working students; however, for brevity we name them as “workers”

- ***Commuters*:** These are workers/students who primarily or exclusively travel to a work/school location.
- ***Hybrid workers*:** These are workers/students who both physically travel to a work/school location and work/study remotely in similar frequencies.
- ***Remote workers*:** These are workers/students who primarily or exclusively work/study remotely, in locations separated from a work/school location (*19*, *20*).
- ***Neither workers nor students***: These are individuals who are not currently working or pursuing an educational degree.

To gain a deeper understanding of commuting and remote working patterns and how they relate to each other, the second part of our study focuses on two key variables: (a) the proportion of workers who commuted physically versus worked remotely for different timepoints during the pandemic, and (b) the frequency with which they engaged in physical commuting versus remote work, if at all. We measured the frequency of activities by including survey questions featuring a Likert scale. To make the frequency categories comparable, we converted them into their corresponding monthly medians (e.g., 1 to 3 times a month was converted to 2 times a month and 3 to 4 times a week was converted to 14 times a month) (*21*). This enabled us to compare the self-reported monthly frequency of physical commutes and remote work corresponding to all timepoints.

3.1.3 Findings

There were changes in the proportion of work arrangements across the four timepoints we studied (Figure 3-1). Prior to the pandemic, *Commuters* constituted the largest group with 44.4% of respondents in the weighted full sample (i.e., consisting of students/workers and non-students/workers), or 70.8% of students/workers. However, due to stay-at-home policies, this number decreased to 15.1% by Fall 2020. The largest group of *Commuters*, 39.3% of students/workers, transitioned to remote work, while 35.7% reported they had become *Hybrid Workers*. By Summer 2021, a smaller portion of individuals—19.2% of respondents in the weighted sample, or 30.5% of students/workers—were *Remote Workers*, as many businesses had resumed in-person work. Meanwhile, a larger proportion of individuals (29.6% of respondents in the weighted sample, or 46.9% of students/workers) were engaged in hybrid work schedules. Respondents’ expectations suggest that the percentage of hybrid work arrangements will continue to increase through Summer 2022. This accounts for the expectations of 39.4% of weighted sample or 60.2% of students/workers. This outcome would primarily be driven by the gradual return of previous *Remote Workers* to their workplace, at least on certain days of the week.

When comparing the likelihood of adopting remote work and hybrid work across socio-demographic categories at four timepoints. Some notable differences across sociodemographic groups arise. These include:

- The 18 to 34 age group had a higher share of *Remote Workers* and *Hybrid Workers* across almost all timepoints.
- Individuals with higher levels of education comprised a much higher share of *Hybrid Workers* before and during the pandemic, and this share continually increased over time.
- Students comprised much higher shares of *Remote Workers* and *Hybrid Workers* across all timepoints compared to non-students.
- High-income households (with annual household income of $100,000 or more) comprised the highest share of *Remote Workers* and *Hybrid Workers* during the pandemic.
- Individuals living with other household members comprised a higher share of *Remote Workers* and *Hybrid Workers*.
- Urban residents a higher proportion of *Hybrid Workers* at all timepoints. Rural residents comprised a higher share of *Remote Workers* in Fall 2019, but the share of urban and suburban residents in the *Remote Workers* category drastically increased during the pandemic.

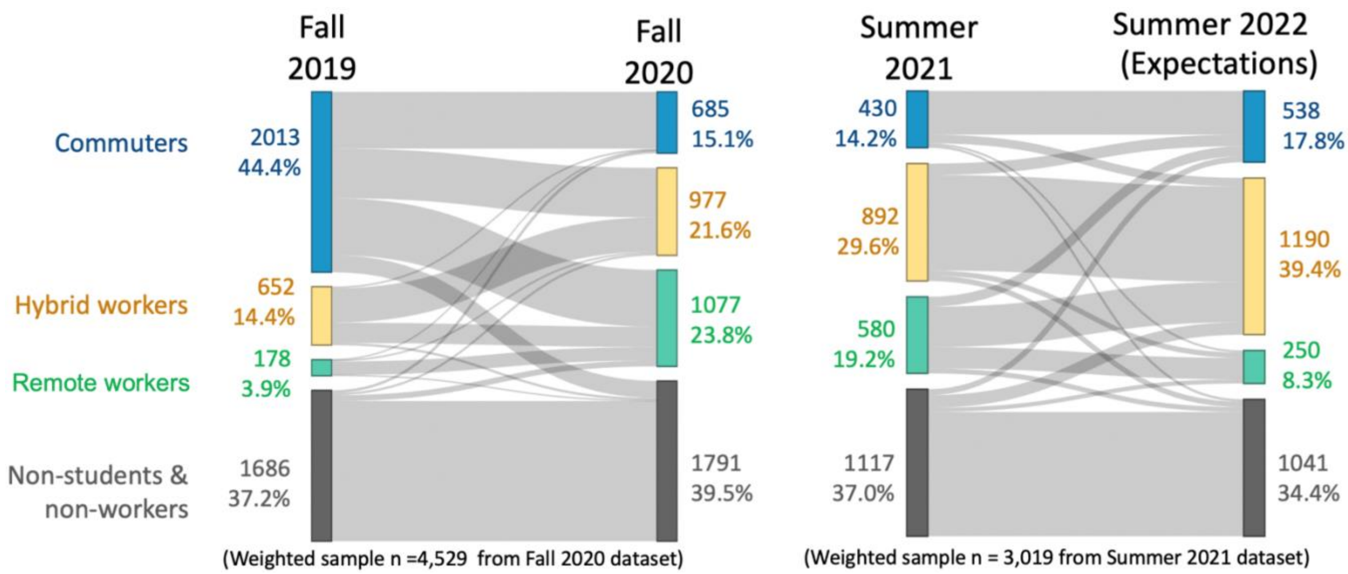

Figure 3-1. Transition in work arrangement in the SCAG region(weighted repeated cross-sectional data)

Notes: The figure indicates the proportion of different work arrangements (i.e., Commuters, Hybrid workers, Remote workers and Non-students/workers) across the four timepoints (i.e., Fall 2019, Fall 2020, Summer 2021, Summer 2022).

We compare the shares of workers who commuted physically (left) and worked remotely (right) during different phases of the pandemic, along with their average monthly frequency of doing so (Figure 3-2). The proportion of workers commuting at least once a month experienced a sharp decline from 87% in the Fall of 2019 to 64% in the Fall of 2020. Although this percentage partially recovered to 77.5% by Summer 2021, it remained approximately 10 percentage points below pre-pandemic levels. In-person work was expected to increase further by Summer 2022. Similar trends were observed in commuting frequency, with a drop from 17.9 to 14.7 days per month among commuters in Fall 2020, and a slight increase to 16.5 days per month by Summer 2021, still 8% below pre-pandemic levels. Among all workers, the average number of commuting days per month dropped more noticeably from 15.6 pre-pandemic to 9.4 in Fall 2020, and then increased slightly to 12.8 by Summer 2021.

In contrast to physical commuting, the percentage of individuals working remotely at least once a month substantially increased from 23% pre-pandemic to 61.7% in Fall 2020, remaining high at 76.6% in Summer 2021, with expectations of continued remote work adoption in the future. The frequency of remote working, especially among adopters, increased during the early phase of the pandemic from an average of 12.6 to 16.5 days per month, then declined in the later phase in Summer 2021 to 13.9 day per month. This suggests that, while many individuals transitioned to working entirely remotely during the "peak COVID-19 time," they later shifted to hybrid forms of work that combined remote and in-person work. Many individuals expect to continue engaging in hybrid forms of work, either on different days of the week or month or during the same day.

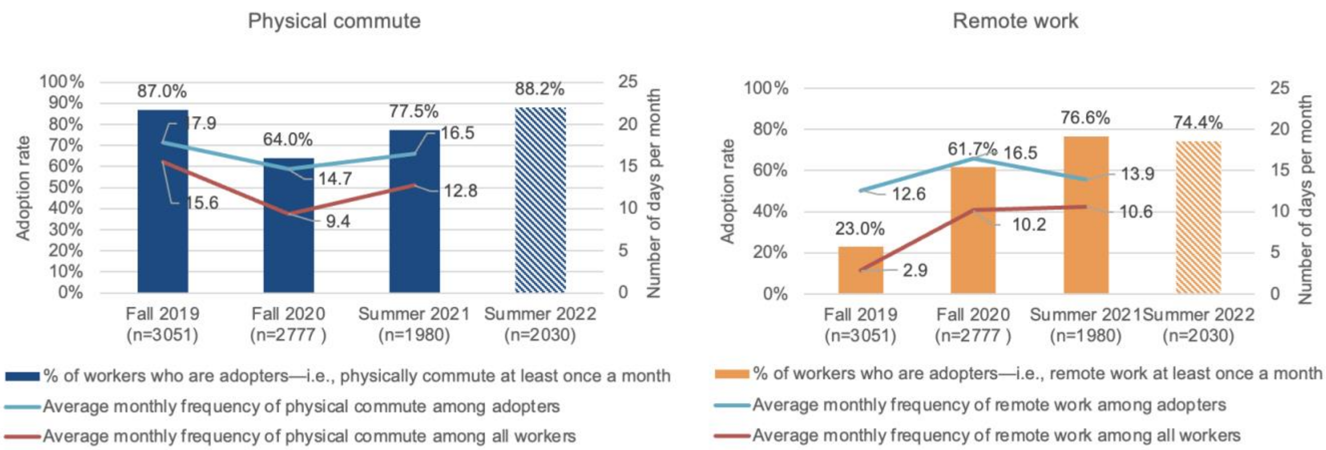

Figure 3-2. Changes in the adoption and frequency of physical commute and work from home, respectively

Notes: Values shown are weighted repeated cross-sectional data. The hatched blue bar indicates a future percentage based on individual predictions of what respondents expected do to in Summer 2022. In the left panel, the three blue bars indicate the percentage of workers who physically commuted to work at least once a month (i.e., adopters of physical commute) at each timepoint in Fall 2019, Fall 2020, and Summer 2021. The hatched blue bar on the far right denotes a then-future expectation for Summer 2022. The light blue line marks the average monthly commute frequency among in-person commuters and hybrid workers, while the red line marks the average monthly commute frequency among all workers. As this also includes remote workers, it provides insight into the changing number of commute trips in the entire worker population. The right panel reports similar information for remote workers.

3.2 Changes in Travel Behavior Among Commuters and Telecommuters [2]

[2] The following section is a short version of a book chapter that was published in the book *Pandemic in the Metropolis*. Please use the following citation to cite the full book chapter (65): *Malik, J., Affolter, B., Circella, G. (2023). Adoption of Telecommuting and Changes in Travel Behavior in Southern California During the COVID-19 Pandemic. In: Loukaitou-Sideris, A., Bayen, A.M., Circella, G., Jayakrishnan, R.*

3.2.1 Introduction

In the early stages of the pandemic, VMT in California and in other parts of the country saw a sharp decline due to the widespread adoption of telework (*5*). The pandemic also brought a major shift in travel mode choice, due to the perceived threats of transmission of the COVID-19 virus and the need for social distancing. More socially isolated modes such as walking, bicycling, and the use of personal vehicles took precedence over shared modes of transportation including public transit, ride-hailing, and ride sharing, and micromobility services such as shared e-scooters and/or e-bikes. At the same time, residential relocation may be a facilitator, or consequence of, the ability to telecommute, which in turn impacts the increase or decrease in VMT among the telecommuting population (*22*, *23*) This study focuses on the greater Los Angeles region and investigates the differences in residential choices and travel behavior of commuters vs. telecommuters.

3.2.2 Data and Method

The study uses responses from the Fall 2020 COVID-19 Dataset administered in the SCAG region. We evaluate change in work-related as well as non-work travel behavior patterns for employed telecommuters and employed non-telecommuters. First, to determine telecommuting status, respondents were asked for their current employment status. Employees were classified as those who work full time, part time, have multiple jobs, or are in an unpaid working arrangement. Those who answered affirmatively to any of these options were then asked where they were performing their job duties as of Fall 2020, and on how many days per week they worked. Choices included telecommuting, a regular work site, and other work locations outside of the home. Respondents were also asked about their weekly frequency with which they participated in work-related online meetings via technological platforms such as Zoom, Skype, or Microsoft Teams. These same questions were asked again of every survey respondent in reference to their Fall 2019 work patterns. Respondents were only eligible to answer how many days they telecommuted if they had first responded that they had the option to telecommute back in 2019 (no matter whether they actually chose to telecommute or not). To examine trip frequencies by mode and purpose, responses were broken up into three categories based on telecommuting status: non-telecommuters (who telecommuted 0 days per week), partial telecommuters (who telecommuted 1 to 4 days per week), and full-time telecommuters (who telecommuted 5 or more days per week), regardless of their total amount of workdays per week.

(eds) Pandemic in the Metropolis. Springer Tracts on Transportation and Traffic, vol 20. Springer, Cham. https://doi.org/10.1007/978-3-031-00148-2_13.

3.2.3 Findings

As shown in Figure 3-3, full-time teleworkers who teleworked 5 or more days per week were more likely to be living in a suburban location in both 2019 (49.2%) and 2020 (53.2%) as compared to partial telecommuters in both years. In 2020, 53.5% of non-telecommuters reported living in a suburban location, and 36.3% in an urban area. The proportion of non-telecommuters living in either a small town or rural area was greater than that of telecommuters (11% vs. 4%). Thirty-eight percent of telecommuters and 36% of non-telecommuters lived within five miles or less of their workplace. About 93% of all non-telecommuters and 88% of telecommuters lived within 30 miles or less of their workplace.

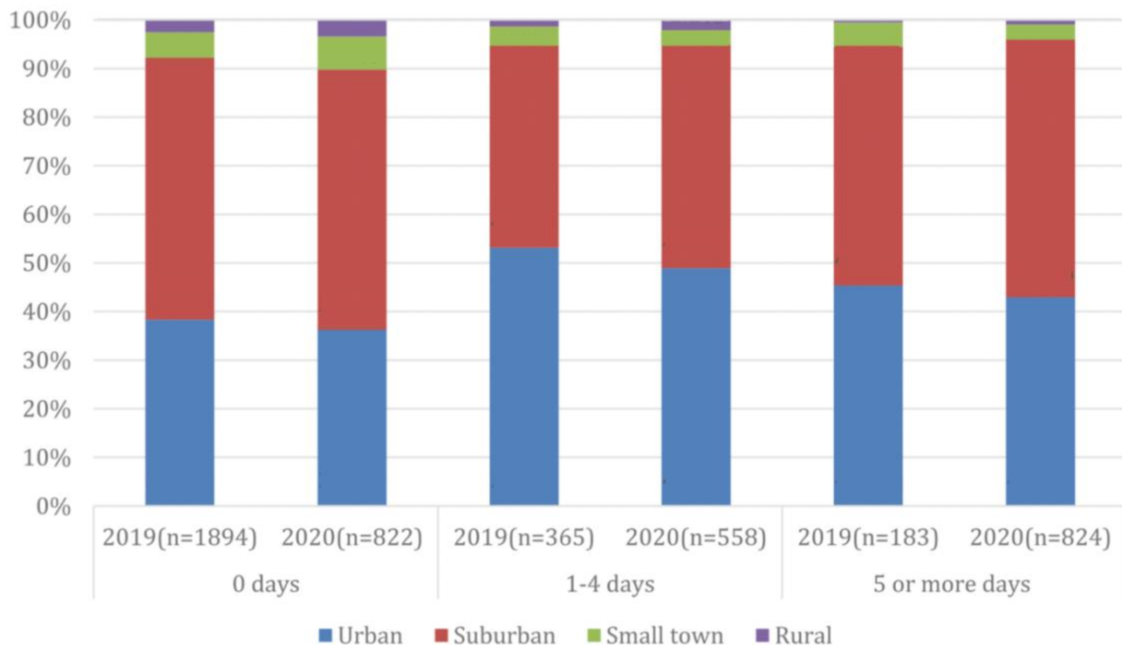

Figure 3-3. Distribution of home location types of non-telecommuters, partial telecommuters and full-time telecommuters who telecommuted 0 days, 1-4 days and 5 or more days per week, respectively, in 2019 and 2020

During the pandemic, the non-telecommuting group had a mean VMT of 115.2 miles per week, while the mean VMT for telecommuters was just 65.4 miles per week. T-tests confirmed that the differences between the VMT of the two groups were statistically significant at the 0.05 level. This question was asked only for Fall 2020, so this comparison could not be carried out with the 2019 data. Additionally, respondents were asked not to consider any miles driven while on the clock, if the nature of their job required driving, like trucking or driving for a ride-hailing company. Not surprisingly, employed individuals tended to have a higher mean VMT than the average respondents in the region.

In terms of mode choice, there were statistically significant differences in the mean monthly frequencies of travel by mode among telecommuters and non-telecommuters in both Fall 2020 and Fall 2019. In the survey, respondents were asked about the frequency with which they used specific travel modes. For the purposes of this analysis, we grouped the main travel mode categories as active modes (including walking and bicycling), personal vehicle use (aggregated individual categories of carpooling or single-occupancy car use), public transit (rail or bus services), carsharing, and other miscellaneous modes. Respondents were asked to report their mode use separately for non-commute and commute purposes. Total travel frequency was calculated for each respondent by summing up all travel modes. For non-commute travel, total travel frequency in Fall 2020 was greater among telecommuters than non-telecommuters. Total trip frequency decreased in 2020 across all telecommuting respondent groups compared to 2019.

Respondents were asked about the frequency of trips for specific travel purposes (e.g., commuting, social, recreational). The average total trip frequency for all purposes combined, for all groups, declined from 2019 to 2020.The trip purpose categories that saw the largest decline among all telecommuting statuses were trips made for social purposes—with the largest reductions observed among non-telecommuters (–61%), followed by partial telecommuters (–47%) and full-time telecommuters (–76%). In both 2019 and 2020, full-time telecommuters reported the highest average trip frequencies for recreational travel such as walking, biking, or going to the park with about eight trips per month. In 2020, non-telecommuters reported the largest percent decrease of all groups with an average of 5.79 trips per month; full-time telecommuters dropped to about 7.62 trips per month or one less monthly trip, in terms of averages, and partial telecommuters remained about the same monthly trip frequency. In 2019, the average errand trip frequency was the greatest among full-time telecommuters at about five trips per month and declined the most to almost two trips per month, on average.

Self-reported VMT for non-telecommuters had a higher average mean than that for telecommuters. Nevertheless, further examination is necessary to understand the relationship between VMT and trip frequency. Perhaps, the total number of trips was indeed higher, but the estimated VMT was lower for telecommuters because they tended to stay closer to their place of residence and were more available or likely to make short trips. This may also relate to residential location and density. The majority of 2020 telecommuters lived in urban or suburban settings (93.4%), while a higher proportion of non-telecommuters (10.2%) reported living in a small town or rural area as compared to telecommuters(4.6%).

Consistent with the current understanding of travel behavior during the pandemic, we observed a major difference in total trip frequency between 2019 and 2020. Non-telecommuters saw a steeper decline in total trip frequency by purpose and mode choice when compared to telecommuters. Further examination is necessary to understand why there were significantly higher means for commute travel among telecommuters when, logically, commute travel should have diminished. One explanation is that travel frequency does not necessarily make up for the whole travel volume. Distance and time are also indicators. Many small trips might be a result of needing to gather equipment or resources that are typically kept at the office and necessary for job tasks. Alternatively, telecommuters may have to come into the office for short periods of time to conduct certain tasks, while still having the profile of full-time telecommuters. Therefore, respondents' own interpretation of their telecommuting status and what constitutes commute travel may affect results.

3.3 Remote-Work Adoption of Respondents from Different Survey Recruitment Methods [3]

3.3.1 Introduction

We found that the capability and practice of remote work vary greatly among workers with different socio-demographic characteristics. In this part of the study, we aim to further explore the differences in remote work practice in the pre-COVID-19, 2021, and 2022 (expected) periods among respondents recruited by different survey recruitment methods.

Many studies assume the quality and representativeness of the information collected with surveys administered through an online opinion panel are similar to those obtained with other sampling and distribution channels, such as traditional mail-based printed questionnaires or in-person interviews. The importance of unpacking this assumption has become elevated during the COVID-19 pandemic, as limits on in-person interaction and the potential for faster data collection increased the use of online opinion panels. However, the emphasis on, for instance, the remote work practice raises serious concerns about potential differences between online opinion panel respondents and the general population. This is an important research topic because, to date, only a few studies in the transportation literature have examined the validity of a dataset taken from the source of an online opinion panel.

However, such a recruitment method relies on the sampling frame provided by a private panel company or crowdsourcing platform. Consequently, the nature of a sample taken from opinion panels could differ from a "representative sample" of the population. There could be two types of biases among opinion panel datasets: (a) in the composition of survey participants regarding factors such as age, income, occupation, race, or educational attainment (Berrens et al., 2003; Paolacci, Chandler, and Ipeirotis, 2010) and (b) in the qualitative aspects of behaviors and choices, including personality (*26*), willingness to pay (*27*), or political opinion (*24*).

By implementing a series of linear regression models, this study revealed that opinion panel users had a stronger practice of hybrid or remote work before the COVID-19 pandemic, while non-opinion-panel users showed a stronger shift to such a home-based workstyle during the pandemic. Future research in transportation needs to further examine additional biases for surveys that are administered only through online opinion panels.

3.3.2 Data and Methods

We analyze the COVID-19 dataset collected in Summer 2021 from four channels including online opinion panel (n=3,206), longitudinal (n=1,381), mail-back (n=225), and mail-online (1,018) while excluding those

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[3] The following section is a short version of a paper that was peer-reviewed and will be presented in 2023 Transportation Research Board annual meeting in Washington D.C. Please use the following citation to cite the full paper (*66*): *Makino, K., Lee, Y., Iogansen, X., Malik, J., & Circella, G. (2023). Assessment of Differences in Individual Attitudes and Impacts of the COVID-19 Pandemic on Remote-work Adoption among Respondents from Online Opinion Panels and Other Recruitment Methods. 2023 Transportation Research Board annual meeting, Washington D.C.*

accessed with convenience sampling 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. We classify respondents into Non-workers, Commuters, Hybrid Workers, or Remote Workers based on the same method discussed in Section 3.1.2. We found that the opinion panel dataset contains slightly more people in the 18 to 34 age group, while the mail-back dataset has much more people at 65 or more. The share of less-educated people (with a degree of a high school diploma or less) is the highest among online opinion panel users. This result is consistent with the literature (*28*). The online opinion panel dataset also contains more low-income people, while the mail-back dataset has a larger share of high-income individuals. Finally, longitudinal and online opinion panel datasets contain more urban residents while mail-back and mail-online datasets have more participants from rural areas. To investigate whether respondents to different recruitment methods have different remote-work practices, we estimate multinomial logit models in the pre-COVID-19, 2021, and 2022 (expected) periods, respectively.

3.3.3 Findings

Here, we summarize the coefficients and significance of independent variables in three multinomial logit models and share our findings (Table 3-1). The first model estimates remote work status before the COVID-19 pandemic started. People in the online opinion panel dataset are the most typical hybrid and remote workers, which is consistent with the finding that they are more technology-oriented than respondents from other datasets. mail-back dataset shows the most negative coefficient, indicating that there is a non-negligible effect on those who cannot be contacted by online survey distributions. The possession of a driver's license has a strong negative effect on hybrid- or remote-work practice, as those who entered a job that requires a driver's license must obtain one. Looking at the effect of age, it seems that the chance of having a hybrid workstyle becomes smaller when the worker is at 50 or more. Our data analysis also suggests that a higher income may lead to a smaller chance of having a hybrid work practice. This result is somehow not aligned with the prior findings (*29*).

The second model estimates remote-work status in 2021. There are some coefficients that show an inverse effect for hybrid and remote workstyles. These results imply that, overall, the number of people working remotely increased, and people likely to respond to longitudinal or mail-online datasets shifted to remote work more strongly than those likely to respond to the online opinion panel dataset. Meanwhile, being in responses to the mail-back dataset was not significant for either a hybrid or remote work practice. In terms of socio-demographics, being an older adult or resident of a more rural area was a negative factor for both remote and on-site workstyles. Those cohorts may have fewer opportunities to adopt hybrid or remote workstyles. On the other hand, higher educational attainment or higher income is associated with hybrid- and remote-work practice. This is a straightforward result as white-collar workers would logically be more likely to work remotely.

The third model estimates the expectation of work practices in 2022. The effect of being in a different dataset was identified as non-significant so that the corresponding variable were removed from the final model. It indicates that the nature of people reached by different recruitment methods does not quite vary about the expectation. Meanwhile, younger adults, highly educated, and/or high-income workers expect to participate in remote work more frequently in the future. The effect of the neighborhood type (i.e., living in either an urban, suburban, or rural area) seems complex. Data suggest that urban workers would prefer to continue hybrid work practices.

Overall, the models indicate that in the pre-COVID-19 period, online panel users have a stronger orientation to hybrid- or remote-work practices. However, as of 2021 in the pandemic era, people in the longitudinal and mail-online datasets showed more likelihood of selecting remote-work practices, or regular commuting (i.e., less chance of adopting a hybrid workstyle). Regarding expectations about future workstyle(s) in 2022, we did not find a significant relationship between the different datasets . Even though respondents to the four survey types generally have different characteristics or practices, the expectation or forecast of one's future situation may not differ among them.

Table 3-1. Model results from three multinomial logit models

Explanatory Variable	Levels	Pre-COVID-19		2021		2022 (expected)	
		Hybrid	Remote	Hybrid	Remote	Hybrid	Remote
Sample size	Opinion panel		1339		966		1089
	Mail-back		583		524		569
	Mail-online		74		67		66
	Longitudinal		425		375		401
Intercept		***1.374	-0.076	***0.712	**-0.573	***0.781	***-2.012
Age (base: 18-34)	35-49	0.013	-0.240	*-0.263	***-0.521	*-0.308	*-0.337
	50-64	***-0.502	-0.263	***-0.976	***-0.709	***-0.742	-0.250
	65 or older	***-1.217	0.150	***-1.452	**-0.631	***-1.262	-0.390
Gender	Male	---	---	---	---	---	---
(base: Female)	Self-describe	---	---	---	---	---	---
Driver license (base: No)	Yes	***-0.857	*-0.742	---	---	---	---
Education	College	-0.119	-0.412	0.085	0.366	-0.089	**0.842
(base: High school or less)	Graduate	0.254	-0.217	**0.550	*0.558	0.315	*0.699
Income	$50,000 -$99,999	**-0.310	**-0.512	0.146	***0.624	0.003	0.299
(base: less than $50K)	$100,000 - $150,000	**-0.339	-0.113	0.167	***0.743	0.037	**0.546
	$150,000 or more	*-0.270	0.290	***0.558	***1.309	**0.372	***1.097
Neighborhood type	Suburban	**-0.235	-0.025	***-0.430	-0.172	***-0.326	0.086
(base: urban)	Town or rural	0.034	-0.245	**-0.497	***-0.591	**-0.433	-0.077
Dataset	Longitudinal	***-0.710	***-0.613	**-0.376	***0.453	---	---
(base: opinion panel)	Mail-back	*-0.457	**-1.286	0.074	-0.158	---	---
	Mail-online	***-0.552	***-0.844	**-0.372	***0.437	---	---
Log-likelihood (null)			-2254		-2107		-2105
Log-likelihood (full)			-2142		-1989		-2034
Number of parameters			30		28		22

Notes: Statistics in the table represent coefficients and significance level (*10%, **5%, ***1%) and "---" indicates that the explanatory variable was removed during a backward stepwise variable selection for the model.

4 The Impact of the Pandemic on Mode Use

4.1 Changes in Travel Frequency by Mode [4]

4.1.1 Introduction

Pandemic-related impacts on transportation over the past year have received widespread attention in the academic and planning sphere. Studies have focused on impacts such as shifting preferences for—and perceptions of—travel modes, public transportation operations and ridership, changes in vehicle use, traffic congestion, pollutant emissions, equity impacts, and others (*30*, *31*). Limiting physical interaction by constraining mobility has been considered one of the most critical actions to contain the spread of the COVID-19 virus. However, the nature, magnitude, and likely duration of changes in mobility are uncertain. This study discusses lifestyle and mobility changes through the analysis of multiple waves of survey data collected in the US.

4.1.2 Data and Methods

Longitudinal data used in this study come from an array of surveys conducted before and during the COVID-19 pandemic. We focused on respondents who participated in at least two survey waves, of which at least one was during the pandemic. We assessed three different time periods: (a) before the pandemic, including responses from the 2018 or 2019 studies and retrospective behaviors from 2019 as reported by respondents in the Fall 2020 survey, (b) the early stage of the pandemic, including responses to the Spring 2020 survey wave, and (c) the late stage of the pandemic, including responses to the Fall 2020 survey wave. In this study, we explore changes in lifestyles and attitudes by investigating responses to attitudinal statements and self-reported changes in work habits. Changes in mobility were measured by calculating the average days in a month that commuting respondents used each mode of travel and relative differences before versus during the pandemic.

4.1.3 Findings

The most meaningful change in attitudes and preferences for transportation related to vehicle ownership and use. Although the desire to drive (versus being a passenger) remained somewhat constant, the desire to own a car increased during the pandemic. In the meanwhile, there is anecdotal evidence of increased concerns about the use of shared modes of travel during the pandemic compared to pre-pandemic era.

Spending more time at home due to remote work, increased e-shopping, and a reluctance to share travel modes with strangers because of the fear of getting infected may increase a person's willingness to acquire a new vehicle. This signals an increase in the reliance of individuals on personal vehicles (in the already very car-

[4] The following section is a short version of a book chapter that was published in the book *Transportation Amid Pandemics*. Please use the following citation to cite the full book chapter (*67*): *Soza-Parra, J., G. Circella, and D. Sperling (2023). Changes in Activity Organization and Travel Behavior Choices in the United States. In Transportation Amid Pandemics, Elsevier, pp. 191–199. https://doi.org/10.1016/B978-0-323-99770-6.00012-0.*

dependent society in the US), which could lead to potentially negative longer-term consequences in terms of continued personal habits and vehicle use even after the pandemic is over.

There was a marginal increase in support for rising gasoline taxes, both to reduce the negative impacts of transportation on the environment and providing funding for better public transportation. During the pandemic, about 55% of respondents somewhat agree or strongly agree with such a policy, representing an increase in support compared to previous studies. Still, we suspect that this change is probably not a direct consequence of the disruption brought by the pandemic, but rather an effect of the growing evidence of climate change and of the harm caused by transportation in the US society, a growing awareness that did not stop even during the pandemic.

We calculated the average days in a month that commuting respondents used each mode of travel and the relative differences in the "before versus during the pandemic" time periods. The relative ranking in the use of various travel modes for commuting purposes remains similar to the pre-pandemic levels. Relative differences in the use of various modes in the three time periods were: (a) a steep decline in the use of both private vehicles and public transportation in early to mid-2020, (b) a pronounced rebound of dependence on private vehicles in late 2020.

Prior to the pandemic, most US workers commuted to work by driving a private car and the mode share of driving alone expanded during the pandemic. The average monthly number of train trips among the respondents in the sample was 49.2% lower during the early stage of the pandemic compared to pre-pandemic time. This can be explained by adherence to government guidelines aimed at reducing mobility, adoption of full-time or part-time telecommuting, and an aversion to sharing vehicles with others due to increased risk of virus transmission.

The decrease in the use of public buses was less extreme than for rail-based public transportation. This finding is largely explained by the demographics of the users that travel with these public transportation services. White-collar workers who avoided physical commutes with remote work were more likely to use rail- based public transportation. A larger proportion of bus users were captive riders classified as essential workers. They physically reported to work during the pandemic and were less likely to have other travel modes available to them. Observed ridership data in large US metro areas point to an even larger decline in the use of public transportation during the early stage of the pandemic. This difference may be attributable to sampling methods and/or errors in the measurement of travel mode frequency.

The trend is slightly different for ridehailing. There was a decrease in Spring 2020 and ridehailing did not recover during Fall 2020.

The reliance on personal bikes, e-scooters, and walking shows a continuous decrease over time. However, the reduction is proportionally smaller than the one observed for public bus, train, and ridehailing, and the lower adoption of bicycling and walking in Fall 2020 might be due to the seasonal effects of cold weather.

Use of shared micromobility services, including shared e-scooters or shared e-bikes, increased early in the pandemic and then declined. The increase during the early stage of the pandemic might be explained by the limited use of these services during the pre-pandemic time. The low initial use level makes small changes in trip count appear as sizable percentages. The mode shift from public transportation likely contributed to increases in micromobility trips, as many users chose to avoid public transportation during the early stage of the pandemic and micromobility options were a “safe” alternative.

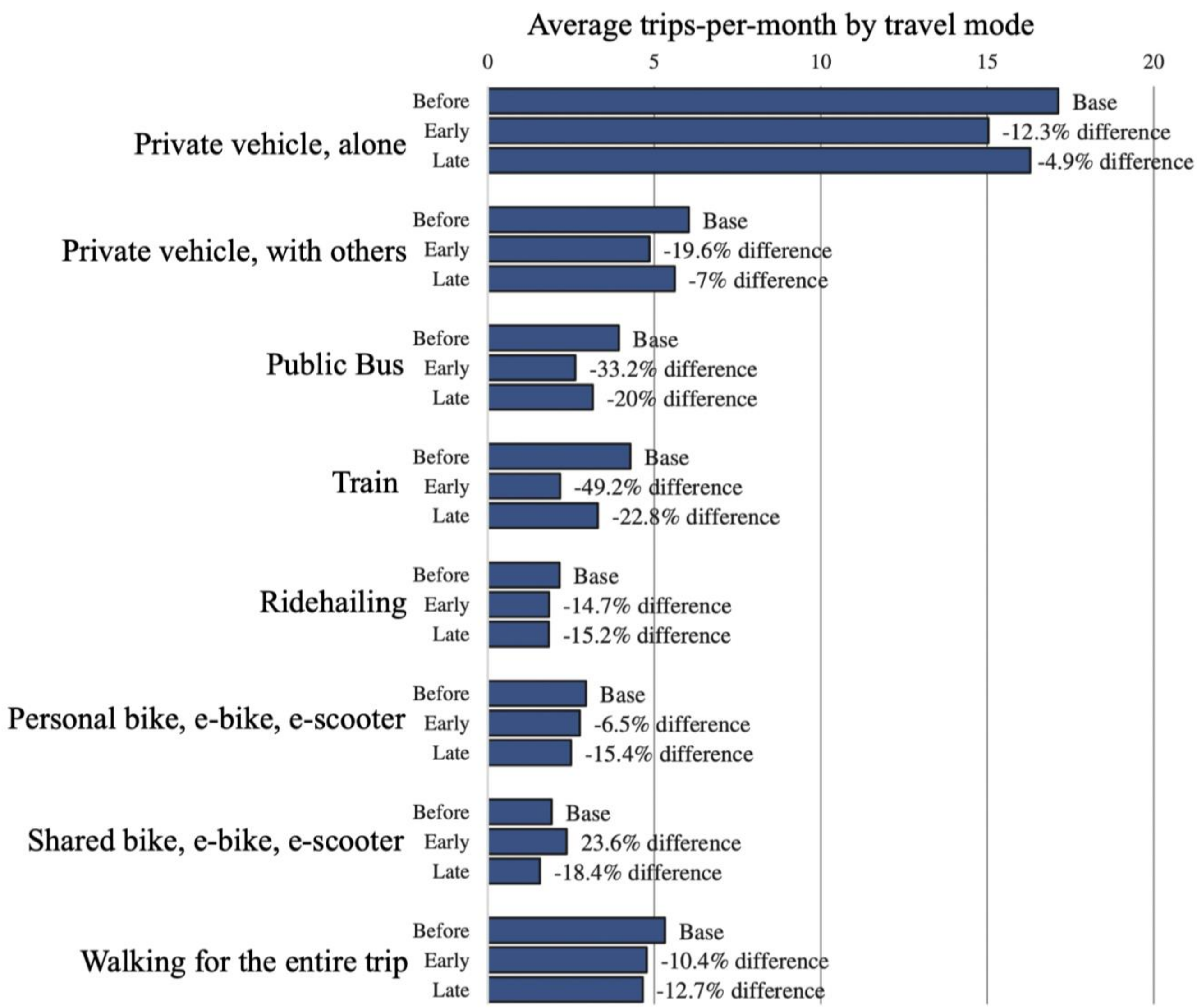

Figure 4-1. Change in average trips-per-month by travel mode among those commuting before and during two stages of the pandemic

4.2 Changes in Household Vehicle Ownership [5]

4.2.1 Introduction

A number of studies have documented the prominent role of private vehicles during the pandemic (*13*, *32–34*) as large segments of the population began to view car travel as the safest option for daily travel needs. Meanwhile, economic uncertainty may have prevented some consumers from buying or replacing cars (*35*). 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".

Research gaps in this topic include: (a) pandemic-specific situations in the US, (b) potential variations in vehicle ownership within households over time (*36*). Existing studies rely on cross-sectional data, which often do not capture the impact of life events on vehicle ownership even though these events can be critical in understanding how and why households make decisions. A comprehensive approach modeling past and anticipated vehicle ownership change can yield insights into individuals' vehicle ownership decision patterns over a longer time horizon and reveal heterogenous impacts of specific variables. This study aims to address these research gaps.

4.2.2 Data and Methods

This study assesses responses from 2,283 longitudinal respondents to a two-wave panel survey collected in the US. It investigated changes in vehicle ownership from months shortly before the COVID-19 began (pre-pandemic) to June/July 2021 (Summer 2021) and expected future changes in vehicle ownership from June/July 2021 to June/July 2022 (Summer 2022). Four levels of vehicle ownership changes are measured: (a) increase, (b) decrease, (c) keeping the same total but replacing one or more vehicles, and (d) no change.

We used an integrated choice and latent variable (ICLV) model to identify factors impacting vehicle ownership changes, focusing on latent attitudes (e.g., tech-savviness), socio-demographics, life events (e.g., starting a job), and COVID-19-related factors (e.g., health concern). The ICLV model combines a latent variable sub-model and a traditional discrete choice sub-model (*37*). The latent variable model evaluates the relationship between observable features of individuals and their underlying psychometric factors. The discrete choice model estimates the utility of different vehicle ownership change decisions in relation to these observable factors(Figure 4-2)

[5] The following section is a short version of a paper that was peer-reviewed and has been presented at the 2023 Transportation Research Board (TRB) Annual Meeting in Washington D.C. Please use the following citation to cite the full paper (*68*): *Iogansen, X; Lee, Y; Malik, J; Johnson, N; & Circella, G. (2023). Investigating the Factors Affecting Changes in Household Vehicles during the COVID-19 Pandemic. 2023 Transportation Research Board (TRB) Annual Meeting, Washington D.C.*

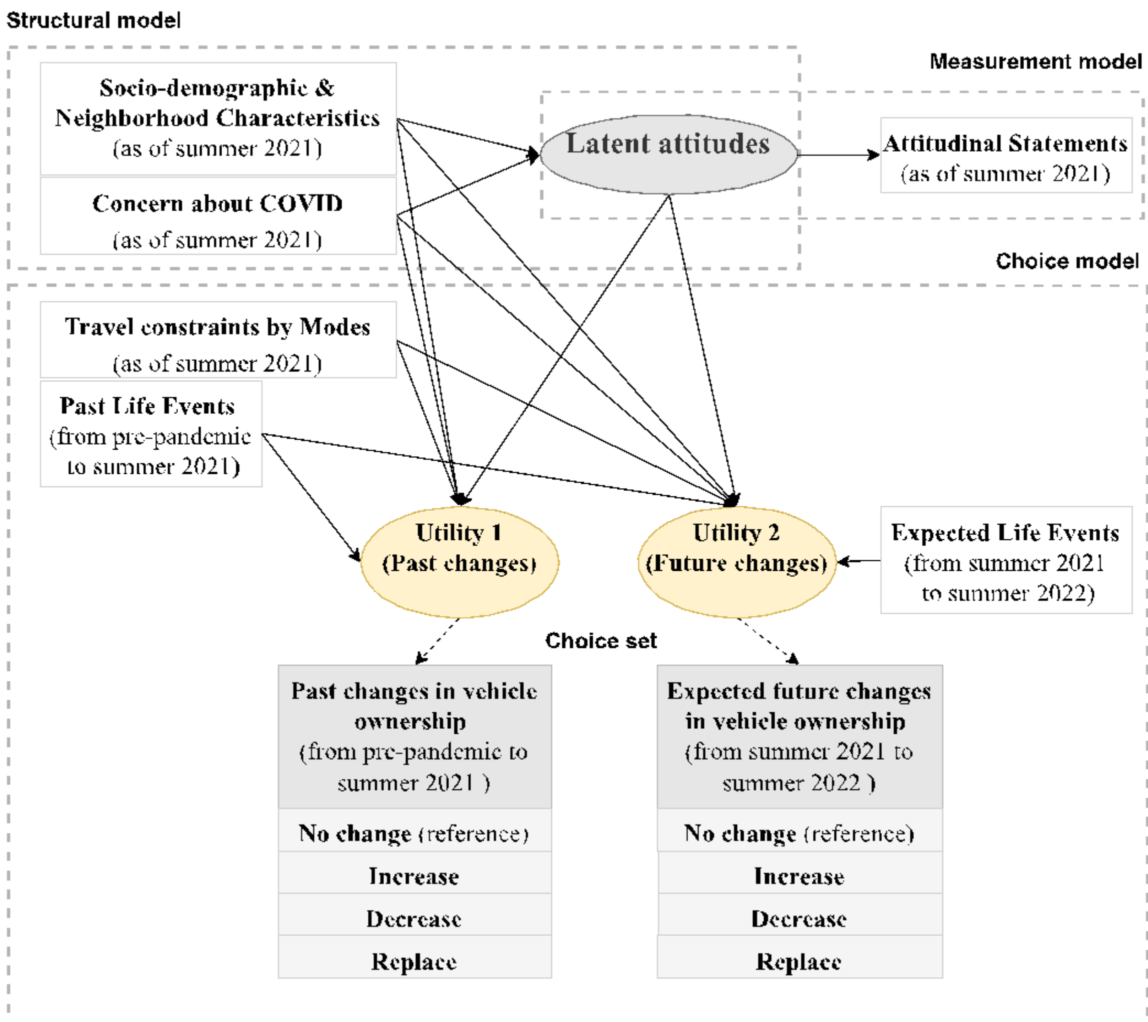

Figure 4-2. Conceptual framework of the ICLV model

4.2.3 Findings

Individuals who are *tech-savvy and variety-seeking* tend to have more fluctuation in their vehicle ownership status. They acquire, dispose of, or replace vehicles more often than other types of owners. On the other hand, during the pandemic, individuals who are more *pro-environment* were more likely to reduce vehicle ownership or expected to decrease the vehicles they owned in the future without replacing them. *Pro-active* individuals are less likely to acquire new vehicles in the future. Their shift towards active modes (e.g., walking, biking) during the pandemic may have become a new normal for them. As a result, pro-active people have learned that they do not need to acquire additional cars, at least in the coming year.

Compared to younger age groups, older individuals—especially those aged 65 or over—tend to exhibit less fluctuation in vehicle ownership patterns. This is because their household structure, financial status, lifestyle, and travel needs tend to be more stable. Females were less likely to consider increasing or replacing their vehicle ownership in the future (*38*, *39*). Individuals with higher educational attainment status by Summer 2021 were less likely to decrease vehicle ownership in the future, compared to their counterparts. Additionally, those who had advanced their education during the pandemic were less likely to have decreased their vehicle ownership.

Those who were students in Summer 2021, as well as those transitioned from non-student to student status during the pandemic, were more likely to plan on increasing their vehicle ownership in the future. With comparison, those who shifted from student to non-student status exhibited more volatile vehicle ownership patterns, with changes in both directions occurring simultaneously. Full-time workers tended to exhibit more stable vehicle ownership patterns compared to non-workers. However, they were also more likely to anticipate replacing their vehicles in the future. In contrast, part-time workers were more likely to plan on increasing or replacing their vehicle in the future. Furthermore, our study found that those who transitioned from workers to non-workers tend to decrease vehicle ownership, while those who transitioned from non-workers to workers were more likely to replace their vehicles.

Individuals from households with higher annual income were more likely to increase or replace their vehicles during the pandemic. Additionally, our results revealed a positive association between increased household income during the pandemic and an increase in vehicle ownership, and vice versa. These findings suggest that financial considerations play a significant role in vehicle ownership decisions, with those in better financial standing have more flexibility to acquire or replace vehicles. Our results indicate a positive association between decreasing household size and a reduction in vehicle ownership during the pandemic. This finding is broadly consistent with a previous study that used panel data (*40*).

We found that households with more members tended to exhibit greater volatility in their vehicle ownership, regardless of the direction of change. This may be because larger households have more dynamic travel needs and preferences. Households with children were more likely to increase or replace their vehicles, but less likely to reduce their vehicles during the pandemic. Moreover, these households were more likely to report plans to increase their vehicles in the future. These findings are consistent with previous research that has described the impact of children on household vehicle ownership decisions (*41*). This is likely because households with children have more complex travel needs. Consistent with a previous study (*42*), we found that a decrease in household size is associated with vehicle reduction. Our study also found that those who relocated their homes during the pandemic were more likely to have decreased their vehicle ownership. However, whether they moved into a more urbanized neighborhood or not did not seem to have an impact.

Finally, we found that, by Summer 2021, individuals who were somewhat or strongly concerned about the health impacts of COVID-19 Summer were more likely to report an intention to increase their vehicle ownership. There is empirical evidence suggesting that many individuals switched to private modes, such as driving, during the pandemic because of lingering concerns about the pandemic (*33*, *34*).

4.3 Changes in Active Travel [6]

4.3.1 Introduction

Dramatic restrictions to social gatherings and fear of infection have impacted walking and bicycling (active travel) during the COVID-19 pandemic in a wide variety of ways (*43*), including surges in sales of bicycles (*44*). Although previous research has examined the impact of the pandemic during its early months on active travel, limited research exists on the changes in walking and bicycling over the entire course of the pandemic. Another gap in the literature is a discussion of the parallel evidence of increasing active travel and increasing sedentary behavior. This study examines the impact of the pandemic on walking and bicycling among US adults and takes into consideration observations of increased sedentary behavior and increased physical activity from active travel during the pandemic.

4.3.2 Data and Methods

We use data from a unique longitudinal panel (n=2,769) from Spring 2020 and Fall 2020 COVID-19 surveys in the US. Both surveys tracked active travel. We first asked respondents to report the number of days per week that they participated in a physical activity during the pandemic, as well as the number of minutes they spent performing each physical activity.

4.3.3 Findings

There were changes in bicycling and walking frequency for both commuting and non-commuting purposes (Figure 4-3 and Figure 4-4). We observed a large decrease in walking for commute purposes, which is apparent in the substantial increase in respondents who either stopped commuting or switched to working from home in Spring 2020. Changes in walking for non-work travel were more common than commute travel.

Among those who increased their walking for non-work purposes during the pandemic, many maintained, or at least did not completely revert, to their prior level of walking by Fall 2020. This was different from outcomes for bicycling and suggests the pandemic may have caused more lasting effects on walking behavior.

Not all people who increased their walking early during the pandemic maintained their walking into Fall 2020, however. The most common walking change profile experienced an increase in walking for non-work travel at the peak of the pandemic during Spring 2020 when in-person work restrictions were in-effect, but then slightly reduced their walking by Fall 2020. Still, they continued to walk more than in their pre-pandemic life. This profile is most apparent in California and Nationwide panel data and corroborates news reports of increases in active modes for non-work travel. Walking trip frequency showed more behavior changes than bicycling for commute and non-work travel. The group of people who showed no behavior change was considerably smaller for walking than for bicycling. This suggests that the barriers to walking were weaker than those for bicycling.

[6] The following section is a short version of a book chapter that was published in the book *Pandemic in the Metropolis*. Please use the following citation to cite the full book chapter (*69*): *McElroy, S., Fitch, D.T., Circella, G. (2023). Changes in Active Travel During the COVID-19 Pandemic. In: Loukaitou-Sideris, A., Bayen, A.M., Circella, G., Jayakrishnan, R. (eds) Pandemic in the Metropolis. Springer Tracts on Transportation and Traffic, vol 20. Springer, Cham. https://doi.org/10.1007/978-3-031-00148-2_12*

This is not surprising, given the overwhelming evidence that traffic safety is still a dominant barrier to bicycling in the US (*45*).

The most common reported behavior was "no change at all," (i.e., people who never rode a bike continued to not ride a bike). The second most common reported behavior change was a reduction in bicycling. The third most common profile showed an increase in bicycling, particularly for non-work travel. This profile accounts for only a small share of respondents but shows up in all three datasets. This group included individuals who reported never bicycling prior to the pandemic but showed regular bicycling activity during the pandemic. This profile is consistent with media reports describing bicycling as a booming mode of transportation during the pandemic (*44*). Policy to encourage these individuals to continue to ride their bicycle after the pandemic would lead to environmental and societal benefits. However, the profile of people who increased bicycling for non-work travel showed some attenuation by Fall 2020. The substantial return to pre-pandemic bicycling levels for many members of this group is particularly evident in the nationwide panel. This suggests that much of the behavioral change that occurred during the early stage of the pandemic had already been reversed by Fall 2020, most likely for the combination of reasons mentioned previously.

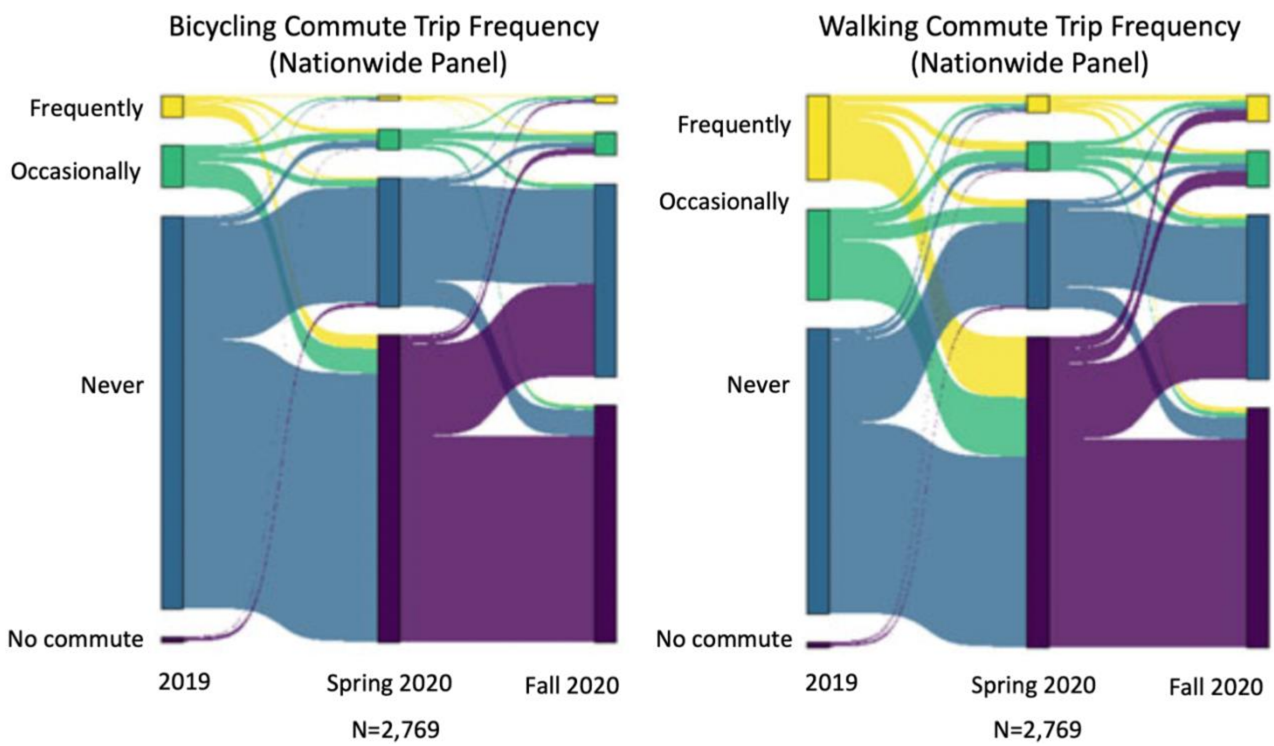

Figure 4-3. Walking and bicycling frequency for commute travel purposes

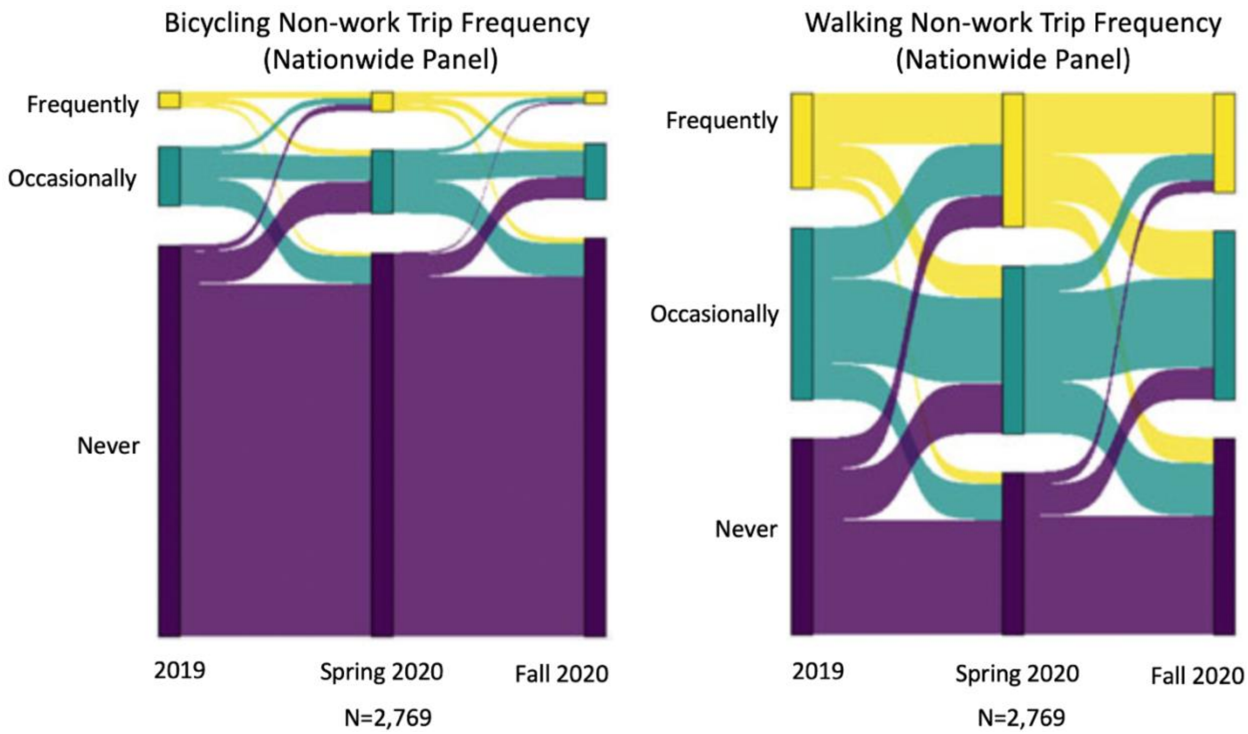

Figure 4-4. Walking and bicycling frequency for non-commute travel purposes

In terms of person-level model substitution, commuters who did not switch from public transit to private vehicles possibly chose walking or bicycling as their preferred alternative for a socially distanced mode of travel during the pandemic months. An examination of the shifts between public transit and bicycling, walking, or driving—as well as shifts between driving and bicycling or walking—revealed similar trends in all three panel datasets. Respondents were more likely to have decreased the frequency of their use of public transit and increased their frequency of driving than to have increased their levels of bicycling or walking as a replacement for public transit. This substitution pattern is expected, considering that many transit trips are made for distances that are more compatible with the use of a private car than with walking or bicycling, in addition to other factors such as concerns about safety when using active modes. Shifts from driving to bicycling or walking were also observed in each panel. These mode shifts accounted for a small proportion of the sample in each panel.

In terms of the average minutes spent per day performing a physical activity, we found a large increase in exercising at a non-home location. This is likely associated with the dropping of restrictions to non-home activities and the end of the stay-at-home orders after the first stage of the pandemic. While exercising at non-home locations saw the largest average increase, active travel changes were more equivocal. Nearly no change was observed for bicycling, and while walking to get to and from places rose slightly, perhaps due to reopening of activity locations, a similar magnitude in the decline in walking for leisure and exercise suggests that changes largely canceled out.

4.4 Changes in the Use of New Mobility Services [7]

4.4.1 Introduction

The COVID-19 pandemic caused a huge disruption worldwide with direct and indirect effects on travel behavior. This paper focuses on fundamental behavioral changes which may lead to longer-term shifts in activity-travel patterns in coming years. We examine the adoption of two measures that help avoid or reduce physical contact through information and communication technology (ICT) devices and services, working from home, and online shopping. In addition, changes are examined in the use of ridehailing and active travel modes for leisure purposes, mainly because of their potential for less car-oriented lifestyles after the pandemic.

Here, we discuss analyses and findings related to ridehailing. Ridehailing services grew rapidly in the years leading up to the pandemic, and these services are now a core component of the transportation system. Therefore, it is important to study how ridehailing users reacted to a disruptive event. Major players in this segment are funded by venture capital and were hemorrhaging money before the pandemic (*46*). Thus, the impacts of the pandemic on ridehailing services may be an indicator of their long-term viability.

4.4.2 Data and Methods

This study analyzes a two-wave individual-level panel (N = 1,274) in the US. In March 2020, the team re-contacted participants of two surveys administered before the pandemic. From these sources, the team-built panel datasets for timespans before the pandemic (T1) and during the pandemic (T2). Pre-pandemic information was collected in June through October 2018 or May through July 2019 and during-pandemic information was collected from March and April 2020. Respondents reported the use of ridehailing services in the past 30 days in each survey at both timepoints.

To examine initial changes attributable to the pandemic, a descriptive statistical analysis of the target variable was conducted, and comparisons were made across household income levels and worker occupation categories. Results are presented in cross-tabulation tables with key results visualized in alluvial diagrams to show the change in behavior over time. We also compared changing trends among respondents with different income groups and occupation types. To group households into different income groups, respondents' self-reported household income (as of March–April 2020) is adjusted based on the size of their household, the age of each of their household member, and their residential location (*24*). In so doing, equivalence scales are applied by assuming that, with each additional member in a household, the needs of the entire household increase, but not in a proportional way. In the end, households are grouped into the following three categories: Low ($23,400 to $31,900), Medium ($31,901 to $63,600), High ($63,601 to $186,000). The categorization for occupation required a recoding process, as the question was asked with an open-ended response. Four occupation groups provided a manageable amount to be implemented efficiently without being too granular:

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[7] The following section is a short version of a journal paper that has been published in the Transportation Research Record. Please use the following citation to cite the full paper (*70*): *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. Transportation Research Record, 2677(4), 298–312. https://doi.org/10.1177/03611981221090241.*

white collar (e.g., attorney, manager, accountant, engineer), blue collar (e.g., waiter, retail worker, cashier), teacher (e.g., grade school to high school teacher, college, and university professor) and other (e.g., peace officer, coach, musician). the cross-tabulation of two categories in the sample (N = 1,274).

Table 4-1. Number of cases by current occupation and adjusted household income level

Adjusted household income level	White collar	Blue collar	Teacher	Other	Not working	Total
High	205	14	17	21	138	395
Medium	154	40	21	15	161	391
Low	81	52	12	12	257	414
Prefer not to answer	23	8	4	1	38	74
Total	463	114	54	49	594	1,274

4.4.3 Findings

For the full sample, those who indicated that they “never used ridehailing” dropped from 44.9% to 40.1%. This difference highlights the growth in the adoption rate in the sample, and in the general population, between 2018 and 2020. The portion of the sample that reported that they have used a ridehailing service “in the last 30 days” dropped from 18.7% to only 7.0% during Spring 2020, however. This may signal a substantial reduction in demand and/or an aversion to ridehailing because of the shared nature of the service.

Ridehailing use patterns differed statistically by income and occupation in the same timepoint. Use patterns compared across income levels reveal that the adoption rate (non-zero responses) is greater for high-income people compared with the middle- and low-income people. This is consistent with the literature, which documents high-income people using ridehailing more often than other groups (*32*). However, the high-income group also had the greatest portion of inactive users at T2 (66.8%). Their occupation allows for telecommuting, with 76.6% telecommuting four or more times a week. Alternatively, they may have more flexibility in their travel mode, as they were not locked into ridehailing services for transportation and have reasonable access to other options. A private car(s) would be the primary alternative. Indeed, 95.5% of high-income, inactive transportation network company (TNC) users have access to at least one car, and 66.7% have access to two or more cars.

The reverse of this pattern is demonstrated by the low-income group. This group has the largest percentage of users actively using ridehailing services in the last 30 days during the peak of the pandemic, at 11.4%. This suggests that ridehailing that has continued to meet the travel demand of many low-income users, consistent with findings from a study in Toronto, Canada (*33*). Many of the low-income cases in the sample have no regular access to a household vehicle (55.3% without a car), and they still needed to physically commute to work (47.4% telecommuted zero times a week). A follow-up study of the extent to which income and vehicle access account for ridehailing use during the pandemic would expand this understanding.

Continuing this line of inquiry, ridehailing data were then analyzed with respect to the occupation category of respondents. White-collar and blue-collar workers mirrored trends in the high/middle-income and low-income categories. Blue collar ridehailing usage patterns also show a larger magnitude of resilience during the pandemic. This group experienced the greatest gain in the overall adoption rate among any occupation group, with an increase of 9.7%, and the largest percentage of active users during the pandemic, at 14.9%. Teachers reported a reduction in ridehailing usage similar to white collar workers, though teachers did not experience an increase in their adoption rate of a similar magnitude. Given the heterogeneous nature of the "other occupation" category, it is not possible to confidently draw conclusions about the changes in travel behavior of the respondents in this category.

Table 4-2. Summary of self-reported ridehailing use in last 30 days

Subsample	Time period	Response		
		Never used (%)	Not in last 30 days (%)	Used in last 30 days (%)
Full sample *** (n=1274)	T1	44.9	36.4	18.7
	T2	40.1	52.9	7.0
HHI: high income*** (n=395)	T1	35.9	39.7	24.3
	T2	28.4	66.8	4.8
HHI: middle income*** (n=391)	T1	42.7	38.1	19.2
	T2	40.9	54.0	5.1
HHI: low income*** (n=414)	T1	54.1	31.6	14.3
	T2	48.8	39.9	11.4
Occupation: white collar *** (n=463)	T1	29.6	40.0	30.5
	T2	23.3	68.9	7.8
Occupation: blue collar *** (n=114)	T1	43.9	40.4	15.8
	T2	34.2	50.9	14.9
Occupation: teacher *** (n=54)	T1	38.9	44.4	16.7
	T2	37.0	57.4	5.6
Occupation: other *** (n=49)	T1	49.0	28.6	22.4
	T2	40.8	46.9	12.2

Notes: HHI = household income level. Homogeneous distributions across different response levels between T1 and T2 are tested with Person's chi-square test, *** $p<0.01$.

5 The Impact of the Pandemic on E-Commerce

5.1 Changes in Online Shopping Patterns [8]

5.1.1 Introduction

Pandemic-related lockdown measures limited people's ability to shop in-person and led to an increase in e-shopping. However, there is uncertainty about the ways in which these shopping behaviors have and may continue to transform our day-to-day activities, travel behaviors, and urban landscapes. One of the big questions is whether e-commerce habits established during the pandemic might carry forward once life returns to "normal." Some new e-customers may revert to shopping in person while others may not. Understanding the factors that influenced grocery shopping behavior in relation to COVID-19 can inform business and government responses in future crises. In this study, we attempt to explore two fundamental questions: (a) who is responsible for the rise in e-commerce from Fall 2019 to Fall 2020 and (b) to what extent will the growth in online shopping induced by COVID-19 persist into the future?

5.1.2 Data and Methods

We focus on respondents who were recruited through the Fall 2020 re-contact method who had previously participated in the Spring 2020 version of the COVID-19 Mobility Study survey (N=1,723). Using this portion of the data, a longitudinal panel with three time periods was created with Fall 2019 responses collected in the Fall 2020 Study serving as the time period before the pandemic (T_1), Spring 2020 COVID-19 Mobility Study representing the time period during the early months of the pandemic (T_2), and Fall 2020 responses collected in the Fall 2020 COVID-19 Mobility Study denoting the time period further along in the pandemic (T_3). Participants in the Spring 2020 Survey were asked to report responses during the period between March and April 2020, whereas participants in the Fall 2020 version of the survey were asked to report responses in the period between October and December 2019 and 2020.

To model online shopping frequency during the three time periods of analysis, a set of consecutive ordinal logit models were estimated. We opted for this method as the nature of our variable of interest, namely online shopping frequency, is ordered and discrete. To address potential inertia and control for past online shopping behaviors when modeling e-shopping frequency during the pandemic, we included the dependent variable of the first time period (Fall 2019) in the specifications of the subsequent models. As these three different models are estimated independently, it is not possible to directly compare the parameters' magnitude to test

[8] The following section is a short version of a paper that was peer-reviewed and published in the journal Regional Science Policy & Practice. Please use the following citation to cite the full paper (*71*): *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 & Practice, 1– 17. https://doi.org/10.1111/rsp3.12514*

differences in the net effect over the dependent variable. Hence, the marginal effects are also calculated for each of the models to facilitate their comparison.

5.1.3 Findings

The temporal variation in online shopping frequency demonstrates how many individuals who never, or rarely, shopped online prior to the pandemic began doing so at least once a week in the Spring 2020 period, but eventually reverted to doing so less frequently, while not giving up this behavior entirely (Figure 5-1).

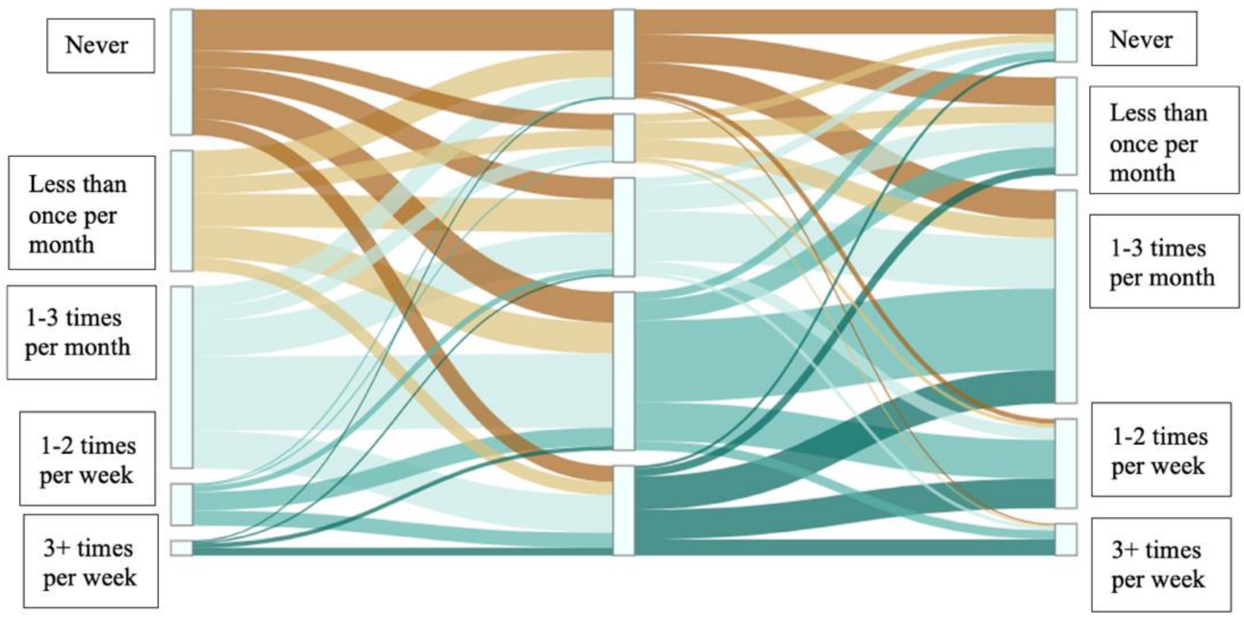

Figure 5-1. Visualization of online shopping frequency over time (n = 1,722)

We then conducted a series of ordered logistic regressions to establish which respondents were most likely to have modified their online shopping behavior during our study period. The dependent variable in our models is *online shopping frequency* and it is divided into five ordered categories: (a) never, (b) less than once per month, (c) one to three times per month, (e) one to two times per week, and (f) three or more times per week.

Prior to the start of the pandemic, younger respondents were more likely to shop online. However, the significance of this relationship subsides once the pandemic started as respondents from all age categories were confronted with the same COVID-19 restriction measures and responded by shifting to shopping online. Men were more likely to shop online than women in Fall 2019 period, yet women became significantly more likely to shop online than men once the pandemic began. Education, which was not a significant factor in online shopping behavior in Fall 2019, appears to have played a role in the early months of the pandemic. In comparison to those having started or only completed a high school degree, respondents with a graduate degree were 8.5% less likely to never shop online and 16.5% more likely to do so three or more times per week. Using the adjusted income variable, modified to account for household composition and regional cost of living, we found that respondents from the highest income group were more likely to shop online in the Fall 2019 and

Fall 2020 periods in comparison to those belonging to the lowest income group (with an annual household income of $24,943 or less). This relationship is not significant in the Spring 2020 period. At this time, respondents from all income categories were confronted with similar in-person shopping restrictions due to strict COVID-19 lockdown measures.

In accordance with Cao et al. (*47*), we find that respondents living in urban neighborhoods shopped online more frequently than their suburban or rural counterparts in Fall 2019. However, this relationship appears to reverse itself once the pandemic begins. This may, perhaps, be due to the proliferation of conventional indoor shopping malls in suburban areas. Those shopping mall facilities with large, enclosed space could not always accommodate curbside pickup. In comparison, centrally located stores were more capable of, and therefore likely to, provide curbside pickup. The lack of curbside pickup options at shopping malls may have led some shoppers to feel averse to shopping in-person. The reduction in this effect over time further supports this hypothesis, as malls were gradually able to reopen.

Owning digital devices appears to have influenced online shopping frequency. Prior to the start of the pandemic, owning fast internet significantly increased the likelihood that respondents would shop online. A respondent without fast Internet, for instance, was 18.3% more likely to never have shopped online in the Fall 2019 period. Conversely, once the pandemic began, the device most positively associated with online shopping frequency became smartphones. Respondents who owned a smartphone were 9.2% more likely shop online three or more times per week in the Spring 2020 period.

Attitudes towards e-shopping influenced the likelihood of respondents to shop online. Respondents who indicated that they were satisfied with online shopping options available to them were more likely to shop online. In contrast, those who stated that they find everything they need when physically going to a grocery stores were significantly less likely to shop online, particularly in the early months of the pandemic when agreeing with this statement correlated to a 3.3% increase in the likelihood that respondents have never shopped online.

Lastly, to account for respondents' initial online shopping behavior, we included their Fall 2019 online shopping frequency levels in the Spring 2020 and Fall 2020 models. We found that those who frequently shopped online in Fall 2019 were more likely to continue doing so. Indeed, respondents who shopped online one to three times per month in Fall 2019 were 12.1% more likely to shop online three or more times per week in Spring 2020 and 7.7% more likely to do so in the Fall 2020 period. Online shopping rates increased for respondents who already shopped online one to two times per week in Fall 2019. The likelihood of people in this group shopping online three or more times per week in Spring 2020 was 29.7% and rose to 47.6% in Fall 2020. This finding suggests that the rise e-commerce induced by COVID-19 was primarily caused by an increase in purchasing frequency by experienced online shoppers rather than the result of this sector now reaching a broader share of the population, especially in the long-term.

5.2 Changes in Grocery Shopping Patterns [9]

5.2.1 Introduction

Following the rapid and widespread adoption of e-commerce during the COVID-19 pandemic, we hypothesize that a significant number of customers would develop a preference for online shopping, potentially resulting in a decline in traditional in-store retail experiences (*48–50*). This study analyzes factors that influenced grocery shopping behavior changes by comparing in-store and online grocery shopping before and during the pandemic. We studied causal effects of pandemic-era changes in activities, personal attitudes around lifestyle, mobility, and the environment, and as socio-demographic characteristics. Insights from this investigation may enable public authorities and regulators to improve responses to emergencies. Findings may also inform market research teams about their customers' needs and changing habits, some of which may extend beyond the end of the current pandemic.

5.2.2 Data and Methods

We base this study on the Spring 2020 COVID-19 survey dataset within the state of California. The survey contains questions that investigate timeframes before COVID-19 (February 2020 or before) and during COVID-19 (March-June 2020). A total of 2,948 respondents fully completed the survey. . Only 0.02% of respondents did not own a phone, laptop, computer desk, and tablet. This may limit the representativeness of the analysis, as it does not account proportionally for the segment of population that was "unconnected" vis information and communication technology at the time of the data collection.

We implement a bivariate probit model to jointly model changes in grocery store visits and on-line grocery shopping before vs. during the COVID-19 pandemic as a function of explanatory variables. We studied the difference between (a) change of in-store trips frequency and (b) change of frequency in online grocery shopping (Table 5-1). About half of the respondents in our sample (52.7%) decreased their visits to the grocery store, while 30.80% increased online grocery shopping.

This study compares in-store and online grocery shopping before and during the pandemic. Examples of shifts that might decrease visits to stores without necessarily decreasing in-store purchases are (1) buying more items per visit or (2) preferring one-stop stores that offer everything vs. specialty stores. Increased online shopping is another possible cause of reduced visits to stores. Factors such as these are accounted for in the conceptual model for this study (Figure 5-2).

[9] The following section is a short version of a paper that was peer-reviewed and is accepted for publication in the journal of Transportation Research Record. Please use the following citation to cite the full paper (*72*): *Compostella, J., K. Wang, X. Iogansen, and G. Circella. Trips to the Grocery Store and Online Grocery Shopping: A Comparison of Individual Behaviors before and during the First Wave of the COVID-19 Pandemic. Transportation Research Record: Journal of the Transportation Research Board, 2023. https://doi.org/10.1177/03611981231172505.*

Table 5-1. Distribution of response variables across the sample; count and percent or total (n= 2,948)

			Grocery shopping online			Total
			Decreased [Other (0)]	Same [Other (0)]	Increased	
Visiting grocery store	Decreased (1)	Decreased	124 (4.2%)	804 (27.3%)	627 (21.3%)	**1,555 (52.7%)**
	Other (0)	Same	79 (2.7%)	902 (30.6%)	235 (8.0%)	**1,216 (41.2%)**
		Increased	24 (0.8%)	107 (3.6%)	46 (1.6%)	**177 (6.0%)**
		Total	**227 (7.7%)**	**1,813 (61.5%)**	**908 (30.8%)**	**2,948 (100%)**

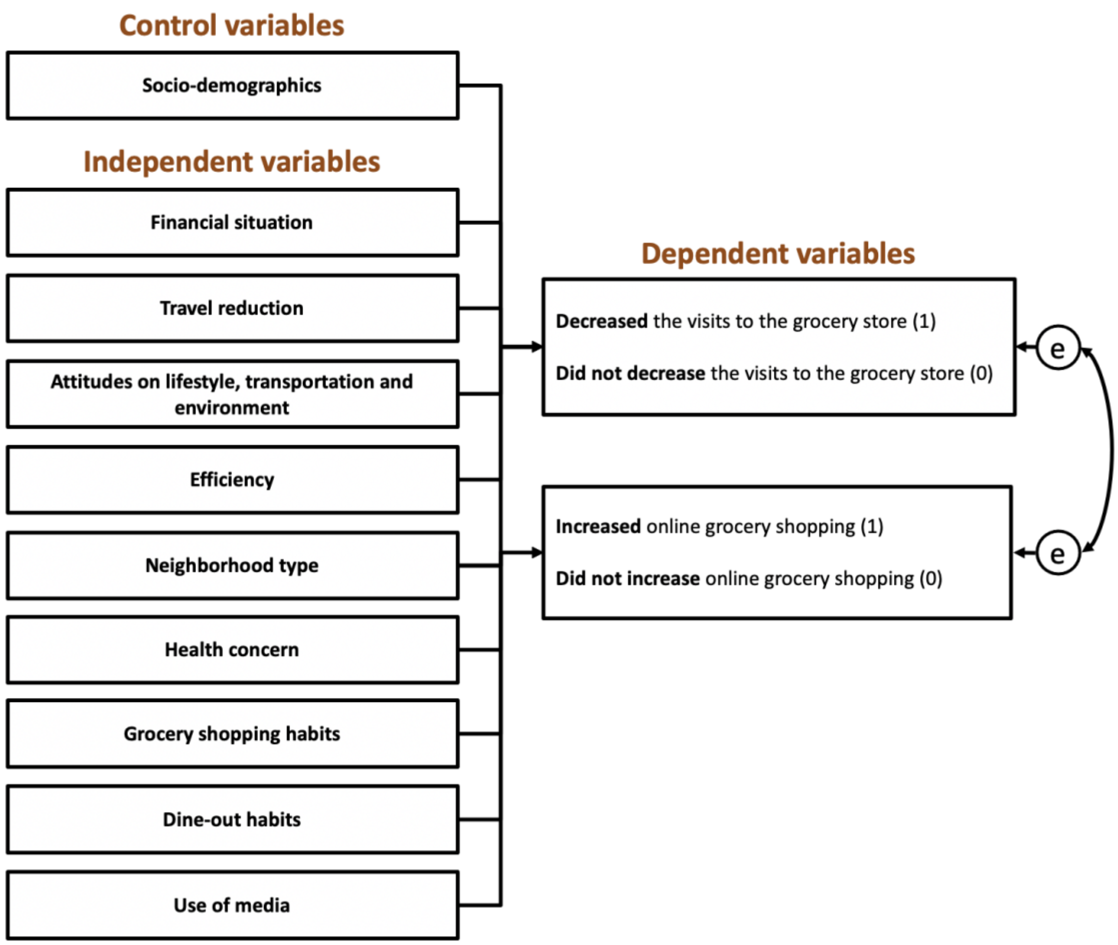

Figure 5-2. Conceptual model

5.2.3 Findings

Those who still traveled to work during the pandemic were less likely to decrease grocery store visits. These people may have linked out-of-home trips in a chain that includes going to the grocery store. Similarly, people who enjoy driving may have been more likely to visiting grocery stores despite the pandemic. These findings relate to previous work (*51*) which identified boredom as a motivator for people to visit stores, regardless of social distancing guidance, as an alternative to spending time at home. We find an association between an individual's proclivity for a variety of online shopping categories (clothing, medicines, etc.) and an increase in online grocery shopping during the pandemic. Individuals who have a consumerist nature who experience stress from traumatic event (e.g., a pandemic) are more likely to spend compulsively as a result (*52*). We found that the use of social media platforms had a powerful effect on pandemic awareness and consequent public behavior (*53*). Our data showed that more frequent media users tended to decrease their visits to the store and increase online shopping. Perhaps those who transition to online commerce are more tech savvy than those who do not. Our findings support the hypothesis that those who applied for an unemployment benefit are less likely to increase online grocery shopping. The reason behind could be that online shopping tends to be costlier than in-person shopping (*54*).

We found that the perceived risk of COVID-19 infection influences people's activities (*55*). Those who reported concern about health impacts of the pandemic were more likely to decrease in-person visits to grocery stores and more likely to increase online grocery shopping than those who were not concerned. While concerned individuals might feel inhibited by stay-at-home orders and follow social distancing rules; neutral people, who did not have a strong opinion, did not exhibit significant changes in behavior.

Our findings confirm that trips to the store during the pandemic were fewer, overall. People who visited few stores than before the pandemic (i.e., visiting one single store that sells everything as opposed to a variety of stores for different products) were more likely to decrease in-person visits to the grocery store. Our research suggests that people who purchased more grocery items per visit compared to pre-pandemic time were more likely to increase online grocery shopping. Our results also confirms that the number of items people purchased per visit went up and people tended to buy more in bulk.

During the pandemic, many restaurants closed, so people who would normally eat at restaurants opted to cook and eat at home. As supported by the US Department of Agriculture, which reported that consumers increased expenditures on groceries and decreased food-away-from-home expenditures, we found that those who decreased dining-out were more likely to increase online grocery shopping and decrease store visits. The latter, perhaps, in accordance with stay-at-home rules.

Other correlations with our responses included: (a) non-white respondents, who represented the minority in our sample, were less likely to increase online grocery shopping as compared to whites and (b) higher percentage of middle-income people increased online shopping (35.5%) than that of high-income people (32.2%), and the former group increased shopping frequency (multiple times per week vs. monthly) more than the latter.

Thus, we found that people in middle-income group were more likely to participate in online grocery shopping than higher income people. On the contrary, lower income people were found to shop online less than higher income people (although not statistically significant in the model).

5.3 Delivery Service Preference for Online Shopping [10]

5.3.1 Introduction

Delivery services associated with online retailers might have changed along with the rapid growth in e-commerce sales during the early phase of the COVID-19 pandemic. Consumer characteristics and e-shopping frequency by type of delivery may also have changed. Few studies have assessed the impact of COVID-19 on home delivery services (*56*), delivery limitations by home location, and/or lessons learned about delivery services. Therefore, this study focuses on the following questions:

- What were the online shopping patterns for delivery services during the COVID-19 pandemic?
- Who shopped online?
- How often did individuals purchase items online during the pandemic?
- Did delivery service preferences differ by demographic characteristics?
- Were there limitations to online shopping and delivery services for people who do not live in urban areas?
- What lessons were learned from the analysis of delivery methods available during the COVID-19 pandemic?

5.3.2 Data and Methods

This study uses the spring 2020 COVID-19 survey dataset which contains information on e-shopping patterns during the early phase of the pandemic. There were questions about which commodities respondents bought online and the type of delivery options that they chose for online purchases in the previous 30 days between March and April 2020. Six delivery options were listed in the survey: same-day delivery (e.g., Amazon Prime Now, Instacart), fast delivery or one-day/ two-day delivery (e.g., Amazon Prime), standard delivery (three or more days), order online with pick-up at a local store (e.g., Costco, Target), order online with delivery to pick-up locker (e.g., Amazon Locker), and international shipments with longer delivery times. With this information, the study explores online shopping frequencies, delivery options, and e-shoppers' attributes such as age, educational background, employment, income group, and type of neighborhood. Frequencies were measured on a Likert-type scale with values ranging from "never" to "five or more times a week".

[10] The following section is a short version of a thesis this is available in ProQuest Dissertations Publishing. Please use the following citation to cite the full thesis (*73*): Silaen, M. *(2022). Evaluating Delivery Service Preference for Online Shopping During the Early Phase of the COVID-19 Pandemic. University of California, Davis.* *https://www.proquest.com/openview/07579552dd285c033adcc25b80e7c951/1?cbl=18750&diss=y&pq-origsite=gscholar&parentSessionId=uhwaATvb67zymUe4akVRxRY6kTMkUdzYt5PiH0vCp7Q%3D (accessed 9 August 2024).*

This study implements three statistical analyses using data from 8,593 respondents. The first analysis employs exploratory data analysis to define a set of variables that influence the online shopping behavior of respondents. The second analysis estimates a set of binomial logistic regression models to analyze the behaviors of respondents who used each delivery option for online purchases and those who did not use them. Results from the exploratory data analysis and the model estimation were used to identify covariates that relate to the sociodemographic of each latent class in the subsequent analysis. The third and final analysis, latent class cluster analysis (LCCA), segments respondents into groups based on their online shopping behavior by counting deliveries for online purchases made in the previous 30 days (i.e., during the early COVID-19 pandemic between March and April 2020)

5.3.3 Findings

The results show that gender is statistically significant in the model for every delivery option. Males positively correlated with same-day delivery, locker pickup, and international delivery. Age negatively influences the use of same-day delivery, fast delivery, and local pickup. Our previous analyses (*57*) using the same survey data showed that books, clothing, medicine, and restaurant delivery were commodities that female e-shoppers were more likely to buy, compared to their male counterparts. Our previous analyses (*57*) found that age has a positive correlation with the frequency of buying medicine online, only.

Education level increases the likelihood of using fast delivery, standard delivery, and local pickup, while student status positively affects the use of same-day delivery, locker pickup, and international delivery. People who do not work are less likely to use same-day delivery, and those who have part-time jobs are more likely to use the locker pickup option. Agreement with the attitudinal statement measuring the degree to which the respondent likes to be among the first people to have the latest technology is found to be a better predictor of e-shopping adoption for every delivery option than attitudinal statements measuring how much the respondent likes to try new things or likes driving. Owning a smart device and having fast internet service increases the likelihood of e-shopping using almost every delivery option. Household income is found to affect the likelihood of using all delivery options, except locker pickup and international delivery. Those with higher incomes are more likely to use every delivery option. People in suburban areas are positively correlated with the use of fast delivery and negatively associated with the use of locker pickup and international delivery. Households with kids and members with health risks are more likely to engage in e-shopping.

Logistic regression results support exploratory data analysis where the five variables of age, educational background, household income, type of neighborhood, and attitudinal characteristics have a strong impact on e-shopping frequency. Other variables that may increase the likelihood of someone shopping online and using one of the delivery options are: student status, and employment.

Our LCCA model reveals three distinctive classes with unique socio-demographic features. Class 1 or Occasional Shoppers (50.7% of all respondents) are respondents who shopped infrequently; some made one to three, or more than three, online purchases in a month, while others made no online purchases. They prefer fast and standard delivery. Class 2 or Non-Shoppers (43.2%) are people who made few or no online purchases, which mainly fall into the zero-frequency category. Class 3 or Super Shoppers (6.1%) are shoppers who made frequent online purchases (three or more purchases in a month).

People in the 55+ age group, compared to the 18 to 34 age group, are more likely to be in the Non-Shoppers class than the Occasional Shoppers class. The same is true of the 35 to 54 age group, but with a lower magnitude. Compared to the 18 to 34 age group, respondents in the 55+ age group are less likely to be in the Super Shoppers class than the Occasional Shoppers class.

People who stated they “somewhat agree” or “strongly agree” that they like to be among the first people who have the latest technology, are less likely to be in the Non-Shoppers class than the Occasional Shoppers compared to those who reported negative attitudes toward adopting new technology. This tendency is even clearer when comparing Super Shoppers and the Occasional Shoppers. People with positive attitudes toward adopting new technology are more likely to belong to the Super Shoppers class.

Respondents with more education are less likely to belong to the Non-Shoppers class than the Occasional Shoppers class. Lower-income respondents are less likely to belong to the Super Shoppers class than the Occasional Shoppers class. People with higher income will be less likely to belong to the Non-Shoppers class compared to the Occasional Shoppers class.

The type of neighborhood that respondents live in clearly relates to online shopping behavior. Compared to people who live in urban areas, those who live in other places are more likely to belong to the Non-Shoppers class or the Super Shoppers class. Those who live in urban areas are more likely to be Occasional Shoppers. Most Super Shoppers are respondents who have positive attitudes toward technology, with more than 80% of respondents belong to this class, while only 26% of Non-Shoppers have this attitude. Occasional Shoppers have a relatively even distribution of respondents who have positive and negative attitudes toward technology. Most Occasional Shoppers and Super Shoppers are part of higher income groups, while the Non-Shoppers class is dominated by lower-income respondents who have less than $50K annual income. Shares of respondents by type of neighborhood are significantly different by class. Super Shoppers is dominated by people who live in urban areas (64%), followed by those who live in suburban areas (30%), while the remaining shares belong to those who live in either small towns or rural areas. Occasional Shoppers and Non-Shoppers have a similar pattern of shares, with the largest group of respondents living in suburban areas, followed by urban areas, small towns, and rural areas.

6 Conclusions and Policy Implications

The COVID-19 pandemic disrupted many aspects of individuals' lives, as evident from our study analyzing three repeated cross-sectional datasets collected in Spring 2020, Fall 2020, and Summer 2021 in California. In this final section of the report, we provide a summary of the findings. We aim to inform planners and policymakers in California about ongoing and future impacts of the pandemic on transportation and society. Strategies based on the policy implications presented in this section will enhance transportation and social equity.

6.1 Support Equitable Transition to New Work Arrangements

The pandemic led to a significant shift to remote work during its early phases. During its later phases, there was widespread adoption of hybrid work among certain groups of workers. The shift towards hybrid work is expected to continue in the future. The persistence of remote and hybrid work arrangements, and the way they will further evolve in the future, remain a topic of relevance for planning and policy making.

Employers should develop policies for flexible work arrangements to attract and retain talent and improve productivity. Changes in work arrangements will have longer-term impacts on the reorganization of workspaces. For example, office space use and ratios between office and parking space may be modified. As such, local governments need policies to manage underutilized space and promote livability in central business districts. Additionally, maintenance of infrastructure and public services should be prioritized for areas with a larger share of workers who are present at job sites, such as manufacturing plants, retail stores, universities, and hospitals.

The impact of the pandemic on employment has not been equitable. Low-income, less educated, or part-time workers in rural areas faced greater challenges in keeping their jobs and adopting remote or hybrid work during the pandemic. Policy discussions should focus on this issue for better economic recovery. In addition, as cities emerge from this era of disruption, transportation agencies must evaluate and adjust services based on emerging needs. This includes providing services for those who have transitioned to remote or hybrid forms of work, while also ensuring that those who commute physically have access to safe travel choices and effective precautionary measures. More in-depth investigation of these topics is necessary to inform tailored policies for a flexible and efficient work environment.

We found that, overall, commuters reduced their commuting trips. Although physical commuting rebounded somewhat by Summer 2021, there is a continuing trend of reduced commutes, relative to pre-pandemic travel. As expected, remote work showed an opposite and complementary trend. The frequency of remote work increased during the pandemic and then slightly declined by Summer 2021 among remote workers.

There is a complex relationship between the pandemic, physical commutes, and remote work. Remote work reduces commute trips, but it may also increase home-based trips for other purposes, potentially offsetting any travel reduction achieved. More studies are called to assess the net effects of remote and hybrid work on travel demand. In particular, data on the activities that remote workers engage in during the day will be critical for informing post-pandemic transportation planning (*58*). We anticipate substantial variations in their non-work trips. This may include trip types, routes, and timing. This could lead to a redistribution of trips from peak hours to non-peak hours or even to "redefined" peak hours, as well as a redistribution of the spatial-temporal patterns of trips.

In response, transportation agencies should deemphasize peak-hour traffic management. Instead, they should take advantage of additional roadway capacity throughout the day as an alternative to physical expansion of roadways. Similarly, public transit services should be redistributed to capture demand for non-work purposes and balance between peak and non-peak time, as well as between regional and local services. Planners may consider combining fixed-route, fixed-schedule transit services with flexible, on-demand services.

6.2 Seize the Window of Opportunity to Reduce Car Dependence

Our study found that individuals with tech-savvy and variety-seeking attitudinal attributes were more likely to have made changes in vehicle ownership. Previous studies suggest that they are also more inclined to embrace options such as electric vehicles (*59*), autonomous vehicles (*60*), and shared mobility services such as ridehailing (*61*), carsharing (*62*) and micromobility (*63*). 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 impact on reducing carbon emissions.

We also demonstrated that individuals who are pro-environment and agree on higher costs for driving were more inclined to relinquish their personal vehicles. However, these sentiments are more prevalent among the highly educated, high-income, and urban residents. Therefore, raising environmental awareness among all individuals, regardless of their demographics, will assist this transition.

Policymakers can implement pricing strategies to disincentivize car use and generate revenue for public transportation. For instance, tolling through managed lanes and congestion pricing policies can increase the cost of driving in congested urban areas. These policies can be designed to be progressive, meaning that they are tailored to the financial situation of individual travelers and can exempt low-income individuals from the financial burden.

Health concerns arising from the COVID-19 pandemic have increased pro-active lifestyle choices. For some, this has reduced the attractiveness of vehicle ownership. This presents a unique opportunity for some people to break long-held travel habits. Cities can invest in walking and biking infrastructure to promote active and sustainable transportation options over cars.

On the other hand, COVID-19 health concerns have also been found to increase private vehicle ownership by some individuals, potentially due to the fear of virus transmission in public with shared travel modes.

Transportation agencies and mobility providers should continue safety measures including regular sanitization of the vehicles and providing ample space for physical distancing.

Our study found that younger individuals experienced more volatile changes in vehicle ownership compared to their older counterparts. This can be attributed to their more dynamic household composition, financial condition, and student/work status. To avoid a COVID-19-induced car ownership boom, policies that divert younger individuals away from increasing vehicle ownership and promote alternative modes of travel are crucial.

In general, students and workers tend to have greater personal mobility needs, making stable or increased vehicle ownership more desirable for them. They tend to change ownership status to meet the needs of their changing student or worker roles.

Despite the meteoric rise in remote work, and the commensurate reduction in travel during the peak of the pandemic, many companies do not have a well-formulated remote working policy. As a result, even though some workers switched to remote work and reduced their commuting days during the pandemic, they may have been hesitant to dispose of their vehicles without knowing what their employer's future remote work policy would be. Therefore, governments should support companies in formulating clear polices to guide and manage remote and hybrid work arrangements. This can create certainty, allowing workers settle into a new pattern of travel and vehicle ownership. For instance, 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 during and after the pandemic, such as part-time essential workers, increased 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. Our study showed that those in the highest income category or those who experienced an increase in income during the pandemic were much more likely to acquire or replace vehicles, compared to low-income individuals. Therefore, it is crucial to provide more travel alternatives for this group. Government and employers could consider offering incentives for active commuting, such as biking or walking, or providing subsidies for ride-hailing services.

Furthermore, our research suggests that understanding household characteristics is crucial when analyzing vehicle ownership patterns. Specifically, households with multiple family members exhibit greater variability in vehicle ownership. Presence of children is positively associated with increased vehicle ownership, while a decrease in household size is linked to a decrease in vehicle ownership. A deeper understanding of how vehicles are shared and utilized among family numbers and how daily trip chaining patterns are structured can help policymakers and car manufacturers meet the needs of families.

6.3 Sustain Momentum in Active Mobility

Our study provides evidence for widespread increases in walking and bicycling during the early months of the pandemic. However, much of the increase was erased or considerably eroded by Fall 2020. This suggests that changes in travel behavior due to the pandemic are not likely to be lasting unless specific policies to promote and/or maintain desired behavioral changes are implemented.

Our results suggest that active travel modes require facilitation. Popular strategies implemented early in the pandemic included full or partial street closures from cities such as Oakland, California. Oakland closed 74 miles of city streets to vehicular through-traffic. Similar traffic calming projects in other cities, often framed as "Open Streets" or "Slow Streets," could become permanent features of the built environment to encourage and facilitate the use of walking and bicycling. Traditional traffic calming strategies such as road diets, lowering speed limits, and restricting streets to local traffic are also available as preexisting tools for transportation planners to make the built environment more accessible for pedestrians and bicyclists.

Accessibility for pedestrians and bicyclists can be improved with infrastructure such as new bike lanes, multi-use trails, and amenities such as pocket parks and urban plazas. Unfortunately, Slow Streets pilot programs in many cities were terminated following the lifting of COVID-19-related restrictions. Low-income and traditionally underserved neighborhoods stand to benefit the most from transportation investments and policies like Slow Streets. In addition to transportation planning solutions, rebates, tax incentives, and other monetary perks can encourage active travel modes. The Electric Bicycle Incentive Kickstart for the Environment Act and the Bicycling Commuter Act of 2019 are examples. Disincentives for car use, such as pricing parking, reducing parking minimums, congestion pricing, or car-free zones are likely to support active travel.

6.4 Support the Quick Recovery of New Mobility Services

COVID-19 impacts on new mobility services, such as ridehailing usage, illuminate underlying inequities in the transportation network that need to be addressed. Data from our study demonstrate that lower-income and blue-collar users are more dependent on ridehailing. These new services are filling a demand in the market. Their use has increased across all segments.

In response to concerns about virus transmission, ridehailing services were quick to stop offering shared rides with other customers. However, rides are inherently shared between passenger(s) and driver in close quarters. This, riders might incorrectly assume they are safe simply because shared ridehailing services were shuttered. This puts a burden on both drivers and riders to be extra cautious, while those who completely stopped using ridehailing services were not exposed to this potential transmission vector.

Ridehailing drivers have less incentive to provide services when demand is low. Efforts to reclassify ridehailing drivers and other gig-economy workers from independent contractors to employees would provide more access to labor and social safety nets, such as unemployment insurance, which other traditional workers were able to utilize during this period. In November of 2020, California passed Proposition 22, a ballot measure exempting certain gig-economy workers from benefits previously established in California's 2019 Assembly Bill 5, which had reclassified many gig-economy workers as employees. Hopefully, this does not set a precedent for other jurisdictions. A more equitable and safer labor market for TNC drivers and other gig economy workers is desirable.

6.5 Accommodate and Drive the Growth of E-Commerce

Online shopping significantly increased during the pandemic. It remains above pre-pandemic levels. Transportation and city planners are advised to follow trends in online shopping, as they may influence residents' housing location decisions and reduce the frequency of shopping-related trips.

The COVID-19 pandemic led to an increase in remote work. This has removed the burden of commuting and increased the appeal of cheaper, distant housing locations. When coupled with the ability to purchase all necessary goods and services online, the decision to relocate further away from urban areas becomes even more enticing. This is particularly true for wealthier, well-educated individuals who are more likely to be able to work from home. As demonstrated in this study, this group was most likely to shop online during the COVID-19 pandemic. As such, many cities may experience an exodus as this segment of the population begins to find that the advantages of living in remote areas outweigh disadvantages.

The rate at which individuals are transitioning to online shopping is less than what was expected when considering the early months of the pandemic. Those responsible for the increase in online shopping during the COVID-19 pandemic are primarily experienced online shoppers. Thus, the effects of the rapid increase in e-shopping on housing location decisions and shopping-related trips may have been exaggerated and temporary. Indeed, longer-term impacts of the pandemic on e-shopping frequency were more modest. We recommend that cities seek out additional information to inform policy decisions in response to the repercussions of online shopping.

Grocery stores should continue to respond to shifts in consumer preferences. Consumers may have developed new habits such as purchasing in bulk and/or visiting one store that sells everything they need instead of visiting multiple specialty stores. Market research might help companies respond to demand volatility.

Groups of people who tended to switch to online grocery shopping could be targeted to expand the online grocery marketplace. These groups include higher and middle-income individuals and those who made online purchases of any sort.

As the influence of the pandemic wanes, we suggest that grocery stores advertise new safety and health protocols to in-person shoppers . Such measures might encourage those who decreased in-person store visits because they were concerned about their health by reestablishing trust

People who frequently use social media platforms to stay informed about the COVID-19 pandemic tend to decrease their visits to the store and increase online shopping. This finding can inform the work of public institutions so that in an eventual new state of emergency such as a pandemic they can establish rules that would make it mandatory for the media to raise public awareness based on experts' advice; as a result, misconceptions would be corrected, leading to safer public behaviors to help control the situation.

The socio-demographics and geographic locations of those who changed their in-person and online shopping patterns during the pandemic. These people are likely to continue shopping according to their new patterns. Shopping online is still largely an urban phenomenon which increased in the US and California during the pandemic. Current infrastructure and services may not be adequate to meet increased demands for goods delivery and curb-side pick-up. Emerging levels of e-commerce require policies for better freight infrastructure, goods delivery services, and curb design.

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